CLASSIFICATION OF CEREAL GRAINS USING MACHINE VISION

A Thesis
Submitted to the Faculty of Graduate Studies
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in partial fulfilment of the requirements for the degree of

Doctor of Philosophy

by

Samir Majumdar

Department of Biosystems Engineering
University of Manitoba
Winnipeg, MB, Canada
R3T 5V6

0-612-23634-X

THE UNIVERSITY OF MANITOBA

FACULTY OF GRADUATE STUDIES

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SAMIR MAJUMDAR

A Thesis/Practicum submitted to the Faculty of Graduate Studies of The University

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DOCTOR OF PHILOSOPHY

Dedicated to my beloved mother
and
in memory of my father

ABSTRACT

Digital image analysis (DIA) algorithms were developed to facilitate classification of bulk samples of Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats, and rye using textural and color features of the grains. To classify individual kernels of CWRS wheat, CWAD wheat, barley, oats, and rye, DIA algorithms were developed based on morphological, textural, and color features of the grains.

The textural features of bulk samples and individual kernels were extracted from different colors (e.g., red, green, or blue) and color band combinations [e.g., black&white {(R+G+B)/3)}, (3R+2G+1B)/6, (2R+1G+3B)/6, or (1R+3G+2B)/6] of images to determine the color or color band combination that gave the highest classification accuracies in cereal grains. For bulk samples, the textural features extracted from the red color band at maximum gray level value 32 gave the highest classification accuracies in cereal grains. The mean accuracy which was the average of the classification accuracies of the cereal grains at a maximum gray level value, was 100.0% when tested on an independent data set. For individual kernels, the textural features extracted from the green color band at maximum gray level value 8 gave the highest classification accuracies in cereal grains. The mean accuracies were 92.0 and 92.9% when the texture model with the first 15 most significant features was tested on an independent data set and on the training data set, respectively. When the original bulk images were partitioned into sub-images and textural or color features extracted from the sub-images were used, the classification accuracies of cereal

grains decreased compared to those based on the original images. The mean accuracy was 100.0% when color features of bulk samples were used for classification of cereal grains in an independent data set.

For classification of individual kernels of cereal grains, the color model with the first 10 most significant color features gave mean accuracies of 93.4 and 94.9% when tested on an independent data set and on the training data set, respectively. The morphological model with the first 10 most significant morphological features gave mean accuracies of 94.2 and 96.0% when tested on an independent data set and on the training data set, respectively. The mean accuracies of 98.6 and 99.3% were achieved when the morphology-texture model with the first 15 most significant features was used to test on an independent data set and on the training data set, respectively. When the morphology-color model (with the first 15 most significant features) was tested on an independent data set and on the training data set, the mean accuracies were 99.4 and 99.6%, respectively. Similarly, using the texture-color model (with the first 15 most significant features) the mean accuracies were 98.4 and 98.0%, respectively for an independent data set and the training data set. The highest classification accuracies were achieved when the morphology-texture-color model was used. The mean accuracies using the first 20 most significant features in the morphology-texture-color model were 99.7 and 99.8% when tested on an independent data set and on the training data set, respectively.

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LIST OF ABBREVIATIONS

CWRS	Canada Western Red Spring
HRW	Hard Red Winter
SWS	Soft White Spring
SWW	Soft White Winter
CPS	Canada Prairie Spring
PSI	Particle size index
SEM	Scanning electron microscopy
GLCM	Gray level cooccurrence matrix
GLRM	Gray level run length matrix
R	Red
G	Green
B	Blue
H	Hue
S	Saturation
I	Intensity
RGB	Red-green-blue
HSI	Hue-saturation-intensity
FOV	Field of view
MF	Morphological features
TF	Textural features
CF	Color features
M	Morphology model
T	Texture model
C	Color model
M-T	Morphology-texture model
M-C	Morphology-color model
T-C	Texture-color model
M-T-C	Morphology-texture-color model
Npar	Non-parametric estimation

CHAPTER I: INTRODUCTION

Canada produced an average of 55 Mt (million tonnes) of grains and oilseeds worth about $ 6 billion annually during the years from 1983 to 1992 (Canada Grains Council 1994). About 70% of these grains are exported through a grain collection, handling, and shipping system. The producers store their grain on farms and usually deliver it in farm-trucks to primary (country) elevators (grain handling facilities). The grain is graded by visual inspection and comparison with standard samples (Anonymous 1994). The standard samples are prepared every year to reflect the year-to-year variation in the environmental conditions during harvest. Grain moves from primary elevator to terminal elevator by train.

In a terminal elevator, grain is received, graded, cleaned, binned, and shipped according to buyers' (importing countries') specifications. At the receiving end, it is necessary to rapidly identify the grain type in a rail car so that the grain can be unloaded into the unloading pit. A machine vision system (MVS) can be installed for rapid identification of different cereal grains (e.g., CWRS wheat, CWAD wheat, barley, oats, and rye). The MVS has to identify the principal grain type; hence bulk sample images of cereal grains can be used to solve the problem. In the cleaning section, the grain is inspected before and after it is passed through the cleaner or a battery of cleaners and the cleaning performance is determined. Such information can be used to optimize the selection and adjustment of the cleaning machines resulting in increased cleaning throughput and enhanced recovery of salvageable grains. The grain is exported (shipped) according to buyers' (importing countries') specifications. In some cases, if the grain is over cleaned, uncleaned and over cleaned grains are blended to meet buyers' specifications. Both at the cleaning and the shipping sections, the MVS can be installed to determine the cleaning performance of the cleaner (or a battery of cleaners) and the visual quality of the grain being exported. To monitor the cleaning performance, the MVS has to analyze two samples: one before the grain goes into the cleaner and the other after the grain comes out of the cleaner. The MVS should correctly identify all constituents of a grain sample in the cleaning and the shipping sections; thus individual kernel images can be used to solve this problem.

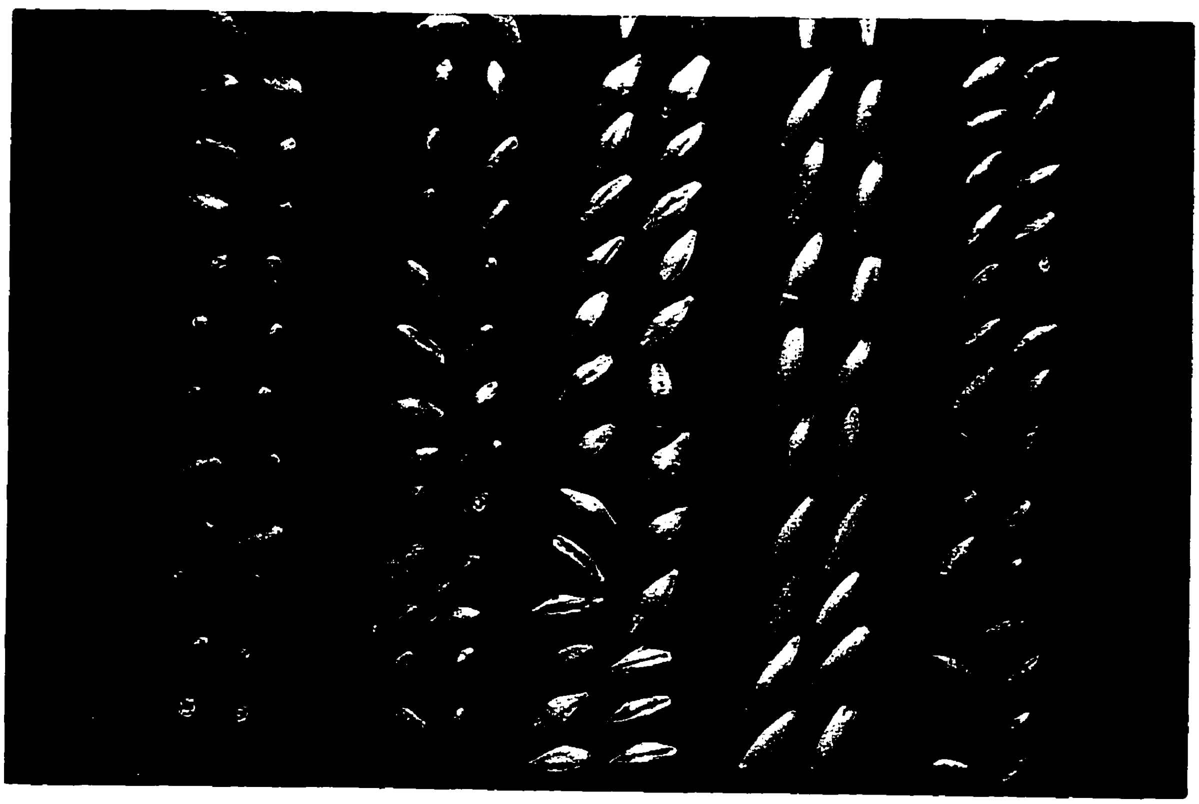
At present, subjective assessment of grain composition and appearance determines the identity and grade of a given sample. The five principal grading factors established by the Canadian Grain Commission are test weight, varietal purity, soundness, vitreousness, and maximum limits of foreign material. Of these, only test weight is objectively determined. Grading decisions on grains and other agricultural products, by and large, require visual inspection of the product sample by trained personnel. Despite training, the grading decisions are inherently subjective and are influenced by the individual experience of an inspector. An objective and quantitative method of measurement of grain characteristics would be highly desirable and beneficial. With the advance of computers and the improvements in the capabilities of computer vision technique, most of the kernels features employed in subjective grain inspection can be rapidly measured with high precision and accuracy.

Substantial work dealing with the use of different morphological (size and shape) features for classification of different cereal grains and varieties has been reported in the literature (Barker et al. 1992a, 1992b, 1992c, 1992d; Draper and Travis 1984; Keefe 1992; Keefe and Draper 1986, 1988; Lai et al. 1986; Myers and Edsall 1989; Neuman et al. 1987; Sapirstein and Kohler 1995; Sapirstein and Bushuk 1989; Sapirstein et al. 1987; Symons and Fulcher 1988a, 1988b; Travis and Draper 1985; Zayas et al. 1985, 1986, 1989). Some investigations were carried out using color features (Hawk et al. 1970; Majumdar et al. 1996a; Neuman et al. 1989a, 1989b) for classification of different cereal grains and their varieties and for correlating vitreosity and grain hardness of CWAD wheat (discussed in details in Chapter III). With clean samples, high classification accuracies among cereal grains have been reported using morphological and reflectance features (e.g., Neuman et al. 1989a, 1989b). The classification accuracy might change (most probably would be reduced) if tested on commercial samples, collected from different growing regions. The classification accuracy can be potentially improved by adding additional features based on texture (Petersen 1992). Addition of color features may also improve the classification accuracy. Figure 1.1 shows different types of cereal grains used in this study.

The objective of the proposed research was to test the following hypotheses:

(1) textural features of bulk samples can be used for rapid identification of different cereal grains, e.g., Canada Western Red Spring (CWRS) wheat, CWAD wheat, barley, oats, and rye.

  (i) reduction in the number of gray levels to a certain extent improves the classification accuracy and reduces computation time.



CWRS Wheat | **CWAD Wheat** | **Barley** | **Oats** | **Rye**

Fig. 1.1 Types of cereal grains used in this study

(ii) textural features extracted from the red color band give better classification accuracy than other color bands (e.g., green or blue) or color band combinations.

(iii) the classification accuracy improves when sub-images of an original bulk image are used for classification instead of the original bulk image.

(2) color features of bulk samples can be used for rapid identification of different cereal grains, e.g., CWRS wheat, CWAD wheat, barley, oats, and rye.

(3) morphological features of individual kernels can be used for classification of different cereal grains, e.g., CWRS wheat, CWAD wheat, barley, oats, and rye.

(4) textural features of individual kernels can be used for classification of different cereal grains, e.g., CWRS wheat, CWAD wheat, barley, oats, and rye.

(i) reduction in the number of gray levels to a certain extent improves classification accuracy and reduces computation time.

(ii) textural features extracted from the red color band give better classification accuracy than other color bands (e.g., green or blue) or color band combinations.

(5) limited color features of individual kernels can be used for classification of different cereal grains, e.g., CWRS wheat, CWAD wheat, barley, oats, and rye, and

(6) inclusion of textural and color features with morphological features of individual kernels can improve the classification accuracy of different cereal grains, e.g., CWRS wheat, CWAD wheat, barley, oats, and rye.

The material presented in this thesis is organized into eight chapters. The first chapter addresses the justification, importance, and the objectives of the research. Chapter II begins with a brief overview of the digital image processing system. It continues with an explanation of the principles of the machine vision technique. After that, discussion is presented on different morphological, color, and textural features. Chapter II is concluded with an overview of the object classification techniques, giving emphasis on the statistical classifier.

Chapter III discusses the past research conducted in the area of wheat grading using morphological and color features. It also reports different works in the agricultural area using textural features.

Chapter IV discusses the vision hardware, samples, and sampling and image acquisition techniques.

Development of DIA algorithms for textural, color, and morphological features is discussed in Chapter V.

Chapter VI contains the procedures for analysis of bulk samples and individual kernel images of cereal grains.

Results are presented in Chapter VII with discussions. The presentation of results follow the flow of experiments starting with classification of cereal grains using textural and color features extracted from bulk samples. The classification of individual kernels of cereal grains using morphological, textural, and color features are discussed. Results of different models for classification of individual kernels of cereal grains are reported. Chapter VII is concluded with the selection of the model that gives the highest classification accuracies in individual kernels of cereal grains.

Chapter VIII includes the conclusions and some recommendations made from the experimental results.

CHAPTER II: IMAGE PROCESSING AND OBJECT CLASSIFICATION

2.1 Digital image processing system

A digital image processing system is a configuration of hardware and software components that can acquire, store, display, and process digital images, as shown in Fig. 2.1. Although these components may be physically separated, each is fundamentally necessary to complete the digital image processing cycle.

2.1.1 Image acquisition devices The first stage in any digital image processing system is to acquire a digital image. This is achieved by using two separate devices: a sensor and a digitizer. The sensor device is sensitive to a band in the electromagnetic energy spectrum and produces an electrical signal output proportional to the level of energy sensed. The digitizer converts the analog electrical output of the sensor into a digital form.

Besides x-ray based imaging systems, most common sensors deal with visible and infrared light. Most frequently used sensors are vidicon cameras and solid-state arrays.

The operation of vidicon cameras is based on the principle of photo-conductivity. An image focussed on the tube surface produces a pattern of varying conductivity that matches the distribution of brightness in the optical image. An independent, finely focussed electron beam scans the rear surface of the photoconductive target and by charge neutralization, this beam creates a potential difference that produces a signal on a collector proportional to the input brightness pattern. A digital image is obtained by quantizing this signal, as well as the corresponding position of the scanning beam.

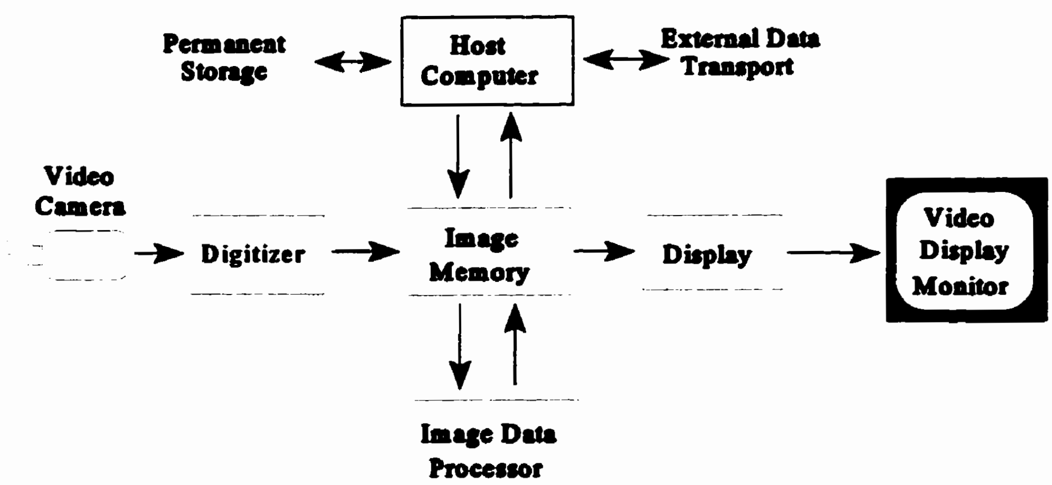


Fig. 2.1 The fundamental components of a digital image processing system

Solid-state arrays are composed of discrete silicon imaging elements, called photosites, that have voltage output proportional to the intensity of the incident light. Line-scan and area-scan sensors are the two types of solid-state sensors. A line-scan sensor consists of a row of photosites and produces a 2-D image by relative motion between the scene and the detector. An area-scan sensor is composed of a matrix of photosites and is therefore capable of capturing an image in the same manner as a vidicon tube. A significant advantage of solid-state array sensors is that they can be electronically shuttered at very high speed (e.g., 1/10 000 s). This makes them ideal for applications in which freezing of motion is required.

The line-scan sensors have resolutions ranging from 256 to 4096 elements. The resolution of the area-scan sensors ranges from 32 x 32 elements at the low end to 2048 x 2048 elements at the high end.

2.1.2 Storage An 8-bit image of size 1024 x 1024 pixels requires about 1 Mb (mega byte) of storage. One method of providing short term storage is through computer memory. Another is by specialized boards, called frame buffers, that store one or more images and can be accessed rapidly, usually at video rates (30 images per s). On-line storage generally takes the form of magnetic disks. The magneto-optical drives allow a Gb (one billion bytes) of storage memory on a 5.25" optical platter. Archival storage is characterized by massive storage requirements but infrequent need for access. Magnetic tapes and optical disks are the usual media for archival applications.

2.1.3 Processing Processing of digital images involves procedures that are usually expressed in algorithmic form. Thus, with the exception of image acquisition and display, most image processing functions can be implemented in software. The only reason for specialized image processing hardware is the need for speed in some applications or to overcome some fundamental computer limitations. Image processing is characterized by specific solutions. Hence, techniques that work well in one area may be inadequate in another. The actual solution of a specific problem generally requires significant research and development.

2.1.4 Communication Communication in digital image processing primarily involves local communication between components of an image processing system or between image processing systems and remote communication from one point to another, typically in connection with the transmission of image data.

2.1.5 Display Monochrome and color TV monitors are the principal display devices used in modern image processing systems. Monitors are driven by the output(s) of a hardware image display module in the back-plane of the host computer or as part of the hardware associated with an image processor. The signals at the output of the display module can also be fed into an image recording device that produces a hard copy (slides, photographs, or transparencies) of the image being viewed on the monitor screen. Other display media include printing devices.

A host computer controls the entire system. It provides the interface to the user along with the sequencing of acquisition, storage, display, and processing. The digital image stored in memory is freely accessible for processing by the host computer. Although the host computer has the full ability to carry out any conceivable operation upon a stored image, its execution speed can be limited. To augment the host computer, specialized high-speed processors are usually a part of a digital image processing system.

This additional processing hardware can take the form of high-speed hardware circuits or secondary microprocessors, optimized to handle common digital image processing operations. For applications that must run fast enough to keep up with real-time events, like a moving conveyer line of parts, the high-speed hardware approach is often essential.

2.2 Digital image

An image is a two dimensional (2-D) function generated by sensing the radiometric information of a scene. A scene is frequently a collection of three dimensional (3-D) objects and usually governed by the physical laws of nature. The image is represented by an image function f(x, y) where the arguments of the image function (the independent variables x, y) are spatial coordinates in the image and f is the intensity or gray level at these locations. In a color image, f is a vector with three components representing hue (H), saturation (S), and intensity (I), or red (R), green (G), and blue (B).

2.2.1 Image resolution The quality of a digital image is directly related to the number of pixels and the range of brightness values in the image. These aspects are known as image resolution. The image resolution is the capability of the digital image to resolve the elements of the original scene. For digital images, the resolution characteristics can be broken into two ways — the spatial resolution and the brightness resolution (or color resolution for a color image). The number of pixels in an image is described by its spatial resolution. The more pixels in an image, the greater is its spatial resolution. Every pixel in a digital image represents the intensity of the original image at the spatial location where it was sampled. The concept of brightness resolution addresses how accurately the digital pixel's brightness can represent the intensity of the original image.

The aspect ratio is a measure of an image's rectangular form. It is calculated by dividing the image's horizontal width by its vertical height. In case of commercial broadcast television and common video equipment, images have an aspect ratio of 1.333. Commonly this aspect ratio is denoted as 4:3. This means that the horizontal dimension of the image is 1.333 times wider than the vertical dimension. An image with a 1:1 aspect ratio appears as a square.

2.2.2 Color image If one looks very closely at a color video display screen, whether it's a cathode ray tube (CRT) or liquid crystal display (LCD), one will notice individual dots of solid colors. These dots emit light in the colors of R, G, and B. This is called the additive color property, and it works for the mixing of primary colors that are emitting light. When R, G, and B are mixed together, an entire spectrum of colors can be created and it can be represented by a color space cube as shown in Fig. 2.2.

Subtractive color mixing is based on reflective colors rather than emissive colors. Instead of emitting light like a video display, subtractive colors reflect the light shined upon them. The subtractive colors, called secondary colors, are cyan (C), magenta (M), and yellow (Y). Subtractive colors are used primarily in the printing industry.

Although RGB color space is the fundamental color space used to physically detect and generate color light, other derivative color spaces can be created to aid color image processing. The most important derivative color space is the H, S, and I (HSI) space. This color space represents color as we perceive it. Whenever an application requires a human to interpret or control the colors of an image, HSI space is well suited. Hue indicates what color, such as green, dominates the reflected light. Saturation indicates how much of the color is there, i.e. purity of color. For example, a hue of red can have numerous saturation

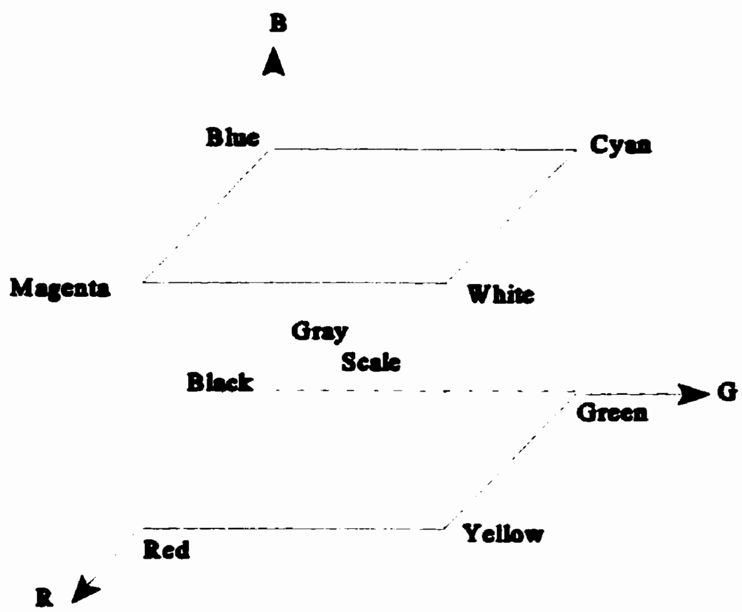


Fig. 2.2 The red, green, and blue (RGB) color cube

levels ranging from deep red (fully saturated) to pink and finally white (no saturation of red at all). Intensity indicates how bright the color is, such as light green.

2.3 Image analysis

Image analysis operations are used in applications that require the measurement and classification of image information. They are different from all other digital image processing operations because they almost always produce non-pictorial results. One mission of image analysis operations is to understand an image by quantifying its elements. The quantification includes such things as measures of size, indicators of shape, and descriptions of outlines. Other elements of interest can include attributes such as brightness, color, and texture.

The first step in image analysis generally is to segment the image. Segmentation subdivides an image into its constituent parts or objects. The level to which this subdivision is carried depends on the problem being solved i.e., segmentation should stop when the objects of interest in an application have been isolated. In general, segmentation is one of the most difficult tasks in image processing. This step in the process determines the eventual success or failure of the analysis. For this reason, considerable care should be taken to improve the probability of rugged segmentation. In some situations, such as industrial inspection applications, at least some measure of control (e.g., lighting, clean environment) over the environment may be possible.

Segmentation algorithms for monochrome images generally are based on one of two basic properties of gray-level values: discontinuity and similarity. In the first category, the approach is to partition an image based on abrupt changes in gray level. The principal areas of interest within this category are detection of isolated points and detection of lines and edges in an image. The principal approaches in the second category are based on thresholding, region growing, and region splitting and merging. The concept of segmenting an image based on discontinuity or similarity of the gray-level values of its pixels is applicable to both static and dynamic (time varying) images. Different segmentation methods are described in detail in standard books of digital image processing (e.g., Gonzalez and Woods 1992; Pratt 1991; Baxes 1994).

2.4 Feature extraction

Once the image has been cleanly segmented into discrete objects of interest, the next step in the image analysis is to measure the individual features of each object. Many features can be used to describe an object. These features are compared with the information from known objects to classify an object into one of many categories. Generally, the features that are the simplest to measure and contribute substantially towards the classification are the best to use.

2.4.1 Morphological features The most common measurements that are made on objects are those that describe shape. Shape features are physical dimensional measures that characterize the appearance of an object. Objects can have regular shapes, such as square, rectangular, circular, or elliptical but in many cases the shape of the object is arbitrary — twisting and turning in apparently random ways. The commonly measured shape features are briefly defined here.

Perimeter — The pixel distance around the circumference of an object is defined as perimeter. It is a measure of the boundary length of the object.

Area — The pixel area of the interior of an object is defined as area. It is computed as the total number of pixels inside, and including, the object boundary. The result is a measure of object size.

Area to Perimeter Ratio — It measures the roundness of the object, given as a value between 0 and 1. The greater the ratio, the rounder the object. If the ratio is equal to 1, the object is a perfect circle.

Roundness = $(4\pi \times \text{Area})/\text{Perimeter}^2$

Major Axis Length — Distance between the (x, y) end points of the longest line that can be drawn through the object is defined as major axis length. The major axis endpoints (x_1, y_1) and (x_2, y_2) are found by computing the pixel distance between every combination of border pixels in the object boundary and finding the pair with the maximum length. The result is a measure of object length.

$$\text{Major Axis Length} = \sqrt{\{(x_2 - x_1)^2 + (y_2 - y_1)^2\}}$$

where (x_1, y_1) and (x_2, y_2) are the major axis end points.

Minor Axis Length — The distance between the (x, y) end points of the longest line that can be drawn through the object while maintaining perpendicularity with the major axis is defined as minor axis length. The result is a measure of object width.

$$\text{Minor Axis Length} = \sqrt{\{(x_2 - x_1)^2 + (y_2 - y_1)^2\}}$$

where (x_1, y_1) and (x_2, y_2) are the minor axis endpoints.

Minor Axis Length to Major Axis Length Ratio — The ratio of the length of the minor axis to the length of the major axis. It is a measure of object elongation. The ratio is between 0 and 1; and if it is equal to 1, the object is generally of square, circular, or diamond shape.

Spatial Moments — The spatial moments of an object are statistical shape measures that do not characterize the object specifically. Rather, they give statistical measures related to an object's characterizations.

The *zero-order spatial moment* is computed as the sum of the pixel brightness values in an object. For a binary image, this is simply the number of pixels in the object, because every object pixel is equal to 1 (white). Therefore, the zero-order spatial moment of a binary object is its area. For a gray level image, an object's zero-order spatial moment is the sum of the brightness of pixels and is related to the object's energy.

The *first-order spatial moments* of an object contain two independent components, x and y. They are the x and y sums of the pixel brightness in the object, each multiplied by its respective x or y coordinate in the image. In the case of a binary image, the first-order x spatial moment is just the sum of the x coordinates of the object's pixels, because every object pixel is equal to 1. Similarly, the y spatial moment is the sum of the y coordinates of the object's pixels.

Fourier Descriptors — Fourier descriptors represent the boundary of a region and obtain information about the shape as a periodic function which can be expanded in a Fourier series. The information used are the spectral information, i.e., frequencies and amplitudes of the waves approximating the contour. A Fourier transform is an approximation of an arbitrary function by trigonometric functions (sine and cosine). The mathematical expression is dependent on the function to be approximated. If the function is periodic it will be expanded as a Fourier series, otherwise as a Fourier integral (Gonzalez and Woods 1992). Consider an object with an N-point digital boundary in the xy plane. Starting at an arbitrary point (x_0, y_0), coordinate pairs (x_0, y_0), (x_1, y_1), (x_2, y_2), ... (x_{N-1}, y_{N-1}) are encountered in traversing the boundary, say, counter-clockwise. These coordinates can be expressed in the form $x(k) = x_k$ and $y(k) = y_k$. Now, the boundary can be represented as the sequence of coordinates $s(k) = [x(k), y(k)]$, for k = 0, 1, 2, ..., N-1. Each coordinate pair can be treated as a complex number so that $s(k) = x(k) + j\,y(k)$ for k = 0, 1, 2, ..., N-1, i.e., the x axis is treated as the real axis and the y axis as the imaginary axis of a sequence of a complex numbers. The discrete Fourier transform of s(k) is:

$$a(u) = \frac{1}{N}\sum_{k=0}^{N-1} s(k)\exp[-j2\pi uk/N] \tag{2.1}$$

for u = 0, 1, 2, ..., N-1. The complex coefficients a(u) are called the Fourier descriptors of the boundary. The inverse Fourier transform of the a(u)'s restores s(k), i.e.,

$$s(k) = \frac{1}{N}\sum_{u=0}^{N-1} a(u)\exp[j2\pi uk/N] \tag{2.2}$$

for k = 0, 1, 2, ..., N-1.

2.4.2 Color features Color features of an object can be extracted by examining every pixel within the object's boundary. The histogram of these pixels shows the brightness distribution found in the object. For color objects, R, G, and B pixel component values of the object can be converted to H, S, and I or brightness color space. Then looking at the histogram of the hue-component, image will instantly show the predominant hue of the object.

Statistics of the brightness in an object can also be useful measures. The mean brightness represents the average brightness of an object. The standard deviation of brightness gives a measure of how much the object's brightness vary from the mean value. The mode brightness is the most common brightness found in the object. The sum of all pixel brightness in an object relates to the energy, or aggregate brightness, of an object. This measure is called an object's zero-order spatial moment. The application of these statistical measures to brightness histograms, or color-component histograms can help in classifying the brightness or color characteristics of an object.

2.4.3 Textural features Texture is an important characteristic for the analysis of many types of images. It can be seen in all multi-spectral scanner images obtained from aircraft or satellite platforms (which the remote sensing community analyzes) to microscopic images of cell cultures or tissue samples (which the biomedical community analyzes). Despite its importance and ubiquity in image data, a formal approach or precise definition of texture does not exist. The texture discrimination techniques are, for the most part, *ad hoc*. Visual texture is a difficult concept to define, but it is commonly attributed to images containing repetitive patterns in which "elements" or "tonal primitives" are arranged according to certain "placement rules". The image texture is considered as non-figurative and cellular. It has two basic dimensions — the first is for describing the tonal primitives out of which the image texture is composed, and the second dimension is for describing the spatial dependence or interaction between the primitives of an image texture. Tonal primitives are regions with tonal properties. The tonal primitives can be described in terms such as the average tone, or maximum and minimum tone of its region. The region is a maximally connected set of pixels having a given tonal property. The tonal region can be evaluated in terms of its area and shape. The tonal primitive includes both its gray tone and tonal regional properties.

Image texture can be qualitatively evaluated as having one or more of the properties of fineness, coarseness, smoothness, granulation, randomness, or irregular. Each of these adjectives translates into some property of the tonal primitives and the spatial interaction between the tonal primitives. Tone and texture are not independent concepts. They bear an inextricable relationship to one another very much like the relationship between a particle and a wave. There really is nothing that is solely particle or solely wave. Whatever exists has both particle and wave properties and depending on the situation, the particle or wave properties may predominate. Similarly, in the context of an image, tone and texture are always there, although at times one property can dominate the other. The basic relationships in the tone-texture concept are the following. When a small-area of an image has little variation of tonal primitives, the dominant property of that area is tone. When a small-area has wide variation of tonal primitives, the dominant property of that area is texture. Crucial in this distinction are the size of the small-area, the relative sizes and types of tonal primitives, and the number and placement or arrangement of the distinguishable primitives. As the number of distinguishable tonal primitives decreases, the tonal properties predominate. As the number of distinguishable tonal primitives increases, the textural properties predominate.

There have been many statistical and structural approaches to the measurement and characterization of image texture: autocorrelation functions, autoregressive models, optical transforms, digital transforms, structural elements, spatial gray tone co-occurrence probabilities, gray level run lengths, and sum and difference histograms. For classification of irregular texture and natural scenes, approaches like spatial gray level co-occurrence matrices, neighbouring gray level dependence matrices, gray level run lengths, and sum and difference histograms give good results (Haralick 1979).

2.4.3.1 Gray level co-occurrence matrix model This model was first described by Haralick et al. (1973). Suppose an image to be analyzed is rectangular and has N_x resolution cells in the horizontal direction, N_y resolution cells in the vertical direction, and the gray level appearing in each resolution cell is quantized to N_g levels. Let $L_x = \{1, 2, 3, ..., N_x\}$ be the horizontal spatial domain, $L_y = \{1, 2, 3, ..., N_y\}$ be the vertical spatial domain, and $G = \{1, 2, 3, ..., N_g\}$ be the set of N_g quantized gray levels. The image, I, can be represented as a function which assigns some gray level in G to each resolution cell or a pair of coordinates in $L_x \times L_y$; $I : L_x \times L_y \rightarrow G$.

An essential component of conceptual framework of texture is a measure of angular nearest-neighbor gray level co-occurrence matrices (GLCMs). A resolution cell, excluding those on the periphery of an image, has eight nearest-neighbor resolution cells (Fig. 2.3).

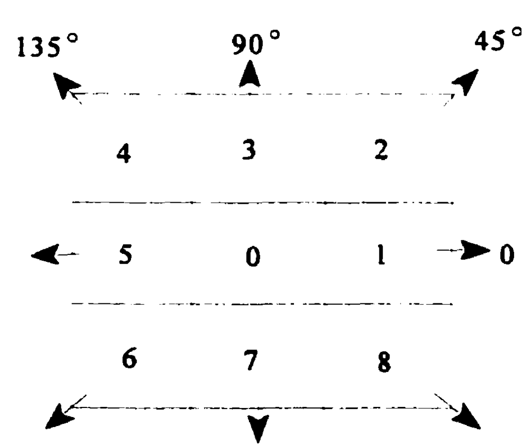


Fig. 2.3 Eight nearest-neighbor resolution cells.

It is assumed that the texture-context information can be adequately specified by the matrix of relative frequencies, P_{ij}, with which two neighboring resolution cells separated by distance, d, occur in the image, one with gray level, i, and the other with gray level, j. Such GLCMs are a function of the angular relationship between the neighboring resolution cells as well as a function of the distance between them. Figure 2.4 illustrates the set of all neighboring resolution cells separated by 1 pixel distance. For angles quantized to 45° intervals, the unnormalized frequencies are defined by:

$$P(i, j, d, 0^\circ) = \#\{((k, \ell), (m, n)) \in (L_x \times L_y) \times (L_x \times L_y) \mid (k - m = 0, |\ell - n| = d), I(k, \ell) = i, I(m, n) = j\}$$

$$P(i, j, d, 45^\circ) = \#\{((k, \ell), (m, n)) \in (L_x \times L_y) \times (L_x \times L_y) \mid (k - m = d, \ell - n = -d) \text{ or } (k - m = -d, \ell - n = d), I(k, \ell) = i, I(m, n) = j\}$$

$$P(i, j, d, 90^\circ) = \#\{((k, \ell), (m, n)) \in (L_x \times L_y) \times (L_x \times L_y) \mid (|k - m| = d, \ell - n = 0), I(k, \ell) = i, I(m, n) = j\}$$

$$P(i, j, d, 135^\circ) = \#\{((k, \ell), (m, n)) \in (L_x \times L_y) \times (L_x \times L_y) \mid (k - m = d, \ell - n = d) \text{ or } (k - m = -d, \ell - n = -d), I(k, \ell) = i, I(m, n) = j\}$$

where # = number of elements in the set.

(1, 1)	(1, 2)	(1, 3)	(1, 4)
(2, 1)	(2, 2)	(2, 3)	(2, 4)
(3, 1)	(3, 2)	(3, 3)	(3, 4)
(4, 1)	(4, 2)	(4, 3)	(4, 4)

Fig. 2.4. Coordinates of resolution cells of a 4 x 4 image.

For a 4 x 4 image [$L_x = \{1, 2, 3, 4\}$ and $L_y = \{1, 2, 3, 4\}$] (Fig. 2.4), the set of all distance-1 horizontal-neighboring-resolution cells (i.e., a resolution cell and its immediate neighbor in horizontal direction) is given by:

$R_H = [\{(k, \ell), (m, n)\} \in (L_y \times L_x) \times (L_y \times L_x) \mid k - m = 0,\ |\ell - n| = 1]$

$R_H = [\{(1, 1), (1, 2)\}, \{(1, 2), (1, 1)\}, \{(1, 2), (1, 3)\}, \{(1, 3), (1, 2)\}, \{(1, 3), (1, 4)\}, \{(1, 4), (1, 3)\}, \{(2,1), (2, 2)\}, \{(2, 2), (2, 1)\}, \{(2, 2), (2, 3)\}, \{(2, 3), (2, 2)\}, \{(2, 3), (2, 4)\}, \{(2, 4), (2, 3)\}, \{(3, 1), (3, 2)\}, \{(3, 2), (3, 1)\}, \{(3, 2), (3, 3)\}, \{(3, 3), (3, 2)\}, \{(3, 3), (3, 4)\}, \{(3, 4), (3, 3)\}, \{(4,1), (4, 2)\}, \{(4, 2), (4, 1)\}, \{(4, 2), (4, 3)\}, \{(4, 3), (4, 2)\}, \{(4, 3), (4, 4)\}, \{(4, 4), (4, 3)\}]$

Note that these matrices are symmetric, i.e., $P(i, j, d, a) = P(j, i, d, a)$. Consider Fig. 2.5(a), which represents a 4 x 4 image with four gray levels, ranging from 0 to 3. Figure 2.5(b) shows the general form of any GLCM. For example, the element in the (2, 1) position of the 1 pixel-distance horizontal matrix (P_H) is the total number of times two gray levels of value 2 and 1 occurred horizontally adjacent to each other. To determine this number, we count the number of pairs of resolution cells in R_H such that the first resolution cell of the pair has gray level value 2 and the second resolution cell of the pair has gray level value 1. Figures 2.5(c - f) give all four 1 pixel-distance GLCMs. Using these matrices many textural features can be extracted which are described in Chapter V.

All textural features extracted from the GLCMs are functions of distance and angle. The angular dependencies present a special problem. Suppose an image, I, has features m, n, o, and p for angles 0°, 45°, 90°, and 135°, respectively; and image, J, is identical to I except that J is rotated 90° with respect to I. Then J will have features o, p, m, and n for

0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

(a)

		Gray Level			
		0	1	2	3
Gray Level	0	#(0, 0)	#(0, 1)	#(0, 2)	#(0, 3)
	1	#(1, 0)	#(1, 1)	#(1, 2)	#(1, 3)
	2	#(2, 0)	#(2, 1)	#(2, 2)	#(2, 3)
	3	#(3, 0)	#(3, 1)	#(3, 2)	#(3, 3)

(b)

$$\text{At } 0^\circ \; P_H = \begin{matrix} 4 & 2 & 1 & 0 \\ 2 & 4 & 0 & 0 \\ 1 & 0 & 6 & 1 \\ 0 & 0 & 1 & 2 \end{matrix}$$

(c)

$$\text{At } 90^\circ \; P_V = \begin{matrix} 6 & 0 & 2 & 0 \\ 0 & 4 & 2 & 0 \\ 2 & 2 & 2 & 2 \\ 0 & 0 & 2 & 0 \end{matrix}$$

(d)

$$\text{At } 135^\circ \; P_{LD} = \begin{matrix} 2 & 1 & 3 & 0 \\ 1 & 2 & 1 & 0 \\ 3 & 1 & 0 & 2 \\ 0 & 0 & 2 & 0 \end{matrix}$$

(e)

$$\text{At } 45^\circ \; P_{RD} = \begin{matrix} 4 & 1 & 0 & 0 \\ 1 & 2 & 2 & 0 \\ 0 & 2 & 4 & 1 \\ 0 & 0 & 1 & 0 \end{matrix}$$

(f)

Fig. 2.5 **(a) A 4 x 4 image with 4 gray level values 0 - 3; (b) General form of any gray level spatial-dependence matrix for image with gray level values 0 - 3; #(i, j) stands for number of times gray levels i and j have been neighbors; (c) - (f) Calculation of all 4 distance-1 GLCMs.**

angles 0°, 45°, 90°, and 135°, respectively. Since the texture context of I is the same as the texture context of J, any decision rule using the angular features m, n, o, p must produce the same results for o, p, m, n. To do this, two functions of m, n, o, and p, their mean and range (which are invariant under rotation), can be used for classification.

2.4.3.2 Gray level run length matrix model This model was first developed by Galloway (1975). A gray level run is a set of consecutive, collinear picture points having the same gray level value. The matrix element (i, j) specifies the number of times a picture contains a run of length j, in a given direction, consisting of points having gray level i (or lying in gray level range i). The gray level run length matrices (GLRMs) are described in detail in Chapter V.

2.5 Object classification

There are two different ways of classifying objects. One way is to find relations among the objects with the purpose of grouping them. For example, the similarities among grains which are used to group them into different classes, like cereal grains, oilseeds, speciality crops, etc. Statistical methods covering this kind of classification are called clustering, and the general principle is to group the observation vectors into clusters of a certain similarity. The second way of classification is to assign objects into defined groups. The statistical method for this classification is called discriminant analysis, and this is the usual kind of classification which follows image analysis for recognition purposes.

The task of discriminant analysis is to find a decision rule which assigns an object described by a number of m features to one of several groups P_i (i = 1, 2, ..., n) in a population. The simplest case is discrimination by one feature (e.g., object area) and two groups. If we know the probability density function of this feature for each group, say $f_1(x)$ and $f_2(x)$, the object should be assigned to the group with the higher probability density, i.e., assigned to group P_1 if $f_1(x) > f_2(x)$. This is called likelihood ratio method.

This method may be improved if we know that a proportion π_1 of the total population belongs to P_1 and the remaining π_2 belongs to P_2. In this case, the object is assigned to P_1 if $\pi_1 f_1(x) > \pi_2 f_2(x)$ which is the Bayesian classifier.

If we assume that x is normally distributed in each group as $N(\mu_i, \sigma_i^2)$ then:

$$f_i(x) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left[-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right] \tag{2.3}$$

If further $\sigma_1 = \sigma_2 = \sigma$ for the two groups then:

$$f_1(x)/f_2(x) = \exp\left[-\frac{(x-\mu_1)^2 - (x-\mu_2)^2}{2\sigma^2}\right] \tag{2.4}$$

Setting this expression equal to 1 (or π_1 / π_2) gives the threshold for group separation.

The corresponding expression for a multivariate normal distribution of feature vectors $\mathbf{x}_i$ with dispersion matrices $\mathbf{\Sigma}_1 = \mathbf{\Sigma}_2 = \mathbf{\Sigma}$ is:

$$f_1(x)/f_2(x) = \exp\left[(\mu_1 - \mu_2)'\sum^{-1} x - \frac{1}{2}(\mu_1 - \mu_2)'\sum^{-1}(\mu_1 + \mu_2)\right] \tag{2.5}$$

In the univariate case a threshold is used for separation of groups, in the bivariate case a line, and in the multivariate case it is the hyperplanes which separate groups in the multidimensional feature space. The hyperplane for separating two groups is defined by setting the discriminant functions equal to $\log(\pi_2 / \pi_1)$:

$$(\mu_1 - \mu_2)'\Sigma^{-1}\, x - \frac{1}{2}(\mu_1 - \mu_2)'\Sigma^{-1}\,(\mu_1 + \mu_2) = \log(\pi_2/\pi_1) \qquad (2.6)$$

In general, the distribution of the features is not known. One approach to estimating the error rate of a classifier is to compute it from the assumed parametric model. However, there are many problems with this approach: (i) estimate is almost always overoptimistic, (ii) characteristics that make the design samples peculiar or unrepresentative are not revealed, and (iii) in more general situations it is very difficult to compute the error rate exactly, even if the probabilistic structure is completely known (Duda and Hart 1973).

An empirical approach that avoids these problems is to test the classifier experimentally. For discrimination, three special cases are considered of practical importance:

The Resubstitution Method — The parameters of the discriminant functions are estimated from the same population which is classified into groups. For example, one observation from n observations is used as the test data and the n observations are used as the training data. The number of incorrectly classified observations m_i of the n_i observations in group P_i define the error rate as $e_i = m_i / n_i$, and $e = \pi_1 e_1 + \pi_2 e_2$ for two groups. The resubstitution method gives over optimistic estimation of classification accuracy; hence for real-world application it should not be used.

The Cross-validation Method — This method (also known as *leaving-one-out* method) estimates the discriminant functions from the sample data minus one (n-1) observations. The omitted observation is then classified as the unknown observation and this procedure is repeated until all observations (n) are classified. The corresponding error rate is $e_i = b_i / n_i$. and $e = \pi_1 e_1 + \pi_2 e_2$ (for two groups) where b_i is the number of misclassified observations in group P_i. The cross-validation method gives very conservative estimation of classification accuracy and it works best for a small sized sample.

The Hold Out Method — This method uses a separate population (training data) for construction of the discriminant functions, and another population for testing the classification results. If the observations are normally distributed, the error rate may be estimated by calculating the area of the region where the density function is overlapped by a density function from another group. For the two group problem, the region is estimated by $R_1 = \{\mathbf{x}: f_1(\mathbf{x} \mid \theta_1) / f_2(\mathbf{x} \mid \theta_2) > \pi_2 / \pi_1\}$ where θ_i are the estimated parameters of the probability density function. The misclassification for group 1 is:

$$e_1 = \int_{R_2} f_1(\mathbf{x} \mid \theta_1)\, d\mathbf{x} \tag{2.7}$$

where:

R_2 = feature space for group 2. The hold out method can be used in real-world applications.

The separation of groups in the feature space depends on how well the parameters of the distribution functions are estimated. For example, if no errors are made on 50 test samples, with probability 0.95, the true error rate is between 0 - 8%. The classifier would have to make no errors on more than 250 test samples to be reasonably sure that the true error rate is below 2% (Duda and Hart 1973).

The need for data to design the classifier and additional data to evaluate it presents the designer with a dilemma. If one reserves most of the data for the design, s/he cannot have confidence in the test. If one reserves most of the data for the test, s/he will not obtain a good design. The question of how best to partition a set of samples into a training set and a test set has received some analysis, and considerable discussion, but has no definitive answer (Duda and Hart 1973).

In fact, there are more options available than just partitioning the data, designing the classifier once, and testing it. For example, one might repeat this process several times, using a different partition each time, and average the resulting error-rate estimates. If computation costs are of no concern, one can use the cross-validation method. The basic advantage of this approach is that virtually all of the samples are used in each design, which should lead to a good design, and all of the samples are ultimately used in the tests. This procedure is particularly attractive when the number of available samples is quite small. When the number of samples is very large it is probably sufficient to partition the data into a single training set and a single test set (hold out method). Although there is no theory to guide the designer in intermediate situations, it is at least pleasant to have a large number of reasonable options.

2.5.1 SAS For a set of observations containing one or more quantitative variables and a classification variable defining groups of observations, PROC DISCRIM of SAS (1990) develops a discriminant criterion to classify each observation into one of the groups. The derived discriminant criterion from this data set can be applied to a second data set during the same execution of DISCRIM. The data set that DISCRIM uses to derive the discriminant criterion is called the *training* or *calibration data set*.

When the distribution within each group is assumed to be multivariate normal, a parametric method can be used to develop a discriminant function. The discriminant function, also known as a *classification criterion*, is determined by a measure of generalized squared distance (Rao 1973). The classification criterion can be based on either the individual within-group covariance matrices (yielding a quadratic function) or the pooled covariance matrix (yielding a linear function); it also takes into account the prior probabilities of the groups. The calibration information can be stored in a special SAS data set and applied to other data sets.

When no assumptions can be made about the distribution within each group, or when the distribution is assumed to be different from multivariate normal distribution, non-parametric methods can be used to estimate the group-specific densities. These methods include the *kernel method* and *k-nearest neighbor methods* (Rosenblatt 1956; Parzen 1962).

Either Mahalanobis distance or Euclidean distance can be used to determine proximity. Mahalanobis distance can be based on either the full covariance matrix or the diagonal matrix of variances. In the *k-nearest neighbor* method, the pooled covariance matrix is used to calculate the Mahalanobis distances. In the kernel method, either the individual within-group covariance matrices or the pooled covariance matrix is used to calculate the Mahalanobis distances.

The DISCRIM procedure can produce an output data set containing various statistics such as means, standard deviations, and correlations. DISCRIM evaluates the performance of a discriminant criterion by estimating *error rates* (probabilities of misclassification) in the classification of future observations. When the input data set is an ordinary SAS data set, the error rate can also be estimated by cross-validation.

Bayes' Theorem — Assuming that the probabilities of group membership are known and the group-specific densities at $\mathbf{x}$ can be estimated, DISCRIM computes $p(t \mid \mathbf{x})$, the probability of $\mathbf{x}$ belonging to group t, by applying Bayes' theorem:

$$p(t|\mathbf{x}) = q_t f_t(\mathbf{x})/f(\mathbf{x}) \tag{2.7}$$

where:

$p(t \mid \mathbf{x})$ = posterior probability of an observation $\mathbf{x}$ belonging to group t,

q_t = prior probability of membership in group t,

$f_t(\mathbf{x})$ = group-specific density estimate at $\mathbf{x}$ from group t, and

$f(\mathbf{x})$ = $\sum_t q_t\, f_t\, (\mathbf{x})$, estimated unconditional density at $\mathbf{x}$.

DISCRIM partitions a p-dimensional vector space into regions R_t, where the region R_t is the subspace containing all p-dimensional vectors $\mathbf{y}$ such that $p(t \mid \mathbf{y})$ is the largest among all groups. An observation is classified as coming from group t if it lies in region R_t.

Parametric methods — Assuming that each group has a multivariate normal distribution, DISCRIM develops a discriminant function or classification criterion using a measure of generalized squared distance. DISCRIM also computes the posterior probability of an observation belonging to each class. The squared distance from **x** to group t is:

$$d_t^2(\mathbf{x}) = (\mathbf{x} - \mathbf{m}_t)' \mathbf{V}_t^{-1} (\mathbf{x} - \mathbf{m}_t) \qquad (2.8)$$

where:

$\mathbf{V}_t$ = $\mathbf{S}_t$, if the within-group covariance matrices are used,

$\mathbf{V}_t$ = $\mathbf{S}$, if the pooled co-variance matrix is used,

$\mathbf{x}$ = a p-dimensional vector containing the quantitative variables of an observation.

$\mathbf{m}_t$ = a p-dimensional vector containing variable means in group t,

$\mathbf{S}$ = pooled covariance matrix,

$\mathbf{S}_t$ = covariance matrix within group t, and

t = a subscript to distinguish the groups.

An observation is classified into group u, if setting t = u produces the largest value of $p(t \mid \mathbf{x})$. If this largest posterior probability is less than the threshold specified, **x** is classified into group '***other***'.

Non-parametric methods — Non-parametric discriminant methods are based on non-parametric estimates of group-specific probability densities. When the *k-nearest neighbor* method is used, the Mahalanobis distances are based on the pooled covariance matrix. The squared distance between two observation vectors, **x** and **y**, in group t is given by

$$d_t^2(\mathbf{x},\mathbf{y}) = (\mathbf{x} - \mathbf{y})' \mathbf{V}_t^{-1} (\mathbf{x} - \mathbf{y}) \qquad (2.9)$$

where:

$\mathbf{y}$ = a p-dimensional vectors containing the quantitative variables of an observation.

The classification is based on the Bayes decision rule which classifies an entity (represented by its pattern vector, e.g., $\mathbf{x}$) to a class for which the entity has a maximum posterior probability (Hand 1981; Duda and Hart 1973). An observation $\mathbf{x}$ is classified into group u, if setting t = u produces the largest value of $p(t \mid \mathbf{x})$. If there is a tie for the largest probability or this largest probability is less than the threshold specified, $\mathbf{x}$ is classified into group '***other***'.

Using the *k-nearest neighbor* rule, the k smallest distances are saved. Of these k distances, let k_t represent the number of distances that are associated with group t. Then the estimated group t density at $\mathbf{x}$ is:

$$f_t(\mathbf{x}) = \frac{k_t}{n_t v_k(\mathbf{x})} \tag{2.10}$$

where:

$v_k(\mathbf{x})$ = volume of the ellipsoid bounded by $\{\mathbf{z} \mid (\mathbf{z} - \mathbf{x})' \mathbf{V}^{-1} (\mathbf{z} - \mathbf{x}) = r_k^2(\mathbf{x})\}$,

$\mathbf{z}$ = a p-dimensional vector, and

n_t = number of training set observations in group t.

The nearest-neighbor method is equivalent to the uniform-kernel method with a location dependent radius $r_k(\mathbf{x})$. Since the pooled within-group covariance matrix is used to calculate the distances used in the nearest-neighbor method, the volume $v_k(\mathbf{x})$ is a constant, independent of group membership. When k = 1 is used in the nearest-neighbor rule, **x** is classified into the group associated with the **y** point that yields the smallest squared distance $d_t^2(\mathbf{x}, \mathbf{y})$.

The nearest-neighbor method is best used in applications where the choice of k is not critical (Silverman 1986, pp 98-99). A practical approach is to try several different values of k within the context of a particular application and to choose the one which gives the most satisfactory results.

CHAPTER III: REVIEW OF LITERATURE

3.1 Background

The application of machine vision technique to the grain industry is a recent development. A machine vision system for grain grading is not available commercially and many of the special needs and problems in applying machine vision technique to the visual inspection tasks have yet to be solved. The research effort in this area, however, has grown rapidly and substantially in the past decade. AgroVision AB (S-223 70 Lund, Sweden) has developed a machine to classify wheat, barley, oats, rye, and triticale but its classification accuracy is not reported in the literature (to the best of my knowledge). Determining the potential of morphological and color features to classify different grain species, classes, varieties, damaged grains, and impurities using statistical pattern recognition technique has been the main focus of the published research. This chapter briefly reviews the published research in applying morphological, color, and textural features of the machine vision technique to the Agri-food industry.

3.2 Potential for objective wheat grading

Several researchers (Barker et al. 1992a, 1992b, 1992c, 1992d; Draper and Travis 1984; Keefe 1992; Keefe and Draper 1986, 1988; Kohler 1991; Lai et al. 1986; Myers and Edsall 1989; Neuman et al. 1987; Sapirstein and Bushuk 1989; Sapirstein et al. 1987; Symons and Fulcher 1988a, 1988b; Travis and Draper 1985; Zayas et al. 1985, 1986, 1989) applied DIA and pattern recognition techniques to derive characteristics of cereal grains that can be used for objective grading. Sapirstein (1995) reviewed work conducted by different researchers for identification of different cereal grains and their varieties. Most of these studies were conducted with limited data sets for testing. The primary and export grade determinants of CWRS wheat are given in Appendix A. In primary grade determinants, the maximum tolerances of foreign materials including other cereal grains are 0.75, 1.5, 3.5, and 10% for grade 1, grade 2, grade 3, and feed grade of CWRS wheat, respectively. In export grade, the maximum tolerances of foreign materials including other cereal grains are 0.4, 0.75, 1.25, and 5% for grade 1, grade 2, grade 3, and feed grade of CWRS wheat, respectively. The primary grade tolerances for wheat of other classes or varieties are 3, 6, and 10% for grade 1, grade 2, and grade 3, respectively. For export grade, these tolerances are 1.5, 3, and 5%, respectively. Tolerances for damaged kernels are also low. All of the grading factors (except the test weight) are subjectively determined. Because of these tight tolerances, an objective grain grading system must achieve a near perfect classification of cereal grains, e.g., CWRS wheat, CWAD wheat, barley, oats, and rye. Majumdar et al. (1996b) discussed different applications of image processing in food industry.

Most of the researchers conducted their studies using morphological features for cereal grain classification. Very limited work was reported on cereal grain classification using color features and no work (to the best of my knowledge) was published on the potential of textural features for classification of cereal grains.

3.2.1 Morphological features Segerlind and Weinberg (1972) first estimated grain shape by a Fourier series expansion of the radial distance from the centre of gravity to the periphery of kernels. A kernel profile was traced on a grid paper to get the image. There was 1% error in separation of oats and barley, and wheat and rye based on extracted shape features. The class [e.g., hard red spring (HRS), hard red winter (HRW), amber durum, soft white spring (SWS), soft white winter (SWW), Canada prairie spring (CPS), and utility wheat are different classes of Canadian wheat] discrimination for wheat was partially successful with 11-25% error.

Draper and Travis (1984) and Travis and Draper (1985) used DIA for identifying seeds of cereals, fodder plants, and oil and fibre vegetables. They reported that five of the crop species could be distinguished from their major contaminants with an overall accuracy of 95% and most of the weed species could be distinguished from each other.

Keefe and Draper (1986, 1988) investigated the potential of image analysis for identifying grains of 5 U.K. wheat cultivars on the basis of size and shape. They used a commercial software and a sample presentation device in the form of a motorized camera unit controlled by a computer. Individual seeds resting horizontally, in dorsal position (i.e., crease down position), and embryo in a fixed position were viewed in side elevation using transmitted light. The time taken to measure 400 seeds of wheat varied in the range from 330 to 515 s. They did not report the classification accuracies of different wheat cultivars.

Keefe (1992) constructed a semi-automatic image analyzer for classification of wheat grains. It takes 33 measurements for each grain and calculates an additional 36 derived parameters for analysis. He did not disclose most of those parameters in the paper due to commercial interests. Twenty varieties of U.K. wheat were tested using the instrument. Each grain was placed manually in a fixed orientation for image capturing. For a sample size of 50 grains, the total time taken from receiving the sample to having the data ready for statistical analysis was approximately 5 min. The overall identification error was 32.9-65.8%.

Zayas et al. (1986) used some of the morphological features used by Keefe and Draper (1986, 1988) and some additional features to differentiate among individual kernels of different American wheat classes and varieties. For different wheat classes and varieties, the average percentages of correctly classified kernels were 77% and 85%, respectively. They used mainly pair-wise discriminations. The work was limited to a single kernel per image frame and it was necessary to immobilize kernels in a fixed orientation prior to analysis.

Zayas et al. (1989) used multivariate discriminant analysis to distinguish between wheat and non-wheat, and between weed seeds and stones in the non-wheat part of a grain sample. They used multivariate discriminant analysis to distinguish between wheat and non-wheat and among weed seeds, and developed a structural prototype to distinguish between wheat and non-wheat using morphological features. The images used for this study were silhouette images, captured with transmitted light. Although their system satisfactorily identified wheat and weed seeds, many times it failed to identify stones present in the sample.

In a later study, Zayas et al. (1990) attempted to discriminate whole corn from broken corn kernels. To evaluate the effect of image resolution on the result of discriminant analysis, they conducted experiments with different optical settings. Their system could correctly identify all of the broken and 98% of the whole kernels. But the main drawback was that the kernels had to be oriented manually with the longest dimension parallel to the vertical axis.

Brogan and Edison (1974) used a pattern classification technique, based on recursive learning, for classifying wheat, barley, oats, rye, soybeans, and corn with an overall accuracy of 98%.

Chen et al. (1989) developed a system that supplemented the two-dimensional (2-D) image with limited elevation information obtained by using a laser scanning device to capture a cross-section profile of the kernel. The use of a single cross-section measurement improved discrimination, but locating the midpoint accurately was somewhat arbitrary and difficult to control. The system suffered from the user's inability to accurately position the kernel and from the complexity associated with the system — both video image capture and laser scanning. In a sample size of 850 kernels, they reported that 16% of rye kernels were misclassified as wheat. There were misclassifications of 8-12% among wheat of different classes and 20-26% among wheat of different varieties within a same class.

Thomson and Pomeranz (1991) modified the laser scanning mechanism developed by Chen et al. (1989) to acquire 3-D images. The system correctly classified 92-94% of the kernels of two American wheat varieties [Daws (soft winter wheat) and Tyee (club)]. The same system when used to identify sprout damage in harvested wheat kernels, could correctly identify 89% of the sprouted kernels and 83% of the unsprouted kernels in independent sets of test kernels.

Neuman et al. (1987) studied the objective classification of Canadian wheat cultivars based on kernel morphology using DIA. They used 576 kernels (sound and uniform) of pedigreed seed of 14 wheat varieties for analysis. Using a transmitted light they captured silhouette images of whole-wheat kernels in 'plan' (top) view and determined spatial size and shape parameters and Fourier descriptors of kernel parameters. Hard Red Spring and CWAD wheat kernels were the most easily differentiated groups while there was considerable overlap between HRW and SWS wheat. Discriminating varieties within classes gave inconclusive results with correct classification ranging from 15 to 96%. Unlike earlier works, random orientation of kernels was not a problem in this case.

Sapirstein et al. (1987) used the technique of Neuman et al. (1987) for classification of HRS wheat, barley, rye, and oats. All cereals were disjoint with oats and wheat being well separated. For a sample size of 580 grains the classification error was 1%. But for a large sample with randomly selected kernels, the discrimination of the cereals was not satisfactory (Sapirstein and Bushuk 1989). For a sample size of 1400 kernels, the classification accuracies for HRS wheat, barley, oats, and rye were 98.4, 93.7, 78.3, and 98.0%, respectively. A substantial improvement in cereal grain discrimination was achieved when the morphology based discriminant model was supplemented with mean kernel reflectance. The classification accuracies of HRS wheat, barley, oats, and rye using reflectance and morphological features were 99.2, 95.7, 95.3, and 98.3%, respectively.

Sapirstein and Kohler (1995) suggested an interesting alternative approach to objective wheat grading by finding a completely new set of grading factors like variability of size, shape, and reflectance features of kernels in a sample, which can be easily administered by machine vision based grading. Cargo (grain being shipped out of terminal elevators) samples of CWRS grades 1, 2, and 3 were successfully classified using the mean and variance of the features as quantitative classification variables. On carlot (grain received at terminal elevators) samples, however, only grades 1 and 3 could be successfully discriminated from each other.

Symons and Fulcher (1988a, 1988b) conducted studies similar to Neuman et al. (1987) for Eastern Canadian wheat classes and varieties. For a sample size of 225, 94% of soft white winter (SWW) and 64% of HRS originating from Europe (HRS_E) were correctly classified using a 4-way classification among SWW, HRW, HRS_E, and HRS originated from Western Canada (HRS_W). About 16% of HRS_W were confused as HRW. The HRS_W sample comprised of the cultivars 'Katepwa' and 'Columbus'. These cultivars were used by Neuman et al.(1987) but the HRW cultivars used in Symons and Fulcher's study were different from those used by Neuman et al. (1987). It is worth mentioning again that Neuman et al. (1987) found no confusion between HRS and HRW wheat classes. Such contradiction in results points to the need for a large database to develop a robust classifier.

Symons and Fulcher (1988a) also experienced inadequacy of morphological features extracted from 'plan' view for discriminating among different varieties of a wheat class. For three varieties of SWW, correct classification was less than 60%. In a subsequent study. Symons and Fulcher (1988b) used some additional features (i.e., bran tissue features like aleurone cell wall thickness, pericarp tissue thickness, and total bran thickness that were measured at 5 different locations in a wheat kernel from 'cut' transverse sections) to aid in classification among different varieties of SWW wheat. Classification results were not satisfactory with errors up to 20%.

Barker et al. (1992a, 1992b, 1992c, and 1992d) used different sets of features for characterizing and discriminating among kernels of eight Australian wheat varieties. The features were ray (i.e., radial distance from the centroid) parameters, slice and aspect ratio parameters, Fourier descriptors, and Chebychev coefficient. The overall classification error ranged from 35 to 48%.

3.2.2 Reflectance features Hawk et al. (1970) used a Beckman DK-2A Spectro-reflectometer to measure the reflectance from cereal grain samples in the 420 to 700 nm spectral range. Statistical analysis of reflectance data showed it to be impossible to separate expected admixture of grains from each other on the basis of reflectance data only.

Neuman et al. (1989a, 1989b) examined color attributes of individual kernels of 10 varieties representing 6 Canadian wheat classes. They used mean red, green, and blue reflectance features of picture elements (pixels) for discriminant analysis and achieved about 88% correct varietal classification for pair-wise discrimination. The correct classification of individual varieties varied from 34 to 90%. Average correct classifications for the SWS, Amber Durum, and red spring classes of wheat were 76, 76, and 62%, respectively. Relatively lower scores of 56% and 34% were achieved for HRW and CPS wheat classes, respectively.

Sapirstein and Bushuk (1989) studied the vitreosity of durum wheat by taking the images of transilluminated kernels and specifying the frequency distribution of grey level.

They found 95% correlation between vitreosity computed by DIA and replicated official inspection of hard vitreous kernels. They also found a linear relationship (correlation coefficient = 0.88) between grain hardness (measured in Particle Size Index or PSI) predicted by the computed vitreosity and the measured PSI value.

3.3 Potential for textural analysis

Al-Janobi and Kranzler (1994) used image processing technique for grading date fruits into quality classes on the basis of color and surface texture. They applied the co-occurrence matrix approach to manually classified dates according to the USDA grading standards. They used a total of 39 features and tested eight models, by applying a non-parametric discriminant analysis procedure to each model and by incorporating subsets of the features. The classification errors for all models ranged between 0.8 and 26.4%.

Bertrand et al. (1992) used the DIA technique for characterization of the appearance of bread crumb. They prepared experimental breads by varying the nature of the surfactants added to the flour to change the textural appearance of the crumb. They tested 142 digital images from seven treatments and extracted textural features from images by a mathematical procedure based on Haar transform (Hall 1979). They used 66 textural features from each digital image of bread crumb and tried to identify the bread treatment from the image of its crumb by applying discriminant analysis on the matrix of textural features. The technique correctly classified 80% of the images, both in the training and in the testing sets.

Gao and Tan (1993) used a set of image features based on texture, color, and morphology to characterize the textural properties of puffed extrudates of corn meal. The image features were extracted using two different approaches (e.g., edge enhancement plus fuzzy edge detection and pixel value run length) from surface and cross-section images of yellow corn puffs. Scanning electron microscopy (SEM) was employed to measure the cell size and density over a cross-section area. A correlation analysis was performed between the image features and the SEM measurements and the majority of the image features were significantly correlated to the SEM measurements.

Gao et al. (1994) further used the geometrical properties of puffed extrudates to predict a number of sensory attributes evaluated by a sensory panel. Most of the sensory attributes were effectively predicted by using the image features (e.g., average pixel value, standard deviation of pixel values, the third moments of the histogram, the peak value of the histogram (P_{max}), and value of the most occurrence which is the pixel value corresponding to the P_{max}) with correlation coefficient values ranging from 0.8 to 0.94.

Han and Hayes (1990) developed an interactive image processing technique to estimate soil cover using the textural difference between soil and residue or canopy. They compared the method with the photographic grid method and found that it can measure percent soil cover quickly, accurately, and with less human error. The image classification algorithm using textural features was able to classify residue or canopy regions even when the average gray level of residue or canopy was overlapping with that of the soil background.

Kranz et al. (1994) used automatic image segmentation algorithms based on textural features namely busyness, variance, and gradient magnitude to determine the percent water cover from images recorded during rainfall simulations. They evaluated the performance of these features by comparing them with percent water cover obtained through manual tracing.

The approach using Prewitt gradient magnitude (Gonzalez and Wood 1992) as a measure of texture performed better than the other two (Roberts and Sobel Operators) with a mean absolute deviation of 6.2%. Data extracted from successive frames were used to determine estimates of surface water storage. Evaluation of the procedure indicated that computer generated estimates of soil surface ponding were more likely to be greater than the manually traced area where large distinct ponding areas were present.

Langford et al. (1990) carried out a textural analysis using co-occurrence matrix of gray levels for identification of 6 different types of pollen grains. They used SEM photographs of pollen grains for the test, and with a leave-one-out strategy and available selection procedure, the proportion of pollen grains correctly classified was up to 94.3%. The procedure required 10 s of processing time on a VAX computer for each grain.

Murase et al. (1994) used a set of textural features (e.g., contrast, homogeneity), extracted from a video image of a population of growing plants (lettuce). They found that the textural features of plants varied with their growth stage and there was an agreement between the estimated leaf size values and the actual measured data. The results indicated that the reflection of light over the population of plants varied with the increase in the area where mostly the green leaves covered. They also reported that the apparent roughness change of overall surface of the plant population altered the values of textural features. They used neural network to relate the varying textural features to the various plant growth stage.

Park and Chen (1994) used textural features (based on co-occurrence matrices) of multi-spectral images containing visible and near-infrared wavelengths for discriminating abnormal poultry carcasses from normal poultry carcasses. For statistical models, the accuracy of separation of normal carcasses was 94.4% and that of abnormal carcasses was 100% whereas with neural network models the accuracy of separation was 100% for both normal and abnormal carcasses. When neural network models were employed to classify poultry carcasses into 3 classes (normal, septicemic, and cadaver), the accuracies of separation were 88.9%, 92%, and 82.6%, respectively.

Petersen (1992) used morphological and textural features for classification of 40 species of weed seeds, 25 seeds per species. The classification performance of various shape and textural analyses ranged from 26.2 to 77.0% and from 31.7 to 61.3%, respectively. When a combination of features describing size, shape, and texture was used, with 25 features (1 size feature, 10 shape features, and 14 textural features, selected using the stepwise selection procedure) a maximum classification rate of 97.7% was achieved.

Shearer et al. (1994) developed a maturity classification algorithm for analysis of line-scan images of broccoli plants using textural features extracted from gray level co-occurrence matrices. They reported results for 480 observations from three broccoli cultivars. They achieved the maximum accuracy of 90.0% for individual cultivars and 83.1% for multiple cultivars, at a gray level resolution of 64. When the gray level values were reduced from 256 to 16, image processing times were reduced by a factor of 50 for vector processing with minimum loss of classification accuracy.

Burks et al. (1994) conducted a study to evaluate the application of neural networks to the identification of plant canopy images from color textural features. They used a counter propagation approach to train a neural network classifier to differentiate among as many as seven cultivars of containerized nursery stock using up to 33 color texture features.

Depending on the number of species in the model, the use of co-occurrence texture statistics as the network parameters had a high discriminating capability with classification accuracies in the range of 77 to 96%. The use of statistical analysis tools proved to be invaluable in the design and tuning of the network.

Wilhoit et al. (1990) studied the feasibility of using digital image processing technique for selecting mature broccoli heads based on size. They took images of 48 broccoli plants, with a wide range of head sizes under controlled lighting conditions, and developed and tested a model based on the gray level run lengths for textural analysis. The model exhibited an exponential relationship between the head area and the numerical texture measure and had a standard error of prediction of ± 16 cm^2, which corresponds to an error of less than ± 1.0 cm in a head diameter of 10 cm. The results indicated that the model had good capability for classifying broccoli heads into immature and harvestable sizes.

Zayas (1993) investigated the potential of DIA for bread crumb grain assessment using textural features. For quality control of bread making operation, she developed a ranking scale for evaluating the degree of coarseness of crumb grain with visual judgement. She used 18 textural features from two commercial bread brands (BRRA and BRDI) for multivariate discriminant analysis. She reported that 100% of BRRA and 97.5% of BRDI sub-images (128 x 128) from the middle area of a slice were correctly recognized. The location of sub-images on a slice affected the textural features because crumb grain varied across a slice.

Sapirstein et al. (1994) developed an instrumental system for direct quantitative assessment of bread crumb grain using digital image processing. They developed a software for measurement of crumb grain features like cell area, cell density, cell-wall thickness, cell-total area ratio, crumb brightness, and uniformity of cell size. Image processing time to compute the crumb cell structure for a single bread slice (307, 200 pixels per image) was about 10 s. The precision and accuracy of the system were tested by analysis of results of experimental bread making using control and oxidant-formula loaves. Compared with control loaves, bread crumb containing oxidants was determined to be 6% brighter and to have, on average, 21% more cells/cm^2, 17% smaller cells in cross-sectional area, 13% thinner cell walls, and 16% more uniform grain. These values were consistent with the finer crumb grain of bread containing oxidants, as observed visually.

Zhang et al. (1994) used image processing techniques to extract structural features from SEM images of puffed extrudates. They extracted a number of image features based on the gray level run length of SEM images and total edge length. They found that some features were highly correlated to cell size and cell size uniformity. The average run length and the total edge length appeared to be effective image features to predict cell sizes. They suggested that this approach could be used for rapid and consistent evaluation of some important texture-related geometric characteristics of expanded-food products.

Ruan et al. (1995) conducted a rapid analysis of scabby wheat using machine vision and neural networks. They used different combinations of color and color-texture features as input and deoxynivalenol (DON) levels (ppm) of the corresponding samples (measured with HPLC) as output for the training of a three layer back propagation neural networks. They used a total of 31 features (13 color features, 6 intensity texture features, 6 saturation texture features, and 6 hue texture features) for the development of neural network models.

Training set contained 16 typical samples (200 wheat kernels per sample) with a wide range of DON level (from 0 to 32.86 ppm). The trained networks were used to estimate the DON levels of wheat kernels (approximately 20 additional wheat kernels per sample). The average difference between the predicted and measured DON value was 1.97 ppm when all 31 features were used for network training.

Most of the researchers used clean and pedigreed samples for classification of cereal grains, and different classes and varieties of wheats. Some researchers placed the grains manually in a specific orientation which defeats the main purpose of automation. In many cases, the sample size was small and an overall classification accuracy of about 96% was achieved using morphological and reflectance features for classification of cereal grains. Because of the tight tolerances in the primary and export grade determinants (Appendix A), a near perfect classification of all objects in a sample should be achieved to develop an objective grain grading system. Use of morphological features alone cannot achieve such high classification accuracies. Inclusion of color and textural features with morphological features can improve the classification accuracies of cereal grains. The robustness of the classifier should also be tested with a bigger sample size, collected from different growing regions and with commercial samples (unlike clean samples).

CHAPTER IV. MATERIALS AND METHODS

4.1 Vision hardware

A 3-chip CCD (charge coupled device) color camera (Model DXC-3000A, SONY) was used to acquire images. For image acquisition, a zoom lens (Model VCL-1012 BY, SONY) of 10 - 120 mm focal length was fitted to the camera. The camera was mounted on a stand (Model m3, Bencher Inc., Chicago, IL) which provided easy vertical movement and a stable support for the camera. The camera was connected to a camera control unit (Model CCU-M3, SONY). The iris was selectable to manual or automatic mode. The option of the manual iris control was used to achieve repeatability in the experiments. The automatic gain control of the camera was disabled. The camera was white balanced before each imaging session. The experimental set up is shown in Fig. 4.1.

The R, G, and B video signals from the camera control unit (CCU) were converted to a 24 bit color digital image by a frame grabber board (Model DT 2871, Data Translation Inc., Marlboro, MA). The frame grabber board was installed in an IBM compatible 80386 personal computer. The camera gave three parallel analog video signals, R, G, and B, corresponding to the NTSC (National Television System Committee) color primaries. The frame grabber could convert the R, G, and B color signals to H, S, and I signals in the real time. The frame grabber had three separate eight bit analog-to-digital (A/D) converters and three $512 \times 480 \times 8$ bit frame buffers. The programs to control the frame grabber were written in C programming language using the aurora subroutine library (Aurora, Data

Translation Inc., Marlboro, MA). The image resolutions were 0.202 mm/pixel and 0.160 mm/pixel in the horizontal and vertical directions, respectively. Images were converted to square pixels with 0.202 mm/pixel resolution. Image analysis was carried out on a work station (Model SPARC STATION 2, Sun Microsystems, Inc., Mountain View, CA) and an IBM compatible pentium 75 personal computer.

4.2 Sample illumination

Uniform diffuse lighting was used in all experiments. A circular fluorescent tube (305 mm diameter and 32 W circular lamp; Model FC12T9/CW, Philips, Singapore) was placed around and just below the surface level of the sample placement platform of the light chamber (Fig. 4.2). A semi-spherical steel bowl of approximately 0.39 m diameter, painted white and smoked with magnesium oxide on its inner side, was used as a diffuser (Fig. 4.1). The steel bowl had an opening of 0.125 m diameter at its top, through which images were viewed by the camera. A voltage regulator (Model CVS, Sola Canada Inc., Toronto, ON) controlled the voltage to the lamps within ±0.5 V. A variac was used to maintain a constant voltage (120 ±0.1 V) to the light source. A light controller (Model FX0648-2/120, Mercron, Richardson, TX) was used with the fluorescent lamp. The photodiode light sensor of the light controller automatically detected the illumination level in the light chamber and adjusted the AC frequency of the lamp to maintain a stable level of illumination. The frequency of the AC power output of the controller varied between 140 kHz at the minimum light levels to 60 kHz at full power.

4.3 Illumination standardization

A Kodak white card with 90% reflectance (Model E152-7795, Eastman Kodak Co., Rochester, NY) was used as a white reference to standardise the illumination level. The lamp voltage was set to the rated value of 120 V. An image of the white card was acquired over a small central area of 50 x 50 pixels, and the mean gray level values of the R, G, and B bands were computed and used as the illumination level indicators. By manually adjusting the iris control and performing the white balance with the CCU, all three values (R, G, and B) were adjusted to 250±1.

4.4 Grain samples

Composite grain samples (uncleaned commercial samples) of CWRS wheat (grade 1, 2, and 3), CWAD wheat (grade 1, 2, 3, and 4), barley (grade 1 and EX1), oats (specific grades not known), and rye (grade 1) were collected from 30 growing regions of the Western Canada for the 1994 growing year by the Industry Services Division of the Canadian Grain Commission, Winnipeg, MB. The CWRS wheat comprised 30 samples of each grade. The CWAD comprised 7 samples of 1-CWAD, 10 samples each of 2-CWAD and 3-CWAD, and 3 samples of 4-CWAD. The barley had 15 samples each of grade 1 and EX1. The oats had 30 samples (specific grades not known) and rye also had 30 samples of grade 1. A total of 210 samples were collected. The growing regions were chosen using the climatic subdivisions of the Canadian Prairies (Putnam and Putnam 1970).

For the first set of tests (analysis of bulk samples), grains from all 30 growing regions were used and three images were acquired for analysis from the grain sample collected from each growing region. The number of images used for the first set of tests were 90 (30 growing regions x 3 images per growing region) each for CWAD wheat, barley, oats, and rye, and 270 (30 growing region x 3 images per growing region x 3 grades) for CWRS; total number of images was 630.

For the second set of tests (analysis of individual kernels), 300 kernels (25 kernels per image) from each growing region were randomly selected and used for each grain type (for CWRS wheat, it was 900 kernels: 300 kernels per grade). All three grades of CWRS wheat were collected from 20 growing regions. The CWAD wheat was collected from 20 growing regions (grade 1 from 7, grade 2 from 10, and grade 3 from 3 growing regions). Barley was collected from 20 growing regions (grade 1 from 9 and grade EX1 from 11 growing regions). Oats (specific grades not known) and rye (grade 1) were also collected from 20 growing regions. The number of kernels used for each grain type was 6000 (300 x 20); total number of kernels used was 42000.

4.5 Sampling technique

For overall sampling, each composite grain sample (1000 - 1500 g) was poured into a large plastic container and mixed thoroughly. A scoop was used to take grains randomly from different regions of the container to give a sub-sample of 75 g. Before withdrawing the second sub-sample, the remaining grains in the plastic container were re-mixed. In this way three sub-samples were collected.

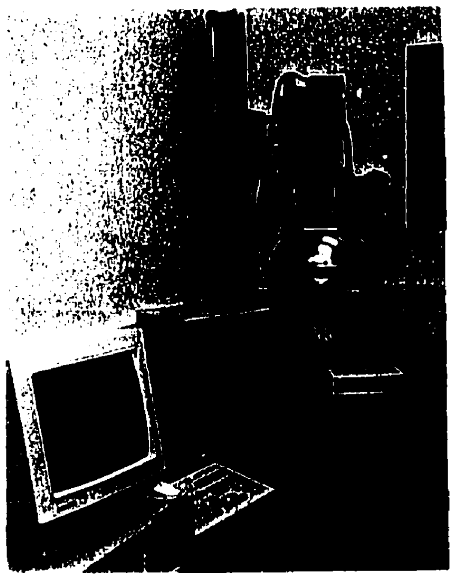
The three sub-samples were re-mixed to give a sample. The sample was mixed thoroughly by passing it four times through a *Boerner Divider*. For image acquisition of bulk samples, the sample was split into three replicate samples. For image acquisition of individual kernel, replicate samples were remixed after acquiring bulk images and 300 kernels were randomly picked from the sample for testing.

4.6 Image acquisition

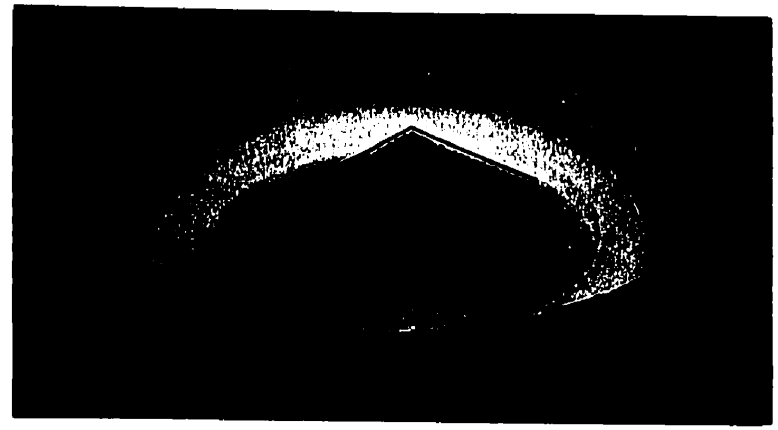
The image acquisition system (i.e., lighting system) was switched on for 30 min prior to acquiring any images for its stabilization. After that the gray level calibration (white balance) of the field of view (FOV) was done using the Kodak white card. The spatial calibration was done with an object of known dimension (a Canadian 25 cent coin). For textural calibration a graph sheet with green lines was used. Variation in mean gray level value (= 60) of the graph sheet images taken over the period of time was ±2 gray level.

For the first set of tests (imaging of bulk samples), each replicate sample (75 g mass) was poured into a transparent rectangular sample holder with dimensions of 135 x 100 x 10 mm (Fig. 4.2a). A piece of epoxy fibreglass (its length and width were little smaller than the sample holder) was placed at the top of the sample presentation device and was manually pressed three times to level the top surface of the bulk sample. Then the sample holder was placed in the FOV of the camera and an image of 512 x 480 was acquired and stored for later analysis.

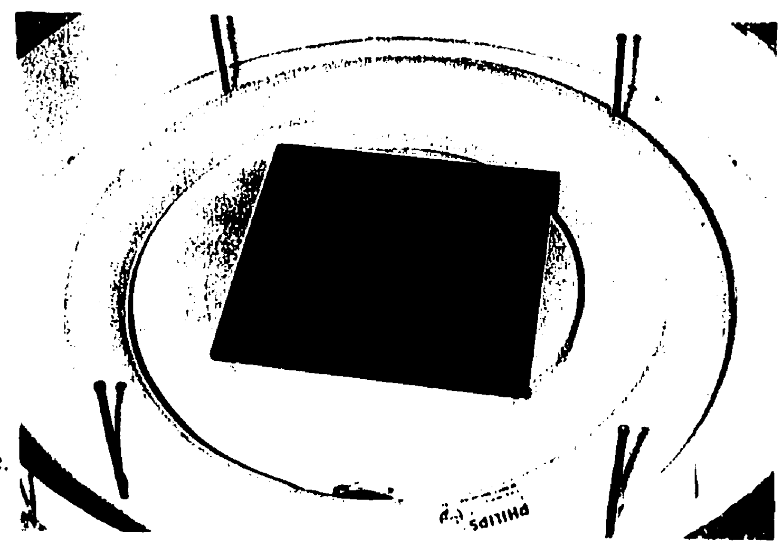
For the second set of tests (imaging of individual kernels), individual kernels were randomly placed (non-touching, 25 kernels per image) on a black background (Fig. 4.2b) and images were acquired and stored for later analysis.



(4.1)

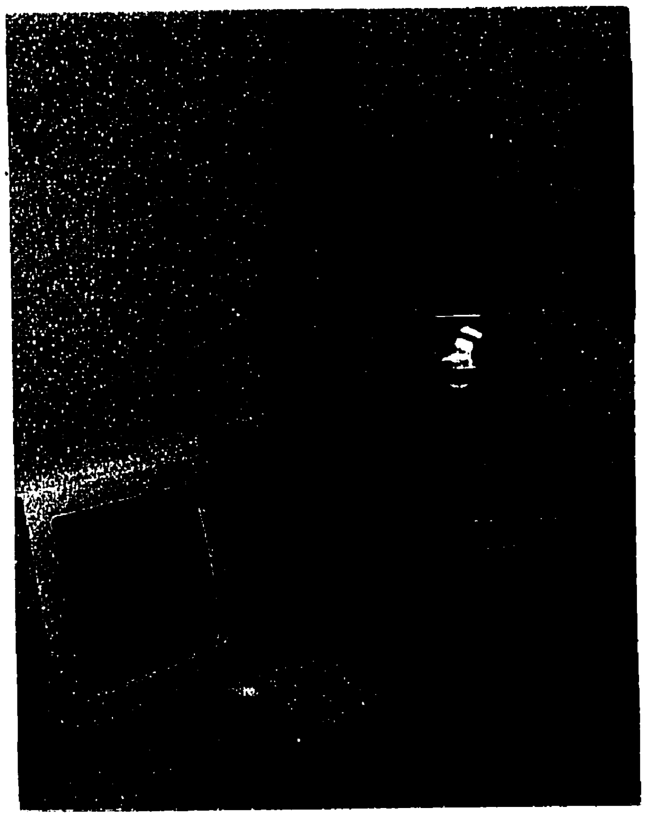


(4.2a)

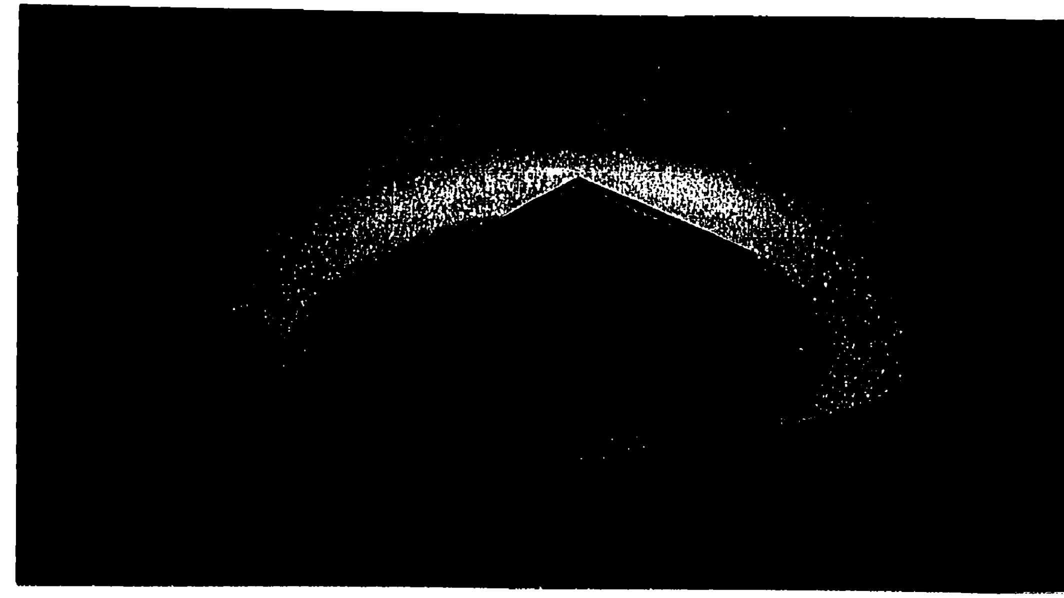


(4.2b)

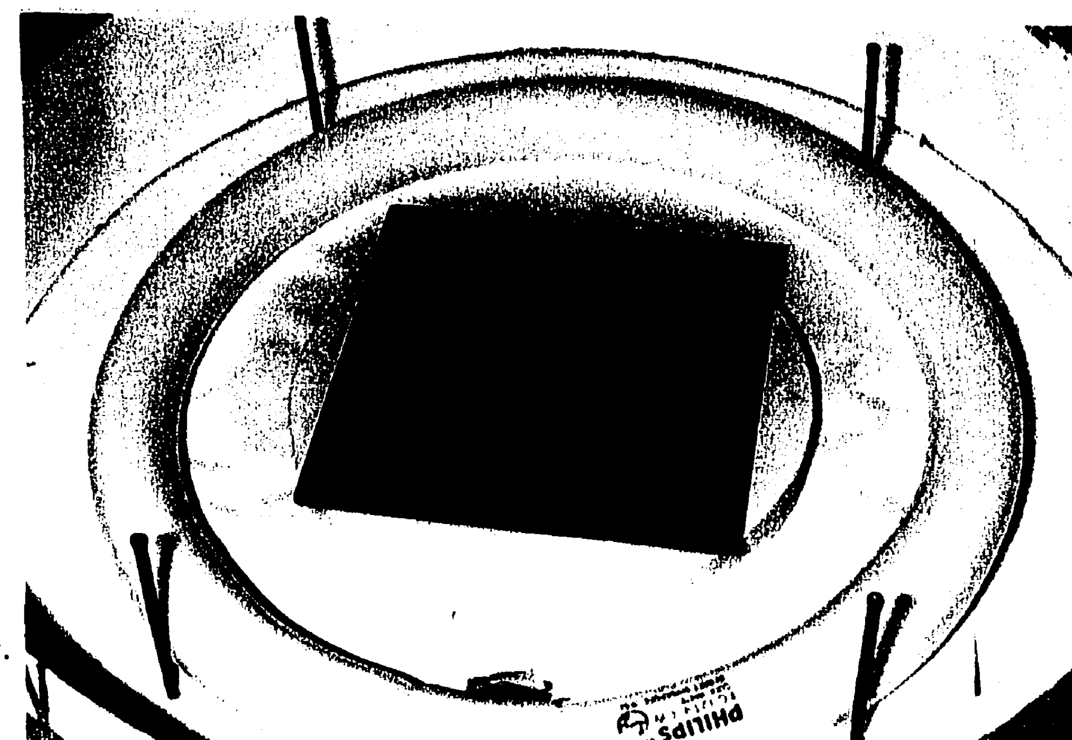
Fig. 4.1 The experimental set up.
Fig. 4.2a The illumination chamber with a bulk sample.
Fig. 4.2b The illumination chamber with individual kernels.



(4.1)



(4.2a)



(4.2b)

ig. 4.1 The experimental set up.
ig. 4.2a The illumination chamber with a bulk sample.
ig. 4.2b The illumination chamber with individual kernels.

CHAPTER V. ALGORITHM DEVELOPMENT

5.1 Gray level co-occurrence matrix (GLCM)

Suppose an image to be analyzed is rectangular and has N_x resolution cells in the horizontal direction, N_y resolution cells in the vertical direction, and the gray levels appearing in resolution cells are quantized to N_g levels. The texture information could be adequately specified by the matrix of relative frequencies, P(i, j), with which two neighboring resolution cells separated by distance, d, occur in the image, one with gray level, i, and the other with gray level, j. Such GLCM is a function of the angular relationship between the neighboring resolution cells as well as a function of the distance between them. The unnormalized frequency when four principal directions (0°, 45°, 90°, and 135°) were considered was defined by:

$$P(i, j, d) = \#\{((k, \ell), (m, n)) \in (L_x \times L_y) \times (L_x \times L_y) \mid (k - m = 0, |\ell - n| = d) \text{ or } (k - m = d, \ell - n = -d) \text{ or } (k - m = -d, \ell - n = d) \text{ or } (|k - m| = d, \ell - n = 0) \text{ or } (k - m = d, \ell - n = d) \text{ or } (k - m = -d, \ell - n = -d), I(k, \ell) = i, I(m, n) = j\} \quad (5.1)$$

where:

#	= number of elements in the set,
(k, ℓ)	= coordinate with gray level i, and
(m, n)	= coordinate with gray level j.

Consider Fig. 5.1, which represents a 4 x 4 image with 4 gray levels, ranging from 0 to 3. Figure 5.2 shows the unnormalized GLCM. For example, the element in the (3, 2) position of the 1 pixel-distance GLCM is the total number of times 2 gray levels of value 3 and 2 occur adjacent to each other in all *four directions*. To determine this, the number of pairs of resolution cells in the GLCM were counted such that the first resolution cell of the pair had gray level 3 and the second resolution cell of the pair had gray level 2. The GLCM was normalized by dividing each entry of the matrix by a normalizing constant, C, as:

$$p(i,j) = P(i,j)/C \tag{5.2}$$

where:

$p(i, j)$ = $(i, j)^{th}$ entry in a normalized GLCM,

$P(i, j)$ = $(i, j)^{th}$ entry in a unnormalized GLCM, and

C = the normalizing constant.

For a square or a rectangular image, the normalizing constant, C, was defined as:

$$C = \{2N_x(N_y - 1) + 2N_y(N_x - 1) + 4(N_x - 1)(N_y - 1)\} \tag{5.3}$$

For Fig. 5.1, the normalizing constant is 84.

0	0	3	1
0	1	1	1
2	2	3	3
2	2	3	1

Fig. 5.1 A 4 x 4 image with 4 gray level values 0 - 3

		Gray Level			
		0	1	2	3
Gray Level	0	6	4	2	1
	1	4	8	3	12
	2	2	3	12	4
	3	1	12	4	6

Fig. 5.2 Gray level co-occurrence matrix for the image in Fig. 5.1

Using the normalized GLCM, the following textural features were extracted (Haralick 1979; Unser 1986):

$$\textbf{Mean } (\mu) = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} i.p(i,j) \tag{5.4}$$

$$\textbf{Variance } (\sigma^2) = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} (i-\mu)^2.p(i,j) \tag{5.5}$$

$$\textbf{Uniformity} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \{p(i,j)\}^2 \tag{5.6}$$

$$\textbf{Entropy} = -\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j)\log(p(i,j)) \tag{5.7}$$

$$\text{Maximum Probability} = \text{Max}\,(p(i,j)) \tag{5.8}$$

$$\text{Correlation} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \frac{(i-\mu)(j-\mu)}{\sigma^2}.p(i,j) \tag{5.9}$$

$$\text{Homogeneity} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \frac{1}{1+(i-j)^2}.p(i,j) \tag{5.10}$$

$$\text{Inertia} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} (i-j)^2.p(i,j) \tag{5.11}$$

$$\text{Cluster Shade} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} (i+j-2\mu)^3.p(i,j) \tag{5.12}$$

$$\text{Cluster Prominance} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} (i+j-2\mu)^4.p(i,j) \tag{5.13}$$

5.2 Gray level run length matrix (GLRM)

A gray level run is a set of consecutive, collinear picture points having the same gray level value. The matrix element q(i, j) specifies the number of times that the picture contains a run of length j, in a given direction, consisting of points having gray level i (or lying in gray level range i). Figures 5.3(a - d) show the GLRMs for the image in Fig. 5.1 for the four principal directions (0°, 45°, 90°, and 135°).

The following features were extracted from all four GLRMs and their mean value and range were calculated for analyses (Galloway 1975).

$$\text{Short Run} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} \{q(i,j)/j^2\}/R \tag{5.14}$$

$$\text{Long Run} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} \{j^2.q(i,j)\}/R \tag{5.15}$$

$$\text{Gray Level Non-uniformity} = \sum_{i=1}^{N_g} (\sum_{j=1}^{N_r} q(i,j))^2/R \tag{5.16}$$

$$\text{Run Length Non-uniformity} = \sum_{j=1}^{N_r} (\sum_{i=1}^{N_g} q(i,j))^2/R \tag{5.17}$$

		Run Length			
	0°	1	2	3	4
	0	1	1	0	0
Gray	1	2	0	1	0
Level	2	0	2	0	0
	3	2	1	0	0

(a)

		Run Length			
	45°	1	2	3	4
	0	1	1	0	0
Gray	1	3	1	0	0
Level	2	2	1	0	0
	3	2	1	0	0

(b)

		Run Length			
	90°	1	2	3	4
	0	1	1	0	0
Gray	1	3	1	0	0
Level	2	0	2	0	0
	3	2	1	0	0

(c)

		Run Length			
	135°	1	2	3	4
	0	3	0	0	0
Gray	1	5	0	0	0
Level	2	2	1	0	0
	3	4	0	0	0

(d)

Fig. 5.3(a - d) Gray level run length matrices at 0°, 45°, 90°, and 135°, respectively for the image in Fig. 5.1

$$\text{Run Percent} = R / \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} j.q(i,j) \tag{5.18}$$

$$\text{GLRM Entropy} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} q(i,j)\log(q(i,j))/R \tag{5.19}$$

where:

$q(i, j)$ = $(i, j)^{th}$ entry in the GLRM,

i = gray level,

j = run length,

N_r = maximum number of run lengths in an image, and

$$R = \sum_{i=1}^{N_g} \sum_{j=1}^{N_r} q(i,j) \tag{5.20}$$

5.3 Color features

From the R, G, and B color bands of an image H, S, and I were calculated using the following equations (Gonzalez and Woods 1992):

$$I = R + G + B \tag{5.21}$$

$$S = 1 - \frac{3\,\mathrm{Min}(R, G, B)}{I} \tag{5.22}$$

$$H = \mathrm{Cos}^{-1}\left\{\frac{1/2\,[(R - G) + (R - B)]}{[(R - G)^2 + (R - B)(G - B)]^{1/2}}\right\} \tag{5.23}$$

Color in the HSI model was defined with respect to normalized R, G, and B. The original R, G, and B values (camera output) were divided by a normalizing constant [(R+G+B)/3] to get the normalized R, G, and B values. The normalizing constant used was 250 because the system was white balanced to 250. The H, S, and I values obtained were within the range [0, 1]. Equation 5.23 yields values of H in the interval $0° \leq H \leq 180°$. If $(B/I) > (G/I)$, then H had to be greater than 180°. So, whenever $(B/I) > (G/I)$, H was calculated as (360° - H). Hue was divided by 180 to normalized to the range [0, 1], i.e., $H = H/180°$. When $R = G = B$, then $S = 0$, making it meaningless to define angle H; in this case H was assumed as 0. When R, G, and B were 0, i.e., when $I = 0$, both S and H were meaningless to define; in this case, S and H were assumed as 0.

From the R, G, and B, and H, S, and I values, their mean values, variances, and ranges were calculated in an image.

5.4 Morphological features

Substantial work has been carried out by researchers using different morphological features for classification of different cereal grains and their varieties. But the effect of growing regions on classification accuracy of different cereal grains using morphological features was not studied.

Algorithms were developed to extract morphological features of individual kernels. Individual kernel images were segmented and labelled. The following morphological features were extracted from labelled images of individual kernels (Nair 1997):

Area — The algorithm calculated the number of pixels inside, and including the kernel boundary, and multiplied by the calibration factor (mm^2/pixel).

Perimeter — It was calculated by adding the Euclidean distances between all the successive pairs of pixels around the circumference of the kernel.

Length — It was the length of the rectangle bounding the kernel.

Width — It was the width of the rectangle bounding the kernel.

Major Axis Length — It was the distance between the (x, y) end points of the longest line that could be drawn through the kernel. The major axis endpoints were found by computing the pixel distance between every combination of border pixels in the kernel boundary and finding the pair with the maximum length.

Minor Axis Length — It was the distance between the (x, y) end points of the longest line that could be drawn through the object while maintaining perpendicularity with the major axis.

Thinness Ratio — It measured the roundness of the kernel.

Thinness ratio = $(\text{Perimeter})^2 / (4\pi \times \text{Area})$.

Aspect Ratio — Major Axis Length / Minor Axis Length.

Rectangular Aspect Ratio — Length / Width.

Area Ratio — (Length x Width) / Area.

Maximum Radius — It was the maximum distance between a pixel on the boundary and the centroid of the kernel.

Minimum Radius — It was the minimum distance between a pixel on the boundary and the centroid of the kernel.

Radius Ratio — Maximum Radius / Minimum Radius.

Standard Deviation of all Radii — It was the standard deviation of distances of all pixels on the boundary from the centroid of the kernel, denoted by σ_r.

Haralick Ratio — μ_r / σ_r, where μ_r was the mean of all radii of the kernel region.

Spatial Moments — They are the statistical measures related to an object's characterizations. The first four invariant moments (invariant to scaling, rotation, and translation) were used:

$$M_1 = \eta_{20} + \eta_{02} \tag{5.24}$$

$$M_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{5.25}$$

$$M_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{5.26}$$

$$M_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{5.27}$$

The normalized central moments, η_{pq}, were calculated from the central moment, μ_{pq}:

$$\eta_{pq} = \mu_{pq} / \mu_{00}^{r} \tag{5.28}$$

where:

r = ½(p + q) +1, and

$$\mu_{pq} = \sum_i \sum_j (i - c_i)^p (j - c_j)^q \tag{5.29}$$

for p, q = 0, 1, 2, ..., k where:

k = user-selected value to calculate a specific order of central moment,

c_i = m_{10} / m_{00},

c_j = m_{01} / m_{00}, and

(c_i, c_j) = the centre of gravity of the kernel.

The two-dimensional $(p + q)^{th}$ order moment was defined as:

$$m_{pq} = \sum_i \sum_j i^p j^q F(i,j) \tag{5.30}$$

for p, q = 0, 1, 2, ..., ℓ where:

ℓ = user-selected value to calculate a specific order of moment, and

F(i, j) = gray level value at coordinate (i, j).

F(i, j) is 1 for any binary image.

Fourier Descriptors — One-dimensional distance function, d, was calculated for all pixels on the boundary of a kernel as:

$$d_k = [(i_k - c_{ik})^2 + (j_k - c_{jk})^2]^{1/2} \tag{5.31}$$

where:

(i_k, j_k) = k^{th} pixel coordinates on the boundary of the kernel, and

(c_{ik}, c_{jk}) = centroid of the k^{th} kernel.

The distance function d_k was converted to milimeters using the calibration factor (mm/pixel).

The magnitude of the Fourier descriptors were calculated as:

$$FD_u = [R_u^2 + I_u^2]^{1/2} \tag{5.32}$$

for u = 0, 1. 2, ... (N-1). The real value of the descriptor was defined as:

$$R_u = \sum_{k=0}^{N-1} d.\cos[\frac{2\pi k u}{N}] \tag{5.33}$$

and the imaginary value of the descriptor was defined as:

$$I_u = \sum_{k=0}^{N-1} d.\sin[\frac{2\pi k u}{N}] \tag{5.34}$$

where:

N = number of pixels on the boundary of the kernel.

The first four Fourier descriptors (u = 0, 1, 2, and 3) were used for analysis.

CHAPTER VI. IMAGE ANALYSIS

6.1 Analysis of bulk samples using textural features

The PROC DISCRIM (SAS 1990) was used to classify bulk samples of CWRS wheat, CWAD wheat, barley, oats, and rye using textural features. The analysis was done using resubstitution, cross-validation (leave-one-out), and hold out methods with normal and non-parametric estimations. In the non-parametric estimation, *k-nearest neighbor* method was used with k value 5. Preliminary experiments were conducted with different k values (e.g., 10, 15, 50, and 100) and k value 5 gave the highest classification accuracies of cereal grains. In the hold out method, bulk sample images from 25 growing regions (3 images per growing region) were used as the training data set and from 5 other growing regions were used as the test data set. These training and test data sets were selected randomly. For the cross-validation and resubstitution methods, bulk sample images from 25 growing regions (used as the training data set in the hold out method) were used. Of the 25 textural features used in the discriminant analysis, 10 were GLCM features (mean, variance, uniformity, entropy, maximum probability, correlation, homogeneity, inertia, cluster shade, and cluster prominence), 12 were GLRM features (short run, long run, gray level non-uniformity, run length non-uniformity, run percent, and GLRM entropy, and their ranges), and remaining 3 were gray level features (mean, variance, and range in gray level). The textural features were extracted from a single color band (R, G, or B) or a color band combination [black&white, i.e., (R+G+B)/3; (3R+2G+1B)/3; (2R+1G+3B)/6; or (1R+3G+2B)/6]. These color band combinations were arbitrarily chosen to determine their effect on classification accuracy when textural features extracted from these color band combinations were used for classification of cereal grains.

6.1.1 Gray level reduction To reduce the computational time of the textural algorithm, the original gray level value (250) was reduced to 32, 16, 8, and 4 gray levels and the textural features extracted from each case were used for classification, and the results were compared. For example, when the gray level was reduced from 250 to 32, the gray levels were grouped into 32 ranges: 0 - 7 as 0, 8 - 15 as 1, 16 - 23 as 2, 24 - 31 as 3, and so on. In case of gray level reduction to 16 gray levels, the ranges were 0 - 15 as 0, 16 - 31 as 1, 32 - 47 as 2, and so on. Similarly for reduction to 8 gray levels, the ranges were 0 - 31 as 0, 32 - 63 as 1, and so on and for reduction to 4 gray levels, the ranges were 0 - 63 as 0, 64 - 127 as 1, and so on.

6.1.2 Color selection Textural features were extracted from R, G, and B color bands and their combinations [black&white, i.e., (R+G+B)/3; (3R+2G+1B)/6; (2R+1G+3B)/6; and (1R+3G+2B)/6] to determine if a particular color band or color band combination gave better classification accuracy than others.

6.1.3 Effect of sub-images on classification accuracy The original image (512 x 480) was partitioned into different sub-images (e.g., 4, 9, or 16 sub-images). All sub-images were treated as original images. Textural and color features extracted from the sub-images were used for classification to determine whether partitioning of images can improve the classification accuracy.

6.1.4 Selection of textural features of bulk samples All 25 textural features used for classification of bulk samples of cereal grains may not contribute significantly to the classifier. Sometimes, the classifier performance declines if there are too many redundant features. To optimize the number of textural features that contributed significantly to the classification, PROC STEPDISC (SAS 1990) was used. Textural features of bulk samples of cereal grains from 25 growing regions (used as the training data set in the hold out method) were used for the STEPDISC analysis. Also, independent rankings of all textural features were determined using the STEPDISC analysis with one feature in the final model. Once the feature with the highest level of contribution (determined by r^2 and average squared canonical correlation, ASCC) was identified, it was removed from subsequent analysis and the second best feature was determined. The analysis was continued till the least important feature was identified.

6.2 Analysis of bulk samples using color features

The PROC DISCRIM (SAS 1990) was used to classify bulk samples of CWRS wheat, CWAD wheat, barley, oats, and rye using color features. The analysis was done using resubstitution, cross-validation (leave-one-out), and hold out methods with normal and non-parametric estimations. In the non-parametric estimation, *k-nearest neighbor* method was used with k value 5. In the hold out method, bulk sample images from 25 growing regions (three images per region) were used as the training data set and from five other growing regions were used as the test data set. These training and test data sets were same as the data sets used for textural analysis. For the cross-validation and resubstitution methods, bulk sample images from 25 growing regions (used as the training data set in the hold out method) were used. The mean, variance, and range of R, G, and B, and H, S, and I were calculated from bulk images and used for classification of cereal grains.

6.2.1 Effect of sub-images on classification accuracy As discussed in analysis of textural features, original images were equally partitioned into sub-images (e.g., 9, 16, or 25) and the sub-images were treated as original images. Discriminant analyses (hold out and leave-one-out methods) were carried out using color features extracted from original images and sub-images and the classification accuracies were compared.

6.2.2 Selection of color features of bulk samples STEPDISC analysis was carried out to select the color features of bulk samples of cereal grains which contributed significantly to the classifier. Color features of cereal grains from 25 growing regions (used as the training data set in the hold out method) were used for the STEPDISC analysis. Independent rankings of all color features were determined using the STEPDISC analysis.

6.3 Analysis of individual kernels using morphological features

After converting the rectangular pixel images into square pixel images, the images were segmented using an automatic thresholding technique (Parker 1994). If there were any holes inside the segmented image of individual kernels, they were filled with a hole filling algorithm. All kernels in the image were labelled to give unique identification. Morphological features (23 features) were extracted from the labelled image. The morphological feature extraction algorithms were developed on an IBM compatible pentium 75 personal computer (Nair 1997).

Discriminant analyses were carried out using resubstitution, cross-validation (leave-one-out), and hold out methods. In each case, normal and non-parametric estimations were used. In the non-parametric estimation, *k- nearest neighbor* method was used with k value 5. In the hold out method, individual kernel images from 15 growing regions (300 kernels per growing region) were used as the training data set and from five other growing regions as the test data set. In the cross-validation and resubstitution methods, individual kernel images from 15 growing regions (used as the training data set in the hold out method) were used for classification.

To determine the level of contribution of morphological features for classification of individual kernels of cereal grains, PROC STEPDISC (SAS 1990) was used. Morphological features of individual kernels from 15 growing regions (used as the training data set in the hold out method) were used for the STEPDISC analysis. Individual rankings of morphological features were determined using the STEPDISC analysis with one feature in the final model.

6.4 Analysis of individual kernels using textural features

After converting the rectangular pixel images into square pixel images, the images were segmented manually. For CWRS wheat, CWAD wheat, barley, and rye the selected threshold value was 50±3, and for oats it was 70±3. To remove noise due to dust and to fill in holes inside kernel images, if there were any, the *opening* and *closing* operations (Gonzalez and Woods 1992) were carried out with structural elements of 3 or 4 pixel diameter. All kernels in the image were labelled to give unique identification. The original gray level values of each kernel were superimposed on the labelled image to make the background pixel values zero. The textural and color features were extracted from each kernel image for classification.

All algorithms to extract textural and color features of bulk samples and individual kernels were developed using a software, named KHOROS (Khoral Research, Inc., New Mexico). The analyses were carried out on a work station (Model SPARC STATION 2, Sun Microsystems, Inc., Mountain view, CA).

Discriminant analysis was conducted using resubstitution, cross-validation (leave-one-out), and hold out methods. In each case, normal and non-parametric estimations were used. In the non-parametric estimation, *k- nearest neighbor* method was used with k value 5. In the hold out method, individual kernel images from 15 growing regions (300 kernels per growing region) were used as the training data set and from other five growing regions as the test data set. In the cross-validation and resubstitution methods, individual kernel images from 15 growing regions (used as the training data set in the hold out method) were used for classification.

6.4.1 Gray level reduction As discussed for bulk sample analysis, the gray level was reduced from 250 to 32, 16, 8, and 4. The textural features extracted from images at different maximum gray levels were used to determine whether reduced gray level improves classification accuracy.

6.4.2 Color selection Similar to bulk sample analyses, textural features of individual kernels were extracted from R, G, and B color bands and their combinations [black&white, i.e., (R+G+B)/3; (3R+2G+1B)/6; (2R+1G+3B)/6; and (1R+3G+2B)/6] to determine if a particular color band or color band combination gave better classification accuracy than others.

6.4.4 Selection of textural features of individual kernels STEPDISC analysis was conducted to determine the level of contribution of each feature to the classifier. Also, it was used to determine the independent rankings of textural features.

6.5 Analysis of individual kernels using color features

Discriminant analysis was carried out using resubstitution, cross-validation (leave-one-out), and hold out methods to determine classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye using color features of individual kernels. In the non-parametric estimation, *k- nearest neighbor* method was used with k value 5. In the hold out method, individual kernel images from 15 growing regions (300 kernels per growing region) were used as the training data set and from other five growing regions as the test data set.

In the cross-validation and resubstitution methods. individual kernel images from 15 growing regions (used as the training data set in the hold out method) were used for classification. STEPDISC analysis was conducted to determine the level of contribution of each color feature to the classifier and also to determine their independent rankings.

CHAPTER VII. RESULTS AND DISCUSSIONS

7.1 Classification of bulk samples using textural features

7.1.1 Gray level reduction The computational time for extraction of textural features is reduced with a decrease in maximum gray level value of an image, because it reduces the size of the co-occurrence and run length matrices. In real-world applications (e.g., on-line quality monitoring of fruits and vegetables, grains), the computational time is very crucial. hence one may sacrifice small classification accuracy for reduced computational time; but it is very much application dependent, e.g., for some application, the classification accuracy is very crucial and for some other application, the computational time is very important. The textural features extracted from red color band of original images (at maximum gray level value 250) and images of reduced gray levels (at maximum gray level values 32, 16, 8, or 4) were used to classify cereal grains. The classification results using the hold out and leave-one-out methods with the normal and non-parametric estimations are given in Appendices B1-B5 and BB1-BB5. Oats were very distinct from other cereal grains in their texture; at all maximum gray level values (e.g., 250, 32, 16, 8, and 4) and in the hold out and leave-one-out methods, oats were 100.0% correctly classified except in two cases (non-parametric estimation in the hold out method at maximum gray level values 8 and 4) where one oat image got misclassified as barley in each case (Appendices B1 - B5 and BB1 - BB5). This is because the brightness of oats is different than other cereal grains and their packing density is different than that of other cereal grains as the oats kernels are elongated in shape. When normal estimation (in the hold out method) was used for classification. five barley images were misclassified as CWAD wheat (Appendices B1a - B5a). This may be because the brightness and the packing density of grains in those barley images were similar to that of CWAD wheat images. But from visual inspection no peculiarities were observed in those images.

The "mean accuracy" which was the average of the classification accuracies of cereal grains (hereafter cereal grains will refer to one or more of CWRS wheat, CWAD wheat. barley, oats, and rye) at a maximum gray level value (e.g., 250, 32, 16, 8, or 4) was used to determine if any particular maximum gray level value gave the highest classification accuracy. When textural features (all 25 features) extracted from images at maximum gray level value 32 were used, the mean accuracies in the majority of the analysis methods [e.g., hold out method (Npar), hold out method (normal), leave-one-out method (Npar), or leave-one-out method (normal)] were higher than that when images at other maximum gray level values were used (Fig. 7.1). Images at gray level value 250 had gray level values sparsely distributed. Hence, the tonal primitives, i.e., the local variations (e.g., fineness, coarseness. granulation) on the surface texture of an image were not prominent (Haralick 1973). As the maximum gray level value decreased, the distinguishable tonal primitives increased; hence the prominence in the textural features increased which improved the classification accuracies. But the reduction in maximum gray level value beyond certain level resulted in an image with little textural variations and the image surface was transformed into a surface having almost same gray level value. Although images at maximum gray level value 32 gave the highest mean accuracies, images at 16 and 8 gray level values also gave comparably good classification accuracies. At maximum gray level value 4, the mean accuracies in the majority of the analysis methods were poorer than when images at maximum gray level value 32 was used (Fig. 7.1). This suggests that at this maximum gray level value, the images of cereal grains started losing the distinctness in their textural features. At maximum gray level value 32, the classification accuracies were 100.0% each for all cereal grains when an independent data set was used for testing (non-parametric estimation, Appendix B2b) and was chosen for further analysis. The classification accuracies were poor when normal estimation was used on the independent data set (five barley and one rye images were misclassified). This suggested that textural features of bulk images did not follow normal distribution.

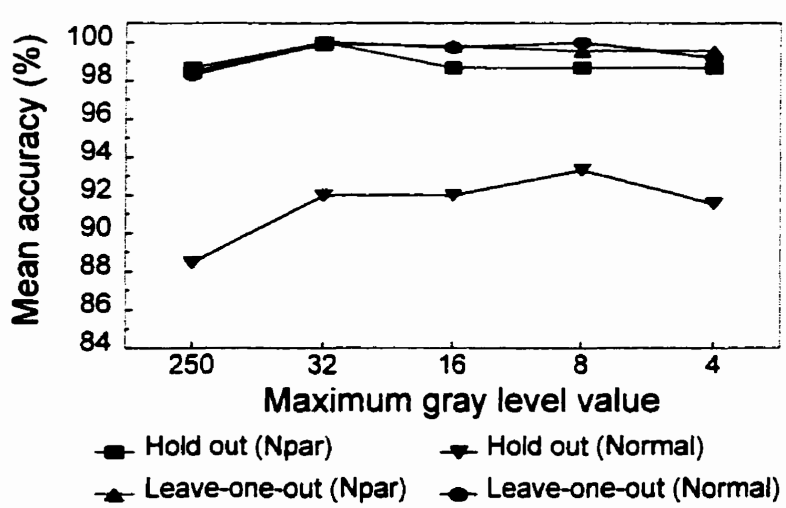


Fig. 7.1 **Classification accuracies of bulk samples of cereal grains using textural features extracted from red color band at different maximum gray level values (Note: Npar denotes non-parametric estimation)**

7.1.2 Color selection The textural features (GLCM, GLRM, and gray level features) were extracted from images at maximum gray level value 32 with a single color band (R, G, and B) and a color band combination [black&white, i.e., (R+G+B)/3; (3R+2G+1B)/6; (2R+1G+3B)/6; and (1R+3G+2B)/6] to determine which color band or color band combination gave the highest classification accuracies. Classification results for cereal grains using the hold out and leave-one-out methods with normal and non-parametric estimations are given in Appendices B2 and B6-B11, and BB2 and BB6-BB11, respectively. The oats were very distinct from other cereal grains in all color bands or color band combinations (Appendices B2 and B6-B11, and BB2 and BB6-BB11). Also, the CWRS wheat and the CWAD wheat in the test data set were 100.0% correctly classified except in one case (when green color was used) where one CWRS wheat image got misclassified as rye (Appendix B6b). Textural features extracted from images with red color band gave the highest mean accuracy in the majority of the analysis methods (in three out of four methods, Fig. 7.2). This conforms with the results of the studies conducted by Majumdar et al. (1996a), Neuman et al. (1989b), and Hawk et al. (1970) where they reported that the reflectance properties of bulk samples of cereal grains were more distinct in the red color band than in other color bands of the visual spectrum. The mean accuracy was poor when an independent data set was used for testing (hold out method) using normal estimation (Fig. 7.2). This suggested that the data set did not follow normal distribution.

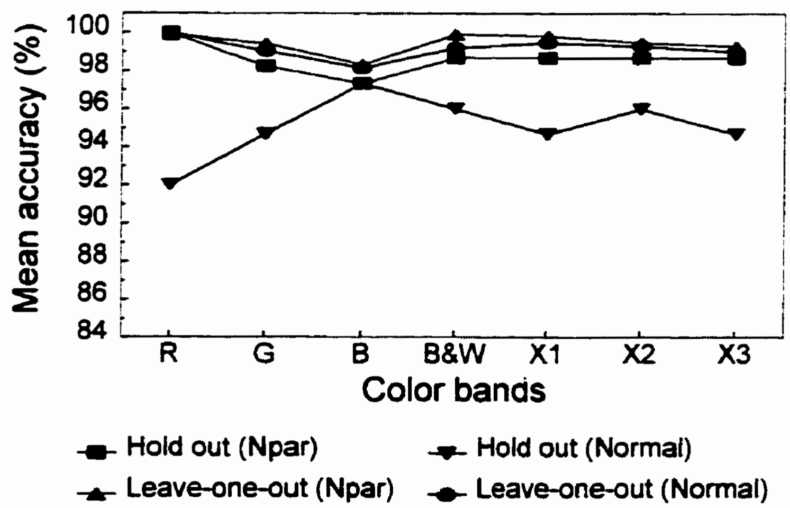


Fig. 7.2 **Classification accuracies of bulk samples of cereal grains using textural features extracted from different color bands and color band combinations at maximum gray level value 32 [R: red, G: green, B: blue, B&W: black&white {(R+G+B)/3}, X1: (3R+2G+1B)/6, X2: (2R+1G+3B)/6, and X3: (1R+3G+2B)/6] (Note: Npar denotes non-parametric estimation)**

7.1.3 Effect of sub-images on classification accuracy It was hypothesized that if an original image was partitioned into many sub-images and were treated as original images, classification accuracies could be improved using textural features. The original images of cereal grains were partitioned into 9, 16, or 25 sub-images and the classification accuracies are shown in Appendices B2, B12-B14, BB2, and BB12-BB14. When original images were used, in the majority of the analysis methods the mean accuracies were higher than when the sub-images were used (Fig. 7.3). As the number of sub-images increased, the classification accuracies of cereal grains decreased except in one case (the normal estimation of the test data extracted from nine sub-images, Fig. 7.3).

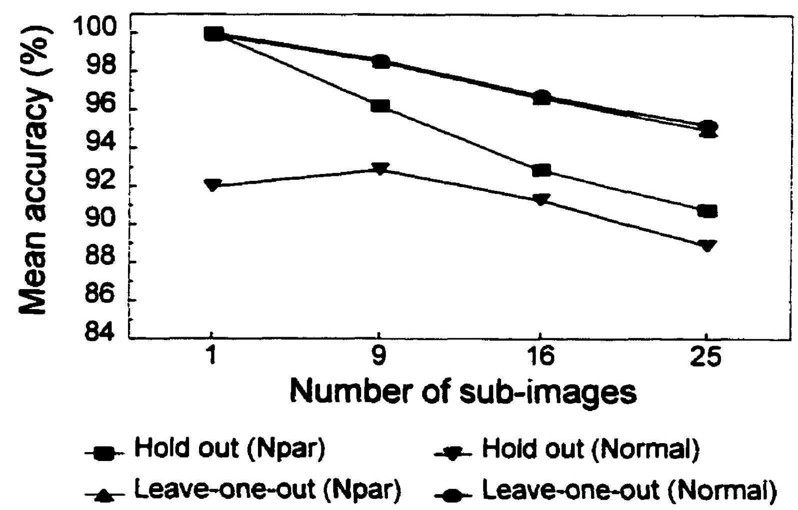


Fig. 7.3 Classification accuracies of bulk sample images of cereal grains, partitioned into different sub-images, using textural features extracted from red color band at maximum gray level value 32 (Note: Npar denotes non-parametric estimation)

The bulk image is not always uniform in its grain packing density along its surface which results in non-uniform shadowing along the image surface. The presence of foreign materials (e.g., other cereal grains) in an image also makes the texture of a bulk image non-uniform along its surface. In a large image, these local irregularities were nullified when GLCM and GLRMs were calculated. As the image size is reduced (due to partitioning), these local variations became prominent, and the textural features extracted from the sub-images of one cereal grain were similar to other grains; hence resulted in increased misclassification.

The textural features extracted from the red color band of bulk images (not partitioned) at maximum gray level value 32 gave the highest classification accuracies in cereal grains and were used for further analysis. Textural features of bulk sample images can be used (non-parametric estimation) for rapid identification of cereal grains with 100% classification accuracy.

7.1.4 Selection of textural features of bulk samples All 25 textural features did not significantly contributed for improvement of the classification accuracy of cereal grains. Many textural features were highly correlated with one another; hence some of them are redundant features (Appendix C1). To determine the level of contribution, textural features of cereal grains, extracted from the red color band at maximum gray level value 32, from 25 growing regions (used as the training set in the hold out method) were used for the STEPDISC analysis. Table 7.1 shows the features in descending order of their level of contribution to the classifier. The STEPDISC analysis removed two features (inertia and GLRM entropy range) because they were not significant to the classifier. The variance is the most important textural feature (average squared canonical correlation, ASCC = 0.210) of bulk sample images.

Discriminant analyses were carried out with the first 5, 10, 15, and 20 features (from Table 7.1) and the classification accuracies were compared with that when all 25 features were used (Fig. 7.4). The mean accuracies using the first five features were poor. When all 25 features were used, the mean accuracies were the highest in the majority of the analysis methods (Fig. 7.4). The first 10 features also gave similar mean accuracies. The level of contribution of features (see ASCC values) beyond the first 10 features was poor (Table 7.1). This suggested that one can use only the first 10 features. If one uses bulk samples to identify the principal grain in a car lot sample, some classification accuracy (e.g., 4-5%) can be sacrificed to save some computational time. Using 10 features instead of 25 features would save computational time, therefore one can use the first 10 textural features for classifying bulk samples of cereal grains. Also, in field situation, one always uses the hold

Table 7.1 Selection of textural features of bulk samples of cereal grains, extracted from the red color band at maximum gray level value 32, using the STEPDISC analysis

Number	Textural features of bulk samples	Average squared canonical correlation	Partial r^2
1	Variance (GLCM)	0.210	0.84
2	Long run (GLRM)	0.374	0.70
3	Short run (GLRM)	0.508	0.69
4	Gray level non-uniformity (GLRM)	0.586	0.54
5	Run length non-uniformity (GLRM)	0.598	0.39
6	GLRM entropy (GLRM)	0.657	0.34
7	Correlation (GLCM)	0.700	0.29
8	Mean (GLCM)	0.721	0.26
9	Uniformity (GLCM)	0.729	0.18
10	Cluster prominence (GLCM)	0.769	0.13
11	Run percent (GLRM)	0.773	0.11
12	Cluster shade (GLCM)	0.776	0.08
13	Entropy (GLCM)	0.788	0.24
14	Mean gray level	0.798	0.14
15	Gray level variance	0.804	0.12
16	Long run range (GLRM)	0.806	0.06
17	Gray level range	0.809	0.05
18	Maximum probability (GLCM)	0.818	0.11
19	Gray level non-uniformity range (GLRM)	0.819	0.04
20	Run length non-uniformity range (GLRM)	0.822	0.04
21	Run percent range (GLRM)	0.827	0.07
22	Short run range (GLRM)	0.828	0.02
23	Homogeneity (GLCM)	0.829	0.02

Note: inertia and GLRM entropy were removed from the selection.

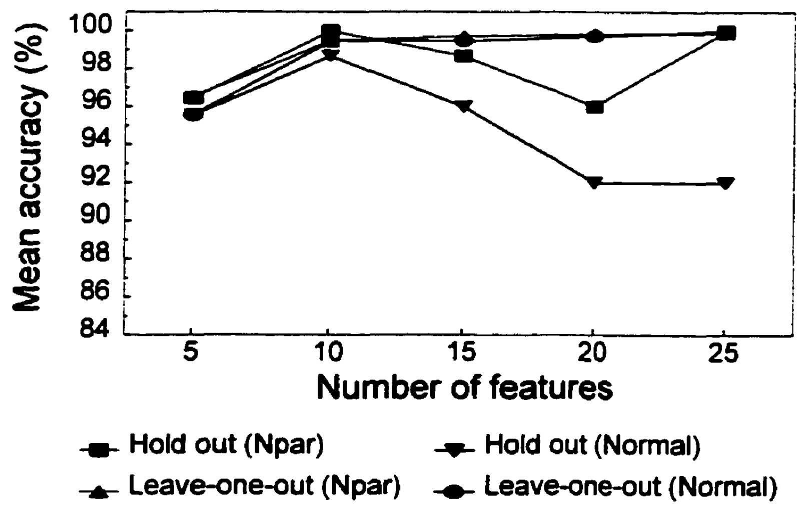


Fig. 7.4 Comparison of classification accuracies of bulk samples of cereal grains using different number of textural features extracted from red color band at maximum gray level value 32 (Note: Npar denotes non-parametric estimation)

out method to test unknown samples. The leave-one-out method was used to determine how well the classifier performed on the training data. The classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye using the first 10 textural features, extracted from red color band at maximum gray level value 32, were 100.0 % in each case when tested on an independent data set (non-parametric estimation, Appendix F1a).

Table 7.2 shows the independent rankings of textural features of bulk samples. Although cluster prominence and cluster shade were the second and third most significant features in terms of their independent levels of contribution (Table 7.2), in the discriminant model they ranked the 10th and 12th most significant features, respectively (Table 7.1). This was because in the STEPDISC analysis, once the most significant feature(s) was (were) selected (for example, here it was variance), the rest of the features were selected depending

Table 7.2 Independent rankings of textural features (extracted from the red color band at maximum gray level value 32) of bulk samples of cereal grains on the basis of their individual level of contribution to the classifier using the STEPDISC analysis

Number	Textural features of bulk samples	Average squared canonical correlation	r^2
1	Variance (GLCM)	0.210	0.84
2	Cluster prominance (GLCM)	0.205	0.82
3	Cluster shade (GLCM)	0.200	0.80
4	Long run (GLRM)	0.179	0.72
5	Mean Gray level	0.176	0.70
6	Gray level variance	0.174	0.70
7	Mean (GLCM)	0.173	0.69
8	Run percent (GLRM)	0.172	0.69
9	Inertia (GLCM)	0.168	0.67
10	Run length non-uniformity (GLRM)	0.167	0.67
11	Short run (GLRM)	0.166	0.66
12	Homogeneity (GLCM)	0.165	0.66
13	GLRM entropy (GLRM)	0.163	0.65
14	Uniformity (GLCM)	0.153	0.61
15	Correlation (GLCM)	0.147	0.59
16	Gray level non-uniformity (GLRM)	0.128	0.51
17	Entropy (GLCM)	0.092	0.37
18	Long run range (GLRM)	0.089	0.36
19	Gray level non-uniformity range (GLRM)	0.026	0.10
20	Run percent range (GLRM)	0.025	0.10
21	Short run range (GLRM)	0.024	0.09
22	GLRM entropy range (GLRM)	0.022	0.09
23	Gray level range	0.021	0.08
24	Maximum probability (GLCM)	0.018	0.07
25	Run length non-uniformity range (GLRM)	0.016	0.06

on their correlation with the feature(s) already being selected, i.e., features with the least correlation with the already being selected feature(s) will be selected first. Appendix C1 shows the between-class correlation coefficients of textural features of bulk samples. Because cluster shade and cluster prominence were highly correlated with variance (≈ 0.99, Appendix C1), once variance was selected in the STEPDISC analysis, their level of contribution went down in the discriminant model (Table 7.1). Contrary to that, long run was the fourth most independently significant feature (Table 7.2) and as its correlation with variance was not high (≈ 0.42), in the discriminant model it became the second most significant feature. Some feature may have a very high level of contribution when used independently but its level of contribution may go down drastically when used with a group of other features, some of which are highly correlated with that feature. Also, from the independent ranking, one can choose an alternative set of features depending on their level of contribution to the discriminant model. For example, instead of variance, if cluster prominence or long run was selected as the first feature, the level of contribution of rest of the features would have changed.

In the discriminant model, the first 10 textural features consists 5 GLCM and 5 GLRM features (Table 7.1). These GLCM features were highly correlated (most of the cases > 0.65) with all primary color features (red, green, and blue) (Appendix C1). Also they were highly correlated with intensity but their correlation with hue and saturation was very poor. This suggested that these GLCM features were manifestation of primary color features. But the correlation of all primary color features (red, green, and blue or hue, saturation, and intensity) and the five GLRM features were very poor (Appendix C1) which suggested that these textural features were independent of primary color features. Also, of the 10 most significant textural features (on the basis of their individual level of contribution, Table 7.2), 5 were highly correlated (variance, cluster prominence, cluster shade, mean gray level, and mean) with primary color features but other 5 were very poorly correlated. This also suggested that all textural features were not a manifestation of primary color features.

7.2 Classification of bulk samples using color features

The classification accuracies of bulk samples of cereal grains using color features are given in Appendices D1 and DD1. When an independent data set was used for testing, the classification accuracy was 100.0% for each cereal grain (Appendix D1b). Also, with the leave-one-out method, all cereal grains were correctly classified except one CWAD wheat image which got misclassified as oats (Appendix DDb1).

7.2.1 Effect of sub-images on classification accuracy Discriminant analyses (hold out and leave-one-out methods) were carried out using color features, extracted from original images and sub-images (Appendices D1-D4 and DD - DD4) and the classification accuracies were compared (Fig. 7.5). The color features extracted from original images (without partitioning) gave higher mean accuracies in the majority of the analysis methods than sub-images. As the number of sub-images per original image increased (e.g., 16 and 25), the classification accuracies decreased. This was because as the image size reduced, the presence of foreign materials and non-uniformity in packing density of grains became prominent which resulted in misclassification of cereal grains.

7.2.2 Selection of color features of bulk samples Some of the color features were highly correlated with one another (> 0.90) (Appendix C1); hence their level of contribution to the classification of cereal grains was poor. Table 7.3 shows the color features of bulk samples in descending order of their level of contribution to the classifier. The STEPDISC analysis

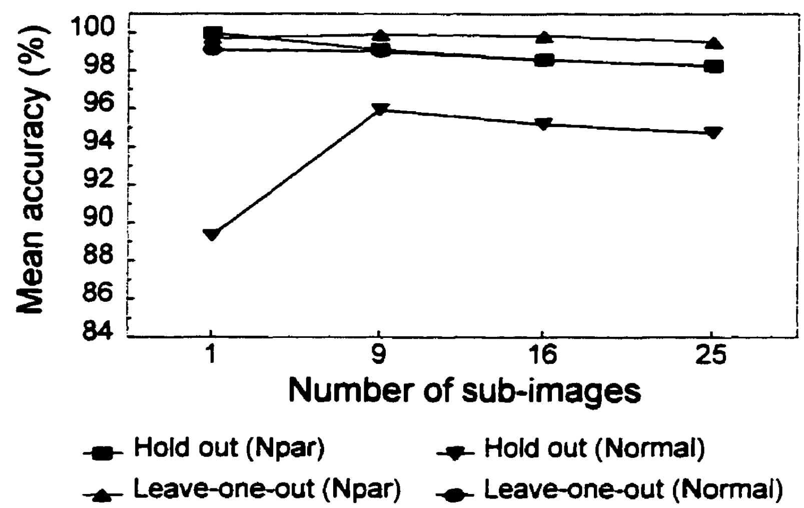


Fig. 7.5 **Classification accuracies of bulk sample images of cereal grains, partitioned into different sub-images, using color features (Note: Npar denotes non-parametric estimation)**

removed intensity as it was not significant to the classifier. Hue is the most significant color feature. The level of contribution of color features (see ASCC values, Table 7.3) beyond the first 10 features was very poor which suggested that one can ignore these redundant features in the classifier.

Discriminant analyses were carried out with the first 5, 10, and 15 features (from Table 7.3) and the classification accuracies were compared with the classification accuracies when all 18 features were used (Fig. 7.6). The mean accuracies in the majority of the analysis methods were higher when the first five features were used compared to that when the first 10, 15, or all 18 features (Fig. 7.6). When an independent data set was used for testing (non-parametric estimation), all cereal grains were 100.0% correctly classified with

Table 7.3 **Selection of color features (bulk images) of cereal grains using STEPDISC analysis**

Number	Color features of bulk samples	Average squared canonical correlation	Partial r^2
1	Hue	0.192	0.77
2	Hue variance	0.346	0.71
3	Red variance	0.508	0.69
4	Green variance	0.582	0.68
5	Saturation variance	0.625	0.40
6	Saturation	0.652	0.40
7	Red	0.675	0.45
8	Blue	0.720	0.36
9	Blue variance	0.740	0.16
10	Saturation range	0.750	0.12
11	Green	0.761	0.14
12	Blue range	0.764	0.09
13	Intensity variance	0.766	0.07
14	Intensity range	0.768	0.04
15	Red range	0.782	0.13
16	Green range	0.784	0.03
17	Hue range	0.784	0.02

Note: intensity was removed from the selection

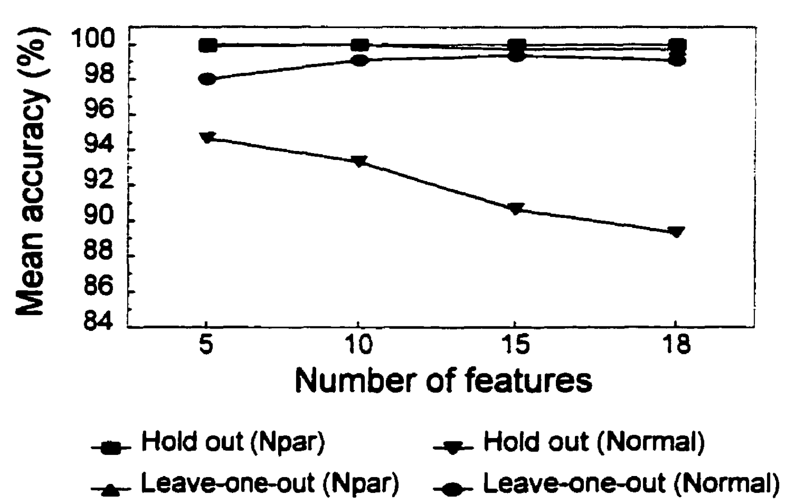


Fig. 7.6 **Comparison of classification accuracies of bulk samples of cereal grains using different number of color features (Note: Npar denotes non-parametric estimation)**

the first 5, 10, 15, or all 18 features (Appendix F2a). The classification accuracies were poorer in the normal estimation than in the non-parametric estimation which suggested that the color features were not normally distributed. Table 7.4 shows independent rankings of the color features. Although red and green were the second and the fourth most important

Table 7.4 Independent rankings of color features (bulk samples) of cereal grains on the basis of their individual level of contribution to the classifier using STEPDISC analysis

Number	Color features of bulk samples	Average squared canonical correlation	r^2
1	Hue	0.192	0.77
2	Red	0.176	0.70
3	Red variance	0.174	0.70
4	Green	0.163	0.65
5	Intensity variance	0.163	0.65
6	Green variance	0.163	0.65
7	Hue variance	0.157	0.63
8	Blue variance	0.147	0.59
9	Intensity	0.142	0.57
10	Blue	0.076	0.31
11	Saturation variance	0.060	0.24
12	Saturation	0.056	0.23
13	Saturation range	0.032	0.13
14	Blue range	0.031	0.12
15	Red range	0.021	0.09
16	Hue range	0.018	0.07
17	Intensity range	0.006	0.02

features (on the basis of independent ranking, Table 7.4), they ranked seventh and eleventh in the discriminant color model because their correlations with hue (0.61 and 0.78) were very high (Appendix C1). Red variance, intensity variance, green variance, and blue variance were poorly correlated (< 0.38 in all cases) with hue as well as with one another; hence their independent ranking (Table 7.4) and their ranking in the discriminant color model (Table 7.3) were similar.

For rapid identification of cereal grains, either textural or color features of bulk sample images can be used with non-parametric estimation. Some of the textural features (e.g., some GLCM features) were highly correlated with some primary color features (e.g., red, green, blue, and intensity) but there were many textural features which were very poorly correlated with color features which suggested that those textural features were very distinct from color features.

7.3 Morphology model: classification of individual kernels

Many researchers conducted substantial work using different morphological features for classification of cereal grains and their varieties. Using clean, pedigreed sample they achieved high classification accuracies. It was hypothesized that the classification accuracies would reduce if tested with commercial samples collected from different growing regions. Morphological features of individual kernels were used for classification of CWRS wheat, CWAD wheat, barley, oats, and rye, collected from different growing regions. When an independent data set was used for testing (the hold out method) with non-parametric estimation, the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye were 99.0, 95.2, 97.3, 99.5, and 82.8%, respectively (Table 7.5b). Also, in the leave-one-out method with non-parametric estimation, the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye were 99.1, 92.1, 97.6, 99.7, and 90.9%, respectively (Table 7.5d). The classification accuracies with the normal estimation were poorer than the non-parametric estimation. This suggested that morphological features did not follow normal distributions. Sapirstein et al. (1987) reported similar classification accuracies of 99.2, 95.7, 95.3, and 98.3% for HRS wheat, barley, oats, and rye, respectively using morphological and reflectance features. They achieved higher classification accuracy (98.3%) for rye when compared with the present study where due to inclusion of the CWAD wheat in the discriminant model, many rye kernels got misclassified in as the CWAD wheat and vice versa (Table 7.5) as they had similar length and perimeter (data not shown). Also, there was no significant effect of growing regions on classification accuracy of cereal grains as the grains used for the training and the testing of the morphology model were collected from different growing region across western Canada.

7.3.1 Selection of morphological features of individual kernels Many morphological features were highly correlated with one another (Appendix C2) and many of them did not contribute significantly to the morphology model. The morphological features were arranged in descending order of their level of contribution to the morphology model (Table 7.6). The kernel length was the most significant (ASCC = 0.223) and the major axis length was the least significant (ASCC = 0.662) feature when used with other features in the model (Table 7.6) because they were very highly correlated (0.99, Appendix C2). In a discriminant model, once the most significant feature is selected, rest of the features are selected depending on their correlation (poorly correlated features are selected first) with the feature already being

Table 7.5a Confusion matrix of individual kernel images of cereal grains using morphological features: Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	4286 (95.2%)	100	0	0	114
CWAD wheat (n = 1500)	10	1406 (93.7%)	17	0	67
Barley (n = 1500)	3	56	1397 (93.1%)	0	44
Oats (n = 1500)	0	1	0	1474 (98.3%)	25
Rye (n = 1500)	1	228	19	1	1251 (83.4%)

Table 7.5b Confusion matrix of individual kernel images of cereal grains using morphological features: Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	4457 (99.0%)	23	1	0	18	1
CWAD wheat (n = 1500)	0	1428 (95.2%)	3	0	58	11
Barley (n = 1500)	0	15	1460 (97.3%)	0	20	5
Oats (n = 1500)	1	0	0	1493 (99.5%)	3	3
Rye (n = 1500)	14	186	18	8	1242 (82.8%)	32

Table 7.5c Confusion matrix of individual kernel images of cereal grains using morphological features: Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	13083 (96.9%)	266	0	0	151
CWAD wheat (n = 4500)	61	4128 (91.7%)	37	0	274
Barley (n = 4500)	0	111	4314 (95.9%)	1	74
Oats (n = 4500)	0	6	0	4441 (98.7%)	53
Rye (n = 4500)	15	569	51	3	3862 (85.8%)

Table 7.5d Confusion matrix of individual kernel images of cereal grains using morphological features: Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	13380 (99.1%)	66	1	0	51	2
CWAD wheat (n = 4500)	48	4145 (92.1%)	20	0	285	2
Barley (n = 4500)	0	57	4392 (97.6%)	2	47	2
Oats (n = 4500)	0	0	0	4486 (99.7%)	12	2
Rye (n = 4500)	18	361	26	0	4092 (90.9%)	3

selected. The level of contribution of features to the morphology model beyond the first 10 features was poor (see ASCC values, Table 7.6).

Table 7.6 Selection of morphological features of individual kernels of cereal grains using STEPDISC analysis

Number	Morphological features of individual kernels	Average squared canonical correlation	Partial r^2
1	Length	0.223	0.89
2	Haralick ratio	0.343	0.51
3	First Fourier descriptor (when u = 0)	0.479	0.61
4	Standard deviation of radii	0.532	0.60
5	Area ratio	0.572	0.25
6	Radius ratio	0.593	0.15
7	First invariant moment, M_1	0.598	0.07
8	Second invariant moment, M_2	0.624	0.25
9	Minimum radius	0.638	0.12
10	Maximum radius	0.644	0.04
11	Perimeter	0.648	0.02
12	Area	0.649	0.02
13	Rectangular aspect ratio	0.651	0.02
14	Thinness ratio	0.652	0.03
15	Width	0.655	0.02
16	Second Fourier descriptor (when u = 1)	0.657	0.01
17	Minor axis length	0.658	0.01
18	Fourth Fourier descriptor (when u = 3)	0.659	0.01
19	Third Fourier descriptor (when u = 2)	0.660	0.01
20	Third invariant moment, M_3	0.661	0.01
21	Fourth invariant moment, M_4	0.661	0.01
22	Aspect ratio	0.662	0.00
23	Major axis length	0.662	0.00

Discriminant analyses were carried out with the first 5, 10, and 15 features (from Table 7.6) and the classification accuracies were compared with that when all 23 features were used (Fig. 7.7). The mean accuracy was the highest in 3 out of 4 analysis methods when the first 10 features were used for classification (Fig. 7.7). Beyond the first 10 features, as the number of features increased, the mean accuracies remained constant because of redundancies in some features (e.g., length and major axis length (0.99)). With the first five features the mean accuracies were very poor. When the morphology model with the first 10 features was tested on an independent data set, the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye were 98.9, 93.7, 96.8, 99.9, and 81.6%, respectively (non-parametric estimation, Appendix F3a). When the model was used on the training data set, the classification accuracies were 98.9, 91.6, 97.9, 100.0, and 91.6%, respectively for CWRS wheat, CWAD wheat, barley, oats, and rye (non-parametric estimation, Appendix F3b).

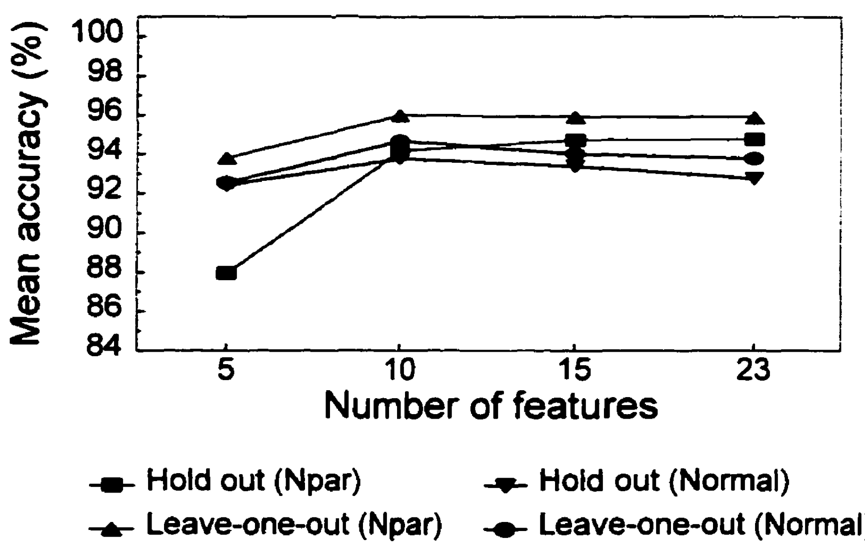


Fig. 7.7 Comparison of classification accuracies of individual kernels of cereal grains using different number of morphological features (Note: Npar denotes non-parametric estimation)

Independent rankings of morphological features are shown in Table 7.7 and their between-class correlation coefficients are shown in Appendix C2. The kernel length, maximum radius, and perimeter were the three most significant features based on independent rankings (Table 7.7). As the maximum radius, perimeter, and length were highly inter-correlated (0.99, Appendix C2), the significance level of maximum radius and perimeter were reduced in the morphology model (Table 7.6). Also, as the correlation of

Table 7.7 Independent rankings of morphological features of individual kernels of cereal grains on the basis of their individual level of contribution to the classifier using STEPDISC analysis

Number	Morphological features of individual kernels	Average squared canonical correlation	r^2
1	Length	0.223	0.89
2	Maximum radius	0.221	0.88
3	Perimeter	0.217	0.87
4	First invariant moment, M_1	0.212	0.85
5	Rectangular aspect ratio	0.211	0.85
6	First Fourier descriptor (u=0)	0.211	0.85
7	Standard deviation of radii	0.211	0.84
8	Thinness ratio	0.208	0.83
9	Second invariant moment, M_2	0.206	0.82
10	Radius ratio	0.202	0.81
11	Haralick ratio	0.196	0.78
12	Area	0.186	0.74
13	Area ratio	0.118	0.47
14	Minor axis length	0.111	0.45
15	Width	0.108	0.43
16	Second Fourier descriptor (u=1)	0.108	0.43
17	Minimum radius	0.104	0.42
18	Major axis length	0.081	0.32
19	Fourth Fourier descriptor (u=3)	0.060	0.24
20	Third Fourier descriptor (u=2)	0.059	0.24
21	Fourth invariant moment, M_4	0.056	0.23
22	Third invariant moment, M_3	0.056	0.22
23	Aspect ratio	0.002	0.01

first invariant moment and rectangular aspect ratio with length was high (0.95 and 0.94, respectively), their ranking in the morphology model was lowered. As many of the morphological features were highly correlated with one another, using all the features in the morphology model would not improve the classification accuracy; also as the number of features is reduced, the time consumed by any classifier (specially classifier like neural network) is reduced.

7.4 Texture model: classification of individual kernels

7.4.1 Gray level reduction and color selection Textural features were extracted from GLCM and GLRMs which were computed from individual kernel images. If the maximum gray level value is m_i and the run length is n_i, the size of GLCM and GLRMs will be m_i x m_i and m_i x n_i, respectively for the i^{th} kernel. When the maximum gray level is reduced, the sizes of the GLCM and GLRMs are also reduced resulting in the reduced computational time. The classification accuracies of cereal grains using textural features extracted from red color band at different maximum gray level values (e.g., 250, 32, 16, 8, and 4) are shown in Appendices E1-E5 and EE1-EE5. Some CWRS and CWAD wheats were misclassified as rye and vice versa because some of the textural features (e.g., mean gray level, gray level variance, gray level range, mean, entropy, correlation) of these grains overlap one another (data not shown). Some of the barley kernels were misclassified as CWAD wheat and some of the oats kernels were misclassified as barley kernels. Some of the textural features (e.g., gray level variance, gray level range, mean, entropy) of barley kernels were overlapped with that of CWAD wheat kernels and some of the textural features (e.g., entropy, short run range, run percent range, entropy) of oats kernels were overlapped with that of barley kernels.

The mean accuracies were higher in the majority of the analysis methods [e.g., hold out method (Npar), hold out method (normal), leave-one-out method (Npar), or leave-one-out method (normal)] at maximum gray level value 4 than at other maximum gray level values (Fig. 7.8). In an individual kernel image, at higher gray level values (e.g., 250, 32) the gray level values were sparsely distributed. Hence, the tonal primitives, i.e., the local variations (e.g., fineness, coarseness, granulation) on the surface texture of a kernel image were not prominent (Haralick 1973). As the maximum gray level value decreased, the distinguishable tonal primitives increased; hence the prominence in the textural features increased which improved the classification accuracies. But the reduction in maximum gray level value beyond certain level would result in an image with little textural variations and the image surface would be transformed into a surface having almost same gray level value. When the maximum gray level value was 250, the computational time was much longer compared to other maximum gray level values (e.g., 4, 8, 16, or 32) because of the size of the GLCM (250 x 250) and GLRMs (250 x n_i) of the i^{th} kernel, where n_i is the run length of i^{th} kernel. For real-world (e.g., on-line) classification it is necessary to have short computation time. Also, at maximum gray level value 250, the classification accuracies of cereal grains were poor compared to other maximum gray level values (Fig. 7.8). Therefore, in subsequent analyses using other color bands, the maximum gray level value 250 was not used and the analyses were carried out at maximum gray level values 32, 16, 8, and 4.

In bulk sample images, the textural features became prominent at maximum gray level value 32 (Fig. 7.1) whereas in individual kernel images the textural features became prominent at maximum gray level value 4 (Fig. 7.8) when red color was used to extract the textural features in both the cases. There is a distinction between a bulk image texture and an individual kernel texture of a cereal grain. The bulk image texture is a manifestation of the packing density and the individual surface texture of the grain where the packing density of the grain (results in shadows) plays a major role in forming the topography of the bulk image texture. For individual kernel image, it is only the surface texture which represents the individual kernel texture. In individual kernel image, the gray level values are distributed across a narrow gray level band whereas in bulk sample images, the gray level values are distributed across a wide gray level band due to the presence of shadows. Hence, the textural features become prominent at different maximum gray level values for bulk sample and individual kernel images.

The classification accuracies of cereal grains using textural features of individual kernels, extracted from the green color band, are shown in Appendices E6 -E9 and EE6 - EE9. The mean accuracies were higher in three out of four analysis methods at maximum gray level value 8 than other gray level values (Fig. 7.9). Similarly, the classification accuracies of cereal grains using textural features, extracted from blue color, black & white color, (3R+2G+1B)/6, (2R+1G+3B)/6, and (1R+3G+2B)/6 are shown in Appendices E10 - E13 and EE10 - EE13, Appendices E14 - E17 and EE14 - EE17, Appendices E18 - E21 and EE18 - EE21, Appendices E22 - E25 and EE22 - EE25, and Appendices E26 - E29 and EE26 - EE29, respectively.

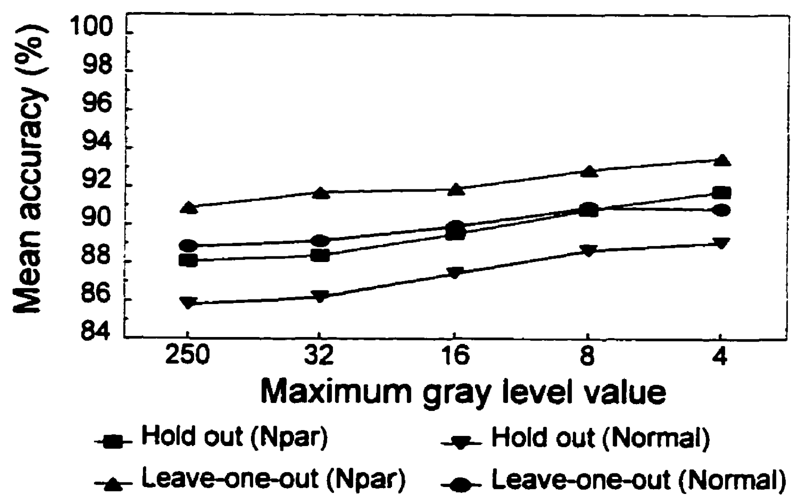


Fig. 7.8 Classification accuracies of individual kernels of cereal grains using textural features extracted from red color band at different maximum gray level values (Note: Npar denotes non-parametric estimation)

When textural features extracted from blue (Fig. 7.10) and black & white colors (Fig. 7.11) were used, the mean accuracies in all analysis methods were higher at maximum gray level value 4 than other maximum gray level values. When textural features extracted from (3R+2G+1B)/6 were used, the mean accuracies were higher in three out of four analysis methods at maximum gray level value 4 than other maximum gray level values (Fig. 7.12). When textural features extracted from (2R+1G+3B)/6 (Fig. 7.13) and (1R+3G+2B)/6 (Fig. 7.14) were used, the mean accuracies in all analysis methods were higher at maximum gray level value 4 than other maximum gray level values.

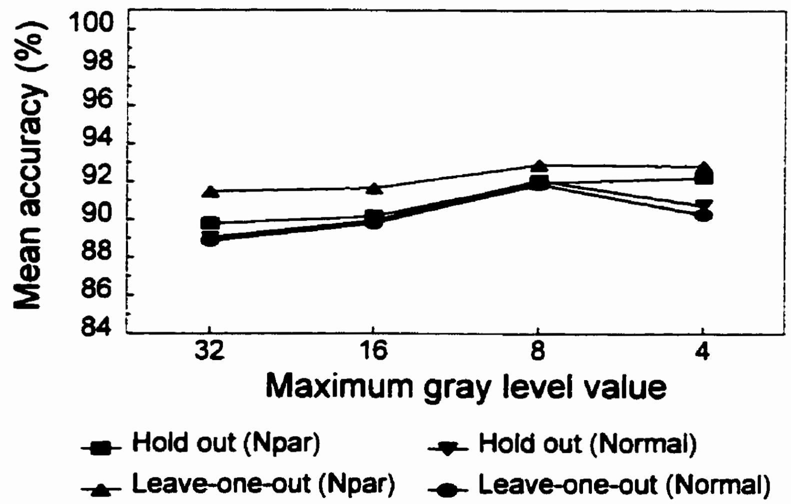


Fig. 7.9 **Classification accuracies of individual kernels of cereal grains using textural features extracted from green color band at different maximum gray level values (Note: Npar denotes non-parametric estimation)**

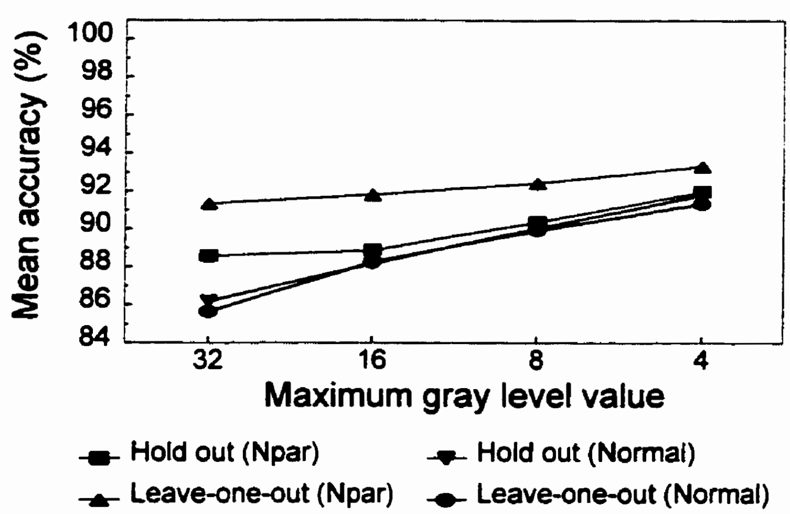


Fig. 7.10 **Classification accuracies of individual kernels of cereal grains using textural features extracted from blue color band at different maximum gray level values (Note: Npar denotes non-parametric estimation)**

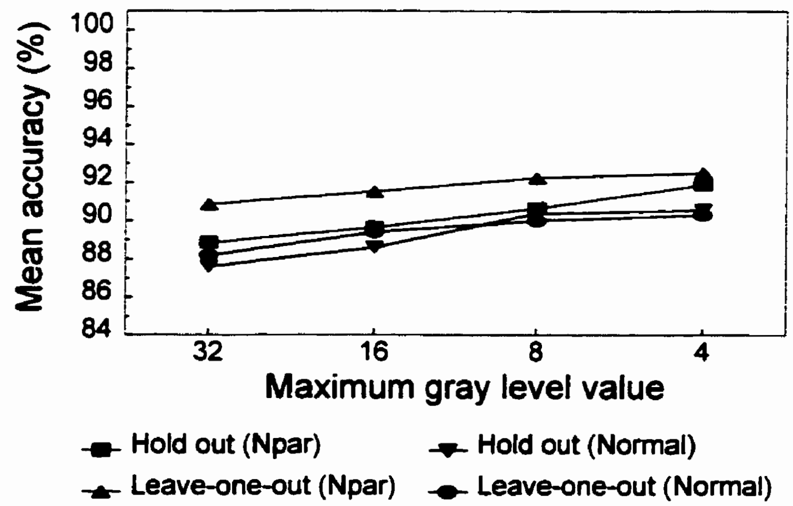


Fig. 7.11 **Classification accuracies of individual kernels of cereal grains using textural features extracted from black & white color at different maximum gray level values (Note: Npar denotes non-parametric estimation)**

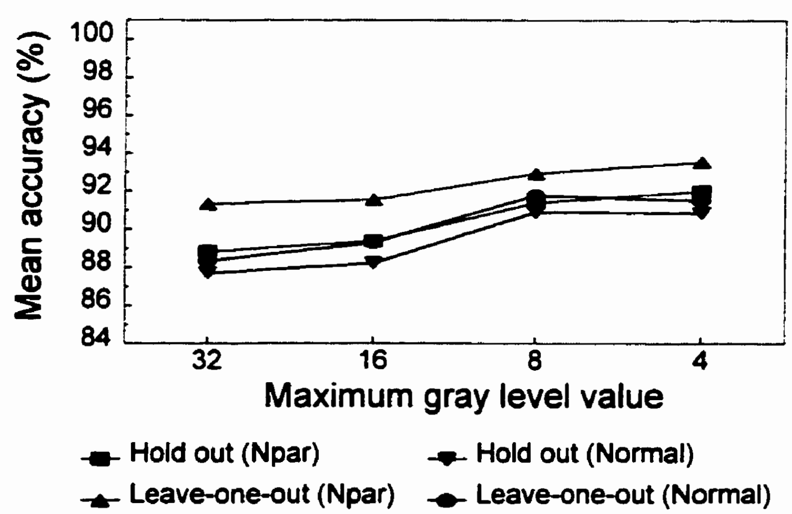


Fig. 7.12 **Classification accuracies of individual kernels of cereal grains using textural features extracted from (3R+2G+1B)/6 at different maximum gray level values (Note: Npar denotes non-parametric estimation)**

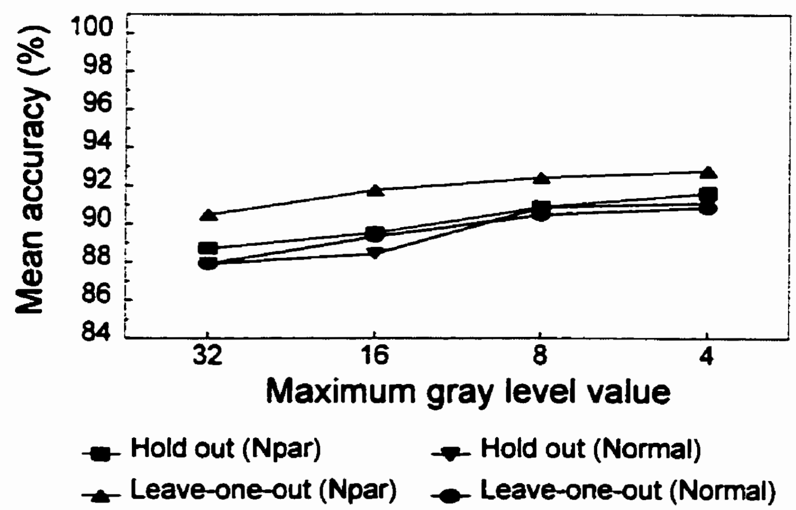


Fig. 7.13 **Classification accuracies of individual kernels of cereal grains using textural features extracted from (2R+1G+3B)/6 at different maximum gray level values (Note: Npar denotes non-parametric estimation)**

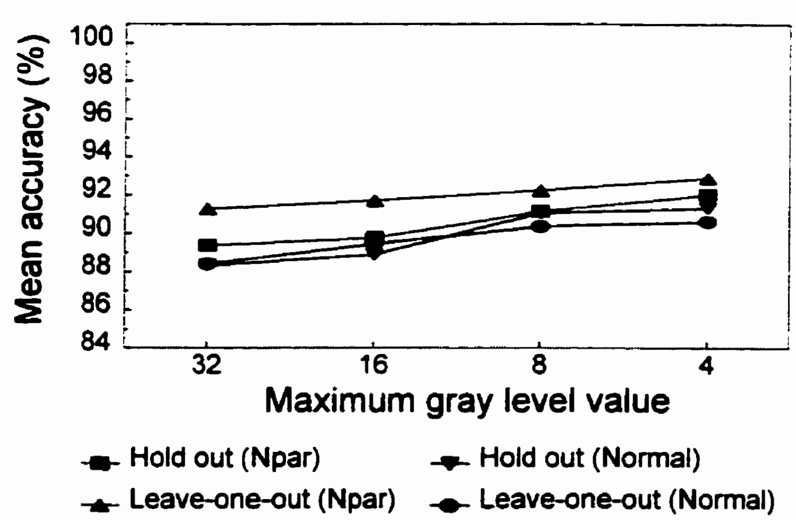


Fig. 7.14 **Classification accuracies of individual kernels of cereal grains using textural features extracted from (1R+3G+2B)/6 at different maximum gray level values (Note: Npar denotes non-parametric estimation)**

Figure 7.15 shows the classification accuracies of cereal grains using textural features of individual kernels, extracted from different color bands and color band combinations at maximum gray level value 4 (for the green color band the maximum gray level value was 8). Textural features extracted from green color band at maximum gray level value 8 gave higher mean accuracies in the majority of the analysis methods than other colors or color band combinations. This is in contrast with bulk sample images where textural features extracted from red color band gave higher classification accuracies than other color band or color band combinations because the bulk sample image and individual kernel image textures are different from each other. Blue color also showed comparably good classification accuracies (Fig. 7.15).

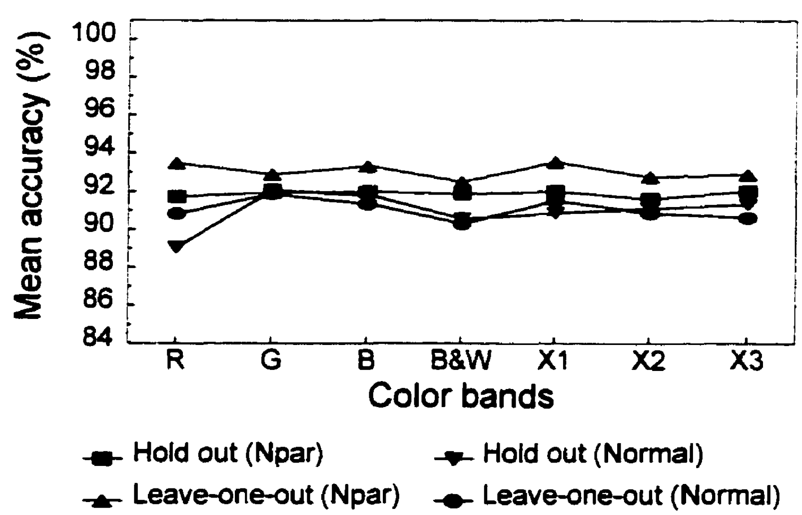


Fig. 7.15 Classification accuracies of individual kernels of cereal grains using textural features extracted from different color bands and color band combinations at maximum gray level value 4 (for green color the maximum gray level value was 8) [R: red, G: green, B: blue, B&W: black & white, X1: (3R+2G+1B)/6, X2: (2R+1G+3B)/6, and X3: (1R+3G+2B)/6] (Note: Npar denotes non-parametric estimation)

When an independent data set was used for testing, the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye using textural features extracted from green color at maximum gray level value 8 were 87.7, 98.1, 100.0, 100.0, and 74.1%, respectively (Appendix E8b). When the training data set was used for testing, the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye using textural features were 88.2, 96.4, 100.0, 100.0, and 79.9%, respectively (Appendix EE8b). The classification accuracies of individual kernels of cereal grains using textural features were poorer than that using morphological features.

7.4.2 Selection of textural features of individual kernels Some of the textural features were highly correlated (≈ 0.99) with one another (e.g., mean, variance, cluster shade, and mean gray level were highly inter-correlated with one another, Appendix C2) and they did not contribute significantly to the texture model. The STEPDISC analysis was carried out to determine the level of contribution of each textural feature of individual kernels to the texture model so that all redundant features could be eliminated. Table 7.8 shows the textural features, extracted from the green color band at maximum gray level value 8 in the descending order of their level of contribution. The gray level non-uniformity range was the most significant feature (ASCC = 0.156) and the GLRM entropy range was the least significant feature (ASCC = 0.517) because they were highly correlated (0.96, Appendix C2). The level of contribution (see ASCC values) of textural features beyond the first 15 features was poor to the model (Table 7.8).

Table 7.8 **Selection of textural features of individual kernels of cereal grains, extracted from green color band at maximum gray level value 8, using STEPDISC analysis**

Number	Textural features of individual kernels	Average squared canonical correlation	Partial r^2
1	Gray level non-uniformity range (GLRM)	0.156	0.62
2	Long run (GLRM)	0.223	0.44
3	Run length non-uniformity (GLRM)	0.284	0.33
4	Entropy (GLCM)	0.298	0.24
5	Short run (GLRM)	0.337	0.30
6	Run percent (GLRM)	0.356	0.20
7	Cluster prominence (GLCM)	0.387	0.18
8	Gray level range	0.414	0.20
9	Mean (GLCM)	0.430	0.14
10	GLRM entropy (GLRM)	0.441	0.14
11	Run percent range (GLRM)	0.460	0.10
12	Mean gray level	0.469	0.12
13	Gray level variance	0.478	0.07
14	Inertia (GLCM)	0.485	0.06
15	Long run range (GLRM)	0.489	0.04
16	Correlation (GLCM)	0.492	0.04
17	Run length non-uniformity range (GLRM)	0.496	0.03
18	Cluster shade (GLCM)	0.501	0.03
19	Homogeneity (GLCM)	0.506	0.04
20	Uniformity (GLCM)	0.509	0.02
21	Gray level non-uniformity (GLRM)	0.510	0.02
22	Maximum probability (GLCM)	0.513	0.02
23	Short run range (GLRM)	0.514	0.01
24	Variance (GLCM)	0.516	0.01
25	GLRM entropy range (GLRM)	0.516	0.01

Discriminant analyses were carried out with the first 5, 10, 15, and 20 features (from Table 7.8) and the classification accuracies were compared with that when all 25 features were used (Fig. 7.16). The mean accuracies were poor when only the first five features were used for classification. As the number of features increased, the mean accuracies increased to certain extent and then remained constant, because of redundancies (e.g., GLRM entropy range, variance, short run range, maximum probability, gray level non-uniformity were highly correlated (> 0.88) with gray level non-uniformity range) in some features (Fig. 7.16). Increase in mean accuracies beyond 15 features was negligible, hence one could use the first 15 features (Table 7.8) for classification of individual kernels of cereal grains (Fig. 7.16). When an independent data set was used for testing, the classification accuracies of CWRS wheat, CWAD wheat, barely, oats, and rye using the first 15 features in the texture model were 85.2, 98.2, 100.0, 100.0, and 76.3%, respectively (non-parametric estimation, Appendix F4a). When used on the training data set, the classification accuracies were 87.0, 95.7, 100.0, 100.0, and 81.8%, respectively (non-parametric estimation, Appendix F4b).

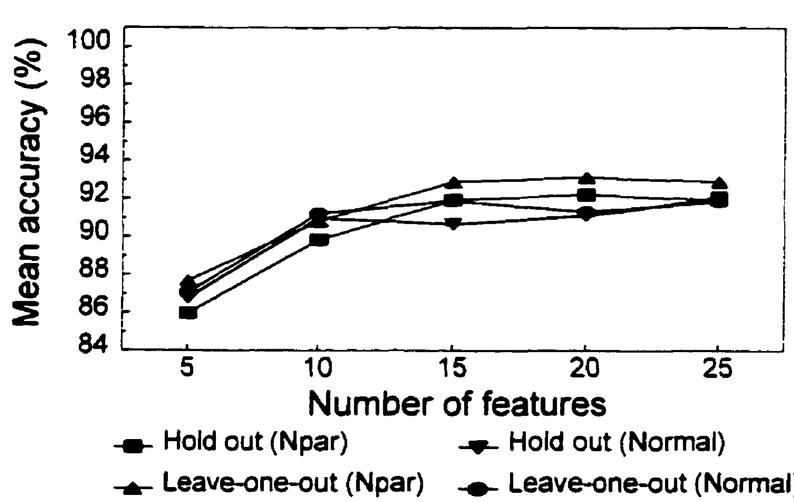


Fig. 7.16 Comparison of classification accuracies of individual kernels of cereal grains using different number of textural features extracted from green color at maximum gray level value 8 (Note: Npar denotes non-parametric estimation)

The independent rankings of textural features are shown in Table 7.9. Depending on the correlation among different textural features (Appendix C2) and their independent rankings, their level of contribution to the texture model was determined (Table 7.9). Although GLRM entropy, gray level non-uniformity, long run range, and run length non-uniformity range were some of the most significant textural features on the basis of their

Table 7.9 Independent rankings of textural features of individual kernels of cereal grains, extracted from green color band at maximum gray level value 8, on the basis of their individual level of contribution to the classifier using STEPDISC analysis

Number	Textural features of individual kernels	Average squared canonical correlation	r^2
1	Gray level non-uniformity range (GLRM)	0.155	0.62
2	Run length non-uniformity (GLRM)	0.152	0.61
3	GLRM entropy (GLRM)	0.144	0.57
4	Gray level non-uniformity (GLRM)	0.142	0.57
5	Long run range (GLRM)	0.135	0.54
6	Run length non-uniformity range (GLRM)	0.129	0.52
7	Cluster prominence (GLCM)	0.117	0.47
8	Mean gray level	0.115	0.46
9	GLRM entropy range (GLRM)	0.114	0.46
10	Cluster shade (GLCM)	0.112	0.45
11	Variance (GLCM)	0.099	0.40
12	Long run (GLRM)	0.089	0.36
13	Run percent range (GLRM)	0.069	0.28
14	Correlation (GLCM)	0.068	0.27
15	Mean (GLCM)	0.066	0.27
16	Gray level range	0.063	0.25
17	Inertia (GLCM)	0.055	0.22
18	Run percent (GLRM)	0.052	0.21
19	Short run range (GLRM)	0.040	0.16
20	Gray level variance	0.037	0.15
21	Maximum probability (GLCM)	0.036	0.14
22	Short run (GLRM)	0.024	0.10
23	Uniformity (GLCM)	0.023	0.09
24	Homogeneity (GLCM)	0.009	0.04
25	Entropy (GLCM)	0.004	0.01

individual level of contribution (Table 7.9), their level of contribution to the texture model reduced significantly (Table 7.8) because their correlations with gray level non-uniformity range were very high (> 0.90 in all cases, Appendix C2).

7.5 Color model: classification of individual kernels

Eighteen color features were used to classify individual kernels of cereal grains and the classification accuracies are shown in Table 7.10. When an independent data set was used for testing, the classification accuracies of cereal grains were higher with the normal estimation than with the non-parametric estimation (Tables 7.10a and 7.10b) and the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye using normal estimation were 87.9, 95.0, 92.1, 97.5, and 96.6%, respectively (Table 7.10a). When the leave-one-out method was used, the classification accuracies were higher with the non-parametric estimation than with the normal estimation (Tables 7.10c and 7.10d) and the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye using the non-parametric estimation were 94.4, 94.3, 93.7, 97.5, and 91.9%, respectively (Table 7.10d).

The majority of the misclassified CWRS wheat were classified as CWAD wheat, oats, and rye. This was because the CWRS wheat had equal number of grade 1, 2, and 3 kernels and variability of size, shape, and reflectance features were used for successful classification of three grades of CWRS wheat (Sapirstein and Kohler 1995). Hence, some of the color features of CWRS wheat (all three grades were treated as a single class) were confused with CWAD wheat, oats, and rye. The majority of the misclassified CWAD wheat were classified as barley and vice versa because they had similar reflectance characteristics.

Table 7.10a Confusion matrix of individual kernel images of cereal grains using color features: Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3956 (87.9%)	182	74	165	123
CWAD wheat (n = 1500)	16	1425 (95.0%)	51	1	7
Barley (n = 1500)	3	111	1381 (92.1%)	3	2
Oats (n = 1500)	37	0	0	1462 (97.5%)	1
Rye (n = 1500)	43	2	1	5	1449 (96.6%)

Table 7.10b Confusion matrix of individual kernel images of cereal grains using color features: Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	4174 (92.8%)	194	31	37	30	34
CWAD wheat (n = 1500)	17	1378 (91.9%)	77	2	5	21
Barley (n = 1500)	1	93	1392 (92.8%)	0	0	14
Oats (n = 1500)	85	0	0	1414 (94.3%)	0	1
Rye (n = 1500)	98	2	0	3	1385 (92.3%)	12

Table 7.10c Confusion matrix of individual kernel images of cereal grains using color features: Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	11309 (83.8%)	513	69	689	920
CWAD wheat (n = 4500)	71	4168 (92.6%)	175	23	63
Barley (n = 4500)	11	413	4022 (89.4%)	18	36
Oats (n = 4500)	23	21	57	4388 (97.5%)	11
Rye (n = 4500)	107	132	49	2	4210 (93.6%)

Table 7.10d Confusion matrix of individual kernel images of cereal grains using color features: Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	12742 (94.4%)	317	25	147	261	8
CWAD wheat (n = 4500)	94	4244 (94.3%)	146	3	9	4
Barley (n = 4500)	3	255	4215 (93.7%)	8	14	5
Oats (n = 4500)	58	18	32	4387 (97.5%)	2	3
Rye (n = 4500)	245	94	21	1	4137 (91.9%)	2

Oats samples from some growing regions (specially from Manitoba province) were brownish in color and some of them were misclassified as CWRS wheat. Most of the misclassified rye kernels were classified as CWRS wheat as their reflectance characteristics were similar (Majumdar et. al 1996) (Table 7.10). Neuman et al. (1989a, 1989b) examined color attributes of individual kernels of 10 varieties representing 6 Canadian wheat classes. Using red, green, and blue reflectance features, they achieved classification accuracies of 76, 76, 62, 56, and 34% for SWS, Amber Durum, HRS, HRW, and CPS wheat classes, respectively. If red, green, and blue features were used with hue and saturation features, the classification accuracy of the wheat classes would have increased as hue and saturation were very poorly correlated with red, green, and blue features (Appendix C2).

7.5.1 Selection of color features of individual kernels Some of the color features were highly correlated (> 0.90) with one another (e.g., red, green, and intensity; and red range, green range, blue range, and saturation range were highly inter-correlated, Appendix C2), hence they did not contribute significantly to the color model. Table 7.11 shows the color features in the descending order of their level of contribution to the color model. The red color had the most contribution (ASCC = 0.122) and intensity had the least contribution (ASCC = 0.537) to the model as they were highly correlated to each other (0.97, Appendix C2). The level of contribution (see ASCC values) of color features beyond the first 10 features was poor (Table 7.11); one could eliminate rest of the features from the color model without affecting the classification accuracies of cereal grains.

Discriminant analyses were conducted with the first 5, 10, and 15 features (from Table 7.11) and the classification accuracies were compared with classification accuracies when all 18 features were used (Fig. 7.17). The classification accuracies of the cereal grains were poor when only the first five features were used in the color model. As the number of color features increased, the mean accuracies increased to certain extent and then became constant because of redundancies in some features in the model. The color model with the first 10 features gave good classification accuracies and the increase in mean accuracies beyond 10 features was negligible. The classification accuracies of CWRS wheat, CWAD

Table 7.11 Selection of color features of individual kernels of cereal grains using STEPDISC analysis

Number	Color features of individual kernels	Average squared canonical correlation	Partial r^2
1	Red	0.122	0.49
2	Blue	0.244	0.56
3	Green	0.390	0.64
4	Red range	0.439	0.29
5	Saturation range	0.449	0.10
6	Blue range	0.473	0.18
7	Red variance	0.479	0.06
8	Green variance	0.492	0.06
9	Saturation variance	0.496	0.03
10	Saturation	0.502	0.05
11	Blue variance	0.508	0.03
12	Green range	0.510	0.02
13	Hue range	0.512	0.02
14	Hue variance	0.514	0.01
15	Hue	0.537	0.12
16	Intensity variance	0.537	0.00
17	Intensity range	0.537	0.00
18	Intensity	0.537	0.00

wheat, barley, oats, and rye using the first 10 color features on an independent data set were 94.1, 92.3, 93.1, 95.2, and 92.5%, respectively (non-parametric estimation, Appendix F5a). When the same model was tested on the training data set, the classification accuracies were 95.7, 94.4, 94.2, 97.6, and 92.5%, respectively (non-parametric estimation, Appendix F5b).

Table 7.12 shows the independent rankings of color features of individual kernels of cereal grains. Red and green colors, and saturation range were the three most significant features when chosen independently. They were also very significant features in the color model (Table 7.11).

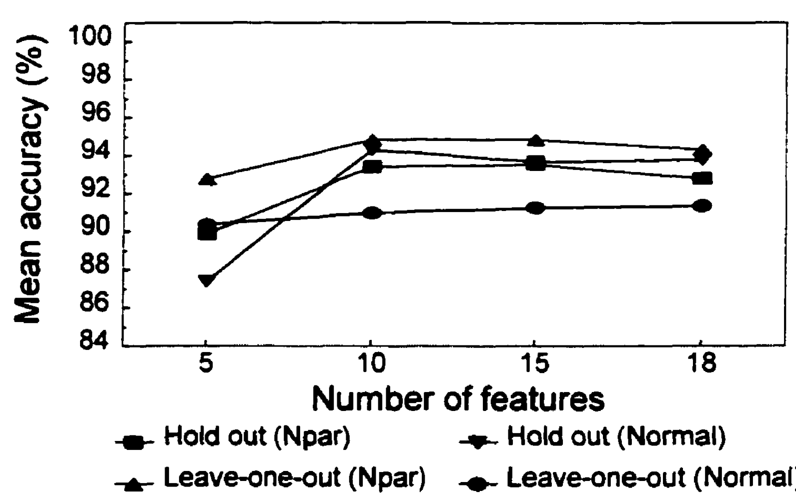


Fig. 7.17 Comparison of classification accuracies of individual kernels of cereal grains using different number of color features (Note: Npar denotes non-parametric estimation)

For bulk sample images, hue, hue variance, red variance, green variance, saturation variance, and saturation were some of the most important features to the color model (Table

7.3) but for individual kernel images, red, green, blue, red range, saturation range, blue range, and red variance were some of the most important features to the color model (Table 7.11). This was because the distribution of color across a bulk sample image and an individual kernel image was different from each other.

From the morphology, texture, and color models of individual kernels of cereal grains, it was observed that no single model could give 100.0% correct classification (an ideal goal for practical implementation) for each type of cereal grain used in this study. The morphology model gave the highest classification accuracies when tested on an independent data set (mean accuracy = 94.2% when the first 10 features were used, Appendix F3a) and on the training data set (mean accuracy = 96.0% when the first 10 features were used, Appendix F3b). The color model gave the second highest classification accuracies when tested on an independent data set (mean accuracy = 93.4% when the first 10 features were used, Appendix F5a) and on the training data set (mean accuracy = 94.9% when the first 10 features were used, Appendix F5b). The texture model gave the poorest classification accuracies when tested on an independent data set (mean accuracy = 92.0% when the first 15 features were used, Appendix F4a) and on the training data set (mean accuracy = 92.9% when the first 15 features were used, Appendix F4b). One can use any of these three models independently or in combinations depending on the requirement of classification accuracy. It was hypothesized that different combinations of these three models might improve the classification accuracies.

Table 7.12 Ranking of color features of individual kernels of cereal grains on the basis of their individual level of contribution to the classifier using STEPDISC analysis

Number	Color features of individual kernels	Average squared canonical correlation	r^2
1	Red	0.122	0.49
2	Green	0.115	0.46
3	Saturation range	0.105	0.42
4	Intensity	0.103	0.41
5	Blue	0.08	0.32
6	Saturation	0.078	0.31
7	Red range	0.067	0.27
8	Green range	0.067	0.27
9	Intensity range	0.057	0.23
10	Hue	0.054	0.22
11	Saturation variance	0.047	0.19
12	Blue variance	0.045	0.18
13	Green variance	0.038	0.15
14	Intensity variance	0.037	0.15
15	Blue range	0.036	0.15
16	Red variance	0.031	0.12
17	Hue variance	0.025	0.10
18	Hue range	0.008	0.03

7.6 Morphology-texture model: classification of individual kernels

The STEPDISC analysis was conducted to select morphological and textural features based on their level of contribution to the discriminant model. Table 7.13 shows the morphological and textural features in the descending order of their level of contribution to the model. The first 4 most significant features were morphological features, kernel length being the most significant feature. The number of morphological and textural features within

Table 7.13 Selection of textural (extracted from green color band at maximum gray level value 8) and morphological features of individual kernels of cereal grains using STEPDISC analysis

Number	Morphological (MF) and textural (TF) features of individual kernels	Average squared canonical correlation	Partial r^2
1	Length (MF)	0.223	0.89
2	Haralick ratio (MF)	0.343	0.51
3	First Fourier descriptor (when u=0) (MF)	0.479	0.61
4	Standard deviation of radii (MF)	0.532	0.60
5	Entropy (TF)	0.560	0.44
6	Area ratio (MF)	0.598	0.23
7	Radius ratio (MF)	0.619	0.16
8	Run length non-uniformity (TF)	0.634	0.13
9	Gray level variance (TF)	0.646	0.09
10	Minimum radius (MF)	0.652	0.06
11	Width (MF)	0.663	0.06
12	Area (MF)	0.676	0.09
13	Short run (TF)	0.680	0.06
14	Run percent (TF)	0.686	0.08
15	Homogeneity (TF)	0.689	0.07
16	GLRM entropy (TF)	0.691	0.08
17	Third invariant moment, M_3 (MF)	0.695	0.05
18	Second invariant moment, M_2 (MF)	0.697	0.04
19	First invariant moment, M_1 (MF)	0.712	0.20
20	Maximum radius (MF)	0.717	0.04
21	Run length range (TF)	0.721	0.03
22	Cluster prominence (TF)	0.722	0.03
23	Cluster shade (TF)	0.726	0.06
24	Mean gray level (TF)	0.727	0.06
25	Variance (TF)	0.733	0.06
26	Uniformity (TF)	0.735	0.03
27	Maximum probability (TF)	0.736	0.02
28	Inertia (TF)	0.737	0.02
29	Rectangular ratio (MF)	0.738	0.02
30	Correlation (TF)	0.739	0.02

Table 7.13 Selection of textural (extracted from green color band at maximum gray level value 8) and morphological features of individual kernels of cereal grains using STEPDISC analysis (cont.)

Number	Morphological (MF) and textural (TF) features of individual kernels	Average squared canonical correlation	Partial r^2
31	Long run range (TF)	0.739	0.01
32	Gray level non-uniformity (TF)	0.740	0.01
33	Second Fourier descriptor (u=1) (MF)	0.740	0.01
34	Perimeter (MF)	0.741	0.01
35	Thinness ratio (MF)	0.743	0.02
36	Aspect ratio (MF)	0.743	0.01
37	Gray level range (TF)	0.744	0.01
38	Fourth Fourier descriptor (u=3) (MF)	0.744	0.01
39	Third Fourier descriptor (u=2) (MF)	0.745	0.01
40	Long run (TF)	0.745	0.01
41	Fourth invariant moment, M_4 (MF)	0.745	0.00
42	Run percent range (TF)	0.746	0.00
43	Gray level non-uniformity range (TF)	0.746	0.01
44	Short run range (TF)	0.746	0.00
45	GLRM entropy range (TF)	0.746	0.00
46	Mean (TF)	0.746	0.00
47	Minor axis length (MF)	0.746	0.00
48	Major axis length (MF)	0.747	0.00

the first 15 features were 9 and 6, respectively. The ranking of morphological and textural features in the morphology-texture model (Table 7.13) was similar to the morphology model (Table 7.6). This was because the independent levels of contribution (see ASCC values) of many morphological features (Table 7.7) was higher than that of many textural features (Table 7.9) which affected the selection of features in the discriminant model. The level of contribution (see ASCC values) of morphological and textural features beyond the first 15 features was poor (Table 7.13); hence one can eliminate those features beyond the first 15 features from the model without affecting the classification accuracies much.

Discriminant analyses were carried out with the first 5, 10, 15, 20, 25, 30, 35, and 40 features and the classification accuracies were compared with that when all 48 features were used (Fig. 7.18). When the first 5 and 10 features were used, the mean accuracies were poor. With an increase in the number of features, the mean accuracies increased to certain extent and then became constant. Increase in mean accuracies beyond 15 features was negligible (Fig. 7.18), hence one could use the first 15 features (Table 7.13) for classification of individual kernels of cereal grains.

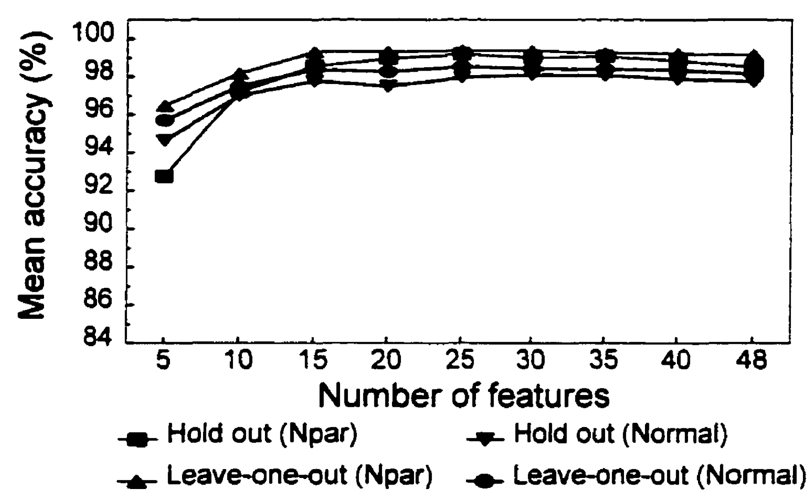


Fig. 7.18 **Comparison of classification accuracies of individual kernels of cereal grains using different number of morphological and textural features (extracted from green color band at maximum gray level value 8) (Note: Npar denotes non-parametric estimation)**

When an independent data set was used for testing, the classification accuracies of CWRS wheat, CWAD wheat, barely, oats, and rye using the first 15 features in the morphology-texture model were 99.4, 99.1, 99.1, 100.0, and 95.2%, respectively (non-parametric estimation, Appendix F6a). When used on the training data set, the classification accuracies were 99.5, 98.7, 99.7, 100.0, and 98.6%, respectively (non-parametric estimation. Appendix F6b). The classification accuracies of morphology-texture model were higher than that of morphology or texture model because some of the morphological and textural features were poorly correlated with one another (Appendix C2).

7.7 Morphology-color model: classification of individual kernels

The STEPDISC analysis was conducted to select features based on their level of contribution to the model. Table 7.14 shows the features in the descending order of their level of contribution to the model. The first five most significant features were morphological features because their independent levels of contributions (see ASCC values, Table 7.7) were higher than that of color features (Table 7.12). Red, intensity, and green were the most significant color features (Table 7.14). Selection of features in the morphology-color model (Table 7.14) conforms with that in the morphology and color models (Table 7.6 and 7.11). The level of contribution (see ASCC values) of morphological and color features beyond the first 15 features was poor (Table 7.14); hence one can eliminate those features beyond the first 15 features from the model without affecting the classification accuracies much.

Discriminant analyses were carried out using the first 5, 10, 15, 20, 25, 30, and 35 features and the classification accuracies were compared with that using all 41 features (Fig. 7.19). The mean accuracies using the first five features were poor. As the number of features increased, the mean accuracies increased to certain extent and then remained constant. Beyond 15 features, increasing the number of features did not contribute much to

Table 7.14 Selection of morphological and color features of individual kernels of cereal grains using STEPDISC analysis

Number	Morphological (MF) and color (CF) features of individual kernels	Average squared canonical correlation	Partial r^2
1	Length (MF)	0.223	0.89
2	Haralick ratio (MF)	0.343	0.51
3	First Fourier descriptor (when u=0) (MF)	0.479	0.61
4	Standard deviation of radii (MF)	0.532	0.60
5	Area ratio (MF)	0.572	0.25
6	Red (CF)	0.594	0.19
7	Intensity (CF)	0.672	0.43
8	Green (CF)	0.682	0.24
9	Radius ratio (MF)	0.694	0.12
10	First invariant moment, M_1 (MF)	0.696	0.05
11	Second invariant moment, M_2 (MF)	0.709	0.22
12	Minimum radius (MF)	0.713	0.07
13	Green range (CF)	0.717	0.04
14	Green variance (CF)	0.721	0.04
15	Red variance (CF)	0.729	0.06
16	Saturation variance (CF)	0.731	0.04
17	Saturation (CF)	0.734	0.05
18	Maximum radius (MF)	0.737	0.03
19	Blue variance (CF)	0.739	0.02
20	Blue range (CF)	0.741	0.02
21	Saturation range (CF)	0.742	0.03
22	Red range (CF)	0.743	0.02
23	Thinness ratio (MF)	0.745	0.01
24	Area (MF)	0.746	0.01
25	Rectangular aspect ratio (MF)	0.746	0.02
26	Perimeter (MF)	0.747	0.02
27	Width (MF)	0.750	0.02
28	Second Fourier descriptor (u=1) (MF)	0.751	0.01
29	Hue variance (CF)	0.752	0.01
30	Hue (CF)	0.757	0.05
31	Aspect ratio (MF)	0.758	0.01

Table 7.14 **Selection of morphological and color features of individual kernels of cereal grains using STEPDISC analysis (cont.)**

Number	Morphological (MF) and color (CF) features of individual kernels	Average squared canonical correlation	Partial r^2
32	Third Fourier descriptor (u=2) (MF)	0.758	0.01
33	Fourth Fourier descriptor (u=3) (MF)	0.759	0.01
34	Third invariant moment, M_3 (MF)	0.759	0.01
35	Fourth invariant moment, M_4 (MF)	0.760	0.01
36	Blue (CF)	0.760	0.00
37	Hue range (CF)	0.760	0.00
38	Intensity range (CF)	0.760	0.00
39	Intensity variance (CF)	0.760	0.00
40	Minor axis length (MF)	0.760	0.00
41	Major axis length (MF)	0.760	0.00

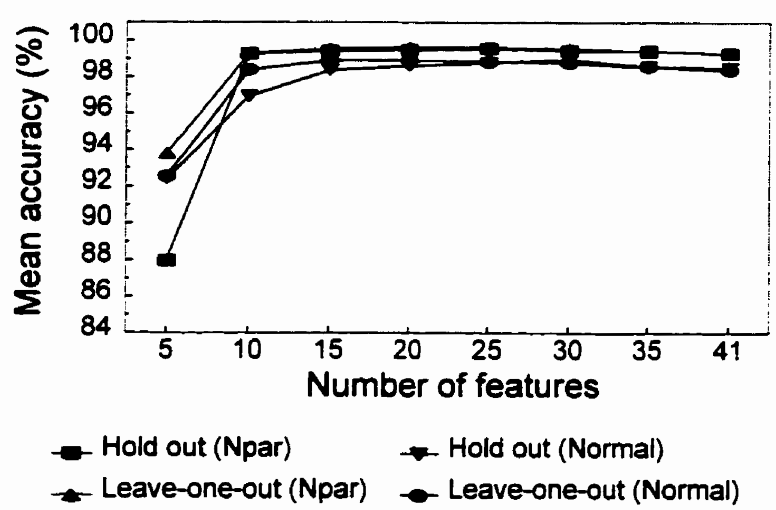


Fig. 7.19 **Comparison of classification accuracies of individual kernels of cereal grains using different number of morphological and color features (Note: Npar denotes non-parametric estimation)**

the morphology-color model (Fig. 7.19). When the model using the first 15 features was tested on an independent data set, the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye were 99.7, 99.7, 98.9, 99.9, and 98.9%, respectively (non-parametric estimation, Appendix F7a). When the model was tested on the training data set, the classification accuracies were 99.8, 99.4, 99.7, 100.0, and 99.0%, respectively (non-parametric estimation, Appendix F7b). The classification accuracies of morphology-color model were higher than that of morphology or color model because some of the morphological and color features were poorly correlated with one another (Appendix C2).

7.8 Texture-color model: classification of individual kernels

Table 7.15 shows the textural and color features in the descending order of their level of contribution to the texture-color model. The ranking of the features in this model conforms with the ranking of features in the texture model (Table 7.8) and the color model (Table 7.11). The level of contribution (see ASCC values) of textural and color features beyond the first 15 features was poor (Table 7.14); hence one can eliminate those features beyond the first 15 features from the model without affecting the classification accuracies much. Some textural (mainly GLCM) features were highly correlated with some primary color features (e.g., red, green, blue, and intensity) but many were poorly correlated with some color features (Appendix C2) which suggested that all textural features of individual kernels were not direct manifestation of color features. Similar relationship between textural and color features was observed in bulk sample images. But with individual kernel images, more textural features were highly correlated with color features than that with bulk sample images (Appendices C1, C2).

Table 7.15 Selection of textural (extracted from green color band at maximum gray level value 8) and color features of individual kernels of cereal grains using STEPDISC analysis

Number	Textural (TF) and color (CF) features of individual kernels	Average squared canonical correlation	Partial r^2
1	Gray level non-uniformity range (TF)	0.155	0.62
2	Long run (TF)	0.224	0.44
3	Saturation range (CF)	0.312	0.40
4	Red (CF)	0.350	0.26
5	gray level mean (TF)	0.460	0.50
6	Blue (CF)	0.498	0.41
7	Run length non-uniformity (TF)	0.523	0.22
8	Inertia (TF)	0.536	0.23
9	Correlation (TF)	0.549	0.15
10	Short run (TF)	0.564	0.18
11	Entropy (TF)	0.571	0.13
12	Run percent (TF)	0.577	0.15
13	Homogeneity (TF)	0.582	0.09
14	GLRM entropy (TF)	0.599	0.12
15	Red range (CF)	0.595	0.07
16	Blue range (CF)	0.606	0.12
17	Run percent range (TF)	0.615	0.06
18	Long run range (TF)	0.619	0.04
19	Cluster prominence (TF)	0.622	0.03
20	Cluster shade (TF)	0.626	0.05
21	Variance (TF)	0.633	0.04

Table 7.15 Selection of textural (extracted from green color band at maximum gray level value 8) and color features of individual kernels of cereal grains using STEPDISC analysis (cont.)

Number	Textural (TF) and color (CF) features of individual kernels	Average squared canonical correlation	Partial r^2
22	Saturation variance (CF)	0.635	0.03
23	Blue variance (CF)	0.638	0.03
24	Saturation (CF)	0.642	0.03
25	Short run range (TF)	0.645	0.03
26	Uniformity (TF)	0.648	0.02
27	Green variance (CF)	0.649	0.02
28	Red variance (CF)	0.652	0.04
29	Maximum probability (TF)	0.653	0.01
30	Hue variance (CF)	0.655	0.01
31	Hue (CF)	0.668	0.09
32	Run length non-uniformity range (TF)	0.669	0.01
33	Hue range (CF)	0.669	0.01
34	Mean (TF)	0.670	0.01
35	Green (CF)	0.670	0.00
36	Green range (CF)	0.670	0.00
37	GLRM entropy range (TF)	0.671	0.00
38	Gray level non-uniformity (TF)	0.671	0.00
39	Intensity variance (CF)	0.670	0.00
40	Gray level variance (TF)	0.671	0.00
41	Intensity range (CF)	0.671	0.00
42	Intensity (CF)	0.671	0.00

Note: gray level range was removed from the selection.

Discriminant analyses were carried out using the first 5, 10, 15, 20, 25, 30, and 35 features and the classification accuracies were compared with that using all 43 features (Fig. 7.20). The mean accuracies were very poor when the first five features were used in the model. As the number of features increased, the mean accuracies increased to certain extent and then remained constant. The increase in mean accuracies beyond 15 features was negligible (Fig. 7.20). When the texture-color model using the first 15 features was tested on an independent data set, the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye were 98.5, 99.4, 99.7, 100.0, and 94.3%, respectively (non-parametric estimation, Appendix F8a). When the model was tested on the training data set, the classification accuracies were 97.6, 99.4, 99.5, 98.7, and 95.0%, respectively (non-parametric estimation, Appendix F8b). The classification accuracies of texture-color model were higher than that of texture or color model because some of the texture and color features were poorly correlated with one another (Appendix C2).

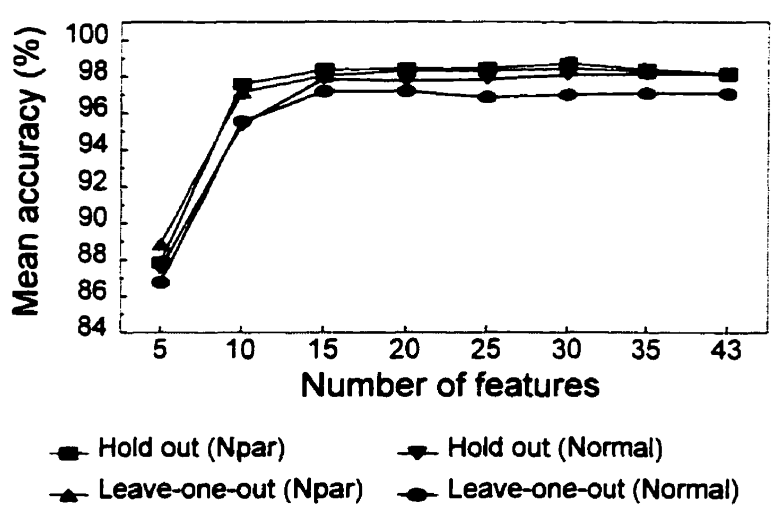


Fig. 7.20 **Comparison of classification accuracies of individual kernels of cereal grains using different number of color and textural features (extracted from green color band at maximum gray level value 8) (Note: Npar denotes non-parametric estimation)**

7.9 Morphology-texture-color model: classification of individual kernels

The STEPDISC analysis was carried out to determine the level of contribution of morphological, textural, and color features (Table 7.16). Some features were removed by the STEPDISC analysis as they were not useful to the model. The between-class correlation of morphological, textural, and color features are given in Appendix C2. The correlation

Table 7.16 Selection of morphological, color, and textural (extracted from green color band at maximum gray level value 8) features of individual kernels of cereal grains using STEPDISC analysis

Number	Morphological (MF), color (CF), and textural (TF) features of individual kernels	Average squared canonical correlation	Partial r^2
1	Length (MF)	0.223	0.89
2	Haralick ratio (MF)	0.343	0.51
3	First Fourier descriptor (u=0) (MF)	0.479	0.61
4	Standard deviation of radii (MF)	0.532	0.60
5	Entropy (TF)	0.560	0.44
6	Area ratio (MF)	0.598	0.23
7	Saturation (CF)	0.629	0.18
8	Red (CF)	0.666	0.31
9	Mean gray level (TF)	0.690	0.23
10	Mean (TF)	0.697	0.14
11	Radius ratio (MF)	0.711	0.14
12	Inertia (TF)	0.720	0.09
13	Run length non-uniformity (TF)	0.725	0.06
14	Run percent (TF)	0.727	0.07
15	GLRM entropy (TF)	0.731	0.10
16	Cluster prominence (TF)	0.734	0.08
17	Short run (TF)	0.738	0.08
18	Blue (CF)	0.739	0.06
19	Minimum radius (MF)	0.741	0.04
20	Third invariant moment, M_3 (MF)	0.743	0.04
21	Width (MF)	0.746	0.04
22	Area (MF)	0.750	0.07
23	Cluster shade (TF)	0.754	0.04
24	Red variance (CF)	0.760	0.04
25	Uniformity (TF)	0.763	0.04
26	Saturation variance (CF)	0.766	0.03
27	Homogeneity (TF)	0.768	0.03
28	Green variance (CF)	0.769	0.03
29	Blue variance (CF)	0.773	0.03
30	Fourth invariant moment, M_4 (MF)	0.774	0.03
31	First invariant moment, M_1 (MF)	0.775	0.03
32	Second invariant moment, M_2 (MF)	0.781	0.13
33	Maximum radius (MF)	0.783	0.03

Table 7.16 Selection of morphological, color, and textural (extracted from green color band at maximum gray level value 8) features of individual kernels of cereal grains using STEPDISC analysis (cont.)

Number	Morphological (MF), color (CF), and textural (TF) features of individual kernels	Average squared canonical correlation	Partial r^2
34	Run length non-uniformity range (TF)	0.785	0.02
35	Maximum probability (TF)	0.786	0.02
36	Hue variance (CF)	0.788	0.02
37	Hue (CF)	0.793	0.06
38	Correlation (TF)	0.793	0.02
39	Red range (CF)	0.794	0.02
40	Blue range (CF)	0.795	0.02
41	Saturation range (CF)	0.796	0.02
42	Rectangular ratio (MF)	0.796	0.01
43	Variance (TF)	0.797	0.01
44	Long run range (TF)	0.797	0.01
45	Gray level non-uniformity (TF)	0.798	0.01
46	Minor axis length (MF)	0.798	0.01
47	Second Fourier descriptor (u=1) (MF)	0.799	0.01
48	Third Fourier descriptor (u=2) (MF)	0.799	0.01
49	Fourth Fourier descriptor (u=3) (MF)	0.800	0.01
50	Perimeter (MF)	0.800	0.00
51	Thinness ratio (MF)	0.801	0.02
52	Short run range (TF)	0.801	0.00
53	Gray level variance (TF)	0.801	0.00
54	Run percent range (TF)	0.801	0.00
55	Gray level non-uniformity range (TF)	0.801	0.00
56	Green (CF)	0.801	0.00
57	Hue range (CF)	0.801	0.00
58	Intensity variance (CF)	0.801	0.00
59	GLRM entropy range (TF)	0.801	0.00
60	Long run (TF)	0.801	0.00
61	Gray level range (TF)	0.801	0.00
62	Intensity range (CF)	0.802	0.00
63	Aspect ratio (MF)	0.802	0.00
64	Intensity (CF)	0.802	0.00

Note: major axis length (MF) and green variance (CF) were removed from the selection with other features and independent level of contribution of a feature determine its importance in a model. The first five most significant features were morphological features; and among the first 15 features, there were 6 morphological features, 7 textural features, and 2 color features (Table 7.16).

Pearson correlation coefficients of morphological, textural, and color features were determined for CWRS wheat, CWAD wheat, barley, oats, and rye using grains from 15 growing regions (used as the training set in the hold out method). The data are available on a diskette and can be obtained by writing to the Head, Department of Biosystems Engineering, University of Manitoba, Winnipeg, MB, R3T 5V6, CANADA. The data may be used in future studies. For example, if one wants to differentiate between some of these cereal grains and other types of grains or between different classes of wheat, these data can be used to get an idea about how different features (morphological, textural, and color) are correlated with one another for each grain type; from this information one can select some useful features for the discriminant model.

Discriminant analyses were carried out using the first 5, 10, 15, 20, 25, 30, 35, 40, and 50 features and the classification accuracies were compared with that using all 66 features (Fig. 7.21). When the first five features were used, the mean accuracies were poor. Beyond first 20 features, the increase in mean accuracies was negligible. When the model using the first 20 features was tested on the independent data set, the classification accuracies of CWRS wheat, CWAD wheat, barley, oats, and rye were 100.0, 99.9, 99.5, 100.0, and 99.1%, respectively (non-parametric estimation, Appendix F9a). Same model when tested on the training data set, the classification accuracies were 99.8, 99.8, 99.9, 100.0, and 99.4%, respectively for CWRS wheat, CWAD wheat, barley, oats, and rye (non-parametric estimation, Appendix F9b).

For all the models discussed, with an increase in the number of features, the increase in classification accuracies to certain extent and then their remaining constant or gradual decrease conforms with the study conducted by Petersen (1992) for identifying weed seeds by shape and textural analysis.

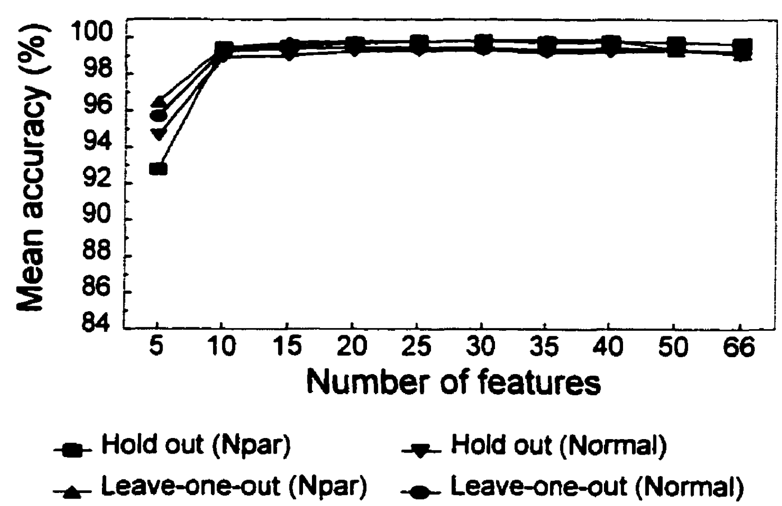


Fig. 7.21 Comparison of classification accuracies of individual kernels of cereal grains using different number of morphological, color, and textural features (extracted from green color band at maximum gray level value 8) (Note: Npar denotes non-parametric estimation)

Table 7.17 shows all the models in the descending order of their classification performance on both the training and the test data sets. The morphology-texture-color model was the best model for classification of individual kernels of cereal grains (Fig. 7.22).

Table 7.17a Comparison of different models depending on their classification accuracies of individual kernels of cereal grains when tested on an independent data set

	Non-parametric Estimation					
% accuracy → Models ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
M-T-C (1st 20 features)	100.0	99.9	99.5	100.0	99.1	99.7
M-C (1st 15 features)	99.7	99.7	98.9	99.9	98.9	99.4
M-T (1st 15 features)	99.4	99.1	99.1	100.0	95.2	98.6
T-C (1st 15 features)	98.5	99.4	99.7	100.0	94.3	98.4
M (1st 10 features)	98.9	93.7	96.8	99.9	81.6	94.2
C (1st 10 features)	94.1	92.3	93.1	95.2	92.5	93.4
T (1st 15 features)	85.2	98.2	100.0	100.0	76.3	92.0

Note: M-T-C is morphology-texture-color model, M-C is morphology-color model, M-T is morphology-texture model, T-C is texture-color model, M is morphology model, C is color model, and T is texture model.

Table 7.17b Comparison of different models depending on their classification accuracies of individual kernels of cereal grains when tested on the training data set

	Non-parametric Estimation					
% accuracy → Models ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
M-T-C (1st 20 features)	99.8	99.8	99.9	100.0	99.4	99.8
M-C (1st 15 features)	99.8	97.4	99.7	100.0	99.0	99.6
M-T (1st 15 features)	99.5	98.7	99.7	100.0	98.6	99.3
T-C (1st 15 features)	97.6	99.4	99.5	98.7	95.0	98.0
M (1st 10 features)	98.9	91.6	97.9	100.0	91.6	96.0
C (1st 10 features)	95.7	94.4	94.2	97.6	92.5	94.9
T (1st 15 features)	87.0	95.7	100.0	100.0	81.8	92.9

Note: M-T-C is morphology-texture-color model, M-C is morphology-color model, M-T is morphology-texture model, T-C is texture-color model, M is morphology model, C is color model, and T is texture model.

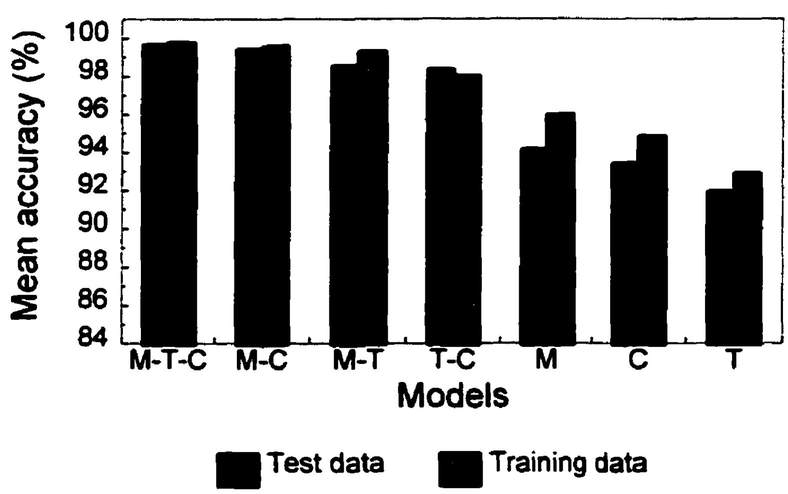


Fig. 7.22 **Comparison of different models depending on their classification accuracies of individual kernels of cereal grains when tested on an independent data set and on the training data set (M-T-C: morphology-texture-color model, M-C: morphology-color model, M-T: morphology-texture model, T-C: texture-color model, M: morphology model, C: color model, and T: texture model)**

CHAPTER VIII: CONCLUSIONS AND RECOMMENDATIONS

The application of computer vision technique for objective classification of cereal grains and varieties can still be considered a very young science. While challenges remain in some areas like automated grain presentation and high sample throughput, considerable progress has been made towards grain classification using DIA. Grain samples, whether they are pure seed lots or commercial grade material, can be effectively characterized by DIA according to size, shape, color, and texture.

Results have shown that cereal grains (e.g., CWRS wheat, CWAD wheat, barley, oats, and rye) could be rapidly identified using either textural or color features of bulk samples. This could be implemented for rapid identification of cereal grains in a rail car at any terminal elevator. Textural features extracted from bulk sample images from the red color at maximum gray level value 32 gave the highest classification accuracies in cereal grains. The classification accuracies reduced when the original bulk sample image was partitioned into different equal size sub-images and their textural or color features were used for classification of cereal grains.

Textural features of individual kernels extracted from the green color at maximum gray level value 8 gave the highest classification accuracies in cereal grains. The highest classification accuracies of cereal grains were achieved when morphology, texture, and color features were used all together. This could be seen as partial advancement towards cereal grain grading, and monitoring of cleaning machines and shipping of grains. Study should be directed towards classification of damaged kernels, other foreign materials like chaff. stone pieces, broken kernels, and other type of grains (e.g., oil seeds, speciality crops).

Robustness is a basic requirement for any image processing system used in the grain industry because of natural variation in grains due to growing seasons, country of origin, and different varieties. Aside from the use of specific training samples for system development, the decision-making methods used in research may be partially responsible for poor system performance. Grain inspection and grading, as performed by human inspectors, is a complex decision-making process that involves many factors such as training and experience of the inspectors. This requires that an image processing system should have some human-like abilities, such as learning and making decisions on ill-defined concepts, for the inspection task. Traditional decision-making methods, as used in many fields, are based on well defined concepts and yes-or-no logic, and implemented in programmed procedures (computer programs), which can only handle the tasks that are predefined by the training samples. Neural network and fuzzy logic techniques are potential solutions for this problem. Neural networks, the electronic simulations of the human brain, have self-learning and self-organizing abilities. Fuzzy logic simulates human reasoning methodology. Applying these techniques in decision making will allow an image processing system to be more robust and human-like.

Considerable progress has been made towards classification of cereal grains and varieties using DIA and the next decade should see continuing improvements in the capability of the technology. However, one should not forget the common problems associated with any visual inspection process; i.e., the ability to distinguish individual kernels can be undermined by the effects of close genetic relationships and the environmental effects. While DIA will not be able to provide absolute perfection in discrimination of grain varieties, the strengths of the technology for this application are clear and compelling.

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APPENDIX A

Primary and Export Grade Determinants for CWRS wheat

(Source: Anonymous 1994)

RED SPRING WHEAT (Canada Western) - PRIMARY GRADE DETERMINANTS

		Standard of Quality			Maximum Limits of			
					Foreign Material		Wheats of Other Classes or Varieties	
Grade Name	Minimum Test Weight kg/hL	Variety	Minimum Hard Vitreous Kernels	Degree of Soundness	Matter Other Than Cereal Grains	Total Including Cereal Grains	Contrasting Classes	Total Including Contrasting Classes
No. 1 Canada Western Red Spring	75.0	Any variety of red spring wheat equal to Neepawa	65.0%	Reasonably well matured, reasonably free from damaged kernels	About 0.2%	0.75%	1.0%	3.0%
No. 2 Canada Western Red Spring	72.0	Any variety of red spring wheat equal to Neepawa	35.0%	Fairly well matured, may be moderately bleached or frost damaged, but reasonably free from severely damaged kernels	About 0.3%	1.5%	3.0%	6.0%
No. 3 Canada Western Red Spring	69.0	Any variety of red spring wheat equal to Neepawa	-	May be frost damaged, immature or weathered, but moderately free from severely damaged kernels	About 0.5%	3.5%	5.0%	10.0%
Canada Western Feed	No Minimum	Any type or variety of wheat excluding amber durum	No Minimum	Excluded from other grades of wheat on account of light weight or damaged kernels, but shall be reasonably sweet	1.0%	10.0%	No Limit 10.0% amber durum only	
Final Grade Name	Canada Western Feed		No. 3 C.W. Red Spring		Over 1.0% grade Wheat, Sample C.W. Account Admixture	Over 10.0% grade Mixed Grain, C.W. Wheat	Canada Western Feed Over 10.0% amber durum grade Wheat, Sample C.W. Account Admixture	

RED SPRING WHEAT - PRIMARY GRADE DETERMINANTS

Grade Name	Sprouted: Severe	Sprouted: Total Incl. Severe Sprouted	Binburnt Severe Mildew Rotted Mouldy	Heated Incl. Binburnt	Fireburnt	Stones	Ergot	Sclerotinia	Smudge	Total Smudge and Blackpoint
No. 1 C.W. Red Spring	0.1%	0.5%	2K	0.1%	Nil	3K	3K	3K	30K	10.0%
No. 2 C.W. Red Spring	-	1.5%	5K	0.75%	Nil	3K	6K	6K	1.0%	20.0%
No. 3 C.W. Red Spring	-	5.0%	10K	2.0%	Nil	6K	24K	24K	5.0%	35.0%
Canada Western Feed	No Limit		10.0%	10.0%	2.0%	10K	0.25%	0.25%	No Limit	No Limit
Final Grade Name	Canada Western Feed		Over 10.0% grade Wheat, Sample C.W. Account Heated		Over 2.0% grade Wheat, Sample C.W. Account Fireburnt	Over grade tolerance up to 2.5% grade Rejected "grade" Account Stones. Over 2.5% grade Wheat, Sample Salvage	Over 0.25% grade Wheat, Sample C.W. Account Ergot	Over 0.25% grade Wheat, Sample C.W. Account Admixture	Canada Western Feed	Canada Western Feed

Grade Name	Shrunken and Broken: Shrunken	Shrunken and Broken: Broken	Shrunken and Broken: Total	* Degermed	** Grass Green	Pink Kernels	Artificial Stain No Residue	Natural Stain	*** Insect Damage: Sawfly Midge	*** Insect Damage: Grasshopper Army Worm	Dark Immature
No. 1 C.W. Red Spring	8.0%	6.0%	7.0%	4.0%	0.75%	1.5%	Nil	0.5%	2.0%	1.0%	1.0%
No. 2 C.W. Red Spring	10.0%	10.0%	11.0%	7.0%	2.0%	5.0%	5K	2.0%	8.0%	3.0%	2.5%
No. 3 C.W. Red Spring	No Limit	15.0%	No Limit Providing Broken Tolerances Not Exceeded	13.0%	10.0%	10.0%	10K	5.0%	25.0%	8.0%	10.0%
Canada Western Feed	No Limit	50.0%		No Limit	No Limit	No Limit	2.0%	No Limit	No Limit	No Limit	No Limit
Final Grade Name	No. 3 C.W. Red Spring	Over 50.0% grade Sample Broken Grain		Canada Western Feed	Canada Western Feed	Canada Western Feed	Over 2.0% grade Wheat, Sample C.W. Account Stained Kernels	Canada Western Feed	Canada Western Feed	Canada Western Feed	Canada Western Feed

*Degermed: Tolerances apply to kernels not classed as sprouted.

**Grass Green Kernels: Tolerances are given as a general guide and may be increased or reduced in the judgment of the inspector after consideration of the overall quality of a sample.

***Insect Damage: Tolerances are not absolute maximums. Inspectors must consider the degree of damage in conjunction with the overall quality of the sample.

NOTE: THE LETTER "K" IN THESE TABLES REFERS TO KERNEL SIZE PIECES IN 500 GRAMS.

RED SPRING WHEAT - EXPORT GRADE DETERMINANTS

Grade Name	Commercial Cleanliness					Total Foreign Material											
	Broken Grain Thru 5 Δ	Material through 4.5 R.H. and Roughage				Seeds and Wild Oats											
		SSDS	RHGE	ATT	TOT	LSDS	SSDS	W.O.	TOT	RHGE	ATT	Stones	Total Mineral Matter	Ergot	Sclerotinia	Other Cereal Grains	Total Foreign Material
No. 1 C.W. Red Spring	0.30%	0.05%	0.05%	0.10%	0.10%	0.20%	0.05%	0.05%	0.20%	0.05%	0.10%	0.03%	0.06%	0.01%	0.01%	0.40%	0.40%
No. 2 C.W. Red Spring	0.30%	0.05%	0.05%	0.10%	0.10%	0.20%	0.05%	0.05%	0.20%	0.05%	0.10%	0.03%	0.10%	0.02%	0.02%	0.75%	0.75%
No. 3 C.W. Red Spring	0.30%	0.05%	0.05%	0.10%	0.10%	0.20%	0.05%	0.05%	0.20%	0.05%	0.10%	0.06%	0.10%	0.04%	0.04%	1.25%	1.25%
Canada Western Feed	0.50%	0.05%	0.10%	0.10%	0.10%	0.50%	0.05%	0.10%	0.50%	0.10%	0.10%	0.10%	0.25%	0.10%	0.10%	5.0%	5.0%

Grade Name	Wheats of Other Classes		Minimum Hard Vitreous Kernels	Sprouted		Heated and Binburnt	Shrunken and Broken		
	Contrasting Classes	Total Including Cont. Classes		Severe	Total Including Severe Sprouted		Shrunken	Broken	Total
No. 1 C.W. Red Spring	0.30%	1.5%	65.0%	0.1%	0.5%	0.05% including 1 binburnt kernel per 1000 g	6.0%	5.0%	7.0%
No. 2 C.W. Red Spring	1.5%	3.0%	35.0%		1.5%	0.4% including 4 binburnt kernels per 1000 g	10.0%	8.0%	11.0%
No. 3 C.W. Red Spring	2.5%	5.0%	No Minimum		5.0%	1.0% including 6 binburnt kernels per 1000 g	No Limit	13.0%	No Limit providing broken tolerances not exceeded
Canada Western Feed	No Limit (10.0% Amber Durum only)		No Minimum	No Limit		2.5% including 2.5% binburnt kernels	No Limit	50.0%	

APPENDIX B

CONFUSION MATRICES OF BULK SAMPLES FOR TEXTURAL ANALYSIS (HOLD OUT METHOD)

Table B1a. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 250): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	43 (95.6%)	0	0	0	2
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0
Barley (n = 15)	0	5	10 (66.7%)	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0
Rye (n = 15)	3	0	0	0	12 (80.0%)

Table B1b. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 250): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	1	14 (93.3%)	0	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0	0
Rye (n = 15)	0	0	0	0	15 (100.0%)	0

Table B2a. **Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 32): Normal estimation (hold out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0
Barley (n = 15)	0	5	10 (66.7%)	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0
Rye (n = 15)	1	0	0	0	14 (93.3%)

Table B2b. **Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	0	15 (100.0%)	0	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0	0
Rye (n = 15)	0	0	0	0	15 (100.0%)	0

Table B3a. **Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 16): Normal estimation (hold out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0
Barley (n = 15)	0	5	10 (66.7%)	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0
Rye (n = 15)	1	0	0	0	14 (93.3%)

Table B3b. **Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 16): Non-parametric estimation (hold out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	1	14 (93.3%)	0	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0	0
Rye (n = 15)	0	0	0	0	15 (100.0%)	0

Table B4a. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 8): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0
Barley (n = 15)	0	5	10 (66.7%)	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0
Rye (n = 15)	0	0	0	0	15 (100.0%)

Table B4b. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 8): Non-parametric estimation (hold out method) with k=5.

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	0	15 (100.0%)	0	0	0
Oats (n = 15)	0	0	1	14 (93.3%)	0	0
Rye (n = 15)	0	0	0	0	15 (100.0%)	0

Table B5a. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 4): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	44 (97.8%)	0	0	0	1
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0
Barley (n = 15)	0	5	10 (66.7%)	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0
Rye (n = 15)	1	0	0	0	14 (93.3%)

Table B5b. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 4): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	0	15 (100.0%)	0	0	0
Oats (n = 15)	0	0	1	14 (93.3%)	0	0
Rye (n = 15)	0	0	0	0	15 (100.0%)	0

Table B6a. Confusion matrix of bulk samples for textural analysis (features extracted from green color band at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0
Barley (n = 15)	0	3	12 (80.0%)	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0
Rye (n = 15)	1	0	0	0	14 (93.3%)

Table B6b. Confusion matrix of bulk samples for textural analysis (features extracted from green color band at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	44 (97.8%)	0	0	0	1	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	1	14 (93.3%)	0	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0	0
Rye (n = 15)	0	0	0	0	15 (100.0%)	0

Table B7a. Confusion matrix of bulk samples for textural analysis (features extracted from blue color band at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0
Barley (n = 15)	0	2	13 (86.7%)	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0
Rye (n = 15)	0	0	0	0	15 (100.0%)

Table B7b. Confusion matrix of bulk samples for textural analysis (features extracted from blue color band at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	1	14 (93.3%)	0	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0	0
Rye (n = 15)	1	0	0	0	14 (93.3%)	0

Table B8a. Confusion matrix of bulk samples for textural analysis (features extracted from black & white color at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0
Barley (n = 15)	0	3	12 (80.0%)	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0
Rye (n = 15)	0	0	0	0	15 (100.0%)

Table B8b. Confusion matrix of bulk samples for textural analysis (features extracted from black & white color at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5.

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	1	14 (93.3%)	0	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0	0
Rye (n = 15)	0	0	0	0	15 (100.0%)	0

Table B9a. **Confusion matrix of bulk samples for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 32): Normal estimation (hold out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0
Barley (n = 15)	0	4	11 (73.3%)	0	06
Oats (n = 15)	0	0	0	15 (100.0%)	0
Rye (n = 15)	0	0	0	0	15 (100.0%)

Table B9b. **Confusion matrix of bulk samples for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	1	14 (93.3%)	0	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0	0
Rye (n = 15)	0	0	0	0	15 (100.0%)	0

Table B10a. Confusion matrix of bulk samples for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0
Barley (n = 15)	0	3	12 (80.0%)	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0
Rye (n = 15)	0	0	0	0	15 (100.0%)

Table B10b. Confusion matrix of bulk samples for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	1	14 (93.3%)	0	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0	0
Rye (n = 15)	0	0	0	0	15 (100.0%)	0

Table B11a. Confusion matrix of bulk samples for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 32): Normal estimation (hold out method).

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0
Barley (n = 15)	0	3	12 (80.0%)	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0
Rye (n = 15)	1	0	0	0	14 (93.3%)

Table B11b. Confusion matrix of bulk samples for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5.

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	1	14 (93.3%)	0	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0	0
Rye (n = 15)	0	0	0	0	15 (100.0%)	0

Table B12a. Confusion matrix of bulk samples (each image partitioned into 9 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n=405)	381 (94.1%)	1	12	0	11
CWAD wheat (n=135)	0	135 (100.0%)	0	0	0
Barley (n=135)	0	24	111 (82.2%)	0	0
Oats (n=135)	0	2	2	131 (97.0%)	0
Rye (n=135)	12	0	0	0	123 (91.1%)

Table B12b. Confusion matrix of bulk samples (each image partitioned into 9 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n=405)	391 (96.5)	0	2	0	12	0
CWAD wheat (n=135)	0	135 (100.0%)	0	0	0	0
Barley (n=135)	0	3	132 (97.8%)	0	0	0
Oats (n=135)	0	0	3	132 (97.8%)	0	0
Rye (n=135)	15	0	0	0	120 (88.9%)	0

Table B13a. Confusion matrix of bulk samples (each image partitioned into 16 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n=720)	649 (90.1%)	13	30	0	28
CWAD wheat (n=240)	0	240 (100.0%)	0	0	0
Barley (n=240)	0	42	197 (82.1%)	1	0
Oats (n=240)	0	4	7	229 (95.4%)	0
Rye (n=240)	27	0	0	0	213 (88.8%)

Table B13b. Confusion matrix of bulk samples (each image partitioned into 16 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n=720)	667 (92.6%)	4	12	0	34	3
CWAD wheat (n=240)	0	240 (100.0%)	0	0	0	0
Barley (n=240)	0	17	223 (92.9%)	0	0	0
Oats (n=240)	0	1	12	226 (94.2%)	0	1
Rye (n=240)	36	0	0	0	203 (84.6%)	1

Table B14a. Confusion matrix of bulk samples (each image partitioned into 25 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n=1125)	975 (86.7%)	35	64	0	51
CWAD wheat (n=375)	0	375 (100.0%)	0	0	0
Barley (n=375)	0	79	294 (78.4%)	2	0
Oats (n=375)	0	11	20	344 (91.7%)	0
Rye (n=375)	46	0	0	0	329 (87.7%)

Table B14b. Confusion matrix of bulk samples (each image partitioned into 25 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n=1125)	1023 (90.9%)	13	9	0	64	16
CWAD wheat (n=375)	0	373 (99.5%)	0	1	0	1
Barley (n=375)	0	36	339 (90.4%)	0	0	0
Oats (n=375)	0	3	27	341 (90.9%)	0	4
Rye (n=375)	65	0	0	0	308 (82.1%)	2

APPENDIX BB

CONFUSION MATRICES OF BULK SAMPLES FOR TEXTURAL ANALYSIS (LEAVE-ONE-OUT METHOD)

Table BB1a. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 250): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	224 (99.6%)	0	0	0	1
CWAD wheat (n = 75)	4	71 (94.7%)	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0
Rye (n = 75)	2	0	0	0	73 (97.3%)

Table BB1b. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 250): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	223 (99.1%)	1	0	0	1	0
CWAD wheat (n = 75)	1	74 (98.7%)	0	0	0	0
Barley (n = 75)	1	0	74 (98.7%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	3	0	0	0	72 (96.0%)	0

Table BB2a. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 32): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	225 (100.0%)	0	0	0	0
CWAD wheat (n = 75)	0	75 (100.0%)	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0
Rye (n = 75)	0	0	0	0	75 (100.0%)

Table BB2b. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	224 (99.6%)	0	0	0	1	0
CWAD wheat (n = 75)	0	75 (100.0%)	0	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	0	0	0	0	75 (100.0%)	0

Table BB3a. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 16): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	225 (100.0%)	0	0	0	0
CWAD wheat (n = 75)	0	75 (100.0%)	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0
Rye (n = 75)	1	0	0	0	74 (98.7%)

Table BB3b. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 16): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	223 (99.1%)	0	0	0	2	0
CWAD wheat (n = 75)	0	75 (100.0%)	0	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	0	0	0	0	75 (100.0%)	0

Table BB4a. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 8): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	225 (100.0%)	0	0	0	0
CWAD wheat (n = 75)	0	75 (100.0%)	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0
Rye (n = 75)	0	0	0	0	75 (100.0%)

Table BB4b. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 8): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	223 (99.1%)	0	0	0	2	0
CWAD wheat (n = 75)	1	74 (98.7%)	0	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	0	0	0	0	75 (100.0%)	0

Table BB5a. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 4): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	225 (100.0%)	0	0	0	0
CWAD wheat (n = 75)	3	72 (96.0%)	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0
Rye (n = 75)	0	0	0	0	75 (100.0%)

Table BB5b. Confusion matrix of bulk samples for textural analysis (features extracted from red color band at maximum gray level value 4): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	223 (99.1%)	0	0	0	2	0
CWAD wheat (n = 75)	0	74 (98.7%)	1	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	0	0	0	0	75 (100.0%)	0

Table BB6a. Confusion matrix of bulk samples for textural analysis (features extracted from green color band at gray level value 32): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	220 (97.8%)	1	0	1	3
CWAD wheat (n = 75)	1	74 (98.7%)	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0
Rye (n = 75)	1	0	0	0	74 (98.7%)

Table BB6b. Confusion matrix of bulk samples for textural analysis (features extracted from green color band at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	222 (98.7%)	0	0	0	3	0
CWAD wheat (n = 75)	1	74 (98.7%)	0	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	0	0	0	0	75 (100.0%)	0

Table BB7a. Confusion matrix of bulk samples for textural analysis (features extracted from blue color band at maximum gray level value 32): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	216 (96.0%)	1	1	1	6
CWAD wheat (n = 75)	2	73 (97.3%)	0	0	0
Barley (n = 75)	0	1	74 (98.7%)	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0
Rye (n = 75)	1	0	0	0	74 (98.7%)

Table BB7b. Confusion matrix of bulk samples for textural analysis (features extracted from blue color band at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	215 (95.6%)	4	0	0	6	0
CWAD wheat (n = 75)	3	72 (96.0%)	0	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	0	0	0	0	75 (100.0%)	0

Table BB8a. Confusion matrix of bulk samples for textural analysis (features extracted from black & white color at maximum gray level value 32): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	222 (98.7%)	1	0	1	1
CWAD wheat (n = 75)	0	75 (100.0%)	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0
Rye (n = 75)	2	0	0	0	73 (97.3%)

Table BB8b. Confusion matrix of bulk samples for textural analysis (features extracted from black & white color at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	224 (99.6%)	0	0	0	1	0
CWAD wheat (n = 75)	0	75 (100.0%)	0	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	0	0	0	0	75 (100.0%)	0

Table BB9a. Confusion matrix of bulk samples for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 32): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	222 (98.7%)	2	0	0	1
CWAD wheat (n = 75)	0	75 (100.0%)	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0
Rye (n = 75)	1	0	0	0	74 (98.7%)

Table BB9b. Confusion matrix of bulk samples for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	223 (99.1%)	0	0	0	2	0
CWAD wheat (n = 75)	0	75 (100.0%)	0	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	0	0	0	0	75 (100.0%)	0

Table BB10a. **Confusion matrix of bulk samples for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 32): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	223 (99.1%)	1	0	1	0
CWAD wheat (n = 75)	1	74 (98.7%)	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0
Rye (n = 75)	1	0	0	0	74 (98.7%)

Table BB10b. **Confusion matrix of bulk samples for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	225 (100.0%)	0	0	0	0	0
CWAD wheat (n = 75)	2	73 (97.3%)	0	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	0	0	0	0	75 (100.0%)	0

Table BB11a. **Confusion matrix of bulk samples for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 32): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	223 (99.1%)	2	0	1	1
CWAD wheat (n = 75)	1	74 (98.7%)	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0
Rye (n = 75)	2	0	0	0	73 (97.3%)

Table BB11b. **Confusion matrix of bulk samples for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	223 (99.1%)	0	0	0	2	0
CWAD wheat (n = 75)	2	73 (97.3%)	0	0	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	0	0	0	0	75 (100.0%)	0

Table BB12a. **Confusion matrix of bulk samples (each image partitioned into 9 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n=2025)	1960 (96.8%)	20	16	0	29
CWAD wheat (n=675)	11	664 (98.4%)	0	0	0
Barley (n=675)	3	2	670 (99.3%)	0	0
Oats (n=675)	0	0	0	675 (100.0%)	0
Rye (n=675)	10	0	0	0	665 (98.5%)

Table BB12b. **Confusion matrix of bulk samples (each image partitioned into 9 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n=2025)	1974 (97.5%)	1	3	0	46	1
CWAD wheat (n=675)	21	654 (96.9%)	0	0	0	0
Barley (n=675)	0	0	673 (99.7%)	0	2	0
Oats (n=675)	0	0	0	675 (100.0%)	0	0
Rye (n=675)	9	0	1	0	665 (98.5%)	0

Table BB13a. **Confusion matrix of bulk samples (each image partitioned into 16 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n=3600)	3382 (93.9%)	53	55	0	110
CWAD wheat (n=1200)	58	1138 (94.8%)	4	0	0
Barley (n=1200)	13	10	1173 (97.8%)	3	1
Oats (n=1200)	0	2	0	1198 (99.8%)	0
Rye (n=1200)	32	0	0	0	1168 (97.3%)

Table BB13b. **Confusion matrix of bulk samples (each image partitioned into 16 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n=3600)	3427 (95.2%)	17	14	0	141	1
CWAD wheat (n=1200)	81	1114 (92.8%)	4	0	1	0
Barley (n=1200)	11	0	1185 (98.8%)	0	4	0
Oats (n=1200)	0	1	5	1194 (99.5%)	0	0
Rye (n=1200)	36	0	1	0	1163 (96.9%)	0

Table BB14a. **Confusion matrix of bulk samples (each image partitioned into 25 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n=5625)	5146 (91.5%)	111	120	1	247
CWAD wheat (n=1875)	129	1730 (92.3%)	15	0	1
Barley (n=1875)	23	18	1814 (96.8%)	13	7
Oats (n=1875)	0	3	7	1865 (99.5%)	0
Rye (n=1875)	70	1	1	1	1802 (96.1%)

Table BB14b. **Confusion matrix of bulk samples (each image partitioned into 25 sub-images) for textural analysis (features extracted from red color band at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n=5625)	5291 (94.1%)	58	36	0	237	3
CWAD wheat (n=1875)	166	1694 (90.4%)	12	1	2	0
Barley (n=1875)	35	6	1823 (97.2%)	1	10	0
Oats (n=1875)	0	3	17	1854 (98.9%)	0	1
Rye (n=1875)	101	0	2	0	1771 (94.5%)	1

APPENDIX C

BETWEEN-CLASS CORRELATION COEFFICIENT MATRICES

Table C1 **Between-class correlation coefficient matrix of textural (extracted from the red color band at maximum gray level value 32) and color features of bulk samples [Note: The training data set (grains from 25 growing regions) is used]**

Between-Class Correlation Coefficients																						
Features↓→	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20	T21	T22
T1	1.00																					
T2	0.46	1.00																				
T3	0.10	0.70	1.00																			
T4	0.99	0.43	0.58	1.00																		
T5	0.83	0.87	0.86	0.80	1.00																	
T6	0.74	0.25	0.12	0.80	0.53	1.00																
T7	-0.14	0.66	0.65	-0.20	0.34	-0.44	1.00															
T8	0.78	0.77	0.98	0.74	0.91	0.32	0.50	1.00														
T9	0.74	-0.21	0.11	0.78	0.27	0.70	-0.59	0.31	1.00													
T10	0.31	-0.22	-0.31	0.41	-.008	0.81	-0.55	-0.11	0.65	1.00												
T11	0.37	0.99	0.77	0.32	0.82	0.13	0.68	0.71	-.33	-0.35	1.00											
T12	0.88	0.82	0.88	0.85	0.99	0.54	0.30	0.94	0.35	0.01	0.76	1.00										
T13	0.81	0.89	0.88	0.79	0.99	0.52	0.39	0.93	0.25	005	0.83	0.99	1.00									
T14	-0.20	0.34	0.44	-0.31	0.14	-0.74	0.62	0.24	-0.62	-0.99	0.46	0.12	0.13	1.00								
T15	-0.68	-0.49	-0.69	-0.60	-0.71	-0.10	-0.10	-0.67	-0.22	0.46	-0.52	-0.73	-0.66	-0.53	1.00							
T16	0.54	0.27	0.07	0.62	0.42	0.93	-0.25	0.25	0.55	0.88	0.13	0.41	0.44	-0.82	0.20	1.00						
T17	0.44	0.47	0.21	0.51	0.49	0.80	0.05	0.35	0.31	0.74	0.35	0.46	0.53	-0.66	0.23	0.95	1.00					
T18	0.19	-0.65	-0.40	0.20	-0.27	0.12	-0.85	-0.32	0.54	0.12	-0.62	-0.21	-0.34	-0.18	-0.27	-0.17	-0.47	1.00				
T19	0.69	0.26	0.10	0.76	0.51	0.99	-0.41	0.29	0.66	0.83	0.14	0.51	0.50	-0.76	-0.04	0.95	0.84	0.06	1.00			
T20	-0.30	0.18	0.31	-0.40	-0.01	-0.82	0.53	0.11	-0.62	-0.99	0.31	-0.03	-0.02	0.99	-0.47	-0.90	-0.77	-0.08	-0.84	1.00		
T21	-0.80	0.08	-0.17	-0.80	-0.40	-0.60	0.64	-0.32	-0.83	-0.30	0.12	-0.47	-0.35	0.27	0.62	-0.28	-0.03	-0.75	-0.53	0.27	1.00	
T22	-0.42	-0.03	0.14	-0.51	-0.20	-0.89	0.41	-0.06	-0.60	-0.97	0.11	-0.21	-0.22	0.93	-0.35	-0.97	-0.87	0.04	-0.91	0.98	0.28	1.00

Table C1 Between-class correlation coefficient matrix of textural (extracted from the red color band at maximum gray level value 32) and color features of bulk samples [Note: The training data set (grains from 25 growing regions) is used] (cont.)

Between-Class Correlation Coefficients																						
Features1→	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20	T21	T22
T23	-0.09	0.35	-.004	-0.03	0.12	0.37	0.32	0.05	-0.15	0.53	0.26	0.06	0.17	-0.49	0.61	0.67	0.83	-0.76	0.44	-0.57	0.52	-0.64
T24	-0.31	-0.40	-0.23	-0.37	-0.37	-0.63	-0.20	-0.34	-0.26	-0.70	-0.26	-0.35	-0.42	0.62	-0.38	-0.86	-0.95	0.60	-0.68	0.72	-0.15	0.81
T25	-0.08	0.18	-0.11	001	018	0.43	0.16	-.028	004	0.67	0.07	-0.02	0.08	-0.64	0.69	0.73	0.84	-0.63	0.50	-0.70	0.43	-0.74
C1	1.00	0.46	0.10	0.99	0.83	0.74	-0.14	0.78	0.74	0.31	0.37	0.88	0.81	-0.20	-0.67	0.54	0.44	0.19	0.69	-0.30	-0.80	-0.42
C2	0.46	1.00	0.70	0.43	0.87	0.25	0.66	0.77	-0.21	-0.22	0.99	0.82	0.89	0.34	-0.49	0.27	0.47	-0.65	0.26	0.18	0.08	-0.03
C3	0.64	0.81	0.66	0.58	0.86	0.12	0.65	0.98	0.11	-0.31	0.77	0.88	0.88	0.44	-0.69	0.07	0.21	-0.41	0.09	0.31	-0.17	0.14
C4	0.97	0.52	0.27	0.95	0.86	0.65	-0.13	0.76	0.61	0.13	0.47	0.89	0.83	-0.03	-0.81	0.40	0.31	0.24	0.60	-0.13	-0.81	-0.26
C5	0.55	0.99	0.60	0.52	0.91	0.35	0.63	0.82	-0.09	-0.09	0.95	0.86	0.93	0.22	-0.46	0.38	0.57	-0.64	0.36	0.06	0.02	-0.14
C6	0.10	0.70	1.00	001	0.52	-0.40	0.68	0.51	-0.53	-0.84	0.79	0.48	0.51	0.90	-0.68	-0.49	-0.30	-0.34	-0.41	0.82	0.15	0.69
C7	0.85	0.47	0.43	0.81	0.78	0.45	-0.14	0.66	0.46	-0.11	0.46	0.81	0.73	0.19	-0.93	0.14	0.05	0.36	0.39	0.11	-0.80	-.000
C8	0.54	0.99	0.64	0.51	0.91	0.33	0.62	0.82	-0.11	-0.14	0.96	0.87	0.93	0.26	-0.50	0.34	0.53	-0.62	0.34	0.10	006	-0.10
C9	-0.92	-0.33	0.23	-0.95	-0.69	-0.85	0.19	-0.67	-0.84	-0.62	-0.19	-0.74	-0.69	0.52	0.33	-0.77	-0.67	-0.08	-0.83	0.61	0.67	0.70
C10	0.61	0.38	0.47	0.57	0.60	0.35	-0.26	0.35	0.21	-0.20	0.43	0.59	0.53	0.25	-0.85	0.02	-0.08	0.43	0.30	0.20	-0.69	0.11
C11	-0.88	-0.08	0.31	-0.90	-0.52	-0.72	0.33	-0.58	-0.95	-0.55	0.05	-0.60	-0.51	0.48	0.36	-0.59	-0.42	-0.32	-0.68	0.52	0.79	0.56
C12	-0.10	0.03	-0.49	-0.04	-0.08	0.21	0.28	0.07	0.11	0.56	-0.10	-0.08	-0.01	-0.53	0.69	0.53	0.63	-0.60	0.26	-0.57	0.44	-0.57
C13	0.30	0.16	-0.46	0.35	0.22	0.47	0.19	0.37	0.43	0.66	008	0.25	0.28	-0.59	0.39	0.70	0.74	-0.46	0.50	-0.66	0.09	-0.69
C14	-0.04	0.72	0.29	-0.04	0.40	0.07	0.77	0.39	-0.43	0.02	0.68	0.33	0.46	0.06	0.23	0.34	0.62	-0.98	0.13	-0.06	0.63	-0.20
C15	-0.22	0.50	0.89	-0.31	0.22	-0.70	0.85	0.36	-0.68	-0.91	0.59	0.19	0.24	0.94	-0.38	-0.67	-0.43	-0.50	-0.70	0.89	0.47	0.81
C16	0.98	0.50	0.24	0.96	0.85	0.66	-0.14	0.76	0.65	0.15	0.44	0.89	0.82	-0.05	-0.80	0.41	0.31	0.25	0.60	-0.15	-0.82	-0.27
C17	0.51	0.99	0.66	0.48	0.90	0.29	0.65	0.80	-0.15	-0.17	0.97	0.85	0.91	0.29	-0.49	0.31	0.51	-0.64	0.31	0.13	0.04	-0.07
C18	-0.61	0.19	0.73	-0.68	-0.18	-0.84	0.59	-0.15	-0.91	-0.90	0.34	-0.24	-0.18	0.87	-0.11	-0.80	-0.60	-0.33	-0.82	0.88	0.62	0.87

Table C1 **Between-class correlation coefficient matrix of textural (extracted from the red color band at maximum gray level value 32) and color features of bulk samples [Note: The training data set (grains from 25 growing regions) is used] (cont.)**

Between-Class Correlation Coefficients																					
Features↓→	T23	T24	T25	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18
T23	1.00																				
T24	-0.90	1.00																			
T25	0.98	-0.92	1.00																		
C1	-0.10	-0.31	-0.08	1.00																	
C2	0.35	-0.40	0.18	0.46	1.00																
C3	000	-0.23	-0.11	0.64	0.81	1.00															
C4	-0.23	-0.13	-0.25	0.97	0.52	0.65	1.00														
C5	0.40	-0.50	0.26	0.55	0.99	0.83	0.57	1.00													
C6	-0.28	0.35	-0.47	0.10	0.70	0.66	0.27	0.60	1.00												
C7	-0.46	0.16	-0.50	0.85	0.47	0.60	0.95	0.48	0.43	1.00											
C8	0.36	-0.46	0.21	0.54	0.99	0.83	0.58	998	0.64	0.50	1.00										
C9	-0.20	0.60	-0.26	-0.92	-0.33	-0.49	-0.80	-0.46	0.23	-0.58	-0.43	1.00									
C10	-0.51	0.35	-0.58	0.61	0.38	0.32	0.78	0.34	0.47	0.91	0.38	-0.29	1.00								
C11	0.06	0.38	-0.05	-0.88	-0.08	-0.41	-0.75	-0.20	0.31	-0.58	-0.18	0.94	-0.26	1.00							
C12	0.83	-0.84	0.88	-0.10	0.03	0.01	-0.32	0.13	-0.49	-0.59	0.07	-0.27	-0.80	-0.16	1.00						
C13	0.72	-0.89	0.79	0.30	0.16	0.25	0.06	0.29	-0.46	-0.23	0.23	-0.62	-0.55	-0.53	0.92	1.00					
C14	0.82	-0.71	0.70	-0.04	0.72	0.44	-0.10	0.73	0.29	-0.25	0.71	-0.08	-0.33	0.20	0.61	0.52	1.00				
C15	-0.19	0.33	-0.35	-0.22	0.50	0.56	-0.10	0.41	0.89	0.04	0.43	0.45	0.04	0.48	-0.23	-0.32	0.38	1.00			
C16	-0.23	-0.14	-0.24	0.98	0.50	0.65	998	0.55	0.24	0.94	0.56	-0.82	0.76	-0.78	-0.30	0.09	-0.11	-0.12	1.00		
C17	0.36	-0.44	0.21	0.51	.997	0.82	0.55	996	0.66	0.48	999	-0.39	0.37	-0.14	0.06	0.21	0.72	0.46	0.53	1.00	
C18	-0.23	0.55	-0.38	-0.61	0.19	0.06	-0.43	0.06	0.73	-0.21	0.09	0.83	-005	0.85	-0.39	-0.62	0.19	0.85	-0.46	0.13	1.00

Note: T1 - Mean gray level, T2 - Gray level variance, T3 - Gray level range, T4 - Mean, T5 - Variance, T6 - Uniformity, T7 - Entropy, T8 - Maximum probability, T9 - Correlation, T10 - Homogeneity, T11 - Inertia, T12 - Cluster shade, T13 - Cluster prominence, T14 - Short run, T15 - Short run range, T16 - Long run, T17 - Long run range, T18 - Gray level non-uniformity, T19 - Gray level non-uniformity range, T20 - Run length non-uniformity, T21 - Run length non-uniformity range, T22 - Run percent, T23 - Run percent range, T24 - GLRM entropy, T25 - GLRM entropy range, C1 - Red, C2 - Red variance, C3 - Red range, C4 - Green, C5 - Green variance, C6 - Green range, C7 - Blue, C8 - Blue variance, C9 - Blue range, C10 - Hue, C11 - Hue variance, C12 - Hue range, C13 - Saturation, C14 - Saturation variance, C15 - Saturation range, C16 - Intensity, C17 - Intensity variance, and C18 - Intensity range.

Table C2 **Between-class correlation coefficient matrix of morphological, textural (extracted from green color band at maximum gray level value 8), and color features of individual kernels [Note: The training data set (grains from 15 growing regions) is used]**

Between-Class Correlation Coefficients

Features↓→	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19	M20	M21	M22	M23
M1	1.00																						
M2	0.98	1.00																					
M3	0.97	0.99	1.00																				
M4	0.38	0.20	0.14	1.00																			
M5	0.38	0.20	0.14	999	1.00																		
M6	0.97	0.99	0.99	0.18	0.18	1.00																	
M7	0.38	0.21	0.15	0.99	0.99	0.17	1.00																
M8	0.96	0.99	999	0.12	0.12	0.99	0.12	1.00															
M9	0.99	998	0.99	0.25	0.25	0.99	0.26	0.99	1.00														
M10	0.99	0.99	0.99	0.29	0.29	0.99	0.28	0.98	0.99	1.00													
M11	0.97	997	999	0.13	0.13	0.99	0.14	999	0.99	0.98	1.00												
M12	0.79	0.89	0.92	-0.26	-0.26	0.90	-0.26	0.92	0.87	0.85	0.92	1.00											
M13	0.89	0.96	0.97	-0.05	-0.05	0.97	-0.05	0.98	0.94	0.94	0.97	0.97	1.00										
M14	-0.32	-0.39	-0.40	0.08	0.08	-0.48	0.15	-0.41	-0.37	-0.44	-0.38	-0.43	-0.52	1.00									
M15	0.82	0.91	0.94	-0.21	-0.21	0.92	-0.21	0.94	0.89	0.87	0.94	0.99	0.98	-0.44	1.00								
M16	0.78	0.89	0.91	-0.27	-0.27	0.90	-0.27	0.92	0.86	0.84	0.91	0.99	0.97	-0.48	0.99	1.00							
M17	0.89	0.96	0.98	-0.05	-0.05	0.97	-0.05	0.98	0.94	0.94	0.97	0.97	998	-0.47	0.98	0.97	1.00						
M18	0.64	0.59	0.55	0.68	0.68	0.61	0.66	0.55	0.60	0.66	0.53	0.24	0.49	-0.49	0.31	0.29	0.48	1.00					
M19	-0.78	-0.86	-0.87	-0.05	0.05	-0.90	0.08	-0.88	-0.84	-0.87	-0.86	-0.87	-0.94	0.79	-0.89	-0.90	-0.92	-0.56	1.00				
M20	0.84	0.93	0.95	-0.18	-0.18	0.93	-0.18	0.95	0.90	0.89	0.95	0.99	0.99	-0.45	999	0.99	0.99	0.36	-0.90	1.00			
M21	0.84	0.93	0.95	-0.17	-0.18	0.93	-0.17	0.95	0.91	0.88	0.95	0.99	0.98	-0.37	0.99	0.99	0.98	0.32	-0.86	0.99	1.00		
M22	0.85	0.92	0.94	-0.13	-0.13	0.90	-0.11	0.94	0.90	0.87	0.94	0.96	0.94	-0.21	0.97	0.95	0.95	0.28	-0.77	0.97	0.99	1.00	
M23	0.80	0.90	0.92	-0.24	0.24	0.90	-0.23	0.93	0.87	0.85	0.92	0.98	0.97	-0.39	0.99	0.99	0.98	0.32	-0.86	0.99	0.99	0.97	1.00

Table C2 **Between-class correlation coefficient matrix of morphological, textural (extracted from green color band at maximum gray level value 8), and color features of individual kernels [Note: The training data set (grains from 15 growing regions) is used] (cont.)**

Between-Class Correlation Coefficients																							
Features↓→	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19	M20	M21	M22	M23
T1	0.97	0.96	0.95	0.32	0.32	0.93	0.34	0.94	0.97	0.95	0.96	0.80	0.86	-0.13	0.82	0.78	0.68	0.54	-0.69	0.83	0.86	0.90	0.81
T2	-0.27	-0.40	-0.44	0.66	0.66	-0.36	0.62	-0.45	-0.36	-0.29	-0.46	-0.69	-0.51	-0.18	-0.66	-0.67	-0.53	0.44	0.28	-0.63	-0.68	-0.72	-0.69
T3	0.11	0.03	-.005	0.64	0.64	0.09	0.58	-0.01	0.05	0.14	-0.03	-0.26	-0.04	-0.60	-0.22	-0.22	-0.08	0.72	-0.23	-0.18	-0.25	-0.35	-0.26
T4	0.95	0.94	0.94	0.26	0.26	0.91	0.28	0.93	0.95	0.92	0.94	0.81	0.85	-0.08	0.83	0.78	0.86	0.43	-0.65	0.83	0.86	0.91	0.81
T5	0.96	0.95	0.94	0.28	0.28	0.92	0.30	0.94	0.96	0.93	0.95	0.81	0.86	-0.09	0.83	0.78	0.87	0.47	-0.66	0.84	0.86	0.91	0.82
T6	0.77	0.81	0.83	-0.15	-0.15	0.78	-0.12	0.82	0.80	0.76	0.84	0.88	0.80	-0.04	0.86	0.83	0.81	0.01	-0.60	0.84	0.88	0.92	0.83
T7	-0.78	-0.88	-0.91	0.28	0.28	-0.89	0.28	-0.92	-0.86	-0.84	-0.91	-0.99	-0.97	0.45	-0.99	-.999	-0.97	-0.26	0.88	-0.99	-0.99	-0.96	-0.99
T8	0.91	0.95	0.96	-.000	-.001	0.95	007	0.96	0.95	0.92	0.97	0.95	0.94	-0.32	0.95	0.92	0.94	0.32	-0.82	0.95	0.96	0.95	0.92
T9	0.78	0.76	0.76	0.14	0.14	0.71	0.18	0.75	0.77	0.72	0.77	0.70	0.65	0.22	0.69	0.64	0.67	0.09	-0.39	0.68	0.74	0.82	0.67
T10	0.38	0.38	0.39	-0.20	-0.20	0.32	-0.15	0.38	0.38	0.31	0.41	0.49	0.33	0.39	0.44	0.41	0.34	-0.44	-0.07	0.41	0.48	0.56	0.41
T11	0.11	0.08	0.06	0.43	0.43	0.15	0.37	0.07	0.09	0.17	0.04	-0.13	0.09	-0.68	-0.08	-0.06	0.06	0.78	-0.35	-0.03	-0.11	-0.22	-0.08
T12	0.96	0.95	0.94	0.27	0.27	0.91	0.30	0.94	0.96	0.93	0.95	0.81	0.86	-0.09	0.83	0.78	0.87	0.47	-0.66	0.84	0.87	0.91	0.82
T13	0.96	0.95	0.94	0.26	0.26	0.91	0.28	0.94	0.96	0.93	0.95	0.81	0.86	-0.09	0.83	0.79	0.87	0.46	-0.66	0.84	0.87	0.91	0.82
T14	0.30	0.35	0.35	0.14	0.14	0.42	0.09	0.36	0.33	0.40	0.32	0.26	0.43	-0.81	0.31	0.34	0.41	0.77	-0.64	0.34	0.27	0.15	0.32
T15	0.79	0.88	0.90	-0.11	-0.11	0.92	-0.13	0.91	0.86	0.87	0.89	0.91	0.97	-0.68	0.93	0.94	0.96	0.55	-0.98	0.95	0.91	0.84	0.93
T16	0.83	0.85	0.86	006	007	0.81	0.03	0.85	0.85	0.81	0.87	0.85	0.80	-0.02	0.84	0.80	0.81	0.12	-0.59	0.82	0.87	0.91	0.81
T17	0.87	0.91	0.92	-0.04	-0.04	0.88	-0.02	0.92	0.90	0.87	0.93	0.92	0.89	-0.14	0.92	0.89	0.89	0.21	-0.70	0.91	0.94	0.96	0.89
T18	0.93	0.91	0.89	0.46	0.46	0.92	0.44	0.89	0.92	0.95	0.88	0.68	0.84	-0.55	0.73	0.70	0.84	0.86	-0.84	0.76	0.73	0.70	0.71
T19	0.97	0.98	0.97	0.28	0.28	0.99	0.27	0.97	0.98	0.99	0.97	0.83	0.94	-0.53	0.86	0.84	0.94	0.72	-0.90	0.88	0.87	0.84	0.84
T20	0.85	0.82	0.80	0.53	0.53	0.84	0.51	0.80	0.83	0.87	0.78	0.55	0.75	-0.59	0.60	0.58	0.74	0.94	-0.79	0.64	0.61	0.56	0.59
T21	0.91	0.91	0.90	0.37	0.37	0.93	0.35	0.90	0.91	0.94	0.89	0.72	0.87	-0.61	0.76	0.74	0.86	0.84	-0.89	0.79	0.76	0.71	0.75
T22	-0.51	-0.50	-0.50	0.05	0.05	-0.44	008	-0.49	-0.51	-0.44	-0.52	-0.54	-0.41	-0.31	-0.50	-0.45	-0.42	0.28	0.17	-0.47	-0.54	-0.62	-0.45

Table C2 **Between-class correlation coefficient matrix of morphological, textural (extracted from green color band at maximum gray level value 8), and color features of individual kernels [Note: The training data set (grains from 15 growing regions) is used] (cont.)**

Between-Class Correlation Coefficients																							
Features ↓ →	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19	M20	M21	M22	M23
T23	0.80	0.87	0.88	0.05	0.05	0.91	0.02	0.88	0.85	0.88	0.86	0.83	0.93	-0.75	0.86	0.86	0.91	0.69	-0.98	0.88	0.83	0.75	0.85
T24	0.88	0.88	0.87	0.40	0.40	0.91	0.38	0.87	0.88	0.92	0.86	0.67	0.84	-0.62	0.72	0.71	0.83	0.88	-0.87	0.75	0.72	0.67	0.71
T25	0.91	0.97	0.98	0.01	0.01	0.98	003	0.98	0.96	0.96	0.98	0.95	0.99	-0.55	0.96	0.95	0.99	0.52	-0.95	0.97	0.96	0.92	0.94
C1	0.96	0.90	0.88	0.46	0.46	0.87	0.48	0.87	0.92	0.91	0.89	0.68	0.76	-0.06	0.70	0.65	0.77	0.52	-0.58	0.72	0.75	0.79	0.68
C2	-0.32	-0.45	-0.49	0.65	0.65	-0.42	0.61	-0.50	-0.41	-0.34	-0.51	-0.73	-0.57	-0.14	-0.71	-0.71	-0.60	0.33	0.34	-0.68	-0.72	-0.76	-0.74
C3	-0.06	-0.13	-0.15	0.52	0.52	-0.06	0.45	-0.16	-0.11	-0.02	-0.18	-0.36	-0.16	-0.60	-0.33	-0.32	-0.20	0.59	-0.14	-0.29	-0.37	-0.48	-0.37
C4	0.97	0.96	0.95	0.32	0.32	0.93	0.34	0.94	0.97	0.95	0.96	0.80	0.86	-0.13	0.82	0.78	0.88	0.54	-0.69	0.83	0.86	0.89	0.81
C5	-0.26	-0.38	-0.42	0.67	0.67	-0.34	0.63	-0.43	-0.34	-0.27	-0.44	-0.68	-0.49	-0.19	-0.65	-0.65	-0.52	0.46	0.26	-0.61	-0.66	-0.71	-0.67
C6	0.11	0.03	-.005	0.64	0.64	0.09	0.58	-0.01	0.05	0.14	-0.03	-0.26	-0.04	-0.59	-0.22	-0.22	-0.08	0.72	-0.23	-0.18	-0.25	-0.35	-0.26
C7	0.77	0.81	0.81	-0.02	-0.02	0.75	0.02	0.81	0.79	0.74	0.83	0.79	0.77	0.15	0.80	0.77	0.80	0.21	-0.49	0.80	0.85	0.92	0.84
C8	-0.24	-0.34	-0.37	0.57	0.57	-0.29	0.51	-0.38	-0.31	-0.23	-0.40	-0.59	-0.40	-0.37	-0.56	-0.55	-0.44	0.48	0.13	-0.53	-0.59	-0.67	-0.59
C9	0.36	0.27	0.23	0.72	0.71	0.32	0.66	0.22	0.29	0.37	0.21	-0.06	0.17	-0.62	-0.02	-0.03	0.14	0.84	-0.39	0.02	-0.04	-0.12	-0.06
C10	0.60	0.68	0.69	0.02	0.01	0.73	-0.02	0.71	0.66	0.70	0.68	0.65	0.78	-0.81	0.69	0.71	0.76	0.73	-0.89	0.72	0.66	0.56	0.70
C11	-0.84	-0.79	-0.77	-0.49	-0.49	-0.82	-0.46	-0.76	-0.81	-0.84	-0.76	-0.58	-0.70	0.59	-0.59	-0.56	-0.67	-0.65	0.76	-0.60	-0.58	-0.52	-0.51
C12	-0.77	-0.79	-0.78	-0.19	-0.19	-0.84	-0.15	-0.79	-0.79	-0.83	-0.77	-0.71	-0.80	0.82	-0.71	-0.71	-0.76	-0.60	0.92	-0.73	-0.68	-0.58	-0.64
C13	0.03	-0.10	-0.13	0.65	0.65	-0.05	0.60	-0.15	-0.06	0.01	-0.15	-0.36	-0.22	-0.39	-0.36	-0.38	-0.26	0.40	-0.02	-0.34	-0.38	-0.45	-0.45
C14	-0.06	-0.16	-0.19	0.62	0.62	-0.10	0.56	-0.20	-0.13	-0.05	-0.22	-0.43	-0.24	-0.49	-0.40	-0.40	-0.28	0.54	-0.04	-0.37	-0.43	-0.52	-0.46
C15	0.11	0.04	0.01	0.52	0.51	0.11	0.45	009	0.06	0.15	-0.01	-0.18	003	-0.70	-0.16	-0.15	-0.04	0.63	-0.30	-0.13	-0.20	-0.32	-0.22
C16	0.94	0.93	0.92	0.27	0.27	0.89	0.30	0.91	0.94	0.90	0.93	0.78	0.83	-0.02	0.80	0.76	0.85	0.45	-0.61	0.81	0.85	0.90	0.80
C17	-0.30	-0.42	-0.45	0.61	0.61	-0.38	0.57	-0.46	-0.39	-0.31	-0.48	-0.69	-0.51	-0.23	-0.66	-0.66	-0.54	0.42	0.26	-0.63	-0.68	-0.73	-0.68
C18	0.11	0.02	-0.01	0.62	0.62	0.08	0.56	-0.02	0.05	0.13	-0.04	-0.26	-0.04	-0.61	-0.22	-0.22	-0.08	0.71	-0.23	-0.18	-0.25	-0.35	-0.26

Table C2 Between-class correlation coefficient matrix of morphological, textural (extracted from green color band at maximum gray level value 8), and color features of individual kernels [Note: The training data set (grains from 15 growing regions) is used] (cont.)

Between-Class Correlation Coefficients																						
Features↓→	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20	T21	T22
T1	1.00																					
T2	-0.41	1.00																				
T3	-0.08	0.87	1.00																			
T4	0.99	-0.49	-0.17	1.00																		
T5	0.99	-0.46	-0.14	.999	1.00																	
T6	0.83	-0.77	-0.48	0.89	0.87	1.00																
T7	-0.78	0.69	0.26	-0.79	-0.79	-0.85	1.00															
T8	0.92	-0.59	-0.19	0.93	0.93	0.94	-0.93	1.00														
T9	0.87	-0.63	-0.45	0.92	0.91	0.93	-0.66	0.85	1.00													
T10	0.49	-0.75	-0.71	0.60	0.56	0.83	-0.45	0.60	0.85	1.00												
T11	-0.06	0.73	0.91	-0.18	-0.14	-0.50	0.10	-0.17	-0.53	-0.86	1.00											
T12	0.99	-0.47	-0.15	999	999	0.87	-0.79	0.93	0.91	0.56	-0.14	1.00										
T13	0.99	-0.48	-0.16	999	999	0.87	-0.80	0.93	0.91	0.57	-0.15	1.00	1.00									
T14	0.16	0.35	0.68	0.05	0.09	-0.19	-0.30	0.13	-0.33	-0.71	0.90	0.09	0.09	1.00								
T15	0.73	-0.40	0.09	0.70	0.71	0.64	-0.93	0.83	0.44	0.11	0.28	0.71	0.71	0.62	1.00							
T16	0.89	-0.69	-0.40	0.94	0.92	0.99	-0.82	0.95	0.96	0.81	-0.44	0.92	0.93	-0.18	0.62	1.00						
T17	0.91	-0.69	-0.34	0.95	0.94	0.98	-0.90	0.98	0.92	0.72	-0.33	0.94	0.94	-0.02	0.75	0.99	1.00					
T18	0.85	-.006	0.41	0.78	0.81	0.50	-0.68	0.76	0.49	003	0.47	0.80	0.80	0.62	0.84	0.58	0.66	1.00				
T19	0.91	-0.23	0.22	0.87	0.88	0.68	-0.83	0.89	0.62	0.19	0.29	0.88	0.88	0.52	0.91	0.73	0.81	0.97	1.00			
T20	0.74	0.17	0.56	0.66	0.69	0.34	-0.56	0.63	0.34	-0.17	0.62	0.69	0.68	0.72	0.77	0.42	0.51	0.98	0.91	1.00		
T21	0.82	-0.04	0.41	0.76	0.78	0.50	-0.72	0.76	0.46	-0.02	0.49	0.78	0.77	0.67	0.88	0.56	0.66	0.99	0.98	0.98	1.00	
T22	-0.61	0.67	0.58	-0.70	-0.66	-0.87	0.49	-0.69	-0.90	-0.98	0.76	-0.67	-0.67	0.62	-0.19	-0.87	-0.78	-0.16	-0.33	009	-0.12	1.00

Table C2 Between-class correlation coefficient matrix of morphological, textural (extracted from green color band at maximum gray level value 8), and color features of individual kernels [Note: The training data set (grains from 15 growing regions) is used] (cont.)

Between-Class Correlation Coefficients																						
Features↓→	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20	T21	T22
T23	0.71	-0.21	0.28	0.66	0.68	0.52	-0.84	0.77	0.35	-0.04	0.45	0.67	0.67	0.73	0.98	0.53	0.66	0.90	0.93	0.87	0.94	-0.07
T24	0.79	0.02	0.46	0.72	0.75	0.45	-0.68	0.72	0.40	-0.09	0.54	0.74	0.74	0.71	0.86	0.51	0.61	0.99	0.96	0.99	997	-0.06
T25	0.87	-0.45	0.03	0.85	0.86	0.79	-0.95	0.95	0.65	0.32	0.13	0.86	0.86	0.45	0.96	0.80	0.88	0.87	0.96	0.78	0.90	-0.42
C1	0.97	-0.30	-0.02	0.97	0.97	0.80	-0.66	0.87	0.89	0.54	-0.09	0.97	0.97	0.04	0.60	0.88	0.87	0.80	0.85	0.71	0.76	-0.67
C2	-0.45	0.99	0.83	-0.51	-0.50	-0.75	0.73	-0.61	-0.61	-0.66	0.63	-0.50	-0.51	0.23	-0.48	-0.67	-0.69	-0.07	-0.29	0.08	-0.12	0.58
C3	-0.25	0.89	0.98	-0.34	-0.31	-0.60	0.35	-0.32	-0.59	-0.78	0.90	-0.32	-0.33	0.65	-.005	-0.53	-0.48	0.26	0.07	0.42	0.26	0.67
C4	1.00	-0.41	-0.08	0.99	997	0.83	-0.78	0.92	0.87	0.50	-0.07	0.99	0.99	0.15	0.73	0.89	0.92	0.84	0.90	0.74	0.82	-0.61
C5	-0.39	1.00	0.88	-0.47	-0.45	-0.76	0.68	-0.58	-0.62	-0.75	0.74	-0.46	-0.47	0.36	-0.38	-0.67	-0.68	0.02	-0.21	0.19	-0.02	0.66
C6	-0.08	0.87	1.00	-0.17	-0.14	-0.48	0.26	-0.19	-0.45	-0.71	0.91	-0.15	-0.16	0.68	0.09	-0.40	-0.35	0.41	0.22	0.56	0.40	0.58
C7	0.88	-0.73	-0.50	0.90	0.90	0.86	-0.78	0.82	0.88	0.63	-0.38	0.91	0.91	-0.06	0.62	0.87	0.89	0.56	0.69	0.42	0.55	-0.66
C8	-0.41	0.98	0.93	-0.49	-0.47	-0.75	0.58	-0.53	-0.68	-0.81	0.82	-0.47	-0.48	0.49	-0.26	-0.68	-0.66	0.06	-0.15	0.24	0.05	0.72
C9	0.18	0.76	0.97	0.08	0.11	-0.26	0.06	0.05	-0.22	-0.57	0.88	0.10	0.09	0.70	0.27	-0.17	-0.11	0.62	0.44	0.74	0.60	0.42
C10	0.50	-0.04	0.41	0.42	0.45	0.24	-0.68	0.53	0.06	-0.34	0.65	0.44	0.44	0.90	0.90	0.24	0.40	0.81	0.79	0.82	0.86	0.25
C11	-0.71	-0.10	-0.49	-0.69	-0.69	-0.52	0.55	-0.73	-0.49	-0.18	-0.35	-0.68	-0.68	-0.38	-0.65	-0.59	-0.62	-0.85	-0.84	-0.83	-0.84	0.34
C12	-0.62	0.02	-0.45	-0.59	-0.60	-0.51	0.70	-0.74	-0.35	-0.07	-0.42	-0.59	-0.59	-0.57	-0.82	-0.53	-0.61	-0.83	-0.86	-0.81	-0.86	0.20
C13	-0.15	0.83	0.86	-0.19	-0.18	-0.38	0.39	-0.20	-0.30	-0.37	0.58	-0.19	-0.20	0.24	-0.17	-0.29	-0.32	0.19	0.04	0.30	0.16	0.25
C14	-0.24	0.93	0.97	-0.32	-0.30	-0.58	0.43	-0.33	-0.52	-0.68	0.81	-0.31	-0.32	0.50	-0.12	-0.50	-0.48	0.22	0.03	0.37	0.20	0.57
C15	-0.10	0.81	0.98	-0.18	-0.16	-0.42	0.18	-0.13	-0.45	-0.65	0.87	-0.17	-0.18	0.66	0.14	-0.35	-0.30	0.39	0.23	0.53	0.40	0.53
C16	0.99	-0.49	-0.19	0.99	0.99	0.86	-0.77	0.90	0.92	0.57	-0.18	997	997	0.05	0.68	0.92	0.93	0.77	0.85	0.66	0.75	-0.67
C17	-0.45	997	0.88	-0.52	-0.50	-0.79	0.68	-0.61	-0.67	-0.77	0.75	-0.51	-0.52	0.38	-0.38	-0.71	-0.71	-0.02	-0.24	0.15	-0.05	0.70
C18	-0.09	0.87	999	-0.18	-0.15	-0.48	0.25	-0.19	-0.45	-0.71	0.91	-0.16	-0.17	0.68	0.09	-0.40	-0.35	0.41	0.22	0.56	0.40	0.59

Table C2 Between-class correlation coefficient matrix of morphological, textural (extracted from green color band at maximum gray level value 8), and color features of individual kernels [Note: The training data set (grains from 15 growing regions) is used] (cont.)

Between-Class Correlation Coefficients																							
Features↓→	T23	T24	T25	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18		
T23	1.00																						
T24	0.93	1.00																					
T25	0.93	0.87	1.00																				
C1	0.59	0.73	0.78	1.00																			
C2	-0.29	-0.07	-0.50	-0.31	1.00																		
C3	0.18	0.31	-0.10	-0.20	0.86	1.00																	
C4	0.71	0.79	0.87	0.97	-0.45	-0.26	1.00																
C5	-0.19	0.04	-0.43	-0.28	0.99	0.90	-0.40	1.00															
C6	0.46	0.03	-0.03	-0.02	0.83	0.98	-0.08	0.88	1.00														
C7	0.52	0.51	0.73	0.80	-0.77	-0.64	0.88	-0.72	-0.50	1.00													
C8	-0.07	0.11	-0.34	-0.32	0.96	0.96	-0.41	0.98	0.93	-0.75	1.00												
C9	0.45	0.64	0.24	0.23	0.71	0.91	0.17	0.77	0.97	-0.27	0.82	1.00											
C10	0.95	0.87	0.78	0.35	-0.15	0.34	0.49	-0.02	0.41	0.32	0.12	0.52	1.00										
C11	-0.73	-0.83	-0.76	-0.76	-0.10	-0.37	-0.71	-0.12	-0.49	-0.32	-0.17	-0.67	-0.55	1.00									
C12	-0.87	-0.85	-0.85	-0.60	0.04	-0.37	-0.62	004	-0.45	-0.28	-0.11	-0.60	-0.75	0.93	1.00								
C13	- 001	0.19	-0.13	007	0.87	0.86	-0.15	0.83	0.86	-0.59	0.84	0.82	0.01	-0.52	-0.38	1.00							
C14	0.07	0.25	-0.16	-0.14	0.92	0.98	-0.25	0.94	0.97	-0.66	0.97	0.90	0.20	-0.39	-0.32	0.93	1.00						
C15	0.32	0.44	0.07	-0.04	0.78	0.98	-0.10	0.81	0.98	-0.54	0.89	0.94	0.43	-0.54	-0.54	0.88	0.96	1.00					
C16	0.63	0.71	0.83	0.97	-0.52	-0.37	0.99	-0.47	-0.19	0.93	-0.50	0.06	0.41	-0.63	-0.53	-0.24	-0.35	-0.22	1.00				
C17	-0.20	009	-0.45	-0.34	0.98	0.91	-0.45	0.99	0.88	-0.76	0.99	0.76	-0.01	-0.09	007	0.83	0.94	0.83	-0.53	1.00			
C18	0.28	0.45	0.03	-0.03	0.83	0.98	-0.09	0.88	999	-0.51	0.93	0.97	0.41	-0.49	-0.46	0.86	0.97	0.98	-0.20	0.88	1.00		

Note M1 - Area, M2 - Perimeter, M3 - Length, M4 - Width, M5 - Minor axis length, M6 - Major axis length, M7 - Minimum radius, M8 - Maximum radius, M9 - Standard deviation of radii, M10 - First Fourier descriptor (FD), M11 - Second FD, M12 - Third FD, M13 - Fourth FD, M14 - Aspect ratio, M15 - Rectangular aspect ratio, M16 - Radius ratio, M17 - Thinness ratio, M18 - Area ratio, M19 - Haralick ratio, M20 -First invariant moment (IM), M21 - Second IM, M22 - Third IM, and M23 - Fourth IM, T24 - Gray level mean, T2 - Gray level variance, T3 - Gray level range, T4 - Mean, T5 - Variance, T6 - Uniformity, T7 - Entropy, T8 - Maximum probability, T9 - Correlation, T10 - Homogeneity, T11 - Inertia, T12 - Cluster shade, T13 - Cluster prominence, T14 - Short run, T15 - Short run range, T16 - Long run, T17 - Long run range, T18 - Gray level non-uniformity, T19 - Gray level non-uniformity range, T20 - Run length non-uniformity, T21 - Run length non-uniformity range, T22 - Run percent, T23 - Run percent range, T24 - GLRM entropy, and T25 - GLRM entropy range, C1 - Red, C2 - Red variance, C3 - Red range, C4 - Green, C5 - Greenvariancee, C6 - Green range, C7 - Blue, C8 - Blue variance, C9 - Blue range, C10 - Hue, C11 - Hue variance, C12 - Hue range, C13 - Saturation, C14 - Saturation variance, C15 - Saturation range, C16 - Intensity, C17 - Intensity variance, and C18 - Intensity range

APPENDIX D

CONFUSION MATRICES OF BULK SAMPLES FOR COLOR ANALYSIS (HOLD OUT METHOD)

Table D1a. Confusion matrix of bulk samples for color analysis : Normal estimation (hold out method).

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0
CWAD wheat (n = 15)	0	14 (93.3%)	0	1	0
Barley (n = 15)	0	3	12 (80.0%)	0	0
Oats (n = 15)	0	0	4	11 (73.3%)	0
Rye (n = 15)	0	0	0	0	15 (100.0%)

Table D1b. Confusion matrix of bulk samples for color analysis : Non-parametric estimation (hold out method) with k=5.

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 45)	45 (100.0%)	0	0	0	0	0
CWAD wheat (n = 15)	0	15 (100.0%)	0	0	0	0
Barley (n = 15)	0	0	15 (100.0%)	0	0	0
Oats (n = 15)	0	0	0	15 (100.0%)	0	0
Rye (n = 15)	0	0	0	0	15 (100.0%)	0

Table D2a. Confusion matrix of bulk samples (each image partitioned into 9 sub-images) for color analysis : Normal estimation (hold out method).

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 405)	401 (99.0%)	2	0	0	2
CWAD wheat (n = 135)	0	135 (100.0%)	0	0	0
Barley (n = 135)	0	0	133 (98.5%)	2	0
Oats (n = 135)	0	0	24	111 (82.2%)	0
Rye (n = 135)	0	0	0	0	135 (100.0%)

Table D2b. Confusion matrix of bulk samples (each image partitioned into 9 sub-images) for color analysis : Non-parametric estimation (hold out method) with k=5.

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 405)	405 (100.0%)	0	0	0	0	0
CWAD wheat (n = 135)	0	134 (99.3%)	1	0	0	0
Barley (n = 135)	0	0	135 (100.0%)	0	0	0
Oats (n = 135)	0	0	4	130 (96.3%)	0	1
Rye (n = 135)	0	0	0	0	135 (100.0%)	0

Table D3a. Confusion matrix of bulk samples (each image partitioned into 16 sub-images) for color analysis : Normal estimation (hold out method).

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 720)	712 (98.9%)	1	0	1	6
CWAD wheat (n = 240)	0	239 (99.6%)	1	0	0
Barley (n = 240)	0	2	234 (97.5%)	4	0
Oats (n = 240)	0	1	46	193 (80.4%)	0
Rye (n = 240)	0	0	1	0	239 (99.6%)

Table D3b. Confusion matrix of bulk samples (each image partitioned into 16 sub-images) for color analysis : Non-parametric estimation (hold out method) with k=5.

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 720)	720 (100.0%)	0	0	0	0	0
CWAD wheat (n = 240)	0	239 (99.6%)	1	0	0	0
Barley (n = 240)	0	1	238 (99.2%)	1	0	0
Oats (n = 240)	0	0	11	226 (94.2%)	0	3
Rye (n = 240)	0	0	0	0	240 (100.0%)	0

Table D4a. Confusion matrix of bulk samples (each image partitioned into 25 sub-images) for color analysis : Normal estimation (hold out method).

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 1125)	1117 (99.3%)	0	0	0	8
CWAD wheat (n = 375)	0	374 (99.7%)	1	0	0
Barley (n = 375)	0	12	353 (94.1%)	10	0
Oats (n = 375)	0	0	71	302 (80.5%)	2
Rye (n = 375)	0	0	0	0	375 (100.0%)

Table D4b. Confusion matrix of bulk samples (each image partitioned into 25 sub-images) for color analysis : Non-parametric estimation (hold out method) with k=5.

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 1125)	1121 (99.6%)	0	0	0	4	0
CWAD wheat (n = 375)	0	374 (99.7%)	1	0	0	0
Barley (n = 375)	0	3	366 (97.6%)	5	0	1
Oats (n = 375)	1	0	18	354 (94.4%)	0	2
Rye (n = 375)	0	0	0	0	375 (100.0%)	0

APPENDIX DD

CONFUSION MATRICES OF BULK SAMPLES FOR COLOR ANALYSIS (LEAVE-ONE-OUT METHOD)

Table DD1a. Confusion matrix of bulk samples for color analysis : Normal estimation (Leave-one-out method).

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 225)	224 (99.56%)	0	0	1	0
CWAD wheat (n = 75)	0	74 (98.67%)	0	1	0
Barley (n = 75)	0	0	74 (98.67%)	1	0
Oats (n = 75)	0	0	1	74 (98.67%)	0
Rye (n = 75)	0	0	0	0	75 (100.0%)

Table DD1b. Confusion matrix of bulk samples for color analysis : Non-parametric estimation (Leave-one-out method) with k=5.

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 225)	225 (100.0%)	0	0	0	0	0
CWAD wheat (n = 75)	0	74 (98.67%)	0	1	0	0
Barley (n = 75)	0	0	75 (100.0%)	0	0	0
Oats (n = 75)	0	0	0	75 (100.0%)	0	0
Rye (n = 75)	0	0	0	0	75 (100.0%)	0

Table DD2a. Confusion matrix of bulk samples (each image partitioned into 9 sub-images) for color analysis : Normal estimation (Leave-one-out method).

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 2025)	2013 (99.41%)	12	0	0	0
CWAD wheat (n = 675)	17	657 (97.33%)	1	0	0
Barley (n = 675)	0	0	673 (99.70%)	2	0
Oats (n = 675)	0	0	6	669 (99.11%)	0
Rye (n = 675)	2	0	1	0	672 (99.56%)

Table DD2b. Confusion matrix of bulk samples (each image partitioned into 9 sub-images) for color analysis : Non-parametric estimation (Leave-one-out method) with k=5.

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 2025)	2024 (99.95%)	0	0	0	1	0
CWAD wheat (n = 675)	0	675 (100.0%)	0	0	0	0
Barley (n = 675)	0	0	675 (100.0%)	0	0	0
Oats (n = 675)	0	0	3	672 (99.56%)	0	0
Rye (n = 675)	0	0	0	0	675 (100.0%)	0

Table DD3a. Confusion matrix of bulk samples (each image partitioned into 16 sub-images) for color analysis : Normal estimation (Leave-one-out method).

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 3600)	3596 (99.89%)	2	0	0	2
CWAD wheat (n = 1200)	47	1149 (95.75%)	3	1	0
Barley (n = 1200)	0	0	1193 (99.42%)	7	0
Oats (n = 1200)	0	0	17	1183 (98.58%)	0
Rye (n = 1200)	9	0	1	0	1190 (99.17%)

Table DD3b. Confusion matrix of bulk samples (each image partitioned into 16 sub-images) for color analysis : Non-parametric estimation (Leave-one-out method) with k=5.

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 3600)	3598 (99.94%)	0	0	0	2	0
CWAD wheat (n = 1200)	4	1194 (99.50%)	1	0	0	1
Barley (n = 1200)	0	0	1198 (99.83%)	2	0	0
Oats (n = 1200)	0	0	1	1199 (99.92%)	0	0
Rye (n = 1200)	0	0	0	0	1200 (100.0%)	0

Table DD4a. Confusion matrix of bulk samples (each image partitioned into 25 sub-images) for color analysis : Normal estimation (Leave-one-out method).

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 5625)	5621 (99.93%)	0	0	1	3
CWAD wheat (n = 1875)	81	1785 (95.20%)	7	2	0
Barley (n = 1875)	4	0	1849 (98.61%)	22	0
Oats (n = 1875)	0	0	30	1844 (98.35%)	1
Rye (n = 1875)	13	0	0	0	1862 (99.31%)

Table DD4b. Confusion matrix of bulk samples (each image partitioned into 25 sub-images) for color analysis : Non-parametric estimation (Leave-one-out method) with k=5.

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 5625)	5621 (99.93%)	1	0	0	3	0
CWAD wheat (n = 1875)	16	1859 (99.15%)	0	0	0	0
Barley (n = 1875)	0	0	1865 (99.47%)	10	0	0
Oats (n = 1875)	0	0	11	1864 (99.41%)	0	0
Rye (n = 1875)	5	0	0	0	1870 (99.73%)	0

APPENDIX E

CONFUSION MATRICES OF INDIVIDUAL KERNELS FOR TEXTURAL ANALYSIS (HOLD OUT METHOD)

Table E1a. **Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 250): Normal estimation (hold out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3010 (66.9%)	6	0	0	1484
CWAD wheat (n = 1500)	11	1428 (95.2%)	3	7	51
Barley (n = 1500)	0	26	1467 (97.8%)	7	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	418	45	0	0	1037 (69.1%)

Table E1b. **Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 250): Non-parametric estimation (hold out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3572 (79.4%)	6	0	0	909	13
CWAD wheat (n = 1500)	5	1478 (98.5%)	3	0	6	8
Barley (n = 1500)	0	19	1480 (98.7%)	0	0	1
Oats (n = 1500)	0	0	1	1499 (99.9%)	0	0
Rye (n = 1500)	445	65	0	0	958 (63.9%)	32

Table E2a. **Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 32): Normal estimation (hold out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3060 (68.0%)	4	0	0	1436
CWAD wheat (n = 1500)	12	1405 (93.7%)	13	3	67
Barley (n = 1500)	0	30	1463 (97.5%)	7	0
Oats (n = 1500)	0	0	1	1499 (99.9%)	0
Rye (n = 1500)	385	39	0	0	1076 (71.7%)

Table E2b. **Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3573 (79.4%)	4	0	0	905	18
CWAD wheat (n = 1500)	5	1475 (98.3%)	3	0	6	11
Barley (n = 1500)	0	23	1477 (98.5%)	0	0	0
Oats (n = 1500)	0	0	1	1499 (99.9%)	0	0
Rye (n = 1500)	441	47	0	0	985 (65.7%)	27

Table E3a. **Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 16): Normal estimation (hold out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3299 (73.3%)	11	0	0	1190
CWAD wheat (n = 1500)	7	1417 (94.5%)	7	3	66
Barley (n = 1500)	0	32	1454 (96.9%)	14	0
Oats (n = 1500)	0	0	3	1497 (99.8%)	0
Rye (n = 1500)	373	38	0	0	1089 (72.6%)

Table E3b. **Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 16): Non-parametric estimation (hold out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3690 (82.0%)	3	0	0	798	9
CWAD wheat (n = 1500)	2	1474 (98.3%)	6	0	6	12
Barley (n = 1500)	0	28	1471 (98.1%)	0	0	1
Oats (n = 1500)	0	0	2	1497 (99.8%)	0	1
Rye (n = 1500)	369	48	0	0	1041 (69.4%)	42

Table E4a. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 8): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3551 (78.9%)	8	0	0	941
CWAD wheat (n = 1500)	8	1388 (92.5%)	18	5	81
Barley (n = 1500)	0	23	1473 (98.2%)	4	0
Oats (n = 1500)	0	0	3	1497 (99.8%)	0
Rye (n = 1500)	355	39	0	0	1106 (73.7%)

Table E4b. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 8): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3918 (87.1%)	6	0	0	570	6
CWAD wheat (n = 1500)	10	1469 (97.9%)	4	0	12	5
Barley (n = 1500)	0	21	1478 (98.5%)	0	0	1
Oats (n = 1500)	0	0	2	1498 (98.9%)	0	0
Rye (n = 1500)	339	64	0	0	1073 (71.5%)	24

Table E5a. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 4): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3576 (79.5%)	10	0	0	914
CWAD wheat (n = 1500)	42	1300 (86.7%)	31	3	124
Barley (n = 1500)	0	22	1475 (98.3%)	3	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	236	50	2	0	1212 (80.8%)

Table E5b. Confusion matrix of individual samples for textural analysis (features extracted from red color band at maximum gray level value 4): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3892 (86.5%)	10	0	0	584	14
CWAD wheat (n = 1500)	10	1449 (96.6%)	5	0	23	13
Barley (n = 1500)	1	43	1455 (97.0%)	0	0	1
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	226	70	0	0	1178 (78.5%)	26

Table E6a. **Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 32): Normal estimation (hold out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3397 (75.5%)	8	0	0	1095
CWAD wheat (n = 1500)	8	1428 (95.2%)	11	6	47
Barley (n = 1500)	0	43	1445 (96.3%)	12	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	289	38	0	0	1173 (78.2%)

Table E6b. **Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3705 (82.3%)	3	0	0	788	4
CWAD wheat (n = 1500)	4	1474 (98.3%)	5	1	11	5
Barley (n = 1500)	0	32	1466 (97.7%)	1	0	1
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	388	36	0	0	1060 (70.7%)	16

Table E7a. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 16): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3598 (80.0%)	5	0	0	897
CWAD wheat (n = 1500)	3	1431 (95.4%)	13	5	48
Barley (n = 1500)	0	39	1448 (96.5%)	13	0
Oats (n = 1500)	0	0	1	1499 (99.9%)	0
Rye (n = 1500)	287	45	0	0	1168 (77.9%)

Table E7b. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 16): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3844 (85.4%)	2	0	0	646	8
CWAD wheat (n = 1500)	5	1469 (97.9%)	9	0	7	10
Barley (n = 1500)	0	42	1458 (97.2%)	0	0	0
Oats (n = 1500)	0	0	1	1499 (99.9%)	0	0
Rye (n = 1500)	362	51	0	0	1056 (70.4%)	31

Table E8a. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 8): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3802 (84.5%)	4	0	0	694
CWAD wheat (n = 1500)	4	1419 (94.6%)	0	3	74
Barley (n = 1500)	0	0	1500 (100.0%)	0	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	246	35	0	0	1219 (81.3%)

Table E8b. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 8): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3940 (87.7%)	3	0	0	550	7
CWAD wheat (n = 1500)	8	1471 (98.1%)	0	0	13	8
Barley (n = 1500)	0	0	1500 (100.0%)	0	0	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	278	77	0	0	1112 (74.1%)	33

Table E9a. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 4): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3982 (88.5%)	12	0	0	506
CWAD wheat (n = 1500)	13	1387 (92.5%)	25	0	75
Barley (n = 1500)	0	44	1443 (96.2%)	10	3
Oats (n = 1500)	0	0	1	1499 (99.9%)	0
Rye (n = 1500)	275	76	0	0	1149 (76.6%)

Table E9b. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 4): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	4046 (89.9%)	8	0	0	424	22
CWAD wheat (n = 1500)	8	1454 (96.9%)	8	0	19	11
Barley (n = 1500)	0	40	1456 (97.1%)	2	0	2
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	244	61	0	0	1158 (77.2%)	37

Table E10a. Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	2485 (55.2%)	37	6	0	1972
CWAD wheat (n = 1500)	1	1430 (95.3%)	20	12	37
Barley (n = 1500)	0	99	1394 (92.9%)	6	1
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	149	38	0	1	1312 (87.5%)

Table E10b. Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3774 (83.9%)	15	35	2	654	20
CWAD wheat (n = 1500)	5	1463 (97.5%)	10	0	11	11
Barley (n = 1500)	0	65	1434 (95.6%)	0	0	1
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	448	34	0	0	989 (65.9%)	29

Table E11a. Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 16): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3104 (69.0%)	15	0	0	1381
CWAD wheat (n = 1500)	6	1446 (96.4%)	16	11	21
Barley (n = 1500)	0	93	1398 (93.2%)	7	2
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	230	34	0	2	1234 (82.3%)

Table E11b. Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 16): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3862 (85.8%)	12	15	4	593	14
CWAD wheat (n = 1500)	2	1461 (97.4%)	19	0	11	7
Barley (n = 1500)	0	65	1428 (95.2%)	4	0	3
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	429	52	0	0	988 (65.9%)	31

Table E12a. Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 8): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3534 (78.5%)	11	0	2	953
CWAD wheat (n = 1500)	9	1438 (95.9%)	21	10	22
Barley (n = 1500)	0	92	1392 (92.8%)	15	1
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	222	32	0	2	1244 (82.9%)

Table E12b. Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 8): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3910 (86.9%)	13	13	0	539	25
CWAD wheat (n = 1500)	3	1467 (97.8%)	10	0	9	11
Barley (n = 1500)	0	49	1445 (96.3%)	0	0	6
Oats (n = 1500)	0	0	1	1499 (99.9%)	0	0
Rye (n = 1500)	362	47	0	0	1064 (70.9%)	27

Table E13a. Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 4): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3883 (86.3%)	26	1	0	590
CWAD wheat (n = 1500)	8	1445 (96.3%)	16	7	24
Barley (n = 1500)	0	93	1397 (93.1%)	9	1
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	214	26	0	9	1251 (83.4%)

Table E13b. Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 4): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	4100 (91.1%)	29	8	0	331	32
CWAD wheat (n = 1500)	6	1457 (97.1%)	15	1	12	9
Barley (n = 1500)	0	74	1419 (94.6%)	2	0	5
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	300	23	0	0	11.56 (77.1%)	21

Table E14a. Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3319 (73.7%)	5	0	0	1176
CWAD wheat (n = 1500)	9	1415 (94.3%)	16	12	48
Barley (n = 1500)	0	50	1441 (96.1%)	9	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	343	47	0	0	1110 (74.0%)

Table E14b. Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3698 (82.2%)	5	1	0	784	12
CWAD wheat (n = 1500)	3	1466 (97.7%)	9	0	12	10
Barley (n = 1500)	0	37	1458 (97.2%)	0	0	5
Oats (n = 1500)	0	0	1	1499 (99.9%)	0	0
Rye (n = 1500)	408	52	0	0	1009 (67.3%)	31

Table E15a. Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 16): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3529 (78.4%)	2	0	0	969
CWAD wheat (n = 1500)	4	1425 (95.0%)	14	6	51
Barley (n = 1500)	0	51	1437 (95.8%)	12	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	360	32	0	0	1108 (73.9%)

Table E15b. Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 16): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3813 (84.7%)	6	0	0	674	7
CWAD wheat (n = 1500)	2	1477 (98.5%)	4	1	9	7
Barley (n = 1500)	0	44	1456 (97.1%)	0	0	0
Oats (n = 1500)	0	0	1	1499 (99.9%)	0	0
Rye (n = 1500)	409	44	0	0	1021 (68.1%)	26

Table E16a. Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 8): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3768 (83.7%)	1	0	0	731
CWAD wheat (n = 1500)	5	1405 (93.7%)	18	10	62
Barley (n = 1500)	0	54	1432 (95.5%)	14	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	287	27	0	1	1185 (79.0%)

Table E16b. Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 8): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3903 (86.7%)	15	1	0	566	15
CWAD wheat (n = 1500)	6	1461 (97.4%)	8	0	14	11
Barley (n = 1500)	0	38	1458 (97.2%)	0	0	4
Oats (n = 1500)	0	0	1	1499 (99.9%)	0	0
Rye (n = 1500)	293	92	0	0	1079 (71.9%)	36

Table E17a. Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 4): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3962 (88.0%)	19	0	0	519
CWAD wheat (n = 1500)	8	1388 (92.5%)	21	1	82
Barley (n = 1500)	0	67	1423 (94.9%)	5	5
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	270	70	0	0	1160 (77.3%)

Table E17b. Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 4): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	4068 (90.4%)	17	0	0	399	16
CWAD wheat (n = 1500)	12	1445 (96.3%)	8	0	26	9
Barley (n = 1500)	0	40	1455 (97.0%)	0	0	5
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	261	71	0	0	1135 (75.7%)	33

Table E18a. Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3321 (73.8%)	9	0	0	1170
CWAD wheat (n = 1500)	10	1405 (93.7%)	12	5	68
Barley (n = 1500)	0	33	1460 (97.3%)	7	0
Oats (n = 1500)	0	0	1	1499 (99.9%)	0
Rye (n = 1500)	342	50	0	0	1108 (73.9%)

Table E18b. Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3634 (80.8%)	5	0	0	851	10
CWAD wheat (n = 1500)	5	1472 (98.1%)	7	1	10	5
Barley (n = 1500)	0	26	1471 (98.1%)	0	0	3
Oats (n = 1500)	0	0	1	1499 (99.9%)	0	0
Rye (n = 1500)	412	43	0	0	1010 (67.3%)	35

Table E19a. Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 16): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3502 (77.8%)	7	0	0	991
CWAD wheat (n = 1500)	6	1401 (93.4%)	15	6	72
Barley (n = 1500)	0	47	1444 (96.3%)	9	0
Oats (n = 1500)	0	0	1	1499 (99.9%)	0
Rye (n = 1500)	354	40	0	0	1106 (73.7%)

Table E19b. Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1C)/6 at maximum gray level value 16): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3795 (84.3%)	2	2	0	693	8
CWAD wheat (n = 1500)	3	1472 (98.1%)	5	1	10	9
Barley (n = 1500)	0	22	1475 (98.3%)	0	0	3
Oats (n = 1500)	0	0	2	1498 (99.9%)	0	0
Rye (n = 1500)	414	57	0	0	994 (66.3%)	35

Table E20a. Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 8): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3698 (82.2%)	12	0	0	790
CWAD wheat (n = 1500)	6	1413 (94.2%)	0	1	80
Barley (n = 1500)	0	0	1500 (100.0%)	0	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	274	53	0	0	1173 (78.2%)

Table E20b. Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 8): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3847 (85.5%)	18	0	0	618	17
CWAD wheat (n = 1500)	3	1467 (97.8%)	0	1	14	15
Barley (n = 1500)	0	0	1500 (100.0%)	0	0	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	276	88	0	0	1105 (73.7%)	31

Table E21a. Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 4): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3848 (85.5%)	4	0	0	648
CWAD wheat (n = 1500)	17	1378 (91.9%)	0	2	103
Barley (n = 1500)	0	0	1500 (100.0%)	0	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	279	66	0	0	1155 (77.0%)

Table E21b. Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 4): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3980 (88.4%)	13	0	0	489	18
CWAD wheat (n = 1500)	10	1444 (96.3%)	0	0	24	22
Barley (n = 1500)	0	0	1500 (100.0%)	0	0	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	232	99	0	0	1130 (75.3%)	39

Table E22a. Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3324 (73.9%)	4	0	0	1172
CWAD wheat (n = 1500)	3	1419 (94.6%)	16	10	52
Barley (n = 1500)	0	43	1449 (96.6%)	6	2
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	340	41	0	0	1119 (74.6%)

Table E22b. Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3737 (83.0%)	3	3	0	741	16
CWAD wheat (n = 1500)	7	1461 (97.4%)	12	1	8	11
Barley (n = 1500)	0	40	1452 (96.8%)	1	0	7
Oats (n = 1500)	0	0	1	1499 (99.9%)	0	0
Rye (n = 1500)	438	52	0	0	997 (66.5%)	13

Table E23a. Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 16): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3484 (77.4%)	4	0	0	1012
CWAD wheat (n = 1500)	3	1421 (94.7%)	16	10	50
Barley (n = 1500)	0	55	1432 (95.5%)	13	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	354	27	0	1	1118 (74.5%)

Table E23b. Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 16): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3806 (84.6%)	4	14	0	666	10
CWAD wheat (n = 1500)	4	1465 (97.7%)	13	3	11	4
Barley (n = 1500)	0	33	1465 (97.7%)	0	0	2
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	397	51	0	0	1017 (67.8%)	35

Table E24a. Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 8): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3799 (84.4%)	5	0	0	696
CWAD wheat (n = 1500)	9	1419 (94.6%)	18	8	46
Barley (n = 1500)	0	51	1439 (95.9%)	10	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	277	30	0	1	1192 (79.5%)

Table E24b. Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 8): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3914 (87.0%)	11	6	0	549	20
CWAD wheat (n = 1500)	5	1453 (96.9%)	10	1	18	13
Barley (n = 1500)	0	30	1464 (97.6%)	0	0	6
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	279	78	0	0	1095 (73.0%)	48

Table E25a. Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 4): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	4016 (89.2%)	18	0	0	466
CWAD wheat (n = 1500)	3	1412 (94.1%)	29	2	54
Barley (n = 1500)	0	89	1401 (93.40)	5	5
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	252	66	0	0	1182 (78.8%)

Table E25b. Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 4): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	4044 (89.9%)	22	0	0	415	19
CWAD wheat (n = 1500)	5	1452 (96.8%)	9	0	19	15
Barley (n = 1500)	0	49	1444 (96.3%)	3	0	4
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	285	61	0	0	1128 (75.2%)	26

Table E26a. Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 32): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3387 (75.3%)	7	0	0	1106
CWAD wheat (n = 1500)	7	1413 (94.2%)	20	10	50
Barley (n = 1500)	0	40	1450 (96.7%)	10	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	321	44	0	0	1135 (75.7%)

Table E26b. Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 32): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3729 (82.9%)	5	1	0	753	12
CWAD wheat (n = 1500)	4	1468 (97.9%)	9	1	6	12
Barley (n = 1500)	0	23	1474 (98.3%)	0	0	3
Oats (n = 1500)	0	0	2	1498 (99.9%)	0	0
Rye (n = 1500)	413	44	0	0	1021 (68.1%)	22

Table E27a. Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2)/6 at maximum gray level value 16): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3562 (79.2%)	6	0	1	931
CWAD wheat (n = 1500)	2	1415 (94.3%)	16	10	57
Barley (n = 1500)	0	60	1429 (95.3%)	11	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	333	30	0	0	1137 (75.8%)

Table E27b. Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 16): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3849 (85.5%)	3	2	0	633	13
CWAD wheat (n = 1500)	2	1470 (98.0%)	9	0	10	9
Barley (n = 1500)	0	43	1453 (97.1%)	0	0	0
Oats (n = 1500)	0	0	1	1499 (99.9%)	0	0
Rye (n = 1500)	392	52	0	0	1024 (68.3%)	32

Table E28a. Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 8): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	3803 (84.5%)	1	0	0	696
CWAD wheat (n = 1500)	5	1418 (94.5%)	14	11	52
Barley (n = 1500)	0	52	1440 (96.0%)	8	0
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	262	33	0	0	1205 (80.3%)

Table E28b. Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 8): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	3953 (87.8%)	17	0	0	514	16
CWAD wheat (n = 1500)	5	1457 (97.1%)	10	1	14	13
Barley (n = 1500)	0	29	1466 (97.7%)	1	0	4
Oats (n = 1500)	0	0	1	1499 (99.9%)	0	0
Rye (n = 1500)	286	86	0	0	1097 (73.1%)	31

Table E29a. Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 4): Normal estimation (hold out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 4500)	4044 (89.9%)	22	0	0	434
CWAD wheat (n = 1500)	5	1412 (94.1%)	26	1	56
Barley (n = 1500)	0	80	1409 (93.9%)	6	5
Oats (n = 1500)	0	0	0	1500 (100.0%)	0
Rye (n = 1500)	247	72	0	0	1181 (78.7%)

Table E29b. Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 4): Non-parametric estimation (hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 4500)	4090 (90.9%)	15	0	0	376	19
CWAD wheat (n = 1500)	8	1459 (97.3%)	6	0	13	14
Barley (n = 1500)	0	41	1455 (97.0%)	1	0	3
Oats (n = 1500)	0	0	0	1500 (100.0%)	0	0
Rye (n = 1500)	283	65	0	0	1124 (74.9%)	28

APPENDIX EE

CONFUSION MATRICES OF INDIVIDUAL KERNELS FOR TEXTURAL ANALYSIS (LEAVE-ONE-OUT METHOD)

Table EE1a. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 250): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10038 (74.4%)	207	0	28	3227
CWAD wheat (n = 4500)	70	4052 (90.0%)	40	9	329
Barley (n = 4500)	0	85	4344 (96.5%)	61	10
Oats (n = 4500)	0	5	40	4455 (99.0%)	0
Rye (n = 4500)	626	84	0	0	3790 (84.2%)

Table EE1b. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 250): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11319 (83.8%)	140	0	0	2029	12
CWAD wheat (n = 4500)	30	4321 (96.0%)	39	0	110	0
Barley (n = 4500)	0	36	4460 (99.1%)	4	0	0
Oats (n = 4500)	0	2	48	4450 (98.9%)	0	0
Rye (n = 4500)	965	88	0	0	3447 (76.6%)	0

Table EE2a. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 32): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10392 (77.0%)	188	0	15	2905
CWAD wheat (n = 4500)	121	3957 (87.9%)	48	10	364
Barley (n = 4500)	0	86	4339 (96.4%)	64	11
Oats (n = 4500)	1	3	47	4449 (98.9%)	0
Rye (n = 4500)	558	97	1	0	3844 (85.4%)

Table EE2b. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11545 (85.5%)	163	0	0	1784	8
CWAD wheat (n = 4500)	42	4336 (96.4%)	24	0	98	0
Barley (n = 1500)	0	43	4455 (99.0%)	2	0	0
Oats (n = 1500)	0	2	51	4447 (98.8%)	0	0
Rye (n = 1500)	885	72	0	0	3543 (78.7%)	0

Table EE3a. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 16): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10760 (79.7%)	136	0	26	2578
CWAD wheat (n = 4500)	86	4020 (89.3%)	51	11	332
Barley (n = 4500)	0	98	4309 (95.8%)	82	11
Oats (n = 4500)	1	0	44	4455 (99.0%)	0
Rye (n = 4500)	558	82	1	0	3859 (85.8%)

Table EE3b. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 16): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11757 (87.1%)	146	0	0	1589	8
CWAD wheat (n = 4500)	39	4360 (96.9%)	23	2	76	0
Barley (n = 4500)	0	53	4443 (98.7%)	4	0	0
Oats (n = 4500)	0	2	72	4426 (98.4%)	0	0
Rye (n = 4500)	889	85	0	0	3526 (78.4%)	0

Table EE4a. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 8): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	11317 (83.8%)	107	2	24	2050
CWAD wheat (n = 4500)	78	4027 (89.5%)	75	8	312
Barley (n = 4500)	0	83	4343 (96.5%)	64	10
Oats (n = 4500)	0	0	69	4431 (98.5%)	0
Rye (n = 4500)	537	86	1	0	3876 (86.1%)

Table EE4b. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 8): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	12003 (88.9%)	199	0	0	1289	9
CWAD wheat (n = 4500)	38	4351 (96.7%)	36	1	74	0
Barley (n = 4500)	0	65	4434 (98.5%)	1	0	0
Oats (n = 4500)	0	0	70	4430 (98.4%)	0	0
Rye (n = 4500)	698	124	0	0	3682 (81.8%)	0

Table EE5a. Confusion matrix of individual kernels for textural analysis (features extracted from red color band at maximum gray level value 4): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	11349 (84.1%)	155	0	8	1988
CWAD wheat (n = 4500)	140	3770 (83.8%)	181	6	403
Barley (n = 4500)	0	70	4399 (97.8%)	12	19
Oats (n = 4500)	0	4	30	4466 (99.2%)	0
Rye (n = 4500)	397	84	1	1	4017 (89.3%)

Table EE5b. Confusion matrix of individual samples for textural analysis (features extracted from red color band at maximum gray level value 4): Non-parametric estimation (Hold out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	12013 (89.0%)	150	0	0	1321	16
CWAD wheat (n = 4500)	53	4313 (95.8%)	37	0	97	0
Barley (n = 4500)	0	67	4431 (98.5%)	2	0	0
Oats (n = 4500)	0	2	27	4471 (99.4%)	0	0
Rye (n = 4500)	563	123	1	0	3813 (84.7%)	0

Table EE6a. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 32): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	9717 (72.0%)	156	1	18	3608
CWAD wheat (n = 4500)	44	3976 (88.4%)	66	10	404
Barley (n = 4500)	3	108	4324 (96.1%)	56	9
Oats (n = 4500)	0	5	48	4447 (98.8%)	0
Rye (n = 4500)	356	124	3	0	4017 (89.3%)

Table EE6b. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11595 (85.9%)	98	0	0	1793	14
CWAD wheat (n = 4500)	40	4339 (96.4%)	41	1	79	0
Barley (n = 4500)	0	46	4454 (99.0%)	0	0	0
Oats (n = 4500)	0	0	61	4439 (98.6%)	0	0
Rye (n = 4500)	929	83	0	0	3488 (77.5%)	0

Table EE7a. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 16): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10310 (76.4%)	130	0	20	3040
CWAD wheat (n = 4500)	41	4053 (90.1%)	69	9	328
Barley (n = 4500)	1	106	4290 (95.3%)	95	8
Oats (n = 4500)	0	1	59	4440 (98.7%)	0
Rye (n = 4500)	399	108	1	2	3990 (88.7%)

Table EE7b. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 16): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11796 (87.4%)	99	0	0	1594	11
CWAD wheat (n = 4500)	36	4338 (96.4%)	37	2	87	0
Barley (n = 4500)	0	52	4442 (98.7%)	6	0	0
Oats (n = 4500)	1	0	85	4413 (98.1%)	0	1
Rye (n = 4500)	915	86	0	0	3499 (77.8%)	0

Table EE8a. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 8): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10667 (79.0%)	93	0	34	2706
CWAD wheat (n = 4500)	27	4113 (91.4%)	0	16	344
Barley (n = 4500)	0	0	4500 (100.0%)	0	0
Oats (n = 4500)	0	11	0	4489 (99.8%)	0
Rye (n = 4500)	390	91	0	3	4016 (89.2%)

Table EE8b. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 8): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11905 (88.2%)	162	0	0	1421	12
CWAD wheat (n = 4500)	48	4340 (96.4%)	0	1	111	0
Barley (n = 4500)	0	0	4500 (100.0%)	0	0	0
Oats (n = 4500)	0	1	0	4499 (100.0%)	0	0
Rye (n = 4500)	747	157	0	0	3596 (79.9%)	0

Table EE9a. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 4): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	11494 (85.1%)	129	2	5	1870
CWAD wheat (n = 4500)	57	3847 (85.5%)	161	7	428
Barley (n = 4500)	2	76	4305 (95.7%)	98	19
Oats (n = 4500)	0	0	100	4400 (97.8%)	0
Rye (n = 4500)	472	99	2	0	3927 (87.3%)

Table EE9b. Confusion matrix of individual kernels for textural analysis (features extracted from green color band at maximum gray level value 4): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	12263 (90.8%)	137	0	1	1088	11
CWAD wheat (n = 4500)	48	4258 (94.6%)	64	1	129	0
Barley (n = 4500)	0	69	4421 (98.2%)	9	1	0
Oats (n = 4500)	0	0	80	4419 (98.2%)	0	1
Rye (n = 4500)	657	141	0	0	3702 (82.3%)	0

Table EE10a. **Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 32): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	6743 (50.0%)	303	1	26	6427
CWAD wheat (n = 4500)	31	4173 (92.7%)	89	26	181
Barley (n = 4500)	8	187	4232 (94.0%)	71	2
Oats (n = 4500)	0	1	65	4433 (98.5%)	1
Rye (n = 4500)	185	126	1	4	4184 (93.0%)

Table EE10b. **Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11678 (86.5%)	131	2	1	1680	8
CWAD wheat (n = 4500)	40	4368 (97.1%)	46	1	44	1
Barley (n = 4500)	2	89	4387 (97.5%)	22	0	0
Oats (n = 4500)	0	0	105	4394 (97.6%)	0	1
Rye (n = 4500)	864	122	0	0	3514 (78.1%)	0

Table EE11a. **Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 16): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	8633 (64.0%)	190	0	27	4650
CWAD wheat (n = 4500)	39	4195 (93.2%)	93	24	149
Barley (n = 4500)	7	164	4242 (94.3%)	84	3
Oats (n = 4500)	0	0	68	4431 (98.5%)	1
Rye (n = 4500)	286	95	1	6	4112 (91.4%)

Table EE11b. **Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 16): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11912 (88.2%)	111	2	1	1467	7
CWAD wheat (n = 4500)	35	4365 (97.0%)	43	2	53	2
Barley (n = 4500)	1	75	4405 (97.9%)	19	0	0
Oats (n = 4500)	0	2	95	4402 (97.8%)	0	1
Rye (n = 4500)	897	86	0	0	3517 (78.2%)	0

Table EE12a. **Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 8): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10023 (74.2%)	121	0	56	3300
CWAD wheat (n = 4500)	34	4195 (93.2%)	101	36	134
Barley (n = 4500)	7	144	4216 (93.7%)	129	4
Oats (n = 4500)	0	1	80	4417 (98.2%)	2
Rye (n = 4500)	344	75	1	13	4067 (90.4%)

Table EE12b. **Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 8): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11994 (88.8%)	112	0	2	1381	11
CWAD wheat (n = 4500)	20	4374 (97.2%)	47	4	54	1
Barley (n = 4500)	1	62	4415 (98.1%)	22	0	0
Oats (n = 4500)	0	0	113	4386 (97.5%)	0	1
Rye (n = 4500)	757	119	0	0	3624 (80.5%)	0

Table EE13a. **Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 4): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	11108 (82.3%)	202	0	25	2165
CWAD wheat (n = 4500)	46	4134 (91.9%)	120	45	155
Barley (n = 4500)	5	106	4284 (95.2%)	103	2
Oats (n = 4500)	0	0	57	4443 (98.7%)	0
Rye (n = 4500)	390	113	0	6	3991 (88.7%)

Table EE13b. **Confusion matrix of individual kernels for textural analysis (features extracted from blue color band at maximum gray level value 4): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	12443 (92.2%)	139	0	0	911	7
CWAD wheat (n = 4500)	40	4330 (96.2%)	51	2	75	2
Barley (n = 4500)	0	73	4396 (97.7%)	27	0	4
Oats (n = 4500)	0	1	89	4410 (98.0%)	0	0
Rye (n = 4500)	648	132	0	0	3720 (82.7%)	0

Table EE14a. **Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 32): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	9441 (69.9%)	150	0	20	3889
CWAD wheat (n = 4500)	41	3940 (87.6%)	71	20	428
Barley (n = 4500)	2	131	4312 (95.8%)	45	10
Oats (n = 4500)	1	3	41	4455 (99.0%)	0
Rye (n = 4500)	393	114	1	1	3991 (88.7%)

Table EE14b. **Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11547 (85.5%)	147	0	0	1795	11
CWAD wheat (n = 4500)	47	4317 (95.9%)	45	0	91	0
Barley (n = 4500)	0	57	4439 (98.6%)	3	0	1
Oats (n = 4500)	0	0	51	4439 (98.6%)	0	0
Rye (n = 4500)	976	123	0	0	3401 (75.6%)	0

Table EE15a. **Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 16): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10076 (74.6%)	127	0	27	3270
CWAD wheat (n = 4500)	37	4035 (89.7%)	68	14	346
Barley (n = 4500)	1	129	4273 (95.0%)	90	7
Oats (n = 4500)	0	3	51	4446 (98.8%)	0
Rye (n = 4500)	398	95	0	2	4005 (89.0%)

Table EE15b. **Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 16): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11731 (86.9%)	142	1	0	1611	15
CWAD wheat (n = 4500)	40	4350 (96.7%)	39	1	70	0
Barley (n = 4500)	0	59	4438 (98.6%)	3	0	0
Oats (n = 4500)	0	0	90	4410 (98.0%)	0	0
Rye (n = 4500)	903	110	0	0	3487 (77.5%)	0

Table EE16a. **Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 8): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10588 (78.4%)	93	0	45	2774
CWAD wheat (n = 4500)	34	4003 (89.0%)	95	15	353
Barley (n = 4500)	3	100	4278 (95.1%)	109	10
Oats (n = 4500)	0	1	62	4437 (98.6%)	0
Rye (n = 4500)	414	82	0	1	4003 (89.0%)

Table EE16b. **Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 8): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11948 (88.5%)	180	0	0	1361	11
CWAD wheat (n = 4500)	32	4359 (96.9%)	32	1	76	0
Barley (n = 4500)	0	56	4439 (98.6%)	5	0	0
Oats (n = 4500)	0	0	95	4405 (98.0%)	0	0
Rye (n = 4500)	763	165	0	0	3572 (79.4%)	0

Table EE17a. Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 4): Normal estimation (leave-one-out method)

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	11475 (85.0%)	150	0	16	1859
CWAD wheat (n = 4500)	48	3913 (87.0%)	144	11	384
Barley (n = 4500)	3	99	4289 (95.3%)	93	16
Oats (n = 4500)	0	4	131	4365 (97.0%)	0
Rye (n = 4500)	456	114	3	0	3927 (87.3%)

Table EE17b. Confusion matrix of individual kernels for textural analysis (features extracted from black & white color at maximum gray level value 4): Non-parametric estimation (leave-one-out method) with k=5

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	12230 (90.6%)	125	0	1	1133	11
CWAD wheat (n = 4500)	49	4284 (95.2%)	58	2	107	0
Barley (n = 4500)	0	74	4418 (98.2%)	7	0	1
Oats (n = 4500)	0	0	87	4413 (98.1%)	0	0
Rye (n = 4500)	711	166	0	0	3623 (80.5%)	0

Table EE18a. **Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 32): Normal estimation (eave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	9795 (72.6%)	174	0	19	3512
CWAD wheat (n = 4500)	49	3886 (86.4%)	61	13	491
Barley (n = 4500)	0	113	4325 (96.1%)	47	15
Oats (n = 4500)	1	2	40	4457 (99.0%)	0
Rye (n = 4500)	442	109	0	0	3949 (87.8%)

Table EE18b. **Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11531 (85.4%)	108	0	0	1849	12
CWAD wheat (n = 4500)	43	4323 (96.1%)	36	1	97	0
Barley (n = 4500)	0	53	4446 (98.8%)	1	0	0
Oats (n = 4500)	0	0	57	4442 (98.7%)	0	1
Rye (n = 4500)	897	107	0	0	3496 (77.7%)	0

Table EE19a. **Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 16): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10297 (76.3%)	135	0	31	3037
CWAD wheat (n = 4500)	47	3998 (88.8%)	58	12	385
Barley (n = 4500)	0	106	4289 (95.3%)	93	12
Oats (n = 4500)	0	2	53	4445 (98.8%)	0
Rye (n = 4500)	466	99	0	1	3934 (87.4%)

Table EE19b. **Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 16): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11737 (86.9%)	127	0	0	1626	10
CWAD wheat (n = 4500)	40	4351 (96.7%)	37	1	71	0
Barley (n = 4500)	0	55	4439 (98.6%)	6	0	0
Oats (n = 4500)	0	0	78	4422 (98.3%)	0	0
Rye (n = 4500)	919	104	0	0	3477 (77.3%)	0

Table EE20a. **Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 8): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10666 (79.0%)	106	0	31	2697
CWAD wheat (n = 4500)	27	4136 (91.9%)	0	17	320
Barley (n = 4500)	0	0	4500 (100.0%)	0	0
Oats (n = 4500)	0	10	0	4490 (99.8%)	0
Rye (n = 4500)	441	86	0	2	3971 (88.2%)

Table EE20b. **Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 8): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11856 (87.8%)	171	0	0	1457	16
CWAD wheat (n = 4500)	36	4359 (96.9%)	0	1	104	0
Barley (n = 4500)	0	0	4500 (100.0%)	0	0	0
Oats (n = 4500)	0	1	0	4499 (100.0%)	0	0
Rye (n = 4500)	746	150	0	0	3604 (80.1%)	0

Table EE21a. **Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 4): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	11261 (83.4%)	98	0	9	2132
CWAD wheat (n = 4500)	75	3934 (87.4%)	0	10	481
Barley (n = 4500)	0	0	4500 (100.0%)	0	0
Oats (n = 4500)	0	22	0	4478 (99.5%)	0
Rye (n = 4500)	475	96	0	0	3929 (87.3%)

Table EE21b. **Confusion matrix of individual kernels for textural analysis (features extracted from (3R+2G+1B)/6 at maximum gray level value 4): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	12117 (89.8%)	192	0	0	1173	18
CWAD wheat (n = 4500)	57	4316 (95.9%)	0	0	127	0
Barley (n = 4500)	0	0	4500 (100.0%)	0	0	0
Oats (n = 4500)	0	1	0	4499 (100.0%)	0	0
Rye (n = 4500)	643	160	0	0	3697 (82.2%)	0

Table EE22a. **Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 32): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	9190 (68.1%)	137	0	33	4140
CWAD wheat (n = 4500)	46	3971 (88.2%)	88	23	372
Barley (n = 4500)	4	145	4291 (95.4%)	54	6
Oats (n = 4500)	0	1	44	4455 (99.0%)	0
Rye (n = 4500)	388	110	2	1	3999 (88.9%)

Table EE22b. **Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11601 (85.9%)	143	0	0	1745	11
CWAD wheat (n = 4500)	41	4351 (96.7%)	24	1	83	0
Barley (n = 4500)	0	65	4430 (98.4%)	5	0	0
Oats (n = 4500)	1	0	60	4439 (98.6%)	0	0
Rye (n = 4500)	1001	132	0	0	3367 (74.8%)	0

Table EF23a. **Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 16): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	9899 (73.3%)	126	0	31	3444
CWAD wheat (n = 4500)	41	4078 (90.6%)	64	24	293
Barley (n = 4500)	4	129	4271 (94.9%)	91	5
Oats (n = 4500)	0	2	56	4442 (98.7%)	0
Rye (n = 4500)	387	96	0	3	4014 (89.2%)

Table EE23b. **Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 16): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11880 (88.0%)	116	1	0	1493	10
CWAD wheat (n = 4500)	43	4358 (96.8%)	30	0	66	3
Barley (n = 4500)	0	60	4430 (98.4%)	10	0	0
Oats (n = 4500)	0	0	84	4416 (98.1%)	0	0
Rye (n = 4500)	893	120	0	0	3487 (77.5%)	0

Table EE24a. **Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 8): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10468 (77.5%)	118	0	51	2863
CWAD wheat (n = 4500)	44	4092 (90.9%)	90	20	254
Barley (n = 4500)	4	97	4311 (95.8%)	80	8
Oats (n = 4500)	0	0	50	4450 (98.9%)	0
Rye (n = 4500)	408	72	1	1	4018 (89.3%)

Table EE24b. **Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 8): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	12032 (89.1%)	177	0	0	1271	20
CWAD wheat (n = 4500)	45	4372 (97.2%)	40	0	43	0
Barley (n = 4500)	0	56	4431 (98.5%)	13	0	0
Oats (n = 4500)	0	0	89	4411 (98.0%)	0	0
Rye (n = 4500)	775	155	0	0	3570 (79.3%)	0

Table EE25a. **Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 4): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	11422 (84.6%)	201	1	17	1859
CWAD wheat (n = 4500)	37	4075 (90.6%)	120	16	252
Barley (n = 4500)	4	128	4270 (94.9%)	87	11
Oats (n = 4500)	0	8	120	4372 (97.2%)	0
Rye (n = 4500)	450	128	2	0	3920 (87.1%)

Table EE25b. **Confusion matrix of individual kernels for textural analysis (features extracted from (2R+1G+3B)/6 at maximum gray level value 4): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	12284 (91.0%)	147	0	0	1064	5
CWAD wheat (n = 4500)	56	4312 (95.8%)	42	0	89	1
Barley (n = 4500)	0	72	4415 (98.1%)	12	0	1
Oats (n = 4500)	0	0	82	4418 (98.2%)	0	0
Rye (n = 4500)	712	151	0	0	3637 (80.8%)	0

Table EE26a. **Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 32): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	9420 (69.8%)	152	0	28	3900
CWAD wheat (n = 4500)	51	3982 (88.5%)	81	14	372
Barley (n = 4500)	6	122	4304 (95.6%)	62	6
Oats (n = 4500)	0	2	43	4455 (99.0%)	0
Rye (n = 4500)	371	115	1	0	4013 (89.2%)

Table EE26b. **Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 32): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11643 (86.2%)	128	0	0	1714	15
CWAD wheat (n = 4500)	41	4309 (95.8%)	49	0	101	0
Barley (n = 4500)	0	53	4446 (98.8%)	0	0	1
Oats (n = 4500)	0	0	70	4430 (98.4%)	0	0
Rye (n = 4500)	912	115	0	0	3473 (77.2%)	0

Table EE27a. **Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 16): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	9984 (74.0%)	123	0	33	3360
CWAD wheat (n = 4500)	44	4068 (90.4%)	78	21	289
Barley (n = 4500)	2	137	4270 (94.9%)	86	5
Oats (n =4500)	0	3	49	4448 (98.8%)	0
Rye (n = 4500)	368	113	0	1	4018 (89.3%)

Table EE27b. **Confusion matrix of individual kernels for textural analysis (1R+3G+2B)/6 at maximum gray level value 16): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	11822 (87.6%)	134	0	0	1534	10
CWAD wheat (n = 4500)	34	4356 (96.8%)	39	2	68	1
Barley (n = 4500)	0	57	4436 (98.6%)	7	0	0
Oats (n = 4500)	0	0	93	4406 (97.9%)	0	1
Rye (n = 4500)	871	130	0	0	3499 (77.8%)	0

Table EE28a. **Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 8): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	10557 (78.2%)	102	0	51	2790
CWAD wheat (n = 4500)	35	4079 (90.6%)	89	16	281
Barley (n = 4500)	2	109	4275 (95.0%)	105	9
Oats (n = 4500)	0	0	60	4440 (98.7%)	0
Rye (n = 4500)	404	73	0	1	4022 (89.4%)

Table EE28b. **Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 8): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	12053 (89.3%)	175	0	0	1252	20
CWAD wheat (n = 4500)	44	4347 (96.6%)	50	0	59	0
Barley (n = 4500)	0	53	4443 (98.7%)	3	1	0
Oats (n = 4500)	0	0	87	4413 (98.1%)	0	0
Rye (n = 4500)	795	171	0	0	3534 (78.5%)	0

Table EE29a. **Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 4): Normal estimation (leave-one-out method)**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye
CWRS wheat (n = 13500)	11486 (85.1%)	190	1	16	1807
CWAD wheat (n = 4500)	35	4012 (89.2%)	146	11	296
Barley (n = 4500)	4	127	4261 (94.7%)	94	14
Oats (n = 4500)	0	8	124	4368 (97.1%)	0
Rye (n = 4500)	448	131	2	0	3919 (87.1%)

Table EE129b. **Confusion matrix of individual kernels for textural analysis (features extracted from (1R+3G+2B)/6 at maximum gray level value 4): Non-parametric estimation (leave-one-out method) with k=5**

Categories (to)→ (from) ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Other
CWRS wheat (n = 13500)	12302 (91.1%)	162	0	0	1026	10
CWAD wheat (n = 4500)	65	4296 (95.5%)	48	2	89	0
Barley (n = 4500)	0	80	4405 (97.9%)	15	0	0
Oats (n = 4500)	0	0	82	4418 (98.2%)	0	0
Rye (n = 4500)	662	154	0	0	3683 (81.8%)	1

APPENDIX F

CLASSIFICATION ACCURACIES USING DIFFERENT MODELS WITH DIFFERENT NUMBER OF FEATURES

Table F1a Comparison of classification accuracies of bulk samples of cereal grains with different number of textural features, extracted from red color band at maximum gray level value 32: Hold out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	95.6	100.0	100.0	100.0	86.7	96.5
First 10 features	100.0	100.0	100.0	100.0	100.0	100.0
First 15 features	100.0	100.0	100.0	100.0	93.3	98.7
First 20 features	100.0	100.0	93.3	100.0	86.7	96.0
All 25 features	100.0	100.0	100.0	100.0	100.0	100.0
Normal Estimation						
First 5 features	97.8	100.0	100.0	100.0	80.0	95.6
First 10 features	100.0	100.0	93.3	100.0	100.0	98.7
First 15 features	100.0	100.0	86.7	100.0	93.3	96.0
First 20 features	100.0	100.0	66.7	100.0	93.3	92.0
All 25 features	100.0	100.0	66.7	100.0	93.3	92.0

Table F1b Comparison of classification accuracies of bulk samples of cereal grains with different number of textural features, extracted from red color band at maximum gray level value 32: Leave-one-out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	90.7	98.7	100.0	100.0	93.3	96.5
First 10 features	97.3	100.0	100.0	100.0	100.0	99.5
First 15 features	98.7	100.0	100.0	100.0	100.0	99.7
First 20 features	99.1	100.0	100.0	100.0	100.0	99.8
All 25 features	99.6	100.0	100.0	100.0	100.0	99.9
Normal Estimation						
First 5 features	87.1	100.0	98.7	100.0	92.0	95.6
First 10 features	98.7	100.0	100.0	100.0	98.7	99.5
First 15 features	98.7	100.0	100.0	100.0	98.7	99.5
First 20 features	100.0	100.0	100.0	100.0	98.7	99.7
All 25 features	100.0	100.0	100.0	100.0	100.0	100.0

Table F2a Comparison of classification accuracies of bulk samples of cereal grains with different number of color features: Hold out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	100.0	100.0	100.0	100.0	100.0	100.0
First 10 features	100.0	100.0	100.0	100.0	100.0	100.0
First 15 features	100.0	100.0	100.0	100.0	100.0	100.0
All 18 features	100.0	100.0	100.0	100.0	100.0	100.0
Normal Estimation						
First 5 features	100.0	93.3	93.3	86.7	100.0	94.7
First 10 features	100.0	100.0	80.0	86.7	100.0	93.3
First 15 features	100.0	93.3	80.0	80.0	100.0	90.7
All 18 features	100.0	93.3	80.0	73.3	100.0	89.3

Table F2b Comparison of classification accuracies of bulk samples of cereal grains with different number of color features: Leave-one-out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	99.6	100.0	100.0	100.0	100.0	99.9
First 10 features	100.0	100.0	100.0	100.0	100.0	100.0
First 15 features	100.0	98.7	100.0	100.0	100.0	99.7
All 18 features	100.0	98.7	100.0	100.0	100.0	99.7
Normal Estimation						
First 5 features	99.6	96.0	97.3	97.3	100.0	98.0
First 10 features	99.6	98.7	98.7	98.7	100.0	99.1
First 15 features	99.6	100.0	98.7	98.7	100.0	99.4
All 18 features	99.6	98.7	98.7	98.7	100.0	99.1

Table F3a Comparison of classification accuracies of individual kernels of cereal grains with different number of morphological features: Hold out method

			Non-parametric Estimation			
% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
First 5 features	98.9	87.7	95.9	99.9	57.5	88.0
First 10 features	98.9	93.7	96.8	99.9	81.6	94.2
First 15 features	98.8	94.0	97.4	99.9	83.5	94.7
All 23 features	99.0	95.2	97.3	99.5	82.8	94.8
			Normal Estimation			
First 5 features	98.1	83.1	95.2	99.1	86.7	92.4
First 10 features	96.1	93.5	94.4	98.8	86.3	93.8
First 15 features	95.7	94.0	94.5	98.5	84.3	93.4
All 23 features	95.2	93.7	93.1	98.3	83.4	92.8

Table F3b Comparison of classification accuracies of individual kernels of cereal grains with different number of morphological features: Leave-one-out method

			Non-parametric Estimation			
% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
First 5 features	99.0	85.0	97.1	100.0	88.1	93.8
First 10 features	98.9	91.6	97.9	100.0	91.6	96.0
First 15 features	99.0	91.5	98.2	99.8	91.2	95.9
All 23 features	99.1	92.1	97.6	99.7	90.9	95.9
			Normal Estimation			
First 5 features	98.5	79.8	98.5	99.2	86.8	92.6
First 10 features	97.6	91.8	98.0	98.8	87.3	94.7
First 15 features	97.3	91.5	97.1	98.6	85.6	94.0
All 23 features	96.9	91.7	95.9	98.7	85.8	93.8

Table F4a **Comparison of classification accuracies of individual kernels of cereal grains with different number of textural features, extracted from green color band at maximum gray level value 8: Hold out method**

Non-parametric Estimation						
% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
First 5 features	83.0	91.9	99.9	100.0	54.9	85.9
First 10 features	84.5	95.9	100.0	100.0	68.9	89.9
First 15 features	85.2	98.2	100.0	100.0	76.3	92.0
First 20 features	86.7	97.8	100.0	100.0	76.6	92.2
All 25 features	87.6	98.1	100.0	100.0	74.1	92.0
Normal Estimation						
First 5 features	84.0	91.3	99.9	99.9	58.8	86.8
First 10 features	84.2	96.3	100.0	100.0	74.4	91.0
First 15 features	84.2	95.8	100.0	100.0	73.3	90.7
First 20 features	82.0	93.6	100.0	100.0	80.1	91.1
All 25 features	84.5	94.6	100.0	100.0	81.3	92.1

Table F4b Comparison of classification accuracies of individual kernels of cereal grains with different number of textural features, extracted from green color band at maximum gray level value 8: Leave-one-out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	80.3	91.2	100.0	99.3	67.7	87.7
First 10 features	84.6	93.8	100.0	99.8	75.9	90.8
First 15 features	87.0	95.7	100.0	100.0	81.8	92.9
First 20 features	87.7	96.6	100.0	100.0	81.4	93.1
All 25 features	88.2	96.4	100.0	100.0	79.9	92.9
Normal Estimation						
First 5 features	79.1	87.2	99.9	99.4	69.6	87.1
First 10 features	80.2	92.9	100.0	99.9	83.2	91.2
First 15 features	80.5	92.2	100.0	100.0	86.8	91.9
First 20 features	76.7	90.8	100.0	99.7	89.4	91.3
All 25 features	79.0	91.4	100.0	99.8	89.2	91.9

Table F5a Comparison of classification accuracies of individual kernels of cereal grains with different number of color features: Hold out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	85.8	85.6	89.7	95.1	93.3	89.9
First 10 features	94.1	92.3	93.1	95.2	92.5	93.4
First 15 features	93.8	92.7	93.0	95.3	93.1	93.5
All 18 features	92.8	91.9	92.8	94.3	92.3	92.8
Normal Estimation						
First 5 features	69.7	84.1	92.8	97.3	93.1	87.4
First 10 features	89.6	94.7	92.5	99.2	95.7	94.3
First 15 features	87.8	94.6	91.9	97.8	96.4	93.7
All 18 features	87.9	95.0	92.1	97.5	96.6	93.8

Table F5b Comparison of classification accuracies of individual kernels of cereal grains with different number of color features: Leave-one-out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	92.9	90.0	93.3	96.4	91.4	92.8
First 10 features	95.7	94.4	94.2	97.6	92.5	94.9
First 15 features	95.5	94.4	94.4	97.6	92.4	94.9
All 18 features	94.4	94.3	93.7	97.5	91.9	94.4
Normal Estimation						
First 5 features	87.4	85.3	91.7	95.9	91.6	90.4
First 10 features	80.7	93.1	89.4	97.6	94.2	91.0
First 15 features	83.2	92.6	89.1	97.6	93.8	91.3
All 18 features	83.8	92.6	89.4	97.5	93.6	91.4

Table F6a Comparison of classification accuracies of individual kernels of cereal grains with different number of morphological and textural features (extracted from green color at maximum gray level value 8): Hold out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	99.4	90.8	97.1	100.0	76.5	92.8
First 10 features	99.4	96.4	98.7	100.0	91.7	97.2
First 15 features	99.4	99.1	99.1	100.0	95.2	98.6
First 20 features	99.6	99.5	99.1	100.0	96.6	99.0
First 25 features	99.6	99.7	99.4	100.0	97.4	99.2
First 30 features	99.7	99.8	99.1	100.0	96.5	99.0
First 35 features	99.6	99.7	99.6	100.0	96.4	99.1
First 40 features	99.6	99.5	99.3	100.0	95.9	98.9
All 48 features	99.6	99.7	98.9	100.0	94.4	98.5
Normal Estimation						
First 5 features	99.0	87.7	95.8	99.7	90.9	94.6
First 10 features	97.7	95.7	97.9	99.8	94.1	97.0
First 15 features	98.2	97.4	97.8	99.9	95.6	97.8
First 20 features	97.3	97.7	97.4	99.8	95.3	97.5
First 25 features	98.3	97.1	98.0	99.9	96.5	98.0
First 30 features	98.5	97.3	98.6	99.9	96.2	98.1
First 35 features	98.3	97.3	98.7	99.9	96.1	98.1
First 40 features	98.2	97.3	98.7	99.9	95.3	97.9
All 48 features	98.2	97.2	98.6	99.9	94.9	97.8

Table F6b Comparison of classification accuracies of individual kernels of cereal grains with different number of morphological and textural features (extracted from green color at maximum gray level value 8): Leave-one-out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	99.4	91.7	98.4	100.0	93.0	96.5
First 10 features	99.4	96.2	99.4	100.0	95.9	98.2
First 15 features	99.5	98.7	99.7	100.0	98.6	99.3
First 20 features	99.6	98.9	99.8	100.0	98.4	99.3
First 25 features	99.6	99.1	99.7	100.0	98.4	99.4
First 30 features	99.6	99.1	99.8	100.0	98.4	99.4
First 35 features	99.5	98.8	99.8	100.0	98.0	99.2
First 40 features	99.6	99.0	99.8	100.0	97.7	99.2
All 48 features	99.7	99.1	99.7	100.0	97.1	99.1
Normal Estimation						
First 5 features	99.2	87.6	99.2	99.7	92.8	95.7
First 10 features	98.7	94.1	99.7	99.7	95.3	97.5
First 15 features	98.8	96.3	99.6	99.7	97.5	98.4
First 20 features	98.5	96.4	99.5	99.8	97.3	98.3
First 25 features	98.7	96.5	99.6	100.0	97.9	98.5
First 30 features	98.6	96.2	99.6	100.0	97.8	98.4
First 35 features	98.5	96.4	99.5	100.0	97.5	98.4
First 40 features	98.6	96.4	99.5	100.0	97.4	98.4
All 48 features	98.5	95.8	99.5	100.0	96.9	98.1

Table F7a Comparison of classification accuracies of individual kernels of cereal grains with different number of morphological and color features: Hold out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	98.9	87.7	95.9	99.9	57.5	88.0
First 10 features	99.8	99.3	98.7	100.0	98.6	92.3
First 15 features	99.7	99.7	98.9	99.9	98.9	99.4
First 20 features	99.6	99.7	99.1	99.9	99.1	99.5
First 25 features	99.6	99.8	99.4	99.9	99.1	99.6
First 30 features	99.5	99.8	99.3	99.9	98.8	99.5
First 35 features	99.5	99.9	99.3	99.9	98.6	99.4
All 41 features	99.5	99.8	99.0	99.9	98.3	99.3
Normal Estimation						
First 5 features	98.1	83.1	95.2	99.1	86.7	92.4
First 10 features	93.6	96.7	95.9	99.6	98.9	96.9
First 15 features	98.0	98.3	97.3	99.7	98.6	98.4
First 20 features	99.0	98.3	97.2	99.8	98.8	98.6
First 25 features	99.1	98.3	98.0	99.8	98.8	98.8
First 30 features	99.0	98.9	98.4	99.8	98.7	99.0
First 35 features	98.8	98.4	97.7	99.8	98.1	98.6
All 41 features	98.8	98.0	97.9	99.8	98.1	98.5

Table F7b Comparison of classification accuracies of individual kernels of cereal grains with different number of morphological and color features: Leave-one-out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	99.0	85.0	97.1	100.0	88.1	93.8
First 10 features	99.7	98.9	99.4	100.0	98.4	99.3
First 15 features	99.8	99.4	99.7	100.0	99.0	99.6
First 20 features	99.8	99.6	99.6	100.0	99.2	99.7
First 25 features	99.8	99.6	99.7	100.0	99.0	99.6
First 30 features	99.8	99.6	99.7	100.0	98.8	99.6
First 35 features	99.8	99.4	99.6	100.0	98.4	99.4
All 41 features	99.8	99.4	99.5	100.0	97.9	99.3
Normal Estimation						
First 5 features	98.5	79.8	98.5	99.2	86.8	92.6
First 10 features	98.7	96.8	99.3	99.5	97.8	98.4
First 15 features	99.1	98.0	99.4	99.6	98.4	98.9
First 20 features	99.2	97.7	99.4	99.8	98.5	98.9
First 25 features	99.2	97.6	99.3	99.8	98.4	98.9
First 30 features	99.1	97.4	99.2	99.9	98.5	98.8
First 35 features	98.9	97.2	98.7	99.8	98.4	98.6
All 41 features	98.8	96.7	98.7	99.8	98.1	98.4

Table F8a Comparison of classification accuracies of individual kernels of cereal grains with different number of color and textural(extracted from green color at maximum gray level value 8) features: Hold out method

Non-parametric Estimation						
% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
First 5 features	91.2	76.4	76.3	99.5	95.7	87.8
First 10 features	95.5	98.1	98.9	100.0	95.4	97.6
First 15 features	98.5	99.4	99.7	100.0	94.3	98.4
First 20 features	98.6	99.3	99.3	100.0	94.8	98.4
First 25 features	98.7	99.4	99.2	100.0	94.9	98.4
First 30 features	98.8	99.9	99.3	100.0	95.5	98.7
First 35 features	98.2	99.7	99.1	100.0	95.0	98.4
All 43 features	98.2	99.5	98.9	100.0	94.3	98.2
Normal Estimation						
First 5 features	91.8	73.7	79.5	99.3	93.2	87.5
First 10 features	87.6	96.4	97.7	100.0	95.2	95.4
First 15 features	97.6	98.7	98.8	100.0	94.3	97.9
First 20 features	97.1	98.9	98.6	100.0	94.3	97.8
First 25 features	95.5	98.5	98.7	100.0	96.5	97.9
First 30 features	96.2	99.0	98.5	100.0	96.7	98.1
First 35 features	96.0	99.2	98.4	100.0	97.2	98.2
All 43 features	95.9	99.2	98.5	100.0	97.3	98.2

Table F8b Comparison of classification accuracies of individual kernels of cereal grains with different number of color and textural (extracted from green color at maximum gray level value 8) features: Leave-one-out method

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	89.0	80.9	88.5	95.4	90.6	88.9
First 10 features	96.9	98.1	98.4	98.3	94.0	97.2
First 15 features	97.6	99.4	99.5	98.7	95.0	98.0
First 20 features	97.9	99.4	99.4	99.4	95.6	98.3
First 25 features	98.4	99.4	99.4	99.5	95.0	98.3
First 30 features	98.6	99.5	99.4	99.6	95.2	98.5
First 35 features	98.4	99.5	99.2	99.5	94.8	98.3
All 43 features	98.3	99.3	99.3	99.5	94.2	98.1
Normal Estimation						
First 5 features	87.9	74.2	86.6	95.5	89.6	86.8
First 10 features	93.3	94.8	95.8	98.4	95.4	95.5
First 15 features	94.7	98.4	97.5	98.8	96.7	97.2
First 20 features	94.3	97.9	98.0	99.1	96.7	97.2
First 25 features	91.9	97.8	98.0	98.9	97.7	96.9
First 30 features	92.4	98.1	98.0	99.0	97.4	97.0
First 35 features	93.1	97.8	97.9	99.3	97.4	97.1
All 43 features	92.5	98.0	98.0	99.4	97.5	97.1

Table F9a **Comparison of classification accuracies of individual kernels of cereal grains with different number of morphological, color, and textural features (extracted from green color at maximum gray level value 8): Hold out method**

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
First 5 features	99.4	90.8	97.1	100.0	76.5	92.8
First 10 features	99.9	99.5	99.1	100.0	98.7	99.4
First 15 features	100.0	99.6	99.2	100.0	98.9	99.5
First 20 features	100.0	99.9	99.5	100.0	99.1	99.7
First 25 features	99.9	99.9	99.7	100.0	99.5	99.8
First 30 features	99.9	99.9	99.6	100.0	99.7	99.8
First 35 features	99.8	99.9	99.7	100.0	99.3	99.8
First 40 features	99.9	99.9	99.7	100.0	99.5	99.8
First 50 features	99.9	99.9	99.7	100.0	99.3	99.8
All 66 features	99.7	99.9	99.7	100.0	99.1	99.7
Normal Estimation						
First 5 features	99.0	87.7	95.8	99.7	90.9	94.6
First 10 features	99.3	98.8	97.9	99.9	99.3	98.9
First 15 features	99.4	98.7	97.9	99.9	99.2	99.0
First 20 features	99.4	98.8	98.9	99.9	99.3	99.3
First 25 features	99.5	99.1	98.9	99.9	99.1	99.3
First 30 features	99.4	99.1	98.9	99.9	99.3	99.3
First 35 features	99.3	99.0	98.9	99.9	98.9	99.2
First 40 features	99.4	98.9	98.8	99.9	99.2	99.2
First 50 features	99.4	98.8	99.3	99.9	99.2	99.3
All 66 features	99.0	98.6	99.2	99.9	99.0	99.2

Table F9b **Comparison of classification accuracies of individual kernels of cereal grains with different number of morphological, color, and textural features (extracted from green color at maximum gray level value 8): Leave-one-out method**

% accuracy → Features ↓	CWRS wheat	CWAD wheat	Barley	Oats	Rye	Mean accuracy
Non-parametric Estimation						
first 5 features	99.4	91.7	98.4	100.0	93.0	96.5
First 10 features	99.8	99.1	99.7	100.0	98.6	99.4
First 15 features	99.8	99.6	99.9	100.0	99.3	99.7
First 20 features	99.8	99.8	99.9	100.0	99.4	99.8
First 25 features	99.8	99.8	100.0	100.0	99.4	99.8
First 30 features	99.8	99.9	100.0	100.0	99.6	99.9
First 35 features	99.9	99.9	100.0	100.0	99.6	99.9
First 40 features	99.9	99.9	100.0	100.0	99.6	99.9
First 50 features	99.4	98.8	99.3	99.9	99.2	99.3
All 66 features	99.00	98.6	99.2	99.9	99.0	99.2
Normal Estimation						
First 5 features	99.2	87.6	99.2	99.7	92.84	95.7
First 10 features	99.6	98.4	99.8	99.9	98.6	99.3
First 15 features	99.4	98.8	99.8	100.0	99.0	99.4
First 20 features	99.3	98.8	99.8	100.0	99.4	99.5
First 25 features	99.2	98.6	99.9	100.0	99.4	99.4
First 30 features	99.2	98.5	99.9	100.0	99.4	99.4
First 35 features	99.1	98.3	99.9	100.0	99.4	99.3
First 40 features	99.2	98.5	99.9	100.0	99.5	99.4
First 50 features	99.1	98.3	99.9	100.0	99.4	99.3
All 66 features	99.0	97.9	99.9	100.0	99.3	99.2