

Using different classification models in wheat grading utilizing visual features

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A b s t r a c t. Wheat is one of the most important strategic crops in Iran and in the world. The major component that distinguishes wheat from other grains is the gluten section. In Iran, sunn pest is one of the most important factors influencing the characteristics of wheat gluten and in removing it from a balanced state. The existence of bug-damaged grains in wheat will reduce the quality and price of the product. In addition, damaged grains reduce the enrichment of wheat and the quality of bread products. In this study, after preprocessing and segmentation of images, 25 features including 9 colour features, 10 morphological features, and 6 textual statistical features were extracted so as to classify healthy and bug-damaged wheat grains of Azar cultivar of four levels of moisture content (9, 11.5, 14 and 16.5% w.b.) and two lighting colours (yellow light, the composition of yellow and white lights). Using feature selection methods in the WEKA software and the CfsSubsetEval evaluator, 11 features were chosen as inputs of artificial neural network, decision tree and discriminant analysis classifiers. The results showed that the decision tree with the J.48 algorithm had the highest classification accuracy of 90.20%. This was followed by artificial neural network classifier with the topology of 11-19-2 and discriminant analysis classifier at 87.46 and 81.81%, respectively.

K e y w o r d s: artificial neural network, bug-damaged wheat, decision tree, feature selection, image processing

INTRODUCTION

Wheat is the most important global cereal crop. According to the World Food Organization (FAO), in 2016, global wheat production was close to 760 million tons. After harvesting, wheat grain is directly transported for food processing or stored in silos for sale at specified intervals. Wheat grain quality is defined by several parameters, with purity being one of the most important factors affect-

ing the purchase price of the product. The presence of seeds damaged by pests and insects is considered to be an impurity (Ebrahimi *et al.*, 2014). In Iran and many other countries, sunn pest is an important pests of cereals, especially wheat and barley (Najafi-mirak, 2012). Tischler (1939) showed that early attacks on wheat fields resulted in the production of wrinkled grains, while late attacks had little effect on grain size and weight, but had the significant effect of generating the presence of dark biting spots on the affected grain with a small area around it (Fig. 1). Sunn pest damages wheat grains through reducing yield, seed germination and gluten levels (Critchley, 1998). The injection of toxic saliva into the wheat grain destroys gluten and reduces the quality of the bakery flour resulting from these grains (Critchley, 1998; Every, 1990; Tischler, 1939). These damaged grains produce a sticky paste and poorly-packaged bread with low volume and unacceptable texture (Vaccino *et al.*, 2006). Thus, by reducing the quality of produced bread,

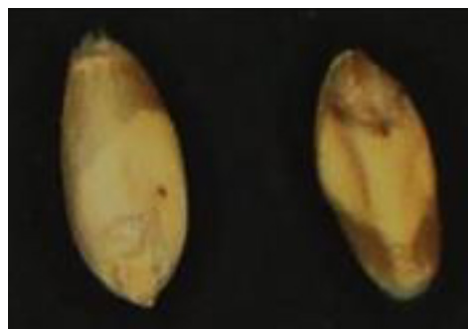


Fig. 1. Bug-damaged wheat specimens.

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the resulted waste also increases. Of note, the damaging of grains by 14% reduces germination by 88% (Critchley, 1998). Therefore, in wheat, which forms the major part of the public food, the quality of wheat (unwanted mixing of bug-damaged wheat and healthy wheat) has particular importance.

Some wheat qualitative assessments are still carried out manually, depending on the percentage of damage (for example, in wheat silos and flour mills). This approach has low accuracy and it is difficult and time-consuming. The visual machine, which has recently developed rapidly, is a quick and visual method for identifying the good quality of agricultural products (Choudhary *et al.*, 2008; Majumdar and Jayas, 2000b). The visual machine has become an acceptable substitute for the decision-making process based on human vision. As a result, many studies have been performed so as to determine the quality and classification of wheat using digital imaging and classification models (Luo *et al.*, 1999; Paliwal *et al.*, 2001; Zayas *et al.*, 1986). Choudhary *et al.* (2008), in a study on grains classification, used colour uniqueness, morphological features, texture and wavelet features and their combination. Subsequently, linear and quadratic statistical classifiers were used to classify the cereal grains. The combined model of colour, morphological, texture and wavelet features along with a linear discriminant classifier were recognized as the best classification model (with accuracies of 99.4, 99.3, 98.6, 98.5, and 89.4% for Canada Western Red Spring (CWRS) wheat, rye, barley, oats and the Canada Western Amber Durum (CWAD), respectively). Zapotoczny *et al.* (2008) used 54 morphological features to identify barley seeds. In this research, principal component analysis (PCA), linear discriminant analysis (LDA) and nonlinear discriminant analysis (NDA) were employed as classification models. Zapotoczny *et al.* (2008) noted that LDA has a higher degree of accuracy for classifying barley cultivars. In addition, Mollazade *et al.* (2012) employed the correlation-based feature selection (CFS) method to classify raisin products into four different classes (green non-tailed, dark non-tailed, green tailed and dark tailed), after extracting colour and shape properties to select top features. Afterwards, they applied support vector machine (SVM), artificial neural network (ANN) and decision tree (DT) to enhance the classification. The results showed that the ANN method (with an accuracy of 96.33%), had the highest classification accuracy. Moreover, Ebrahimi *et al.* (2014) used 52 features of colour, shape and texture, as well as a new algorithm, a combination of the imperialist competitive algorithm (ICA) and artificial neural networks (ANNs), for classifying the 4 wheat cultivars and 8 types of weed seeds found in Iran's agricultural fields so as to find the best parameter of the features and to create a strong classification model. Finally, Golpour *et al.* (2014) used 36 colour features in three colour spaces RGB, HSV and HSI to identify 5 rice cultivars in 3 forms of white rice, brown

rice and rough rice. Using a double-layered back propagation neural network, the classification accuracy for rough rice, brown rice, and white rice was 98.8, 100, and 100%, respectively.

As impurities in wheat (such as the presence of bug-damaged grains) reduce its purchase price and negatively affect bread item production, and as the germination capacity in the bug-damaged grains is also lowered, it is necessary to apply techniques that identify and classify bug-damaged and healthy grains using visual identifying factors. The aim of this study, thus, is to classify and to model wheat of four levels of moisture content and two colours of lighting, into two classes – bug-damaged and healthy, colour using visual features (colour, morphology, and texture) and classifiers of the neural network, decision tree and linear discriminant analysis.

MATERIAL AND METHODS

The proposed algorithm for teaching a computer visual system for identifying and classifying the type of wheat includes sample preparation, preparation of images, pre-processing, extraction of features, selection of effective features and classification, which are explained, respectively (Fig. 2).

In this study, after preparation of the Azar variety wheat grain, the sample was transformed to the biophysical properties laboratory of the biosystems engineering department of the University of Mohaghegh Ardabili. All samples of wheat were first manually cleaned from external substances and then were visually separated into two quality groups of healthy and bug-damaged grains.

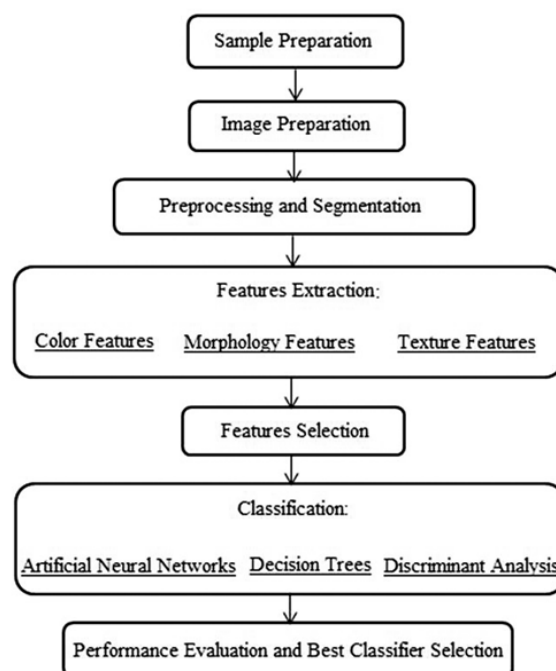


Fig. 2. Proposed algorithm for the classification of wheat.

The initial moisture content of the grain of wheat, measured through a 130°C oven method for 19 h according to the standard procedures (Standard ASAE, 2002), was 9% wb. Experiments were performed at four levels of moisture content: 9, 11.5, 14 and 16.5% wb. To reach moisture content of wheat samples to the higher values of moisture content and to calculate the amount of water needed to be added to the initial mass of wheat, Eq. (1) was used (Mohsenin, 1986):

$$Q = \frac{W(M_f - M_i)}{100 - M_f}, \quad (1)$$

where: Q is the mass of the added water (g), W is the initial mass of the sample (g), M_f is the initial moisture content of the sample (% wb) and M_i is the final moisture content of the sample (% wb).

To prepare the images of healthy and bug-damaged wheat grains, an imaging system, including a parabolic chamber made of stainless steel, a lighting system and a colour CCD camera of 7 MP (SONY model SC-W12), was used. Three circular LED and four fluorescent lamps were placed in the upper half of the chamber at 90° from each other. The order of light sources and the circularity of the chamber with appropriate reflex and regular light radiation properties brought about uniform light within the entire chamber, and as a result, minimized shadow in the images. For each image, 100 grains were randomly selected and placed on the background so that they did not contact with each other. Black Eschenbach paper was used as a background (based on the early experiments) and histogram curves were observed in the range of gray. The camera was installed on top of the container with a distance of 30 cm from the samples and 2x zoom was used for the preparation

of images so that all grains were clearly in the frame of camera. Based on initial experiments, all images were generated within a closed container, while two lighting colours of yellow and a combination of yellow and white were applied. Two types of wheat grains were tested (healthy and bug-damaged) at four levels of moisture and in two lighting colours (yellow and combinations of yellow and white). A total of 16 images were obtained. Since there were 100 grains in each image, 1600 grains were used to produce images. All images were in the JPG format with the size of 2304 x 3072 pixels. These were transferred to a personal computer (4 GB RAM and 2.3 GHz processor). MATLAB R2014b software was then used to process the images. Features extracted from images were divided into three main groups of colour, morphological and texture features. Before extracting these features, pre-processing and segmentation were performed.

The purpose of the pre-processing and segmentation was to generate an improvement of image such that while reducing unwanted features, some image features that are important for further processing are enhanced and the image is divided into areas. The first task after calling up a colour image *via* the software MATLAB, was to remove the background. Figure 3a shows the initial image of the sampled grains. With regard to the proper contrast between background and the wheat grain samples, segmentation was conducted by ordering graythresh via the Otsu method (Otsu, 1979). As Fig. 3bc shows, due to the correct selection of the background colour for the light source, there is good contrast between the sample and the background. Fig. 3d shows the image of grains after removing the background. To remove objects that were on the periphery of the image and noise that were seen as tiny white dots, the

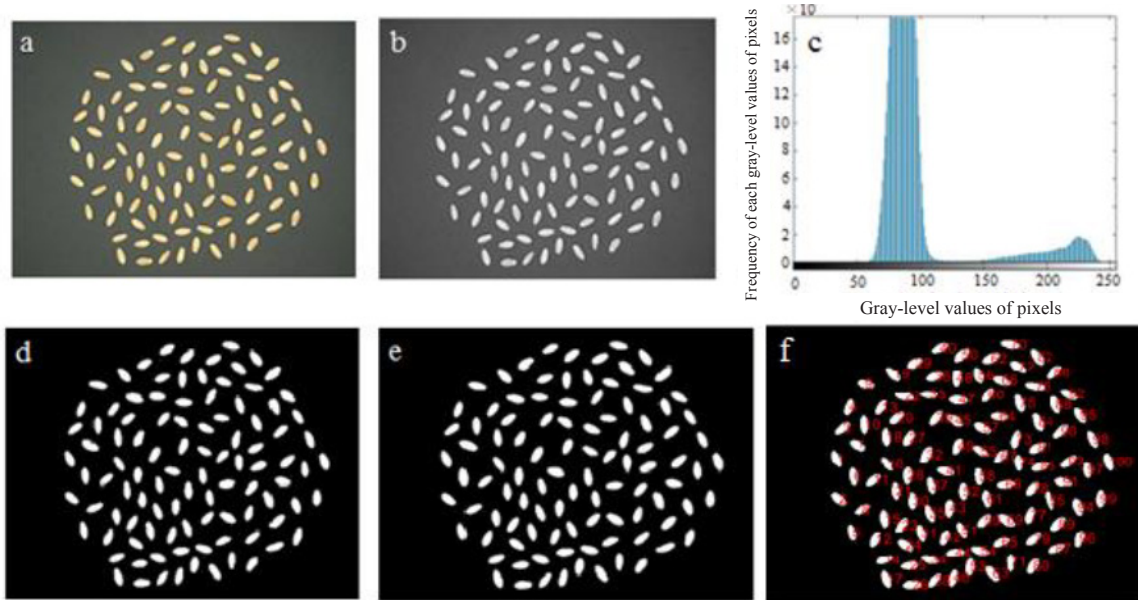


Fig. 3. Initial grain imagery – (a), image of greyscale – (b), histogram of gray levels – (c), Otsu background removal – (d), binary image created after removing noises and filling holes – (e), labeling grains – (f).

imclearborder command and bwareaopen morphology operator were used. Imclearborder suppresses structures that are lighter than their surroundings and that are connected to the image border. In other words, this function is employed to clear the image border. The resulting image can be a gray-scale or a binary image. Bwareaopen removes from a binary image all connected components (objects) that have fewer than P pixels, producing another binary image. This operation is known as an 'area opening'. Imfill command was used then to fill cavities (Gonzalez *et al.*, 2004). Finally, a smooth and uniform black and white image was created that included only the grain of wheat, and the background pixels were assigned a value of zero, and the sample pixels were assigned a value of one (Fig. 3e). By applying the bwlable command to the black and white image, the individual grains were assigned a label so to distinguish each grain (Arefi *et al.*, 2011) (Fig. 3f).

Since the colour, morphological and texture features are considered important in identifying agricultural products (Neelamma *et al.*, 2011) and are also the basis of several previous studies (Arefi *et al.*, 2011; Ebrahimi *et al.*, 2014; Majumdar and Jayas, 2000a; Paliwal *et al.*, 2001), in this research, identifying healthy and bug-damaged wheat samples was performed based on colour, morphological and texture features (Table 1). To identify healthy and bug-damaged wheat grains by way of colour, colour models of RGB, HSV and Lab were used.

Today, the use of colour index is more common than other components in most of commercial separation and gradation systems. In the first years of using the machine vision technique, the colour of the product was evaluated based on the gray-scale taken by a monochrome camera. Now, video cameras based on RGB are used in the preparation and processing centers. A large proportion of the

Table 1. Available features measured by image analysis for each wheat grain

Colour feature		Morphology feature		Texture feature	
Colour models	Feature description	Feature name	Feature description	Feature name	Feature description ^a
RGB HSV Lab	Mean $[\mu = \frac{1}{N} \sum_{i=1}^N x_i]$	Area	Number of pixel inside and including the wheat kernel boundary	Average gray level (Agl)	$\sum_{i=0}^{L-1} z_i p(z_i)$
		Perimeter	Algorithm calculates the distance around the boundary of the wheat kernel	Average contrast (Ac)	$\sqrt{\mu_2(z)}$
		Major axis length (Majal)	Llongest diameter of ellipse bounding wheat kernel	Smoothness	$1 - \frac{1}{(1+\sigma^2)}$
		Minor axis length (Minal)	Shortest diameter of ellipse bounding wheat kernel	Third moment (Thm)	$\sum_{i=0}^{L-1} (z_i - m)^3 p(z_i)$
		Excentricity	It is the ratio of the distance between the foci of the ellipse and its major axis length	Uniformity	$\sum_{i=0}^{L-1} p^2(z_i)$
		Solidity	It describes the extent to which the shape is convex or concave	Entropy	$-\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i)$
		Compactness	$4\pi(\text{area}) / (\text{perimeter})^2$		
		Circularity	$(\text{perimeter})^2 / \text{area}$		
		Area ratio (Ar)	area/ (major axis)(minor axis)		
		Aspect ratio (Asr)	major axis/minor axis		

^a μ , z_i , $p(z_i)$, land m represent mean nth moment, random variable related to intensity, normalized histogram of intensity levels, number of possible intensity levels and mean value of z , respectively.

colours visible to humans colour can be created by different combinations of the three primary colours of red (R), green (G) and blue (B). Hue (H), saturation (S) and value (V) are based on cylindrical coordinates. Converting RGB to HSV involves creating equations for mapping values of RGB (in Cartesian coordinates) and modifying these to cylindrical coordinates. This conversion can be done via MATLAB software, utilizing the function `rgb2hsv`. The lab colour model is based on the theory of colour contrast. In this theory, the human eye receptors observe colours in contrast pairs: light-dark, red-green and yellow-blue. In this work, the red-green colour dimension is indicated by the symbol of 'a' (Redness), while the yellow-blue colour dimension is labeled utilizing the symbol 'b' (Yellowness). The third dimension of colour is lightness. Herein, the symbol 'L' is used. To convert the RGB colour space to Lab, two orders `cform = makecform('srgb2lab')` and `Lab = applycform(~, cform)` were applied. Therefore, as Table 1 shows, 9 colour features, including means of colour components (R, G, B, H, S, V, L, a and b) were extracted from individual labeled grains.

Morphology can be defined as a theory for the analysis of spatial structures. The objective of this scientific branch is to analyze the shape and structure of objects. In this study, 10 morphological features of wheat grains were measured. Some features were obtained in MATLAB by `regionprops` function and others were obtained using the functions presented in Table 1. Texture provides criteria of properties such as flatness, coarseness and regularity. One of the simplest methods used to characterize the texture is the statistical moments related to the intensity histogram of an image or objective (Gonzalez *et al.*, 2004).

To extract four moments average gray level (Agl), average contrast (Ac), smoothness and third moment (Thm) and two features of uniformity and entropy of each wheat grain, related codes were developed in MATLAB programming environment (Table 1). Finally, to identify healthy and bug-damaged grains, 25 colour, morphological and texture features were extracted using the orders available in MATLAB software, and by employing appropriate coding.

All feature reducing methods include the two main categories, methods based on feature extraction and methods based on feature selection. Methods based on feature extraction draw a multidimensional space into a smaller space. In fact, by combining the values of the existing attributes, they create fewer attributes such that these features have all (or a large part) the information contained in the original features. These methods are divided into linear (discrete Fourier transform, discrete wavelet transform, principal component analysis) and non-linear groups (vector quantization, principal curves, regression). However, feature-based methods actually select a subset of features to enhance the prediction accuracy. In other words, it includes reducing the size of the structure without significantly reducing the classification predictive accuracy obtained using the given features (Holmes and Nevill-Manning, 1995; Koller and Sahami, 1996). Feature selection is one of the issues discussed in the topic of machine learning, as well as in pattern statistical identification. This is important in many applications (such as categorization) since there are a lot of features in these applications, many of which are either useless or without a great deal of information. Excluding these features does not pose a problem in terms of information, rather it raises the computational load for the desired application. In addition, a huge deal of non-useful information along with useful data, is stored (Dash and Liu, 1997). Moreover, Dash and Liu (1997) state that the feature selection process in most commonly used methods is to select features based on Fig. 4.

In this study, since the large volume of input data has a negative effect on the classifier performance and causes complexity (Rahimi Ajdadi *et al.*, 2016), instead of directly employing the 25 extracted features from the images, the used features were that which were selected out through employing the feature selection algorithms found in Waikato environment for knowledge analysis (WEKA) software. Obviously, choosing the appropriate features will have a profound effect on the good performance of the classifier. The WEKA software that was created at the Waikato University of New Zealand is one of the most powerful

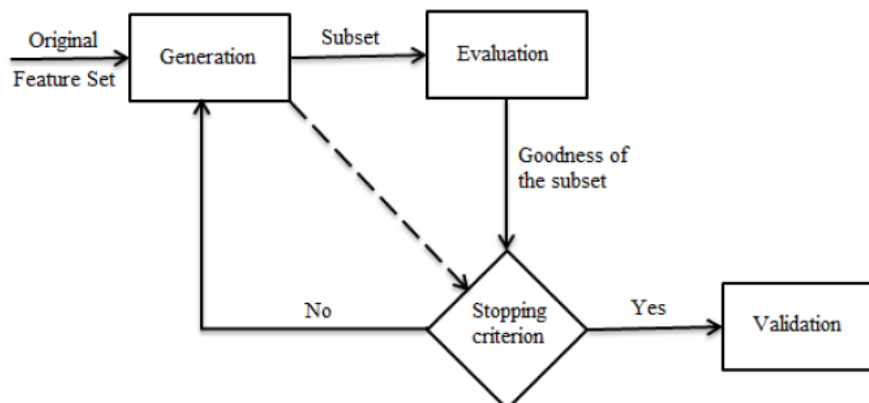


Fig. 4. Feature selection process.

tools available for data mining, and WEKA has a variety of tools for implementing data mining algorithms. Among these are CfsSubsetEval, ChiSquaredAttributeEval, ClassifierSubseEval and InfoGainAttributeEval. As per current literature recommendation (Mollazade *et al.*, 2012; Rahimi Ajdadi *et al.*, 2016), we employed the CfsSubsetEval evaluator. In this evaluator, the values of the parameters are assessed explicitly using correlation. In this method, the best subset of the feature is the features that have the highest correlation to predict the target attribute (class). However, the degree of correlation between the features in the subset is low, as the degree of the competency of these subsets is equal to the degree of correlation of the desired feature with existing features / degree of correlation of the desired attribute with the target feature (Hall, 1999). In addition, we utilized GreedyStepwise as a searching method (Rahimi Ajdadi *et al.*, 2016).

Artificial neural networks (ANNs) are the extended approach to modeling complicated real-world problems by imitation of the structure and function of the human brain (Ebrahimi *et al.*, 2014). Multi-layer perceptron (MLP) is one of the most prolific neural networks in classification. The MLP consists of three layers: input, hidden, and output (Mollazade *et al.*, 2012). These depend on the number of input features, the complexity of the classification problem, and the number of output classes. In this study, for classifying the inputs according to target classes, we applied a pattern recognition of pre-existing networks as used in the Neural Network Toolkit, the Matlab software R2014b version. Employing pre-existing networks as MLP networks can solve problems in a non-linear way. Such an approach consists of establishing a series of layers wherein the first layer is the connection of input networks. Each of the subsequent layers has a connection from the previous layer. The final layer also creates the output of the network. The topology is initially identified and the network is trained with input and output data. The goal of training is to minimize network error.

In our work, the input pattern has 11 feature vectors that were obtained during the data mining step to select the feature. The network topologies were tested by selecting the number of hidden neurons in the network and by applying the scaled conjugate gradient (SCG) training algorithm. Furthermore, the samples were divided into three categories: training, validation, and evaluation. These were of ratios of 60%, 20%, and 20%, respectively.

A prediction model in machine learning is called a 'decision tree'. This is a graph with a tree-like pattern similar to the data structure of the flow chart (Xue and Zhu, 2009). The decision tree is a tree in which the samples are classified in a way that grows from a root to a bottom and eventually, reaches the leaf nodes. Each inner or non-leaf node is characterized by a feature. This feature raises a question regarding the input example. In each inner node, with the number of possible answers to this question, there are

branches, each branch is determined by the quality or fitness of that answer. The leaves of this tree are characterized by a class or a series of answers (Wu and Yen, 2009). In this present study, four different algorithms belonging to the tree data structure in the WEKA software were used to classify the wheat type into two classes: healthy and bug-damaged. These algorithms include the J48 algorithm (Mollazade *et al.*, 2012; Omid, 2011), REPTree (Mollazade *et al.*, 2012), NBTree and BFTree. About 70% of all input data was used for training, while 30% was used for testing.

In this study, for classifying healthy and bug-damaged wheat, discriminant analysis (DA) was used as a linear statistical classifier (Choudhary *et al.*, 2009; Zapotoczny *et al.*, 2008). The goal in DA is to obtain a relationship that can determine the membership in the grouped variable. The decision is based on independent variables. In generating a DA classifier, a function or a set of functions is constructed. For class k , a $k-1$ detection function is created. The first function yields the best linear combination for predicting the group membership. Considering the existence of two classes of wheat (healthy and bug-damaged), in this research, only one discriminant function is generated for separating the two classes (healthy and bug-damaged). Assuming that all predictive variables have a normal distribution and the changes in all groups are the same, DA on variables was performed using IBM SPSS Statistics 22 software.

The classifiers performance was evaluated by statistical criteria extracted from the values of the confusion matrix. The confusion matrix is a matrix that the classification results show so that each matrix column contains a classifier output, and each row contains real classes. The contours on the main diameter of the confusion matrix represent the correct predictions and the contours beyond the original diameter indicate the wrong predictions.

In this study, the statistical criteria of precision, sensitivity, specificity and accuracy were calculated for evaluating the classifier (Omid, 2011; Rahimi Ajdadi *et al.*, 2016).

The formulas related to these criteria are given in Eqs (2)-(5):

$$Precision = \frac{TP}{TP+FP} \quad , \quad (2)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad , \quad (3)$$

$$Specificity = \frac{TN}{TN+FP} \quad , \quad (4)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad , \quad (5)$$

where: TP , TN , FP , and FN are positive true, negative true, positive false and negative false, respectively.

Since there were two classes in this study (healthy and bug damaged), the confusion matrix was obtained with a dimension of 2×2 . For example, the calculation of TP , TN , FP and FN values for a healthy wheat class using the confusion matrix ($C.M.$) is shown in Eq. (6):

$$C.M. = \begin{bmatrix} TP & FN \\ FP & TN \end{bmatrix}, \quad (6)$$

the number of the samples predicted to be healthy if they are really: TP – healthy; and FP – bug-damaged; the number of the samples predicted to be bug-damaged if they are: TN – really bug-damaged and FN – really healthy.

RESULTS AND DISCUSSION

Table 2 shows that among the 25 extracted features of the images, 11 features were selected as the most effective features in the wheat type classification. Additional data with no role in the classification were deleted, and the number of attributes, totaling 25, was reduced to 11. The results of selecting the features showed that the colour features of H, S, and V, the morphological features of perimeter, area, Minal, Ar and Asr, as well as the texture features of Agl, Thm and entropy can be effective in classifying the wheat type. Moreover, the morphological features have the most number of effective attributes in classification.

The neural network topology is an important factor in designing the ANNs, since the type of topology has a significant effect on the learning rate and the accuracy of the network classification. The number of hidden layers and the number of neurons are the main factors in designing the ANNs (Gnana Sheela and Deepa, 2013). The number of neurons in the input and output layers depends on the number of attributes vectors and the number of classes, respectively. The input layer consists of 11 neurons based on the feature selection operation. Since we needed to place the sample material into two classes (healthy and bug damaged wheat), the number of neurons in the output layer consisted of 2 neurons in which [0 1] was related to the healthy wheat class and [1 0] was related to the bug-damaged wheat class. Several combinations of the neurons number in the hidden layer were tested via trial and error (the varied number of neurons from 7 to 28). In order to determine the best com-

Table 2. Results of feature selection by the CfsSubsetEval method

No.	Colour features	No.	Morphology features	No.	Texture features
1	H	4	Perimeter	9	Agl
2	S	5	Area	10	Thm
3	V	6	Minal	11	Entropy
		7	Ar		
		8	Asr		

bination of classifiers in different topologies as generated through the statistical criteria (accuracy, sensitivity, specificity, and accuracy) and as extracted from the values of the confusion matrix, the evaluation stage was investigated.

Table 3 shows the classification results of a neural network with different topologies. Among the number of classes classified into a particular category by the classifier, the statistical accuracy criterion determines the percentage of real percentage relevant to that class. As shown in Table 3, the precision varies in different topologies. Herein, the maximum precision was obtained in the topology of 11-19-2 with 87.26%, while the lowest precision is obtained in the topology of 11-13-2 with 80.18%. The sensitivity criterion indicates the percentage of the samples that are correctly detected as actually belonging to a particular class. The specificity criterion among the samples which are not related to a class determines the percentage that have been recognized correctly as false. According to Table 3, in terms of the sensitivity and specificity, the best classifier performance was in the topology of 11-19-2, with 87.46% and 87.46%, respectively. The degree of effectiveness of classifier performance is categorized by the accuracy statistical criterion. This indicates the correct diagnosis of positive and negative cases. In the topologies of 11-19-2 and 11-13-2, the highest and lowest accuracy of the classification were obtained with values of 87.46 and 79.76%, respectively. Thus topology 11-19-2 was the best neural network topology for categorizing the chosen wheat type into two classes (healthy and bug-damaged). This topology classified healthy and bug-damaged grains with a precision of 91.71 and 82.82%, respectively.

The results of the classification of wheat by J.48, REFTree, BFTree, and NBTree in the training phase are shown in Table 4. The criterion of the best performance is high correctly classified instances (CCI), low root mean squared error (RMSE) and mean absolute error (MAE). According to the results, the J.48 tree has the highest CCI (90.98) and the lowest values of RMSE (0.275) and MAE (0.1514) as compared to the other trees. Hence, this tree was chosen as the best classifier for classification.

According to the confusion matrix obtained from the test (Table 5), the precision of the J.48 tree classifier for classifying the healthy and bug-damaged grains was 94.16 and 86.25%, respectively. Totally, this system correctly classified the healthy and bug-damaged grains with a precision of 90.20%. Furthermore, in classifying the wheat *via* the J.48 tree, the mean sensitivity, specificity, and accuracy were 90.45, 90.45, and 90.20%, respectively (Table 5). The structure of this tree consists of 28 stems and 15 leaves, as shown in Fig. 5.

In the DA classifier, a linear function was used to classify the wheat grains into two qualitative groups (healthy and bug-damaged) *via* 11 selected features. In so doing, maximum Eigenvalue and minimum Wilks' Lambda values were obtained for the detection function (Table 6). The

Table 3. Classification of ANN for healthy and bug-damaged wheat

ANN topology	Class	Statistical criterion			
		Precision (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
11-7-2	Healthy	82.66	83.75	77.50	80.62
	Bug-damaged	78.82	77.50	83.75	
	Average	80.74	80.62	80.62	
11-10-2	Healthy	84.96	88.16	74.83	81.49
	Bug-damaged	79.67	74.83	88.16	
	Average	82.31	81.49	81.49	
11-13-2	Healthy	84.39	86.07	73.45	79.76
	Bug-damaged	75.97	73.45	86.07	
	Average	80.18	79.76	79.76	
11-16-2	Healthy	87.27	85.81	83.72	84.76
	Bug-damaged	81.93	83.72	85.81	
	Average	84.16	84.76	84.76	
11-19-2	Healthy	91.71	91.21	83.72	87.46
	Bug-damaged	82.82	83.72	91.21	
	Average	87.26	87.46	87.46	
11-22-2	Healthy	86.85	86.36	84.02	85.19
	Bug-damaged	83.44	84.02	86.36	
	Average	85.14	85.19	85.19	
11-25-2	Healthy	87.05	89.28	79.60	84.44
	Bug-damaged	82.87	79.60	89.28	
	Average	84.96	84.44	84.44	
11-28-2	Healthy	85.06	85.53	81.36	83.45
	Bug-damaged	81.92	81.36	85.53	
	Average	83.49	83.45	83.45	

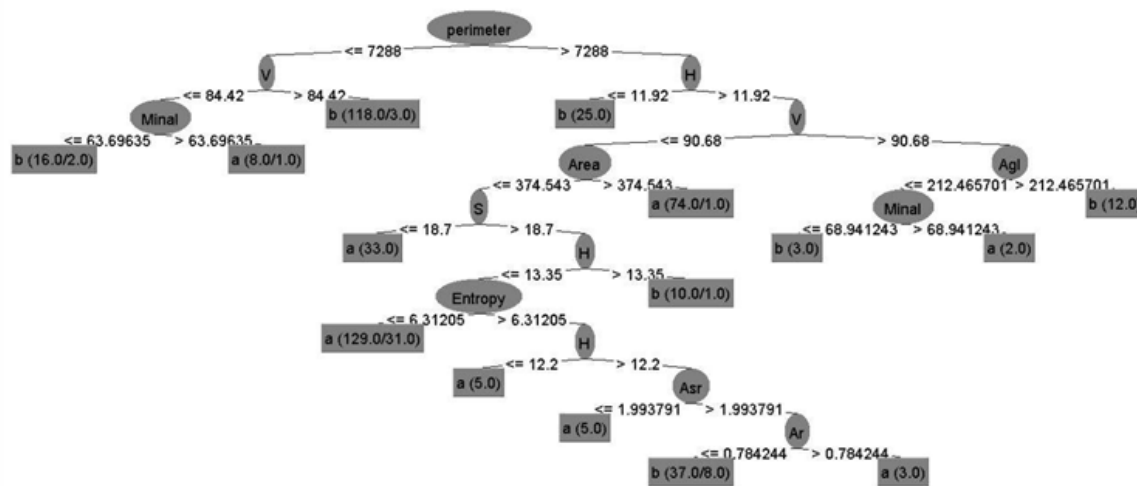
Table 4. Results of classification in the training stage with different Dts

Tree type	CCI	RMSE	MAE
J.48	90.98	0.275	0.1514
REFTree	86.60	0.326	0.2128
BFTree	87.41	0.318	0.204
NBTree	88.57	0.294	0.173

Eigenvalue is the ratio of the collected squares between groups, to the collected squares in the group, and indicates the power of the detection function. The more difference between the two groups with regard to the variation within the groups, the greater the power to differentiate will be. Table 6 shows that the resulting function is a function with an Eigenvalue of 0.799. In the DA classifier, after the calculation of Eigenvalue, a significance test was performed. Since the Wilks' Lambda value (0.556) is smaller than 1, based on its significance level ($\text{Sig} < 0.001$) and Chi-square (935.266), the obtained function can significantly

Table 5. Performance of the J.48 tree classifier in the testing stage for healthy and bug-damaged wheat grains

Actual datasets label	Predicted results		Statistical criterion			
	Healthy	Bug-damaged	Precision (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Healthy	226	14	94.16	93.66	87.25	
Bug-damaged	33	207	86.25	87.25	93.66	90.20
Average			90.20	90.45	90.45	

**Fig. 5.** Structure J.48 tree: a – healthy class; b – bug-damaged class.**Table 6.** Results of applying the DA classifier, as well as the values of the linear function components

Function	Eigenvalue	% of variance	Canonical correlation	Wilks Lambda	Chi-square	df	Kappa	Sig.
1	0.799	100.0	0.666	0.556	935.266	11	0.636	> 0.0001

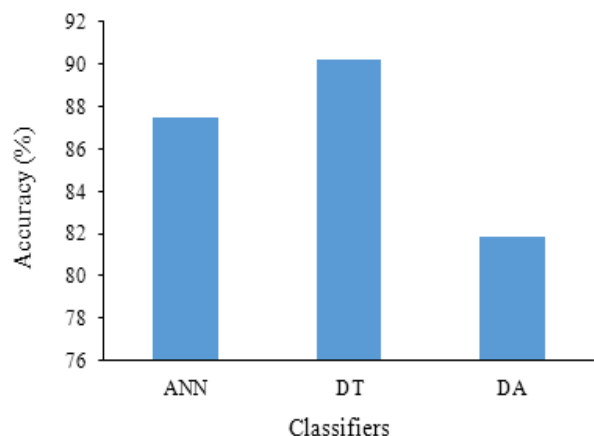
differentiate between the two wheat groups. By subtracting 1 from the Wilks' Lambda value, a number is obtained which shows the unexplained value of variance. However, about 0.45 of the variances of the two groups are explained by the selected features. Hence, the linear combination of the selected features can predict the group membership of two samples grains. In addition, the high level of canonical correlation (0.666) also indicates the greater desirability of the function for predicting healthy and bug-damaged grains. The kappa coefficient is then applied. This is a correlation coefficient that examines the classification agreement. The closer the coefficient is to 1, the more agreement exists within the categorization. However, when the kappa value is closer to 0, we see less agreement. In our work, with a value of 0.636 for the function, good agreement exists for this classification.

As shown in Table 7 and considering the obtained confusion matrix, the DA classifier function is able to precisely attribute 81.81% of the sampled grain to the related groups. This analysis classified the healthy and bug-damaged grains correctly with a precision of 84.75 and 87.87, respectively. Moreover, for classifying wheat via DA classifier, the mean sensitivity, specificity and accuracy were 81.91, 81.91 and 81.81, respectively.

According to the results for the three classifiers (ANN, DT and DA), the DT – with the J.48 algorithm showed the highest sensitivity (90.45%) when compared to the other classifiers. In addition, the sensitivity of this classifier in the class of healthy grains (93.66%) is higher than that of bug-damaged grains (87.25%). This means the J.48 algorithm classifies a lesser number of healthy grains incorrectly. Yet, in comparing the value of sensitivity, DA (with value of

Table 7. Performance of the DA classifier for classifying healthy and bug-damaged wheat

Actual datasets label	Predicted results		Statistical criterion			
	Healthy	Bug-damaged	Precision (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Healthy	678	122	84.75	83.79	79.95	
Bug-damaged	169	631	78.87	79.95	83.79	81.81
Average			81.81	81.91	81.91	

**Fig. 6.** Accuracy of three classifiers used in this study for classification of wheat grains.

81.91%), is inferior to ANN (with value of 87.46%). Still, the specificity value of the J.48 tree is more than that of the ANN and DA classifiers. For example, the specificity of bug-damaged grains class is 93.66% for the J.48 tree, while for the ANN and DA classifiers, the comparable figure is 91.21 and 83.79%, respectively. In comparing the results of ANN and DA, we also found that ANN is superior to DA in specificity. However, by comparing the accuracy criterion of three classification methods, we observed that the accuracy of the DT classifier is more than that of the ANN and DA classifiers (Fig. 6). Still, in comparing the precision of both the ANN and DA methods, it turns out that the precision of placement into the two classes via the ANN method is better than that of the DA method. In addition, the sensitivity, specificity, accuracy and precision of the related classes of healthy and bug-damaged wheat using the DA classification, show the weakness of this classification method for the data used in this study, when compared to DT and ANN. In general, by comparing each of the statistical criterion of the three classification methods, it can be concluded that the DT classifier has a better performance than that held by the other classifiers. In addition, DT has less error in predicting the class of wheat grains when utilizing the features that influence decision-making and the removal of additional features.

CONCLUSIONS

1. Among the three classifiers (artificial neural network, decision tree and discriminant analysis) decision tree with the -J.48 algorithm had the highest classification accuracy (a mean of 90.20% for healthy and bug-damaged wheat), and was able to categorize the sample wheat into healthy and bug-damaged with a precision of 94.16 and 86.25%, respectively.

2. Four different algorithms belonging to the tree data structure were used to classify the wheat type in two healthy and bug-damaged classes. The decision tree with the J.48 algorithm had the highest correctly classified instances value (90.98%).

3. The results of the classification of the artificial neural network with different topologies indicate that the topology of 11-19-2 had the maximum classification accuracy of 87.46%, while topology 11-13-2 had the minimum classification accuracy of 79.76%.

4. The artificial neural network classifier with topology 11-19-2 and the discriminant analysis classifier had classification accuracies of 87.46 and 81.81%, respectively. Therefore, the J.48 tree classifier acted better than did the artificial neural network and discriminant analysis classifiers.

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