

Yousef Abbaspour-Gilandeh*, Hamed Ghadakchi-Bazaz and Mahdi Davari

Discriminating Healthy Wheat Grains from Grains Infected with *Fusarium graminearum* Using Texture Characteristics of Image-Processing Technique, Discriminant Analysis, and Support Vector Machine Methods

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Abstract: Among agricultural plants, wheat, with valuable foodstuffs such as proteins, vitamins, and minerals, provides about 25% of the world's food calories. Hence, providing its health conditions and quality is of great importance. One of the most important wheat diseases that causes a lot of damages to this product is Fusarium head blight (FHB). In most areas, the causal agent of disease is Fusarium graminearum. This disease not only decreases product quality and efficiency but also has harmful effects on humans and animals by mycotoxin production. FHB discrimination requires experimental work in special conditions and also experts, but these facilities may not be available at customs and other related grain health testing centers. In this study, discriminating healthy wheat grains and the grains infected with F. graminearum was performed with an image-processing technique, an accurate, rapid, and nondestructive method. First, healthy and infected wheat grains were selected, and then digital images of samples were prepared in randomized mass method using cameras and lightening chamber. Then using the image-processing technique, a total of 21 texture characteristics were obtained for each grain. Discrimination and classification of healthy and infected grains were done with 100% accuracy using extracted texture characteristics and two techniques mentioned above. The results of this research could be helpful in the development of automatic devices for rapid discrimination of healthy grains and grains infected with F. graminearum, one of the most destructive wheat diseases.

Keywords: Fusarium graminearum, image processing, classification, discrimination analysis, support vector machine.

1 Introduction

Wheat is one of the oldest and most valuable plants on earth, which is cultivated more than the other plants around the world and supplies more calories than the other plants with the most protein in the human diet. Therefore, its health condition is of paramount importance. In order to increase production of this vital plant, it is important to pay attention to discriminating diseases and pests that threaten wheat health [3, 4]. One of the most important wheat diseases with a lot of damages to this product is FHB (Fusarium head blight) [1]. FHB or scab is a destructive disease that causes million-dollar damages to world grains annually [7, 15]. Fusarium infection is more in green racemes, which whitens a spike and its whole racemes. Because of this disease, a poor plant with fine and dehydrated grains and thousand kernels weight is produced, which decreases the plant cost. This disease not only decreases quality and efficiency of the product but also causes harmful effects on humans and animals by producing mycotoxins such as trichothecenes and fumonisins.

^{*}Corresponding author: Yousef Abbaspour-Gilandeh, Department of Biosystems Engineering, Faculty of Agriculture and Natural Resources, University of Mohaghegh Ardabili, Daneshgah Street, Ardabil 5619911367, Iran, e-mail: abbaspour@uma.ac.ir. https://orcid.org/0000-0002-9999-7845

Hamed Ghadakchi-Bazaz: Department of Biosystems Engineering, College of Agriculture and Natural Resources, University of Mohaghegh Ardabili, Iran

Mahdi Davari: Department of Plant Protection, College of Agriculture and Natural Resources, University of Mohaghegh Ardabili, Ardabil, Iran

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At least 18 different *Fusarium* species were found to cause FHB [7]. The most prevalent species world-wide, however, the Fusarium graminearum species complex is known to be the major cause of FHB in most regions [17]. This species has an important contribution in the production of mycotoxins and infection of cereals. F. graminearum produces deoxynivalenol (DON), trichothecenes, and as the preventive agent of the immune system has many effects on humans such as gastrointestinal cancers [6].

Generally, the discrimination of wheat grains infected with F. graminearum is carried out by cultivating infected grains, in general, and specific cultivating environments, preparing microscopic slides, and microscopic study, which is relatively time consuming and requires laboratories with sterile conditions, special materials and equipment, and experts that may not be available at the customs, and other related grain health testing centers, and the invention of an easy method without the need for high-quality equipment can be of great help in the rapid discrimination and isolation of infected grains. It is believed that computer methods for image analysis can be used to discriminate healthy wheat grains from grains infected with Fusarium without spending a lot of time and expenses. One of the main advantages of this method is the rapid generation of descriptive data from the product, reduction in workload by the user, economical and convenient operation, nondestructive and nonharmful method, and a stable control system [19]. Furthermore, the imageprocessing method has the advantage of extracting new indices in detail from the desired object. For example, product color is calculated and evaluated in different color bands. This method can be used to get complete information about product texture in isolating healthy grains from infected grains. Investigations showed that combining this method with classification techniques such as support vector machine (SVM) can have a potential effect on these applications [5].

Texture is an important aspect of the image, and texture characteristics play a big role in image analysis [12, 18]. The image texture is a collection of information regarding the color space arrangement or its intensity in an image or a selected region. In analyzing images, texture is one of the characteristics representing the specific order of the gray levels of pixels in small intervals. In fact, texture represents small structures in the image and shows the difference between gray-level values at small intervals. If the object is formed by repeated patterns of gray values, then the attribute should specify this pattern. Determining the texture content of the image is an important method for describing the area [8]. Texture analysis based upon the characteristics of the contingency matrix is a powerful tool in image analysis [13]. Patil & Zambre [16], using the image-processing technique and SVMs, classified leaf spots caused by pathogenic fungi and important bacteria in cotton. The researchers, using their camera phones, took photos of healthy leaves and infected spotted leaves in the farm, extracted their color and texture characteristics, and isolated healthy and infected cotton with an SVM. Chen et al. [6] used texture features of multispectral images for isolating rice varieties based on wavelet group and SVM. Their results showed the usefulness of this technique in separating rice varieties. Jirsa & Polisenska [9] performed the discrimination of Fusarium damages on wheat grains using a digital image-processing technique. They classified healthy grains and grains infected with Fusarium, using RGB and HSL color models with 85% accuracy. Alias et al. [2], using features of the contingency matrix extracted from DNA images of healthy wheat grains and grains infected with Fusarium, isolated healthy grains from the infected grains with 97% accuracy. Pourreza et al. [17] used different groups of texture characteristics for identifying nine types of Iranian wheat and classified different wheat types with 98.15% accuracy. These studies indicate that the image-processing technique can discriminate and distinguish different diseases.

Classification is the extraction of groups of individuals or species with one or more similar variables, and inter-group differences [10]. Discriminant analysis, known as audit analysis, is also one of the classification methods. This approach, like logistic regression, is used to predict a sample in a particular group. An audit analysis or discriminant analysis is useful when there are categorical (qualitative) variables and several independent quantitative variables [14].

The basis of the classifier is the linear classification of data, and the linear classification of data selects a line with higher reliability margin. The SVM is one of the methods of supervised learning. The fundamental difference between this classification and statistical classifications is that there is no need to reduce the number of bands for processing and classifying hyperspectral data. In this method, using all bands and an optimization algorithm, samples that form class boundaries are obtained and used to calculate an optimal linear decision boundary for isolating classes. These samples are called support vectors. Maximizing the margin of this super-page maximized class isolation. The SVM algorithm can be used wherever it is necessary to discriminate the pattern or classify objects in specific classes. The SVM can overcome the problem of nonlinear distribution of educational data. SVM, like neural networks, does not require a predetermined model [11].

The main objective of this research is the easy and rapid discrimination of healthy grains from grains infected with F. graminearum as the seed health identification is critical for safe storage of seeds in silos. quarantine programs, maintaining human and animal health due to the contamination of seeds with mycotoxin and their planting as seeds. Discrimination of healthy wheat grains from grains infected with Fusarium was performed with discriminant analysis (DA) and SVM algorithm.

2 Materials and Methods

2.1 Image Acquisition

In this research, Tajan wheat grains infected with Fusarium were provided from research farms of Moghan Agricultural and Natural Resources Research Center and after isolation of F. graminearum on Nash and Snyder's (1962) medium (peptone-pentachloronitrobenzene agar) from infected grains and then isolation of healthy grains from infected grains, 300 samples of healthy wheat grains and 300 samples of grains infected with Fusarium were selected manually in the laboratory. All images of 600 selected wheat grains were prepared from mixed accumulations (but with separate grains) in completely identical conditions. In this way, a 40-cm cube box was prepared for imaging. For indoor lighting, the box was equipped with four 11-W white fluorescent bulbs, which were installed on the roof at equal intervals to prevent shading around the grains. In order to prevent the reflection of light inside, the box was completely closed and dark. There was also a hole at its top (precisely in the center) to position the sensor (lens) of the camera. The camera used in this research, the CanonSX40HS is equipped with a CMOS sensor with 12.1-MP separation power. All images were taken with 5× magnification to cover the entire camera angle of view. Figure 1 shows the image of the hardware system provided for the preparation of images and their processing.

2.2 Image Preprocessing and Texture Analysis

Extracting texture components of images, analyzing images, and classifying data extracted with SVM was done with Matlab R2013a software.

In this research, texture characteristics were used to discriminate healthy grains from infected grains. For this purpose, the images were first de-noised using the median-filter (nonlinear digital filtering) and classified with the Euclidean method. Then, each grain was assigned a label to be identified from other grains. The texture characteristics were extracted from the gray images. The method of converting a color image to a gray-level template is in this way: at first, a pixel is extracted from the RGB parameters, then the numeric

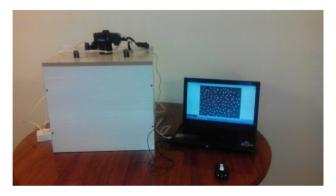


Figure 1: Hardware System of Machine Vision System.

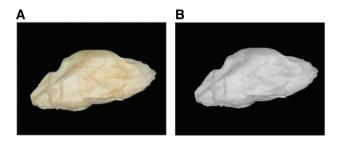


Figure 2: Conversion of a Split Color Image of Wheat Grain Infected with Fusarium to a Gray-Level Image. Image in (A) RGB and (B) gray image.

value of the intensity of each pixel is calculated, and the correct component, instead of the RGB components, is inserted in the same pixel. Figure 2 shows the conversion of a split color image of wheat grain infected with Fusarium to a gray-level image.

The method often used for texture analysis is based on the statistical properties of the intensity histogram. A set of these criteria is based on the statistical moment of the intensity histogram values. The term "central moments" (or average centered moment) [3] used to describe the histogram figure is as follows:

$$\mu_n = \sum_{i=0}^{L-1} (z_i - m)^n p(z_i) \tag{1}$$

In this case, μ is the mean gray level, μ_n represents mean the nth moment, z is a random variable that shows intensity, p(z) is the histogram of intensity levels in the region, and L is the number of intensity levels, and the following is the mean intensity:

$$m = \sum_{i=0}^{L-1} z_i p(z_i) \tag{2}$$

where *n* is the moment, and m is the mean value. As the histogram is assumed to be normal, the sum of all its components is 1, and consequently, we obtain from the previous equation that $\mu_0 = 1$ and $\mu_1 = 0$. The second moment is the variance [3]:

$$\mu_2 = \sum_{i=0}^{L-1} (z_i - m)^2 p(z_i)$$
 (3)

Figure 3 shows a sample of the histogram diagram for healthy grains and grains infected with Fusarium used for obtaining central moments.

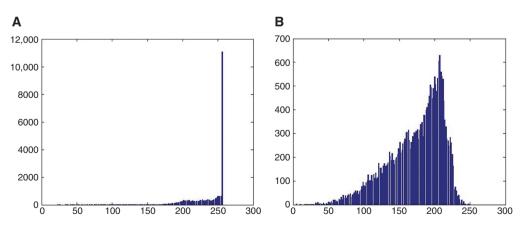


Figure 3: Samples of the Histogram Diagram for Healthy Grains and Grains Infected with Fusarium used for Obtaining Central Moments.

(A) Desired histogram diagram for healthy grains. (B) Histogram diagram for grains infected with Fusarium.

In this study, a total of eight texture characteristics of intensity histogram diagram and six texture characteristics based on the contingency matrix were obtained from the image of each split grain, as shown in Tables 1 and 2, respectively [8].

The two-dimensional moment (p + q) of the digital image f(x, y) with size of $M \times N$ is defined as follows [3]:

$$m_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} x^p y^q f(x, y)$$
 (4)

Table 1: Texture Moments Based on Intensity Histograms.

Moment	Phrase description		
Mean	$m = \sum_{i=0}^{L-1} z_i p(z_i)$ is a measure of mean intensity		
Standard deviation	$\sigma = \sqrt{\mu_2} = \sqrt{\sigma^2}$ is a measure of mean contrast		
Smoothness	$R=1-rac{1}{(1+\sigma^2)}$ The relative smoothness measures intensity in the region. R is 0 for a region with constant intensity and is about 1 for regions with an increase in their intensity levels. In practice, the variance, σ^2 , used in this scale, was normalized to the interval of $[0,1]$ by dividing it by $(L-1)^2$.		
The third moment	$\mu_3 = \sum_{i=0}^{\infty} (z_i - m)^3 p(z_i)$ It measures the skewed histogram. This scale is zero for symmetric histograms, positive for right-skewed histograms, and negative for left-skewed histograms. The values of this scale are in the range of values equal to other five scales by dividing μ_3 by $(L-1)^2$, which is used to normalize the variance.		
Monotony	$U = \sum_{i=0}^{L-1} p^2(z_i)$ It measures monotony. This scale is maximum when all intensity values are equal (maximum monotony) and, hence, decreases.		
Entropy	$e = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i)$ This is a scale of randomness.		

Table 2: Characteristics of Contingency Matrix.

Feature	Description	Formula	
Contrast	Is a measure of contrast intensity between a pixel and its neighbor on the entire image. Interval = $[0(\text{size}(G,1) - 1)^2]$	$\sum_{i=1}^K \sum_{j=1}^K (i-j)^2 p_{ij}$	
Correlation	Shows how a pixel correlates with its neighboring image on the entire image. Interval $= [-1, 1]$ The correlation for the positive or negative correlated image is 1 or -1 , respectively. Correlation is not defined for a still image.	$\sum_{i=1}^{K} \sum_{j=1}^{K} \frac{(i-m_r)(j-m_c)p_{ij}}{\sigma_r \sigma_c} \sigma_r \neq 0$ $\sigma_c \neq 0$	
Energy	Shows the total of square elements in G. Interval $=$ [0 1] Energy for the still image is 1.	$\sum_{i=1}^K \sum_{j=1}^K p_{ij}^2$	
Homogeneity	Shows a value that determines the proximity of element distribution in G to the diameter of G. Interval $= [0 \ 1]$ Homogeneity for diagonal G is 1.	$\sum_{i=1}^{K} \sum_{j=1}^{K} \frac{p_{ij}}{1 + i - j }$	
Maximum probability	Measures the strongest response of the contingency matrix.	$max = (p_{ij})$	
Entropy	An entropy measures the randomness of matrix G.	$-\sum_{i=1}^K\sum_{j=1}^Kp_{ij}\log_2p_{ij}$	

where p = 0, 1, 2, ..., and q = 0, 1, 2, ... are integers. The corresponding central moment (p + q) is defined as follows:

$$\mu_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x - \bar{x})^p (y - \bar{y})^q f(x, y)$$
 (5)

for $p=0,1,2,\ldots$, and $q=0,1,2,\ldots$ and $\bar{x}=\frac{m_{10}}{m_{00}}$ and $\bar{y}=\frac{m_{01}}{m_{00}}$. The normalized central moment (p+q) is defined as:

for
$$p + q = 2, 3, \eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}$$
 and $\gamma = \frac{p + q}{2}$ (6)

In this research, a set of seven static two-dimensional moments that are not sensitive to transitions, changes in scale, mirroring, and rotations are calculated for each image using the following equations [8]

$$\varphi_1 = \eta_{20} + \eta_{02} \tag{7}$$

$$\varphi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{8}$$

$$\varphi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{9}$$

$$\varphi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{10}$$

$$\varphi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12}) \left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 \right]$$

$$+ (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03}) \left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 \right]$$
(11)

$$\varphi_6 = (\eta_{20} - \eta_{02}) \left[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 \right] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$
(12)

$$\varphi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12}) \Big[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 \Big]$$

$$+ (3\eta_{21} - \eta_{30})(\eta_{21} + \eta_{03}) \Big[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 \Big]$$
(13)

Totally, 21 texture characteristics from images of healthy grains and grains infected with *Fusarium* were extracted separately. A flow diagram of the image processing and analysis based on these characteristics is shown in Figure 4.

2.3 SVM and DA Classifier

To discriminate healthy wheat grains and grains infected with *F. graminearum* and classify them in two different groups, the SVM algorithm and discriminant analysis (DA) were used.

In discriminant analysis, the goal is to obtain a relation that can determine membership in the categorical variable by the independent variables. By performing a discriminant analysis, a function or a set of functions is constructed. The first function gives the best linear combination for predicting membership in groups. For k classes, k-1 discriminant functions are created. This method was performed on data to discriminate healthy wheat grains from grains infected with *Fusarium* using the SPSS software. To determine the best discriminant function, Wilks' lambda index was used. Wilks' lambda indicates the significance of the discriminant function. This index is between zero and one. The smaller this value for a function is, the better its discrimination power.

In this research, in addition to discriminant analysis, an SVM was used to discriminate healthy grains and grains infected with *F. graminearum*. The goal was to determine how many grains can be predicted accurately with SVM in their groups. To implement this method, 80% of the data were selected for training and

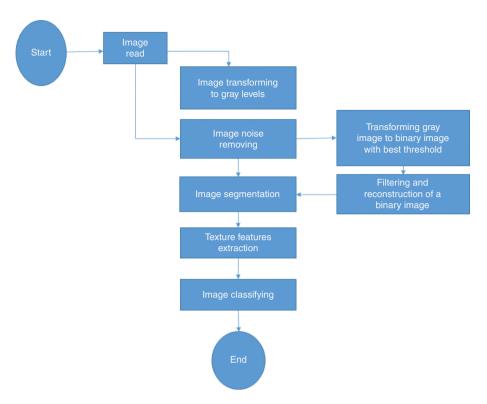


Figure 4: Flowchart of the Image Processing and Analysis Based on Texture Characteristics.

20% for testing the structure created with the algorithm. Given that the variables had different variations, all the data were normalized linearly with the following equation and before classification with discriminant analysis and SVM:

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \times (r_{\max} - r_{\min}) + r_{\min}$$
 (14)

In this relation, x is the initial raw data, x_n is the normalized data, x_{max} and x_{min} are the maximum and minimum values of the initial data, and r_{max} and r_{min} are, respectively, the upper and lower limits of change in converted data. Classification with SVM is such that SVM finds the best hyper level separating the data of two classes with the maximum margin. The main idea is to select an appropriate separator, a separator with the greatest margin with the neighboring points of both classes. This solution actually has the largest boundary with the points of two different classes and can be joined with two parallel hyper levels that cross at least one of two points. The closest training examples to this boundary are support vectors. Using the kernel function, the system can be trained in a higher dimensional environment. The inputs of the algorithm are the texture characteristics extracted from healthy wheat grains and the infected grains, and the output is a code vector determined due to the presence of two grain groups with two different labels. The programming of the SVM algorithm models was performed in Matlab R2013a software. The accuracy of classification with the SVM algorithm was calculated using equation (15):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
 (15)

In the above relation, TP is the number of correct positive samples, TN is the number of correct negative samples, FP is the number of false-negative samples, and FN is the number of false-positive samples.

3 Results and Discussion

3.1 Classification Based on Discriminant Analysis (DA)

In this study, a total of 21 texture features including the characteristics derived from contingency matrix, statistical characteristics, and image moments were calculated. Regarding the existence of two data groups (healthy grains and infected grains), in the isolation of healthy grains from infected grains with discriminant analysis, only one discriminant function was obtained for the separation of data in two groups. The value of Wilks' lambda obtained for the disjunctive function was calculated based on texture characteristics and was 0.91, which indicates that the above function has high ability in isolating two groups of wheat grain with texture variables. Table 3 shows the magnitude of standard and nonstandard canonical coefficients of the discriminant function with 21 texture characteristics.

The discriminant function, F, is obtained using the nonstandard coefficients of the above table. This function, using the texture characteristics of the image, isolates healthy grains from the infected grains:

```
F = 36.296 First Central moment -62.582 Second Central moment +25.8 Mean -3.013 Std
   +905.978 Smoothness -92.001 Entropy +2.142 Contrast -195.605 Correlation
    +396.770 Energy +861.998 Entropy (GLCM) +14987.085 Maximum probability
    -4179.780\varphi_1 + 833.541\varphi_2 - 0.096\varphi_3 + 0.097\varphi_5 - 0.955\varphi_6 - 0.060\varphi_7 - 13436.682
                                                                                                 (16)
```

In this function, the maximum probability property has the maximum role in grain isolation. The results of predicting grain membership with the texture characteristics of the image are shown in Table 4.

The accuracy of the classification indiscriminant method, and based on the texture characteristics of grain images, was 100%. In this analysis, 300 healthy grains and 300 infected wheat grains were correctly placed in their respective groups.

Table 3: Standard and Nonstandard Canonical Coefficients of Discriminant Function Based on Texture Character	ictics
Table 3: Standard and Nonstandard Canonical Coefficients of Discriminant Function based on Texture Character	istics.

Texture features	Nonstandard coefficients	Standard coefficients
First central moment	36.296	1.290
Second central moment	-62.582	-0.201
Mean	25.800	1.314
Std	-3.013	-0.163
Smoothness	905.978	0.144
Third moment	0	0
Uniformity	0	0
Entropy	-92.001	-0.378
Contrast	2.142	0.087
Correlation	-195.605	-0.240
Energy	396.770	0.239
Homogeneity	0	0
Entropy (GLCM)	861.998	3.556
Maximum probability	14978.085	4.153
$arphi_1$	-4179.780	-2.404
$arphi_2$	833.541	1.992
φ_3	-0.096	-0.001
$arphi_4$	0	0
$oldsymbol{arphi}_5$	0.097	0.028
$oldsymbol{arphi}_6$	-0.955	0.190
$oldsymbol{arphi}_7$	-0.060	0.025
constant	-13436.682	_

Table 4: Classification Results by Discriminant Analysis Method with Texture Characteristics.

	Group	Predicting the n	umber of members in each group	Total
		Fusarium infected	Healthy	
Frequency	Fusarium infected	300	0	300
	Healthy	0	300	300
Percentage	Fusarium infected	100	0	100
	Healthy	0	100	100

3.2 Classification Based on Support Vector Machine (SVM)

After submitting 21 texture features into the MATLAB software, SVM analysis was performed on them. To classify, first, the pre-determined training samples were educated, and then the test samples were classified. Classification with this algorithm is such that a structure is first created with the data allocated to training; then, the class of each input test data of this structure, created by training data, is predicted. Table 5 shows the support vector points created with training data and the weights assigned to them.

According to the table above, after educating image texture data with linear SVM, 12 samples (grains) were identified as support vector points or border points. With respect to the values of α , which are weight vectors of support vectors, it is clear that from these 12 points, 5 points belong to the negative group and 7 points belong to the positive group. Changing weight marks indicates a change in sample classes. All support vectors belonging to the grains infected with *Fusarium* have negative weight, and all support vectors of healthy grains have a positive weight and are trained with 100% accuracy.

In training with nonlinear SVM, 580 border points with RBF, a kernel function, and a radius of 3 were obtained. In greater and smaller radial amounts, accuracy of classification decreases. As the decision is based only on boundary vectors, the SVM with a few training patterns will have a near-realistic and optimal response. Also, it is not biased or deviated excessively toward educational data because it regulates itself based on educational boundary vectors that are important in isolating two categories. The bias value was 0/00126 for the linear mode and -0.30802 for the nonlinear mode. These values indicate that classification with the linear method is more acceptable than the nonlinear method because in the nonlinear mode values are biased toward educational data. Table 6, using linear and nonlinear SVM, shows the results of classifying texture values from images of healthy grains and grains infected with F. graminearum.

The results indicate that all data are classified with 100% accuracy in both methods. All healthy wheat grains and all infected data are correctly predicted in their respective classes. One of the most important features of SVM algorithm is data classification based on minimizing test data error, while in other classes such

Table 5: Support Vector Points for Texture Values.

Samples	Weights (α)
10	-1
81	-0.4652
103	-0.6995
131	-1
133	-0.2526
241	0.000602
290	0.093602
337	1
341	1
363	0.51748
403	0.321504
479	0.4843

Method	Data	Groups	Fuzarium infected	Healthy grains	Accuracy
Linear	Train	<i>Fusarium</i> infected	240	0	100%
		Healthy grains	0	240	
	Test	Fusarium infected	60	0	100%
		Healthy grains	0	60	
	Total				100%
Nonlinear	Train	<i>Fusarium</i> infected	240	0	100%
		Healthy grains	0	240	
	Test	Fusarium infected	60	0	100%
		Healthy grains	0	60	
	Total				100%

Table 6: The Results of Grain Classification with Linear and Nonlinear SVM Algorithm for Texture Values.

as neural networks, performance is based on minimizing educational data error. That is why in SVM, there is no longer a concern about placing in a local minimum.

4 Conclusion

- 1. In this research, we used image processing, discriminant analysis (DA), and SVM algorithm to discriminate and classify healthy wheat grains from grains infected with F. graminearum.
- 2. A total of 21 textures were extracted separately from the image of each healthy grain and grains infected with F. graminearum.
- 3. Using discriminant analysis method, only one discriminant function was obtained due to the existence of two groups of grains.
- 4. The amount of Wilks' lambda obtained from the discriminant function based on texture characteristics was 0.91. This value indicates that the above function has a high ability in separating two groups of wheat grain with texture variables.
- 5. The maximum probability variable has the highest contribution in grain isolation. Discrimination of healthy grains from grains infected with Fusarium was done with texture features of their images and discriminant analysis (DA) with 100% accuracy.
- 6. A total of 12 support vectors were obtained for linear SVM and 580 with RBF, kernel function, and a radius of 3 for nonlinear mode. Increasing and decreasing the amount of radius specified for kernel function in Matlab increased border points and the accuracy of classification for training data, and decreased test
- Results showed that classification by linear SVM method is better than nonlinear SVM. Discrimination of healthy grains from grains infected with Fusarium was carried out using the texture characteristics of the images and SVM, in linear and nonlinear mode with 100% accuracy.
- 8. The results of this research could be useful for the development of automatic devices for the rapid discrimination of healthy grains from grains infected with F graminearum, a major and destructive disease of wheat.
- 9. Also, as the major symptoms of *Fusarium* are caused by wheat spikes, it is suggested that the distinction between Fusarium-infected spikes and healthy spikes be investigated using the above techniques. This discrimination could be used in precision spraying of infected fields using automatic devices during precision farming operations.

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