Discrimination of Normal and Abnormal Grapes' Leaves Using Image Processing and Artificial Intelligence Approach

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ABSTRACT

The vital role of the agriculture draws the attention of the researchers to introduce different types of techniques and approaches to improve the agricultural products both qualitatively and quantitatively. One of the most focused issues is the detection, diagnosis and treatment of different types of plant diseases that degrades the quality and quantity of agricultural products e.g. fruits, vegetables and other crops. Traditionally, these diseases are detected, diagnosed and treated manually which requires a continuous monitoring of crops' farms which may lead to wastage of time and human physical hard work involvement. The human inspection also fails in providing accurate results as different human beings follow different procedure to resolve a specific issue. Therefore, to overcome all the deficiencies, an automatic plants' diseases detection process is required. This automatic system will provide accurate results as well as will be universally acceptable and applicable. The first step towards the automatic plants' disease detection is the classification of plants' normal and abnormal parts. In this work, an easy approach is presented for the classification of grapes' leaves into normal and abnormal using artificial neural network and image processing technique. The proposed approach consists of five stages namely image acquisition, pre-processing, feature extraction, classification and performance evaluation. Total of 120 grapes' leaves images were used in the experiments. Out of these 120 images, 60 were normal and 60 were abnormal images. Different performance parameters have been used to evaluate the performance of the proposed approach and the comparison of the proposed approach has been made with many state of the art techniques used for automatic detection of plants' diseases.
KEYWORDS: Plants diseases detection, Image processing, Machine learning, Filtering, Color features, Multi-layer perceptron

1 INTRODUCTION

There are many plant diseases that degrade the quality and quantity of fruits and vegetables which are addressed by various researchers for bringing considerable amount of improvements in overall capacity building. The major sources of these diseases are mainly bacterial, viral, and fungal infections in addition to the unacceptable climate and environmental conditions. The main target of these diseases may be one of the stem, leaves, fruits, vegetables or all these parts of the plants. For the production of more fruits and vegetables with the least possible effects of the dangerous diseases, a high quality agricultural production control system is required. The major component of this system will be the detection system for different diseases causing damaging effects to both fruits and vegetables [1].
For the detection of different diseases in plants, different parts of plants can be kept under consideration but the leaves' diagnosis is the main target of experts due to the fact that leaves are the primary part affected by different abnormalities. The conventional method of disease detection using plants' leaves has been the manual inspection by experts which is suffered from two major drawbacks; firstly, a continuous monitoring of plants by experts is required which is very expensive in terms of time and cost: secondly, the accuracy of the detection may not be too enough to completely recover the disease.
Therefore, this process needs to be automatic to overcome both of these drawbacks. In the automatic detection and diagnosis of diseases, a computer aided application is required that takes assistance from different other software and hardware applications. In this regard, the importance of applications of image processing and artificial intelligence techniques cannot be under estimated. The image processing technique is required for taking images of different parts of plants depending on the case under observation for finding the disease affected areas of plants and

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finding the intensities of disease. After taking the images of the targeted plants, machine learning or artificial intelligence techniques are applied for the classification of leaves into normal and abnormal, or detection of the affected areas.

For discrimination of normal and abnormal leaves, or finding abnormality in the leaves' images, different authors have performed the image processing procedure in different stages but the main stages are: leave image acquisition, pre-processing of leave images, extraction of valuable features, segmentation of leave images into different parts. A brief introduction of all these stages is given as follow [2].

Image acquisition: In the image acquisition stage, the leave images are captured using some high resolution image capturing device e.g. digital camera or high resolution camera of high quality mobile.

Pre-Processing: In pre-processing stage, the quality of data representing the image is improved by applying some image pre-processing technique e.g. different types of filters. The quality of image is improved by eliminating undesired signals and enhancing the image contrast. During this stage, the images may also be converted to other format for better description of features representing the image e.g. to Hue Saturation Value (HSV) format. The reason behind the image conversion is to give proper representation to images for their full description. Using this phenomenon, the extra components are dropped from the images which facilitate further processing.

Image Segmentation: For easier and meaningful analysis of images, the images are divided into different regions e.g. normal and affected part of diseased image. This process is called image segmentation. There are different image segmentation techniques which are applied in image processing e.g. region based segmentation, edge based segmentation, threshold based segmentation, model based segmentation and feature based clustering.

Feature Extraction: In the feature extraction stage, the important features are extracted from the image which in turn reduces computation cost and time for further processing of images. Different types of features can be extracted from the images e.g. texture features, color features and shape features.

Image Classification: After the image processing mechanism has been carried out, some artificial intelligence technique is applied for the discrimination of normal and abnormal leaves or the affected areas of leaves. For the discrimination of normal and abnormal leaves, different types of classifiers are used with each classifier having its own advantages and disadvantages. The major classifiers applied for the diseases identification are K-nearest neighbor, radial basis function, and artificial neural network and support vector machine. For the measurement of performance of classifiers, different parameters can be applied e.g. simplicity, robustness, speed, input specification, problem specification and classification accuracy.

There are many approaches in the literature proposed for automatic detection of different types of diseases in plants. The authors [3] applied image processing technique and support vector machine (SVM) for the automatic detection of plants' diseases. The authors[4] presented a comprehensive discussion on different data mining techniques that could be applied for automatic detection of diseases in various fruit plants. The authors [5] applied support vector machine (SVM) for the classification of normal and diseased soybean leaves. The authors [6] applied K-Nearest neighbors, local binary pattern, and artificial neural network and support vector machines for identification of different types of fungal diseases in various plants.

For the identification of diseases in sugar beet leaves, the authors [7] applied support vector machine. The authors [8] presented a comprehensive survey on different machine learning techniques applied for automatic classification of various diseases affecting the plants' leaves. The authors [9] proposed a four steps procedure for automatic detection of different types of diseases in plants. The authors [10] presented a technique for automatic classification and detection of different diseases affecting plants. A machine learning based identification and disease detection system was developed for saving money, efforts and time. The diseases detection procedure was carried out in four steps by the authors [11]. The authors [12] applied image processing techniques and artificial neural network for classification of plants diseases detection. The authors [13] applied k means clustering technique for classification and recognition of different diseases of plants. For identification of plants' diseases the authors [14] used the histogram matching. The authors [15] applied simple and triangle threshold based approaches for detection of diseases in plants. For the detection of diseases in plants' leaves, the authors [16] applied image processing techniques in combination with statistical methods.

2 PROPOSED METHODOLOGY

The proposed technique consists of four simple stages namely image acquisition, pre-processing, feature extraction and classification. The proposed approach is shown in Figure 2 and all these steps are explained in the following section.

3.1 Image acquisition

In the image acquisition stage, the images of the leaves are captured using high quality digital camera or other image capturing device. In our system, images have been collected from different standard databases available online.

3.2 Pre-processing

Normally, the pre-processing stage is applied for improving the quality of images or to convert the images from one format to another format suitable for further processing according to the application being used. In the proposed approach, following two activities have been performed during pre-processing

- **a.** Filtering
- **b.** Channelization

3.2.1 Filtering

During filtering stage, the images have been smoothened by applying 5x5 linear filters. After applying this filter, the peaks have been removed from the images and the changes in the values of pixels have been smoothly adjusted. The images before and after applying filtering have been shown in Figure 1.

3.2.2 Channelization

Every color images consists of three main channels namely red, green and blue channels. In the physical appearance, these channels are not in red, green or blue channels, respectively but these channels are based on the values of pixels. The pixels values within specific ranges are considered as red, green or blue channels. During the channelization stage, these channels are extracted from the leaves' images. These three channels of leave images are shown in Figure 1.

3.3 Feature extraction

In the feature extraction stage, useful features are extracted from each of the channels extracted during the channelization stage. Total of nine features have been extracted from each image for its full description [17], [18], [19], [20]. In the proposed algorithm, color moments of red, green and blue channels have been used as main features for the description of grapes' leaves images.

3.3. 1 Mean

Mean is the first color moment, representing the average of all pixels' intensities of each color channel.

3.3.2 Variance

Variance is the second color moment, representing variations in distributions of intensities in each color channel

3.3.3 Skewness

Skewness is the third color channel representing the asymmetry of color distribution in each channel.

3.3.4 Mathematical representation of Color Moments

So, a total of nine features (three from each color channel) have been extracted as main features. All these features are represented by following mathematical equations.

$$M_{1,1} = \frac{1}{N}\sum_{J=1}^{N} I_j \tag{1}$$

$$M_{1,2} = \frac{1}{N}\sum_{j=1}^{N}\left(I_j - M_{1,1}\right)^2 \tag{2}$$

$$M_{1,3} = \frac{1}{N}\sum_{1}^{N}\left(I_j - M_{1,1}\right)^3 \tag{3}$$

$$M_{2,1} = \frac{1}{N}\sum_{J=1}^{N} I_j \tag{4}$$

$$M_{2,2} = \frac{1}{N}\sum_{j=1}^{N}\left(I_j - M_{2,1}\right)^2 \tag{5}$$

$$M_{2,3} = \frac{1}{N}\sum_{1}^{N}\left(I_j - M_{2,1}\right)^3 \tag{6}$$

$$M_{3,1} = \frac{1}{N}\sum_{J=1}^{N} I_j \tag{7}$$

$$M_{3,2} = \frac{1}{N}\sum_{j=1}^{N}\left(I_j - M_{3,1}\right)^2 \tag{8}$$

$$M_{3,3} = \frac{1}{N}\sum_{1}^{N}\left(I_j - M_{3,1}\right)^3 \tag{9}$$

Where $M_{1,1}$, $M_{1,2}$, $M_{1,3}$ represents mean, variance and skewness of the red color channel, respectively. $M_{2,1}$, $M_{2,2}$, $M_{2,3}$ represents mean, variance and skewness of the green color channel, respectively. $M_{3,1}$, $M_{3,2}$, $M_{3,3}$ represents mean, variance and skewness of the blue color channel, respectively. I represent the intensity of each pixel in the red, green and blue channel and N represent the total number of pixels in the channels.

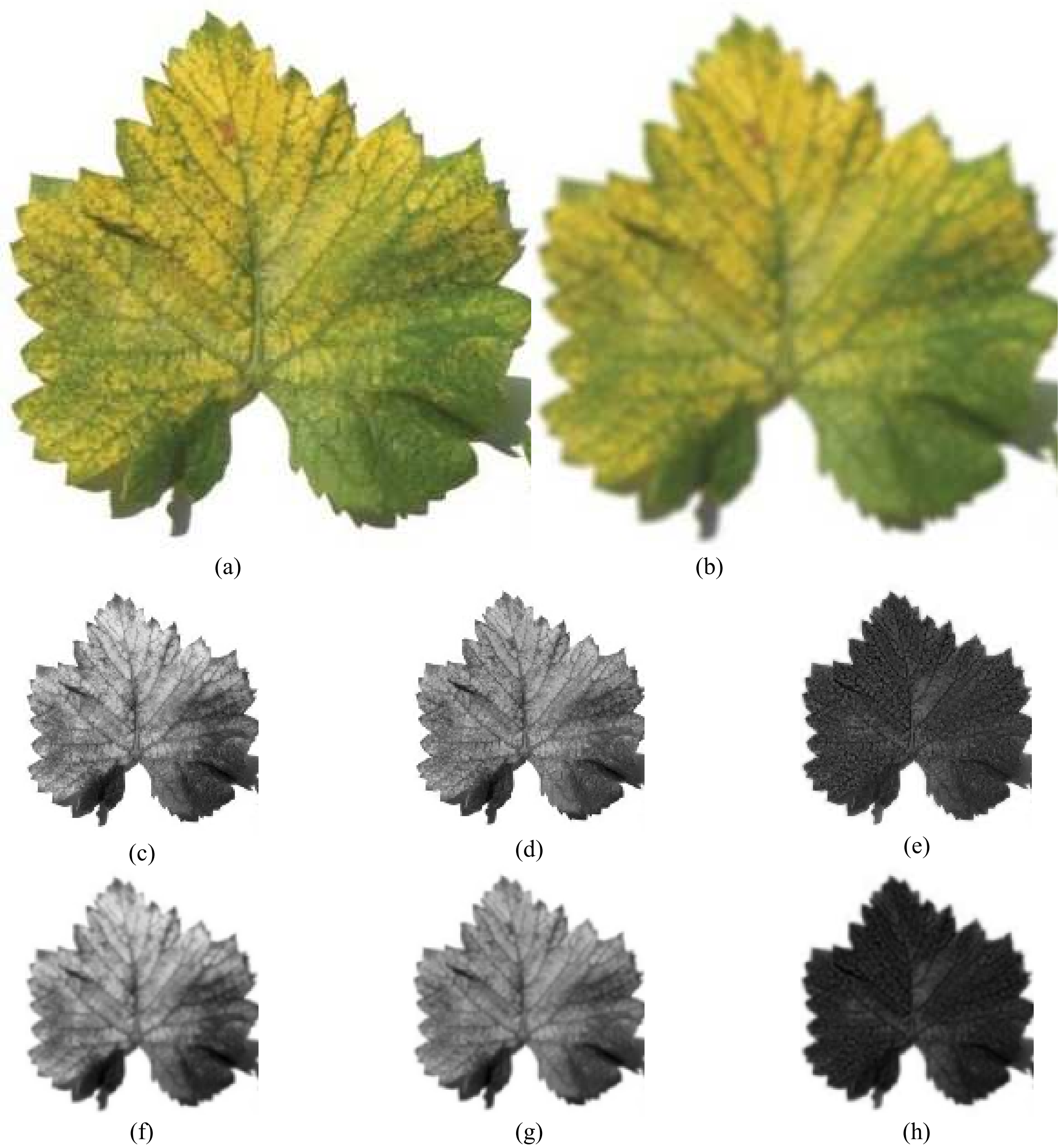

Figure 1:a. Brfore Filtering **b.** After Filtering **c. d. e. f. g. h**. Channels

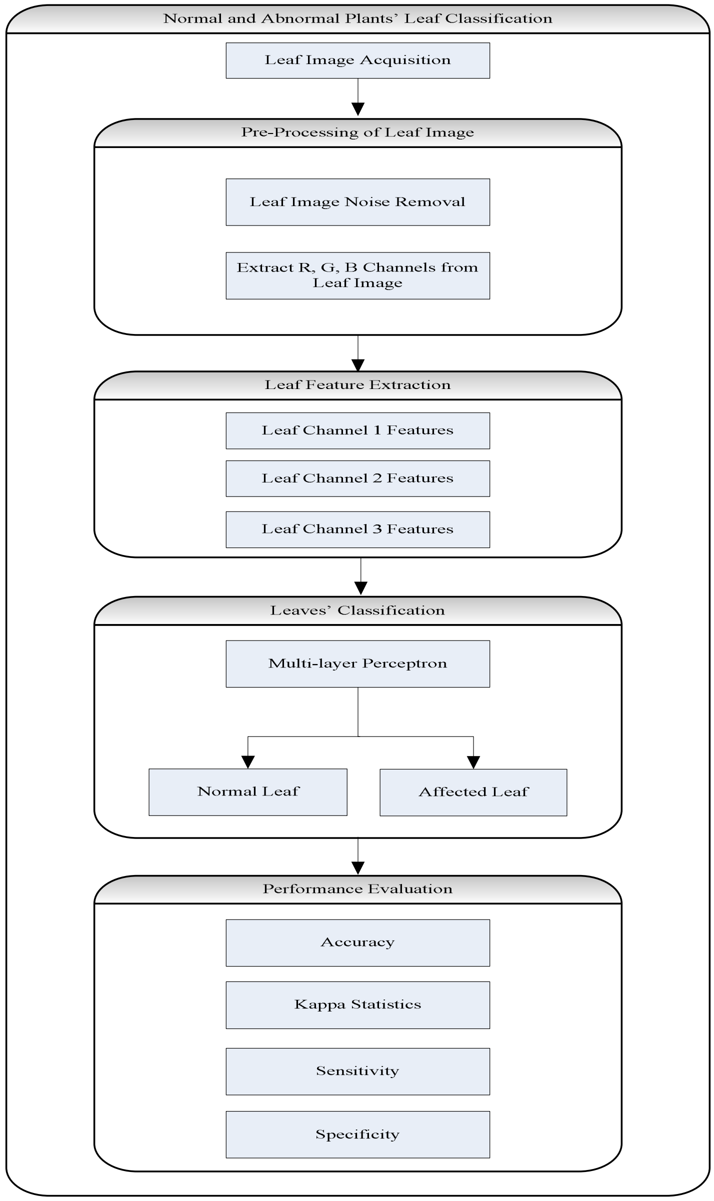

Figure 2: Proposed Methodology

3.4 Classification

In the classification stage, the features extracted during the feature extraction stage are given to machine learning technique to classify them into either normal or abnormal images. In our proposed approach, we have used multi-layer perceptron with different types of architectures for this purpose. The complete descriptions of all the architectures of multi-layer perceptron are shown in results and discussion section.

3.5 Performance Evaluation

The performance of the classifier has been evaluated using Classification Accuracy, Kappa Statistics, Sensitivity (SE), Specificity (SP) and ROC for different training and testing ratios [21], [22]. The formulation of these parameters is shown in Table 1.

Table 1. Performance Measurements

Evaluation Parameter	Equation
Accuracy	(TP+TN)/(TP+TN+FP+FN)
Sensitivity (TPR)	TP/(TP+FN)
Specificity	TN/(TN+FP)
False Positive Rate (FPR)	FP/(FP+TN)
ROC	TPR, FPR required to draw the curve
KS	(P0-PC/(1-PC))

Where
TP = True Positive: Normal leaves identified as normal leaves.
TN = True Negative: Abnormal leaves identified as normal leaves.
FP = False Positive: Abnormal leaves identified as abnormal leaves.
FN = False Negative: Normal leaves identified as abnormal leaves.
P0 represents total agreement probability; PC represents hypothetical probability of chance agreement.

3 EXPERIMENTAL RESULTS

All the experiments have been performed on Intel Core i5 with 4.00 GB of memory with the windows 7 operating system installed on it. For feature, extraction and pre-processing, MATLAB 7.6.0 (R2008a) was used whereas for classification purpose, Weka 3.7.10 was used. The proposed approach was tested on total of 120 grapes' leaves images. Out of these 120 images, 60 images were normal images whereas the remaining 60 images were images affected by different types of diseases.

3.1 Algorithm Accuracy

The total data set was divided into 70% training and 30% testing data set. The algorithm gave 97.50% accuracy for training data set whereas 95.00% for testing data set. The experimental results are shown in the following tables. For making the algorithm more generalized, cross validation was applied, which gave 94.57% accurate results. The experimental results are shown in the following tables.

Table 2. Training Data Set Accuracy

Identification Accuracy of Normal Leaves			
Total Leaves	Correctly Identified Leaves	Incorrectly Identified Leaves	Identification Accuracy
40	39	1	97.50%
Identification Accuracy of Diseased Leaves			
Total Leaves	Correctly Identified Leaves	Incorrectly Identified Leaves	Identification Accuracy
40	39	1	97.50%
Overall Identification Accuracy			
Total Leaves	Correctly Identified Leaves	Incorrectly Identified Leaves	Identification Accuracy
80	78	2	97.50%

Table 3. Testing Data Set Accuracy

Identification Accuracy of Normal Leaves			
Total Leaves	Correctly Identified Leaves	Incorrectly Identified Leaves	Identification Accuracy
20	20	0	100.00%
Identification Accuracy of Diseased Leaves			
Total Leaves	Correctly Identified Leaves	Incorrectly Identified Leaves	Identification Accuracy
20	18	2	90.00%
Overall Identification Accuracy			
Total Leaves	Correctly Identified Leaves	Incorrectly Identified Leaves	Identification Accuracy
40	38	2	95.00%

Table 4. 10 Fold Cross Validation Accuracy

Identification Accuracy of Normal Leaves			
Total Leaves	Correctly Identified Leaves	Incorrectly Identified Leaves	Identification Accuracy
60	56	4	93.33%
Identification Accuracy of Diseased Leaves			
Total Leaves	Correctly Identified Leaves	Incorrectly Identified Leaves	Identification Accuracy
60	55	5	91.66%
Overall Identification Accuracy			
Total Leaves	Correctly Identified Leaves	Incorrectly Identified Leaves	Identification Accuracy
120	111	9	92.50%

For further evaluation of the proposed approach, the data was divided into different training and testing ratios and various performance evaluation parameters were applied e.g. Kapp statistics, sensitivity, specificity and ROC. The values obtained for all of these performance evaluation parameters are shown in Table 5.

Table 5. Performance parameters of MLP

Training/Testing Ratios	Identification Accuracy	KS (Kappa Statistics)	Sensitivity	Specificity	ROC Area
25-75%	87.8269	0.7876	0.8780	0.8783	0.9384
34-66%	90.9231	0.8131	0.9094	0.9092	0.9690
50-50%	93.3077	0.8291	0.9332	0.9333	0.9882
66-34%	97.5000	0.8806	0.9761	0.9763	0.9903
75-25%	92.5897	0.8238	0.9257	0.9254	0.9626
10-Fold Cross Validation	94.5769	0.8394	0.9456	0.9457	0.9791

3.2 Comparative Analysis

Table 6 shows the comparison of the proposed technique with other techniques along with the disease type affecting the plant different parts, the targeted crop, the image processing and machine learning procedure and the accuracies of these approaches [6], [23].

Table 6. Comparison of proposed approach with other approaches

Target Crop	Disease Type	Affected Area	AI and Image processing approach adapted	Identification Accuracy (%)
1. Fruit Crops • **Grapes** • **Mangoes** • **Pomegranate**	• Anthracnose • Powdery mildew • Downy mildew	• Stem • Fruit • Leaf	• Region growing method • Edge detection method • K-means clustering • Neural Network • Canny edge detection • Filtering • GCCM • K-Nearest neighbors	• 84.65 • 76.60 • 91.37 • 86.71 • 94.08
2. Vegetables • **Bengal gram** • **Beans** • **Soybean** • **Tomato** • **Sunflower**	• Late blight • Early blight • Powdery and downy mildew • Anthracnose	• Leaf • Stem • Fruit	• Local binary pattern • Chan-vase • KNN • KNN+ANN	• 84.11 • 91.54
3. Commercial Crops • **Cotton** • **Chili** • **Sugarcane**	• Fruit rot • Gray mildew • Powdery and downy mildew • Red rot etc	• Leaf	• Wavelet based • Grab-cut • Principal component analysis	• 83.17 • 86.48
4. Cereal Crops • **Wheat** • **Jowar** • **Maize**	• Leaf spot • Leaf blight • Leaf rust • Powdery mildew	• Leaf • Stem • Fruit	• Filtering • K-means clustering • Shape features • Support vector machine	• 80.83 • 85.00 • 90.83
5. Grapes Disease Detection	• Powdery Mildew • Down Mildew • Black rot	• Leaf	• Pre-processing • Segmentation • Statistical Analysis	• 91.00 • 93.00 • 94.00

			• Feature extraction • Classification using SVM • Back propagation neural network • Fuzzy logic	• 84.00
6. **Grapes** **Proposed Approach**	• Powdery Mildew • Down Mildew • Black Rot	• Leaf	• Image Acquisition • Pre-processing • Filtering • Channelization • Feature extraction • Classification Using MLP • Performance Evaluation	• 97.50

4 DISCUSSION

After comparison of the proposed technique with the techniques presented in Table 6, a conclusion can be drawn that the proposed algorithm performs better than all these techniques in terms of complexity and accuracy. The architecture of the proposed algorithm is simpler than all these techniques and provides better results as well. Almost all techniques shown in the tables use more features than the proposed architecture due to the fact the color features are more informative features than other features and therefore provide better description of the images. All algorithms have used some feature reduction algorithm to reduce the features whereas in our algorithm; this step has been eliminated, which reduces computational complexity to a large extent. The classifier used in our proposed architecture is also simpler and efficient than classifiers used by authors of above algorithms. The major advantages associated with this new approach is that it can be extended to other types of classification problems e.g. gender classification and different types of classification of normal and abnormal human parts with keeping in considerations the facts explored in this proposed work.

5 CONCLUSION AND FUTURE WORK

In this work, the automatic detection of grapes' diseases has been carried out using image processing and machine learning technique called multi-layer perceptron. The process consists of simple five stages namely image acquisition, pre-processing, feature extraction, classification and performance evaluation. The experimental results of multi-layer perceptron have been compared with many other state of the art classifiers pointed out by other researchers for different types of plant diseases detection as shown in Table 10. It is evident from the above table that the proposed approach gives better results than many other techniques suggested by researchers for detection of diseases affecting different parts of plants.

The proposed approach is simple in terms of total number of features used and the computation complexity due to simple pre-processing and feature extraction stages. Extensive experimentation has been carried out for different types of multi-layer perceptron training function, hidden layer function and output layer function in addition to different number of neurons in the hidden layer and number of epochs. Keeping in consideration, different accuracies obtained from different combination, this approach can be applied in other classification mechanisms as well as its extension can be applied for identification of various types of other diseases in other plants which is left as future work.

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