A Framework for Detection and Classification of Plant Leaf and Stem Diseases

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***Abstract-* We propose and evaluate a framework for detection of plant leaf/stem diseases. Studies show that relying on pure naked-eye observation of experts to detect such diseases can be prohibitively expensive, especially in developing countries. Providing fast, automatic, cheap and accurate image-processing-based solutions for that task can be of great realistic significance. The proposed framework is image-processing-based and is composed of the following main steps; in the first step the images at hand are segmented using the K-Means technique, in the second step the segmented images are passed through a pre-trained neural network. As a testbed, we use a set of leaf images taken from Al-Ghor area in Jordan. Our experimental results indicate that the proposed approach can significantly support accurate and automatic detection of leaf diseases. The developed Neural Network classifier that is based on statistical classification perform well and could successfully detect and classify the tested diseases with a precision of around 93%.**

***Keywords---* K-means; Segmentation; Leaf diseases; Stem diseases Neural Networks.**

I. INTRODUCTION

Plant diseases have turned into a nightmare as it can cause significant reduction in both quality and quantity of agricultural products [1], thus negatively influence the countries that primarily depend on agriculture in its economy [3]. Consequently, detection of plant diseases is an essential research topic as it may prove useful in monitoring large fields of crops, and thus automatically detect the symptoms of diseases as soon as they appear on plant leafs.

Monitoring crops for to detecting diseases plays a key role in successful cultivation [3, 9, 10]. The naked eye observation of experts is the main approach adopted in practice [1]. However, this requires continuous monitoring of experts which might be prohibitively expensive in large farms. Further, in some developing countries, farmers may have to go long distances to contact experts, this makes consulting experts to very expensive and time consuming [3, 9]. Therefore; looking for a fast, automatic, less expensive and accurate method to detect plant disease cases is of great realistic significance [3, 9].

Studies show that image processing can successfully be used as a disease detection mechanism [1, 2]. Since the late 1970s, computer-based image processing technology applied in the agricultural engineering research became a common [1]. In this study we propose and experimentally validate the significance of using clustering technique and neural networks in automatic detection of leaf diseases.

The proposed approach is image-processing-based and is composed of the following main steps; in the first step the images at hand are segmented using the K-Means technique, in the second step the segmented images are passed through a pre-trained neural network. As a testbed we use a set of leaf images taken from Al-Ghor area in Jordan. We test our program on five diseases which effect on the plants; they are: Early scorch, Cottony mold, Ashen mold, late scorch, tiny whiteness.

Our experimental results indicate that the proposed approach can significantly support accurate and automatic detection of leaf diseases.

II. PROBLEM FORMULATION AND THE PROPOSED APPROACH

We propose an image-processing-based solution for the automatic leaf diseases detection and classification. We test our solution on five diseases which effect on the plants; they are: Early scorch, Cottony mold, ashen mold, late scorch, tiny whiteness.

The proposed approach starts first by creating device-independent color space transformation structure. Thus, we create the color transformation structure that defines the color space conversion. Then, we apply device-independent color space transformation, which converts the color values in the image to the color space specified in the color transformation structure. The color transformation structure specifies various parameters of the transformation. Finally, K-means clustering is used to partition the leaf image into four clusters in which one or more clusters contain the disease in case when the leaf is infected by more than one disease. K-means uses squared Euclidean distances.

A. Clustering Method

K-means clustering is used to partition the leaf image into four clusters in which one or more clusters contain the disease in case when the leaf is infected by more than one disease. K means clustering algorithm was developed by J. MacQueen (1967) [4] and then by J. A. Hartigan and M. A. Wong [5]. The k-means clustering algorithms tries to classify *objects* (pixels in our case) based on a set of features into K number of classes. The classification is done by minimizing the *sum of squares* of distances between the objects and the corresponding cluster or class *centroid* [4, 5].

In our experiments, the K-means clustering is set to use squared Euclidean distances. An example of the output of K-Means clustering for a leaf infected with *early scorch* disease is shown in figure 1.

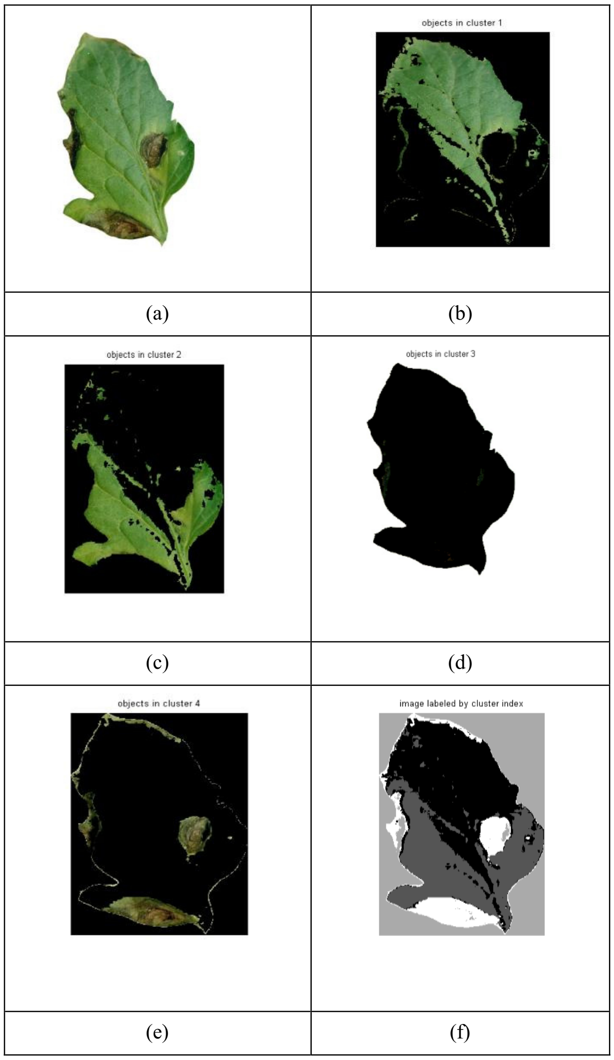

Figure 1: An example of the output of K-Means clustering for a leaf that is infected with early scorch disease. (a) The infected leaf picture. (b, c, d, e) the pixels of the first, second, third and fourth cluster, respectively. (f) a single gray-scale image with the pixels colored based on their cluster index.

B. *Feature Extraction*

The method followed for extracting the feature set is called the *Color Co-occurrence Method* or CCM method in short. It is a method, in which both the color and texture of an image are taken into account, to arrive at unique features, which represent that image. Next we explain this method in more detailed.

Co-occurrence Methodology for Texture Analysis:

The image analysis technique selected for this study was the CCM method. The use of color image features in the visible light spectrum provides additional image characteristic features over the traditional gray-scale representation.

The CCM methodology consists of three major mathematical processes. First, the RGB images of leaves are converted into HSI color space representation. Once this process is completed, each pixel map is used to generate a color co-occurrence matrix, resulting in three CCM matrices, one for each of the H, S and I pixel maps. Hue Saturation Intensity (HSI) space is also a popular color space because it is based on human color perception [6]. Electromagnetic radiation in the range of wavelengths of about 400 to 700 nanometers is called visible light because the human visual system is sensitive to this range. Hue is generally related to the wavelength of a light and intensity shows the amplitude of a light. Lastly, saturation is a component that measures the “colorfulness” in HSI space [6].

Color spaces can be transformed from one to another easily. In our experiment, the following equations were used to transformation the images from RGB to HSI [7]:

$$Intensity\ (I) = \frac{R+G+B}{3} \quad (1)$$

$$Saturation\ (S) = 1 - \frac{3.\min(R,G,B)}{(R+G+B)} \quad (2)$$

$$Hue\ (H) = 2 - ACOS\left\{\frac{[(R-G)+(R-B)]}{\sqrt[2]{(R-G)^2+(R-G)(G-B)}}\right\},\ B > G \quad (3)$$

$$Hue\ (H) = ACOS\left\{\frac{[(R-G)+(R-B)]}{\sqrt[2]{(R-G)^2+(R-G)(G-B)}}\right\},\ B \leq G \quad (4)$$

The color co-occurrence texture analysis method was developed through the use of Spatial Gray-level Dependence Matrices or in short SGDM’s [8]. The gray level co-occurrence methodology is a statistical way to describe shape by statistically sampling the way certain grey-levels occur in relation to other grey-levels.

These matrices measure the probability that a pixel at one particular gray level will occur at a distinct distance and orientation from any pixel given that pixel has a second particular gray level. For a position operator p, we can define a matrix *Pij* that counts the number of times a pixel with grey-level *i* occurs at position *p* from a pixel with grey-level *j*. The SGDMs are represented by the function *P(i, j, d, Θ)* where *i* represents the gray level of the location *(x, y)* in the image *I(x, y)*, and *j* represents the gray level of the pixel at a distance *d* from location *(x, y)* at an orientation angle of *Θ*. The reference pixel at image position *(x, y)* is shown as an asterix. All the neighbors from 1 to 8 are numbered in a clockwise direction. Neighbors 1 and 5 are located on the same plane at a distance of *1* and an orientation of *0* degrees. An example image matrix and its SGDM are already given in the three equations above. In this research, a *one* pixel offset distance and a *zero* degree orientation angle was used.

The RGB image is converted to HIS, and then we calculate the feature set for H and S, we dropped the intensity (I) since it does not give extra information. However, we use GLCM function in MatLab to create gray-level co-occurrence matrix. The number of gray levels is set to 8, and the symmetric value is set to "true", and finally, offset is given a" 0" value.

Normalizing the CCM matrices:

The CCM matrices are then normalized using the equation given below, where $p(i, j, 1, 0)$ represents the intensity co-occurrence matrix.

$$p(i,j) = \frac{p(i,j,1,0)}{\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p(i,j,1,0)} \quad (5)$$

Where N_g is the total number of intensity levels. Next is the marginal probability matrix

$$p_x(i) = \sum_{j=0}^{N_g-1} p(i,j) \quad (6)$$

Sum and difference matrices.

$$p_{x+y}(k) = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p(i,j) \quad (7)$$

Where $k = I + j; for\ k = 0, 1, 2, \dots 2(N_g - 1)$, and

$$p_{x-y}(k) = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p(i,j) \quad (8)$$

Where $k = |I - j|; for\ k = 0, 1, 2, \dots 2(N_g - 1)$, and $p(i, j)$ is the image attribute matrix.

Texture features identification:

The angular moment (I_1) is a measure of the image homogeneity and is defined as

$$I_1 = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} [p(i,j)]^2 \quad (9)$$

The mean intensity level, I_2, is a measure of image brightness and is derived from the co-occurrence matrix as followes

$$I_2 = \sum_{i=0}^{N_g-1} ip(i) \quad (10)$$

Vriation of image intensity is identified by the variance texture feature (I_3) and is computed as

$$I_3 = \sum_{i=0}^{N_g-1} (i - I_2)^2 P_x(i) \quad (11)$$

Correlation (I_4) is a measure of intensity linear dependence in the image.

$$I_4 = \frac{\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} ijP(i,j) - {I_2}^2}{I_3} \quad (12)$$

The produc moment (I_5) is analogous to the covariance of the intensity co-occurance matrix

$$I_5 = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} (i - I_2)(j - I_2)P(i,j) \quad (13)$$

Contrast of an image can be measures by the inverse difference moment (I_6)

$$I_6 = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} \frac{P(i,j)}{1+(i-j)^2} \quad (14)$$

The entropy feature (I_7) is a measure of the amount of order in an image, and is computed as

$$I_7 = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P(i,j)\ lnP(i,j) \quad (15)$$

The sum and difference entropies (I_8 and I_9) can not be easilty interreted, yet low entropies indicates high levels of order. I_8 and I_9 can be computed by

$$I_8 = \sum_{k=0}^{2(N_g-1)} P_{x+y}(k)\ lnP_{x+y}(k) \quad (16)$$

$$I_9 = \sum_{k=0}^{N_g-1} P_{x-y}(k)\ lnP_{x-y}(k) \quad (17)$$

The information measures of correlation (I_{10} and I_{11}) do not exhibit any aparent physical interpretation.

$I_{10} = \frac{I_7 - HXY1}{HX}$ and $I_{11} = \left[1 - e^{-2(HXY2 - I_7)}\right]^{1/2}$. Where

$$HX = -\sum_{i=0}^{N_g-1} P_x(i)\ lnP_x(i) \quad (18)$$

$$HXY1 = -\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P(i,j)\ ln[P_x(i)P_x(j)] \quad (19)$$

$$HXY1 = -\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P_x(i)P_x(j)\ ln[P_x(i)P_x(j)] \quad (20)$$

III. THE PROPOSED APPROACH – STEP-BY-STEP DETAILS

The underlying approach for all of the existing techniques of image classification is almost the same. First, digital images are acquired from environment around the sensor using a digital camera. Then image-processing techniques are applied to extract useful features that are necessary for further analysis of these images. After that, several analytical discriminating techniques are used to classify the images according to the specific problem at hand. This constitutes the overall concept that is the framework for any vision related algorithm. Figure 2 depicts the basic procedure of the proposed vision-based detection algorithm in this research.

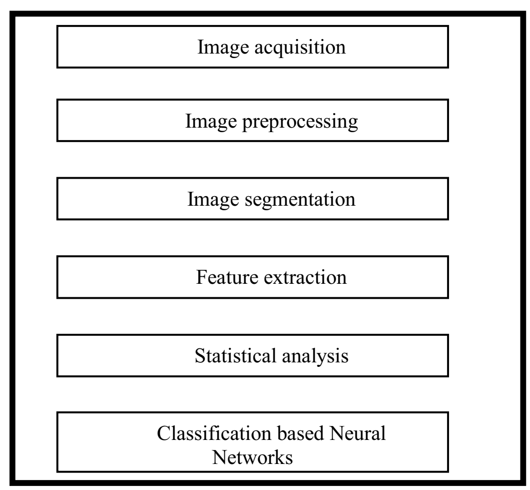

Figure 2: The basic procedure of the proposed vision-based disease detection algorithm.

The first phase is the image acquisition phase. In this step, the images of the various leaves that are to be classifies are taken using a digital camera. In the second phase image preprocessing is completed. In the third phase, segmentation using K-Means clustering is performed to discover the actual segments of the leaf in the image. Later on, feature extraction for the infected part of the leaf is completed based on specific properties among pixels in the image or their texture. After this step, certain statistical analysis tasks are completed to choose the best features that represent the given image, thus minimizing feature redundancy. Finally, classification is completed using neural network detection algorithm.

The detail step by step account of the image acquisition and classification process is illustrated in Figure 3.

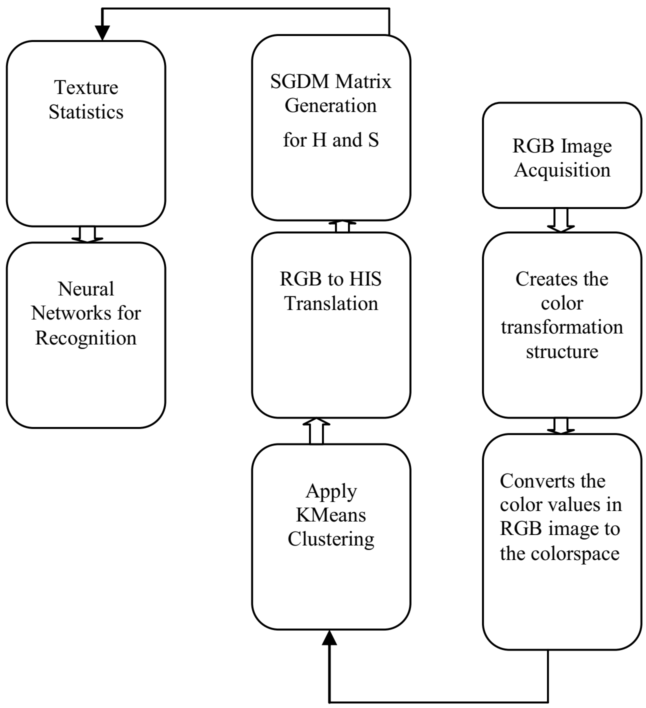

Figure 3: Image acquisition and classification.

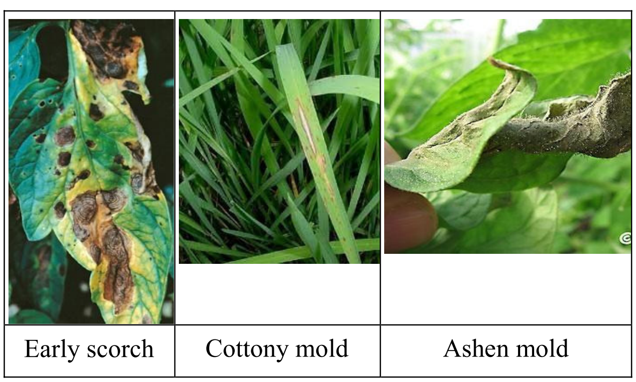

Figure 4: Sample images from our dataset.

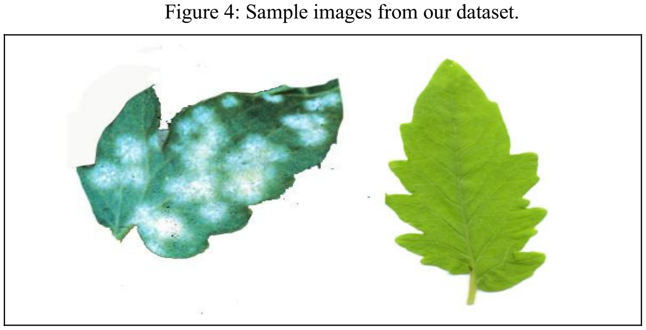

Figure 5: A leaf image infected with tiny whiteness disease (left) and a normal leaf image (right).

Figure 6. Clustered detected image of a leaf sample (Cluster 1).

In the initial step, the RGB images of all the leaf samples were obtained. Some samples of those diseases are shown in the Figure 4.

From figures 4 and 5 it is obvious that leaves belonging to early scorch, ashen mold and normal classes showed significant difference form greasy spot leaves in terms of color and texture. The leaves belonging to these three classes had minute differences as discernible to the human eye, which may justify the misclassifications.

For each image in the data set the subsequent steps were repeated. Image segmentation of the leaf is done on each image of the leaf sample using K-Means clustering. A sample clustered image with four clusters of the leaf sample image is shown in Figure 6.

Once the infected object was determined, the image was then converted from RGB format to HSI format. The SGDM matrices were then generated for each pixel map of the image for only H and S images. The SGDM is a measure of the probability that a given pixel at one particular gray-level will occur at a distinct distance and orientation angle from another pixel, given that pixel has a second particular gray-level. From the SGDM matrices, the texture statistics for each image were generated.

A. Input Data Preparation

Once the feature extraction was complete, two files were obtained. They were: (i) Training texture feature data, and (ii) Test texture feature data. The files had 192 rows each, representing 32 samples from each of the six classes of leaves. Each row had 10 columns representing the 10 texture features extracted for a particular sample image. Each row had a unique number (1, 2, 3, 4, 5 or 6) which represented the class of the particular row of data . '1' represented Early scorch disease infected leaf. '2' represented Cottony mold disease infected leaf. '3' represented Ashen mold disease infected leaf. '4' represented late scorch disease infected leaf. '5' represented tiny whiteness disease infected leaf, and '6' represented normal leaf.

B. Classification Using Neural Network Based on Back Propagation Algorithm:

A software routine was written in MATLAB that would take in **.mat** files representing the training and test data, train the classifier using the 'train files', and then use the 'test file' to perform the classification task on the test data. Consequently, a MatLab routine would load all the data files (training and test data files) and make modifications to the data according to the proposed model chosen.

The architecture of the network used in this study was as follows. The number of hidden layers in the neural network was 10. The number of inputs to the neural network is equal to the number of texture features listed above. The number of output is 6 which is the number of classes representing the 6 diseases (Early scorch, Cottony mold, Ashen mold, late scorch, tiny whiteness) and the normal leafs. The neural network used is the *feed forward back* propagation. The performance function was the Mean Square Error (MSE) and the number of iterations were 10000 and the maximum allowed error was 10^{-5}.

IV. EXPERIMENTAL RESULTS AND OBSERVATIONS

With these parameters, the network was trained. Once the training was complete, the test data for each class of leaves was tested. The results for NN classification strategy that were used are given in table 1.

The results shown in Table 1 were obtained using a NN classifier for five different diseases. The results reported better classification accuracies for all the data models. In particular, model M1 achieved the highest overall classification accuracy. Model M1 achieved an overall accuracy of 89.5 %, Model M2 achieved an overall accuracy of 84.0 % and Model M3 achieved an overall accuracy of 83.66% .

However, it should be noted that models M4 and M5 involve calculation of intensity texture features, which is disadvantageous in terms of computational complexity. Therefore, it is deciphered that model M1 is the overall best model in this classifier. One more advantage of using M1 is the decrease in computational time for training and classification. This is because of the elimination of intensity features and because of the less number of features present in the model.

The recognition rate for NN classification strategy of HS and HSI models for early scorch, cottony mold and normal leaf image were shown in Table 2.

The results shown in Table 1 were obtained using Neural Network based on Back Propagation principle for 10 testing images of the three testing types. In particular, model M1 achieved better overall classification rates than Model M5. Model M1 achieved an overall accuracy of 99.66 % and model M5 an accuracy of 96.66%. However, it should be noted that model M5 involves calculation of intensity texture features as already explained in the above paragraphs. Therefore, model M1 is the overall best model in this classifier.

TABLE 1: PERCENTAGE CLASSIFICATION ACCURACY RESULTS OF THE TEST DATA FROM VARIOUS DISEASES

Model	Color Features	Early scorch	Cottony mold	Ashen mold	Late scorch	Tiny whiteness	Normal	Overall average
M1	HS	95	93	80	83	87	100	89.5
M2	H	89	86	69	79	83	98	84.0
M3	S	88	87	72	80	77	98	83.66
M4	I	89	88	79	81	83	97	86.16
M5	HSI	79	80	70	74	75	100	80.13

TABLE 2. PERCENTAGE CLASSIFICATION ACCURACY RESULTS FOR NEURAL NETWORK USING BACK PROPAGATION

Model	Color Features	Early scorch	Cottony mold	Normal	Overall average
M1	HS	99	100	100	99.66
M5	HSI	93	97	100	96.66

In general, Tables 1 and 2 prove that the results for NN classifier based on statistical classification perform well in both cases, it is not useful in real world applications, since choosing only intensity may be detrimental to the classification task due to inherent intensity variations in an outdoor lighting environment. Hence, model M1 emerges as the best model in classifiers based on statistical classification.

It is evident from Table 1 and 2 that, for models M4 and M5, the classification accuracies for some classes of leaves were inconsistent with the excellent results that were obtained for other models. Similarly, from Tables 4 and 5, the results for neural network classifiers also show some discrepancies in terms of accuracies for some models. In the case of neural network with back propagation as well as with radial basis functions, model M4 (with only intensity features) performs poorly. This can be attributed to the fact that the network did not have enough information (in other words, there was overlapping of data clusters) to make a perfect classification hyperplane to separate the data clusters belonging to various classes of leaves. The intensity of the leaves when considered as a whole may not have incorporated enough information, for the network to make correct classification decisions. This proves the fact that for neural network classifiers using only intensity texture features will not yield good classification. One significant point to be noted in neural network classifiers is that the results may not be consistent across several trials using the same input and parameters. This is because the weight initialization in the network is random. Hence, the outputs vary. The results for neural network classifiers that were shown in this research were the average of outputs (classification accuracies) for three successive trials.

Model M1 emerged as the best model among various models. It was noted earlier, that this was in part because of the elimination of the intensity texture features. Elimination of intensity is advantageous in this study because it nullifies the effect of intensity variations. Moreover, it reduces the computational complexity by foregoing the need to calculate the CCM matrices and texture statistics for the intensity pixel map. However, in an outdoor application, elimination of intensity altogether may have an effect on the classification, since the ambient variability in outdoor lighting is not taken into consideration.

Table 3 shows the number of leaf samples classified into each category for the neural network classifier with back propagation algorithm using model M1.

TABLE 3: CLASSIFICATION RESULTS PER CLASS FOR NEURAL NETWORK WITH BACK PROPAGATION

From species	Early scorch	Cottony mold	Ashen mold	Late scorch	Tiny whiteness	Normal	Accuracy
Early scorch	25	0	0	0	0	1	100
Cottony mold	0	24	0	1	0	0	96
Ashen mold	0	0	25	1	1	1	100
Late scorch	0	0	0	20	1	0	80
Tiny whiteness	0	1	0	1	22	0	88
Normal	0	0	0	2	1	23	92
Average							**92.7**

The results show that a few samples from late scorch and tiny whiteness leaves were misclassified. For the case of Late scorch infected leaves, five test images were misclassified. Two leaf samples were misclassified as belonging to normal leaf class and the others as a Cottony mold, Ashen mold and Tiny whiteness infected leaves. Similarly, in the case of tiny whiteness images, three test images from the class were misclassified as belonging to ashen mold, late scorch and normal classes. In general, it was observed in various trials that misclassifications mainly occurred in four classes; cottony mold, late scorch, tiny whiteness and normal.

V. CONCLUSION AND FUTURE WORK

In this paper an image-processing-based approach is proposed and used for leaf and stem disease detection. We test our program on five diseases which effect on the plants; they are: Early scorch, Cottony mold, ashen mold, late scorch, tiny whiteness.

The proposed approach is image-processing-based. In the first step of the proposed approach, the images at hand are segmented using the K-Means technique, in the second step the segmented images are passed through a pre-trained neural network. As a testbed we use a set of leaf images taken from Al-Ghor area in Jordan.

Our experimental results indicate that the proposed approach can significantly support accurate and automatic detection of leaf diseases. Based on our experiments, the developed Neural Network classifier that is based on statistical classification perform well and can successfully detect and classify the tested diseases with a precision of around 93%.

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