

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor & UGC Approved Journal)

Website: www.ijirset.com

Vol. 6, Issue 8, August 2017

Diseases Identification by GA-SVMs

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ABSTRACT: Agricultural yield is mainly affected by differences in climatic conditions and seasonal diseases. There is a strong need of modern agricultural systems that identify disease in the crops. The goal of this study to design, develop and evaluate GA-SVM based methodology for automatic classification of pomegranate related diseases. This innovative method would be a boon to many and would have lot of advantages over the traditional method of grading. Presently, plant pathologists follow a tedious technique that mainly relies on naked eye prediction. Manual procedure is not only time consuming but also does not give accurate results. Studies show that relying on pure naked-eye observation of experts to detect and classify pomegranate related diseases can be prohibitively expensive, especially in developing countries. This methodology is fast and accurate in detecting diseases like bacterial blight, cercosporal leaf spot and wilt of pomegranate. Present experimental results indicate that the proposed approach can significantly support an accurate and automatic detection and recognition of leaf diseases. Current paper proposes GA-SVM based methodology to deal with one of the main issues of plant pathology. The results are proved to be accurate and satisfactory in contrast to manual procedure and hopefully take a strong leap forward in establishing itself in the market as one of the most efficient and effective process. In conclusion, the proposed detection models based GA-SVM are very efficient in detecting and classifying bacterial blight, cercosporal leaf spot. The developed Genetic Algorithm based SVM classifier that based on statistical classification perform well in all sample types of leaf diseases and can successfully detect and classify the examined diseases with accuracy 94%.

KEYWORDS: Leaf diseases, cercosporal leaf spot, bacterial blight and texture attributes.

I. INTRODUCTION

Plant diseases have turned into a night mare as it can cause significant reduction in both quality and quantity of agricultural products (Weizheng et al., 2008), thus negatively influence the countries that primarily depend on agriculture in its economy. 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 leaves [1].

Monitoring crops for to detecting diseases play a key role in successful cultivation [2]. The naked eye observation of experts is the main approach adopted in practice (Weizheng et al., 2014). However, this requires continuous monitoring of experts which might be prohibitively expensive in large farms [3]. Further, in some developing countries, farmers may have to go long distance to contact experts, this makes consulting experts to very expensive and time consuming. Therefore; looking for a fast, automatic, less expensive and accurate method to detect plant disease cases is of great realistic significance [4, 5, 6, 7].

Studies show that image processing can successfully be used as a disease detection mechanism [8]. Since, the late 1970s, computer-based image processing technology applied in the agricultural engineering research became a common (Weizheng et al., 2008; Moshashai et al., 2015). In this study we propose and experimentally validate the significance of using clustering technique and neural networks (Soltanizadeh and Shahriar, 2010) in automatic detection of leaf diseases.

We test our program on five diseases which effect on the plants; they are: Early scorch, Cottony mold, Ashen mold, late scorch and tiny whiteness. Using the proposed frame work, we could successfully detect and classify the examined diseases with a precision of around 95% on an average. Present experimental results indicate that the proposed approach can significantly support accurate and automatic detection of leaf diseases.

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II. PREPROCESSING

Next we describe our proposal with more details. We also compare it to the other solutions already presented in literature. We select from literature the works that have addressed the topic of plant detection and classification. We test our solution on five diseases which effect on the plants. Those diseases are early scorch, cottony mold, ashen mold, late scorch and tiny whiteness.

The concept of automatic plants leave disease detection presented in the following sections was developed on the plant leaves images acquired from Telangana. Detection and recognition of leaves diseases are likely to give better performance and can provide clues to treat the diseases in its early stages. Visual interpretation of plant diseases in its early stages. Visual interpretation of plant diseases manually is both inefficient and difficult; also, it requires the expertise of trained botanist. A closer inspection of the plant diseases images several difficulties for the possible leaves diseases detection [9,10,11 and 12]

Bauer et al. (2015) the authors have worked on the development of methods for the automatic classification of leaf diseases based on high resolution multispectral and stereo images. Leaves of sugar beet are used for evaluating their approach. Sugar beet leaves may get infected by several diseases, such as rusts (*Uromycesbetae*), powdery mildew (*Erysiphebetae*). The developed system classifies the leafs at hand into infested and not-infested classes. Compared to the work of Bauer et al. (2014), our system can: 1. Identify disease type in addition to disease detection. 2. Be directly expanded to cover even more diseases. 3. Detect diseases that infect plant leaves and stems. Our proposal can identify and classify diseases that infect the stem part part of plants as well. Figure 1 shows an example of such infection cases.



Fig.1.plant stem is infected by white mold disease

Weizheng et al. (2013), a fast and accurate new method is developed based on computer image processing for grading of plant diseases. For that, leaf region was segmented by using otsu method (Sezgin and Sankur, 2016). After that the

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disease spot regions were segmented by using Sobel operator to detect the disease spot edges. Finally, plant diseases are graded by calculating the quotient of disease spot and leaf areas. Our proposal is different as it aims at classifying diseased leaves based on disease type [13,14,15 and 16].

The next step in our proposal is that 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. A device dependent color space is the one where the resultant color depends on the equipment used to produce it. For example the color produced using pixel with a given RGB values will be altered as the brightness and contrast on the display device used. Thus the RGB system is a color space that is dependent. To improve the precision of the diseases detection and classification process, a device independent color space, the coordinates used to specify the color will produce the same color regardless of the device used to draw it.



Fig. 2: An example of the output of GA-SVM for leaf that is infected with early scorch disease

Finally, GA-SVM 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. GA-SVM is designed based on different kernels.

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 space specified in the color transformation structure. The color transformation structure specifies various parameters of the transformation. Finally, GA-SVM 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. GA-SVM uses various kernels [17,18, 19].

GA-SVM is used to partition the leaf image into four clusters in which one or more clusters contain the disease. GA-SVM algorithm tries to classify objects based on a set of features into clusters. The classification is done by minimizing the sum of squares of distances between the objects and the corresponding cluster or class centroid [20].

The method followed for extracting the feature set is called the the color co-occurrence 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 is more detailed.

The image analysis technique selected for this study was the GA-SVM model. The use of color image features in the visible light spectrum provides additional image characteristics features over the traditional gray scale representation.

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The GA-SVM 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 GCM 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. Electromagnetic radiation in the range of wavelength of about 400 to 700 nanometer 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.

III. PROPOSED METHODOLOGY

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 methods are used to classify the images according to the specific problem at hand. This constitutes the overall concept that is the frame work for any vision related algorithm.

The first phase is the image acquisition phase. In this step, the images of the various leaves that are to be classifiers are taken using digital camera. In the second phase image pre-processing is completed. In the third phase, segmentation using GA-SVM 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 GA-SVM.



Fig. 3: Early scorch image

From Fig 3 it is obvious that leaves belonging to early scorch, Fig 4 leaves belonging to whiteness image, healthy image of cotton Fig 5 leaves belonging to Cotton mold image and Fig 6 leaves belonging to ashen mold images. It is obvious that leaves belonging to early scorch, ashen mold and normal classes showed significant difference from greasy spot leaves in terms of color and texture.

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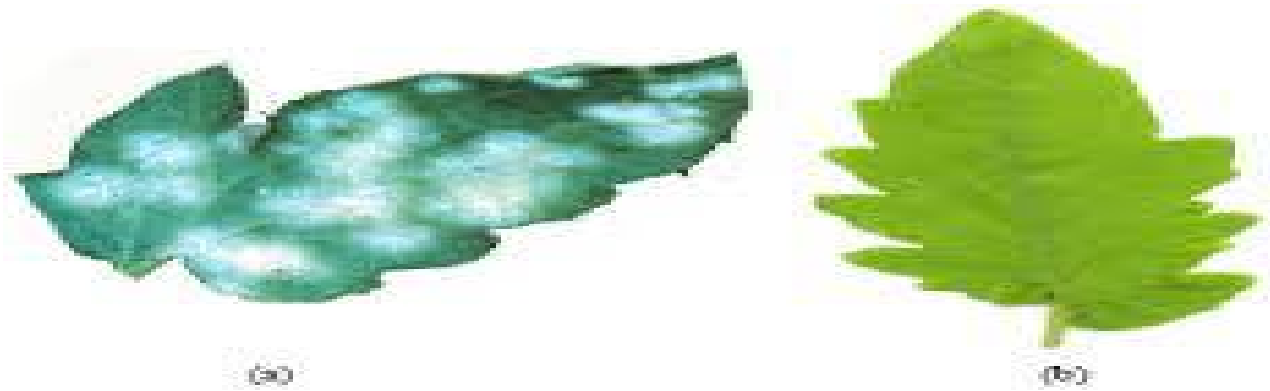


Fig. 4: Tiny whiteness image and healthy leaf



Fig 5: Cotton mold image



Fig 6: Ashen mold image

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The leaves belonging to these three classes had minute differences as discernable 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 GA-SVM algorithm. Once the infected object was determined. The image was then converted from RGB format to HIS 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.

IV. EXPERIMENTAL RESULTS

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

The results shown in Table 1, 2, 3 and 4 were obtained using a GA-SVM 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 85%, model M2 achieved an overall accuracy of 86.0% accuracy and model M3 achieved an overall accuracy of 87%.

However, it should be noted that model 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 texture features and because of the less number of features present in the model. The recognition rate for GA-SVM classification strategy of GA-SVM classification strategy of HS and HIS models for early scorch, cottony mold and normal leaf images were shown in Table 2. It is evident from Table 1 and Table 2 that, for models M4 and M5, the classification accuracies for

SVM CLASSIFIER1						
TEST	1	2	3	4	5	6
1	1228	340	0	0	0	84%
2	562	1000	0	0	1	72
3	0	0	1200	170	0	64%
4	0	0	25	1000	300	66%
5	11	16	0	69	100	66%

Table 1. Classification results per class for GA- SVM with others

SVM CLASSIFIER2						
TEST	1	2	3	4	5	6
1	1228	340	0	0	0	84%
2	562	1000	0	0	1	72
3	0	0	1200	170	0	64%
4	0	0	25	1000	300	66%
5	11	16	0	69	100	66%

Table 2. Classification results per class for GA- SVM with others

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SVM CLASSIFIER3						
TEST	1	2	3	4	5	6
1	1348	450	0	0	0	74%
2	662	1100	0	0	1	73%
3	0	0	1300	1170	0	74%
4	0	0	25	1100	320	76%
5	136	165	0	609	100	76%

Table 3. Classification results per class for GA- SVM with others

1-Early scorch, 2-Cottony mold, 3-Aahen mold, 4-Later scorch and 5-Tiny Whiteness.

SVM CLASSIFIER 4						
TEST	1	2	3	4	5	6
1	1228	340	0	0	0	84%
2	562	1000	0	0	1	72
3	0	0	1200	170	0	64%
4	0	0	25	1000	300	66%
5	11	16	0	69	100	66%

Table 4. Classification results per class for GA- SVM with others

1-Early scorch, 2-Cottony mold, 3-Aahen mold, 4-Later scorch and 5-Tiny Whiteness.

Model M1 emerged as the best model among various models because of elimination of 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 GA matrices and texture statistics for the intensity pixel map. However, in out door 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 GA classifier with support vector machine algorithm using model M1. 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 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.

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GA-SVM		Early scorch	Cotton mold	Ashen mold
	SVM	0.73	0.45	0.654
SVM+RIM	0.89	0.92	0.89	
GA-SVM		Early scorch	Cotton mold	Ashen mold
	SVM-1	0.415	0.538	0.5317
	SVM-2	0.335	0.3223	0.473
	RIM+SVM Linear	0.92	0.92	0.97
	RIM+SVM RBF	0.93	0.94	0.98
RIM+SVM Poly	0.92	0.93	0.93	
DC-SVM		Early scorch	Cotton mold	Ashen mold
	SVM-1	0.5285	0.538	0.531
	RIM+SVM	0.92	0.91	0.92
CV-SVM		Early scorch	Cotton mold	Ashen mold
	SVM-1	0.527	0.5376	0.5337
	RIM+SVM	0.475	0.473	0.5872
GA-SVM		Early scorch	Cotton mold	Ashen mold
	SVM-1	0.93	0.86	0.91
	RIM+SVM	0.96	0.98	0.99

Table 5. Classification results per class for GA-SVM with other SVM

V. CONCLUSION

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

The proposed approach is image-processing-based and is highly based on GA-SVM. Present experimental results indicate that the proposed approach is valuable approach and can significantly support accurate and automatic detection of leaf diseases. Based on our experiments, the developed GA-SVM classifier that is based on statistical classification

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perform well and can successfully detect and classify the tested diseases with a precision of around 94%. For future research, they have been some directions, such as, developing better segmentation technique; selecting better feature extraction and culling classification algorithms.

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