Random Forest based Classification of Diseases in Grapes from Images Captured in Uncontrolled Environments

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***Abstract*—Grapes have proved to be one of the most cost-effective and profitable crops for cultivation in India. This crop however is affected by numerous diseases which cause significant yield losses every year. Early detection of diseases and proper identification of their severity will help to take decisions on proper usage of pesticides in terms of their type and quantity, which eventually will help in maintaining the crop health. In this work, we propose a system for classifying three diseases affecting grapes – Anthracnose, Powdery Mildew and Downy Mildew – and identifying the severity of these diseases using image processing and machine learning algorithms. The key contribution of the proposed system is to consider images of grapes leaves with complex background which are captured under an uncontrolled environment. We compare the performance of four machine learning algorithms, PNN, BPNN, SVM and Random Forest, for separating the background from disease patches and classifying between the different diseases. We also study the performance of different texture features like local texture filters, local binary patterns (LBP), GLCM features, and some statistical features in RGB plane for classification. The proposed system achieves best classification accuracy of 86% using Random Forest and GLCM features.**

I. Introduction

Grapes is a popular fruit in India. While they are grown world-wide for making wines and raisins, they are mainly consumed as fresh fruits in India. Grapes also posses several health benefits due to their high nutrients content and can be used as natural remedies for several health problems. Due to their extensive use and benefits, and ease of growing in variable climatic conditions, cultivation of grapes has proved to be very profitable [1]. According to a report of 2006 from ICAR (Indian Council of Agricultural Research) [2], India was the 13th largest grapes producing country in the world, contributing to around 2.24% of world's grapes production. This report also presents an increasing trend of grapes production in the country in the years 1991-2006. This crop however is very susceptible to different diseases which have caused significant yield losses during this time. Though the disease severity varies from year to year, early and proper identification of diseases has proved to be a key factor for preventing high yield losses and maintaining quality of the crop through proper usage of pesticide. Proper disease-identification becomes difficult because of (a) similar symptoms of different diseases, (b) different symptoms for a single disease at different stages of the crop, and (c) presence of different diseases at the same time [3]. So, a reliable and automatic method is required to avoid subjective errors in disease identification. We have mainly focused on three fungal diseases in grapes causing devastating yield losses in most of the years. These are Anthracnose, Powdery Mildew and Downy Mildew. Fungus, *Elsinoe ampelina*, which causes Anthracnose creates small round light brown or greyish black spots on the leaves at an early stage and gradually causes small holes on the leaves [1], [3]. Downy Mildew, caused by fungus *Plasmopara viticola*, is the most destructive disease of grapes in the tropical climatic region of India. This mainly attacks leaves of the plant while sometimes it can affect the flower clusters and young fruits causing severe losses. This fungus causes a yellowish round shaped discolouration on the leaves. At an early stage of the disease, white sporulation can be found at the lower surface of the leaves which turns into yellow or brown spot with time [3]. Powdery Mildew, which is caused by *Erysiphe necator*, creates a powdery like texture on both surfaces of the leaf.

The objectives of the work presented in this paper are:

- To propose a system for receiving images captured under uncontrolled environments with different camera-angles, distances and lighting conditions.
- To develop an algorithm to classify between Anthracnose, Downy Mildew and Powdery Mildew using ensemble of randomized decision trees.
- To study the performance of Random Forest method in comparison to other machine learning approaches like PNN, BPNN, SVM for grapes disease classification.
- To study performance of Local texture filters, local binary patterns compared to GLCM features for grapes disease classification.

We envision to integrate this image processing based automated disease detection module with our existing mKRISHI® agro advisory platform [4] to simplify the work of agricultural experts in providing personalized advisories to the farmers on the usage of pesticides. We also envision the use of this automated detection of diseases with the mKrishi pest-and-disease forecasting module to automatically validate the model outcome with actual scenario of disease occurrences. This

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will help the model to adapt with the actual observations on disease incidences automatically and will improve the model performance gradually. Further, as we consider images captured under an uncontrolled environment, it does not need any special training for the farmers and makes it easier for them to report events using a participatory sensing platform [5], [6].

II. Literature Survey

Image processing techniques in agriculture are broadly extending their applications for disease diagnosis for different crops in an accurate and time efficient way [7], [8]. Sankaran et al.[7] have presented a review of different spectroscopic and imaging techniques currently being used for detecting plant diseases and monitoring plant health. They highlight in this paper (a) fluorescence and hyper-spectral imaging techniques, and (b) different spectroscopic techniques in visible, infra-red, fluorescence and multi-spectral bands for plant disease or stress detection. Barbedo et al.[8] discuss different techniques adopted for detecting, quantifying and classifying diseases or pests mostly affecting stems and leaves of a wide range of crops from the visible band digital images. This survey reveals that one of the challenge of the existing image processing tools for disease detection to be adopted in real time applications is that the algorithms are mainly developed on images which are captured under a particular condition of lighting, with a specific angle of capture and at a particular distance of the image capturing device from the object.

In recent years, some research has gone into plant disease identification considering images captured under uncontrolled environment. Sannakki et al.[9] proposed an algorithm for identification of Downy Mildew and Powdery Mildew affected portion of the leaves while images considered in the study were captured with complex background. Lloret et al. [10] developed a system for capturing the status of health of the plants in a grape vineyard by analysing the images captured with a number of webcams for detecting and quantifying diseased plants. Wang et al. [11] proposed an image processing and neural network based algorithm to classify between Powdery and Downy Mildew diseases of grapes. In this paper, performance of different machine learning approaches like Back Propagation Neural Network, Generalized Regression, Probabilistic and Radial Basis Function Neural Network have been compared.

Our aim is to develop an algorithm to detect and classify between different leaf diseases in grapes while the images considered for the study are captured under uncontrolled environment with complex background. Disease considered in this study are Anthracnose, Powdery Mildew and Downy Mildew. The main contribution of this paper is use of Random Forest classification algorithm using GLCM features for separating disease patches from background and classifying between different disease patches.

III. Disease Detection and Severity Identification Algorithm

A. Data Collection

For this study, 900 images of disease infected grapes leaves were acquired by the farmers and field workers from the fields of Dindori in Nashik district, located in Maharashtra, India. Images were captured using mobile phone cameras with varying resolution starting from less than 1 megapixel to 13 megapixel. Images of single leaf or bunch of leaves captured with background from different distances and at different angles have been considered for this study. The images are of grapes leaves affected by different diseases like Antharcnose, Powdery Mildew and Downy Mildew. For many cases, the leaves were affected by more than one kind of diseases. Keeping this in view, we propose an algorithm that detects if more than one disease is present in a leaf. It also calculates the area of the total leaf that is affected by each of these diseases.

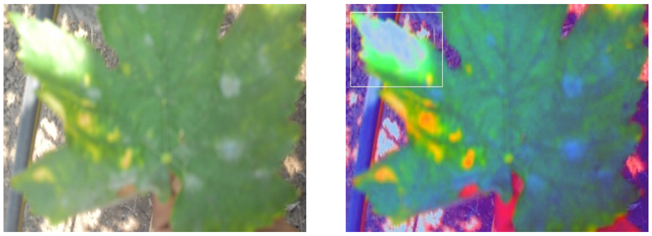
B. Stages of Processing

The proposed disease detection algorithm consists of several processing steps which are mainly divided into four stages: (a) Pre-processing of the input images, (b) Leaf extraction from the background, (c) Disease patch identification and (d) Background removal.

1) Pre-processing: To identify the disease infected patches on the leaf from the input images f, the algorithm first extracts the leaf from the background. Before this, the input images are taken through some processing steps which enable easier and faster evaluation of the algorithm and also significantly increase its reliability. For faster evaluation of the algorithm, the input images of higher resolution are resized to a size of 300 x 500.

Enhancement of Image: It has been shown that Decorrelation Stretching is a useful tool for highlighting the color differences between different segments in an image [12]. In this study, the resized images are enhanced by the Decorrelation Stretching technique followed by contrast stretching to enhance the color differences between healthy and disease-affected segments of the leaves and among different disease patches as well. It shows very distinctive color characteristics for different disease affected areas of the leaves in enhanced images.

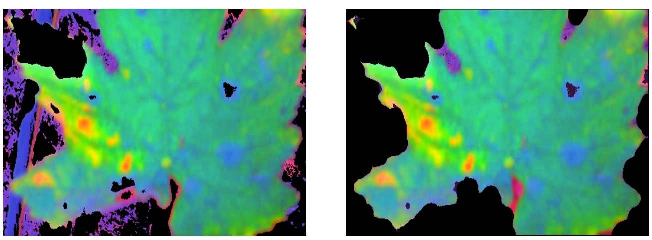
Removal of sun spots from the image: As the images are captured under uncontrolled environment, many images contain sun spots on the leaves. Fig. 1(b) shows area with sun spot (within white box) after enhancement of the image, which can be misrecognized as the powdery mildew disease in further processing steps because of almost similar color characteristics. Since sun spots usually shows higher intensity values than that of powdery mildew, they can be easily removed from the input image by applying a global threshold of value higher than that of intensity values of the diseased areas of leaf. Sun spots are removed using a threshold value of 150, where pixels having gray level intensity value below 150 are retained for further processing.



(a) (b)

Fig. 1: Effect of sunspots (within white box) after decorrelation stretching. (a) Original image, (b) Image after color enhancement.

2) Leaf Extraction – Masking the green pixels: After removing the sun spots, the leaves are separated from the background using color thresholding and image filling. First a global threshold has been applied on the green channel of enhanced RGB image. The pixels for which the green component has higher value than the threshold, are retained for further processing. Then a second level of thresholding has been applied on the resultant image to extract the leaf image f_L as:



(a) (b)

Fig. 2: Leaf Extraction from preprocessed image. (a) Enhanced image after sun spot removal, (b) Extracted leaf after thresholding and image filling.

$$f_L(x,y) = \begin{cases} 1 & \text{if } f_G(x,y) > \frac{f_R(x,y)+f_B(x,y)}{2} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

at each coordinate (x, y). $f_R(x, y)$, $f_G(x, y)$ and $f_B(x, y)$ are R, G, B values of preprocessed image f at coordinate (x, y). This segmentation technique removes the diseased portion of the leaf as disease affected portion of the leaf shows different color characteristics than that of the healthy portions. Then image filling [13] has been applied on binary mask of the segmented leaf part to retrieve the diseased portions of the leaf. Fig. 2(b) shows extracted leaf from enhanced image using thresholding and image filling.

3) Disease patch detection: Each disease in grapes has distinct colour characteristics. Powdery Mildew creates whitish or bluish powdery kind of patches while downy mildew creates yellow patches on the leaf. The enhanced image of extracted leaf is converted into HSV color space and upper and lower thresholds are applied on H-plane to extract the disease patches. Threshold ranges used for Powdery Mildew and Downy Mildew are $127 - 240$ and $40 - 85$ respectively. For Anthracnose, the pixel having value ≤ 30 or ≥ 250 are considered for further processing as it creates brown patches on the leaves.

4) Background removal: Fig. 3 shows initial ROIs (3(d)–(f)) selected using color thresholding on leaf images. Fig. 3(a) is an example of leaf affected by Powdery Mildew and Downy Mildew both and Fig. 3(b) shows an example of an Anthracnose-affected leaf. Colour thresholding sometimes includes backgrounds as well, due to similar color characteristics with the disease affected leaves. Also use of image filling during leaf extraction sometimes captures background in case of a bunch of leaves (Fig. 3(c),(f)). So, further classification algorithms are used to categorize the selected ROIs into four classes: Background, Anthracnose, Downy Mildew and Powdery Mildew affected leaf segments. These algorithms are discussed in Sec. III-C.

The randomness or coarseness in the soil is higher than that of leaf. Also, the presence of veins in leaves show a specific pattern in texture than that of the background. Various local features have been used to capture these texture differences between the ROIs of different classes. Features used in this study are presented in the following section. Performance of different features have been compared in the study.

Local Statistical filters: Each ROI is given as an input to the machine learning tools to classify it as one of the four classes. All the features mentioned in this section have been extracted from H-plane of HSV color space. To capture the local variability and local randomness of the ROIs three local filters [14] have been used which measure statistical features, such as standard deviation, entropy and range of the intensity values within a defined mask h of size $m \times n$. Local filters return image g of same size as that of the input image. The value at (x, y) in the output images for standard deviation, entropy and range filters are calculated as,

$$g(x,y) = \sqrt{\sum_{i=0}^{L-1} (z_i - m)^2 p(z_i)} \quad (2)$$

$$g(x,y) = -\sum_{i=0}^{L-1} p(z_i) log_2 p(z_i) \quad (3)$$

$$g(x,y) = max(z_i) - min(z_i), for\ \{z_i | p(z_i) > 0\} \quad (4)$$

respectively, where, $p(z_i), i = 0, 1, 2..L-1$ is the corresponding histogram with L number of distinct intensity levels z_i within the local region defined by mask h. In this study, mask of size 7×7 has been used for standard deviation and range filters and 9×9 has been used for entropy filter. Some statistical features like mean, standard deviation, range and histogram of filtered images normalized at 1-8 scale have been used as features for classification.

Rotation Invariant Local Binary Pattern: Local Binary Pattern proposed by Ojala et al. [15] shows a wide application in various fields of image analysis because of its low computational complexity, efficiency in capturing fine

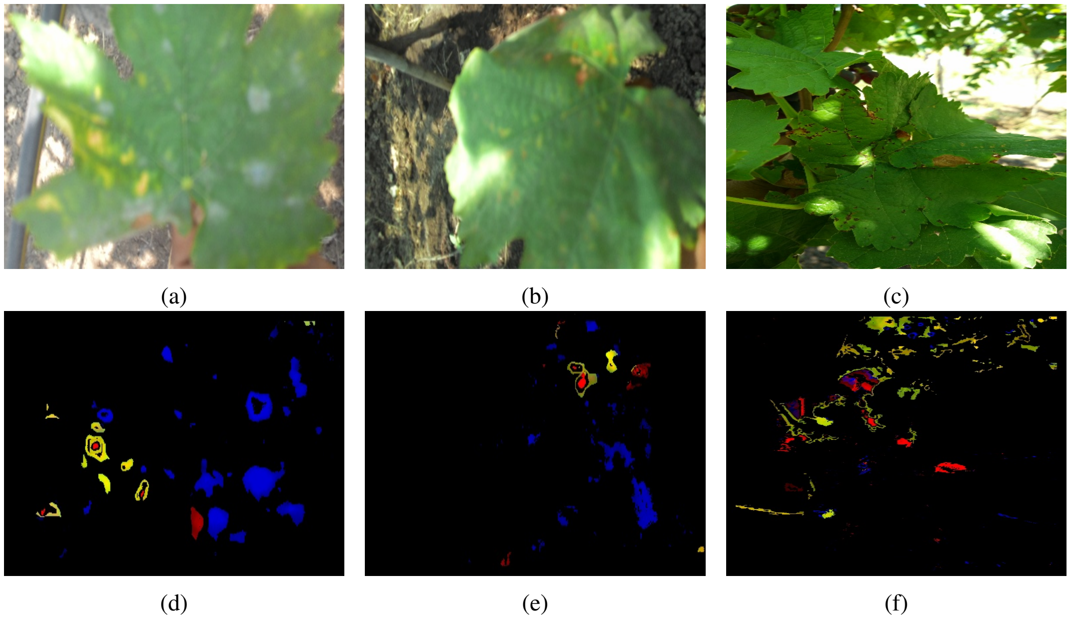


Fig. 3: Example for initial ROI selection using color thresholding.

details of image and robustness to lighting changes [16]. In recent years, many variants of LBP descriptors [17], [18], [19], [20] have been proposed. In this study performance of rotation invariant texture descriptor LBP-HF [21] has been explored for classification of the ROIs. LBP-HF are extracted from non-invariant LBP histogram calculated over the whole region of interest. LBP pattern at pixel $f(x,y)$ for circular neighbourhood (P,R) with P number of neighbours each represented as $f(x_p,y_p)$ at R radius is given by,

$$LBP_{P,R}(x,y) = \sum_{p=0}^{P-1} s(f(x,y) - f(x_p,y_p))2^p \tag{5}$$

Where,

$$s(z) = \begin{cases} 1 : z \geq 0 \\ 0 : otherwise \end{cases} \tag{6}$$

In LBP-HF, coefficients of Discrete Fourier Transform of histogram of uniform LBP patterns are considered as texture descriptors. LBP patterns with 2-spatial transitions of bit 0-1 are considered as uniform LBP patterns. The features used in this study are absolute value of DFT magnitudes, where $H(n,.)$ being the DFT of n^{th} row of the histogram $h_I(U_P^{n,r})$,

$$H(n,u) = |\sum_{r=0}^{P-1} h_I(U_P^{n,r}) e^{-i2\pi nr/P}| \tag{7}$$

for $u = (1,2,...P-1)$. $h_I(U_P^{n,r})$ is the histogram of uniform patterns $U_P^{n,r}$ with n as total number of 1s in the pattern and r as the rotation of the pattern.

GLCM Features: GLCM [14] texture features demonstrates its wide application in many research areas [22], [23], [24]. In agricultural domain, GLCM features perform well in detection of different diseases in fruits or leaves [25], [26]. GLCM matrix of rows and columns equals to the number of gray levels (L) of the input image represents the statistical distribution of different combinations of intensity values in the image. Each element $P(i,j|d,\theta)$ of the matrix denotes how often gray level j occurs at a given distance d and at an angle (θ) with respect to gray level i. Five GLCM features used in this study are [14], [27]:

$$Contrast = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}(i-j)^2 P(i,j) \tag{8}$$

$$Homogeneity = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\frac{P(i,j)}{1+|i-j|} \tag{9}$$

$$Energy = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}P(i,j)^2 \tag{10}$$

$$Entropy = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}P(i,j)log(P(i,j)) \tag{11}$$

$$Variance = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}(i-\mu)^2 P(i,j) \tag{12}$$

C. Classification of ROIs

Features extracted in the previous section are used to train various classification tools for disease detection such as Artificial Neural Network, Support Vector Machine and Random Forest. We have done a comparative study between performance of Random Forest, proposed by Leo Breiman [28] with other machine learning methods. Random Forest shows wide application in many regression [29], [30] and classification [31], [32] problems in image processing. In this paper, we study its performance for extraction of the disease affected leaves from the background and classification between different diseases.

Application of Random Forest: Random forest is an ensemble of decision trees, where each tree is trained with N training samples randomly selected from a training set of N samples with replacement. In this study, we have a set of training ROIs $\{\mathcal{R}_i = (\mathbf{x}_i, c_i)\}_{i=1}^{N}$ which are randomly sampled to form each decision tree. $\mathbf{x}_i = \{x_{1i}, x_{2i}, ..x_{pi}\}$ are p number of image features extracted from each ROI, as mentioned in the previous section. $c_i = \{0, 1, ..C - 1\}$ are the class labels which represents background or leaf areas affected by Athracnose, Powdery Mildew or Downy Mildew. Each tree in the ensemble is trained as follows:

- At each node of the tree, best split feature is identified from a set of features $\phi = \{\phi_k\}$, with $k = \{0, 1, ..K - 1\}$. ϕ is randomly selected from the entire feature set. Number of features K in set ϕ is defined as the number for which the system attains least OOB error rate maintaining a trade off between correlation between the trees and strength of each tree [28].
- In the classification phase, each new test sample $\mathbf{x}_i$ is traversed down through each of the N trees. Each tree assigns the sample to a particular class $\hat{c}_i \in \{0, 1, ..C - 1\}$. The sample is assigned to the class which is predicted by majority of the trees.

		Local	LBP	GLCM	Local & GLCM	LBP & GLCM	All
PNN	Sens.	0.577	0.285	0.815	0.684	0.815	0.488
	Spec.	0.856	0.768	0.948	0.909	0.948	0.843
	Acc.	0.586	0.378	0.858	0.753	0.858	0.581
BPNN	Sens.	0.573	0.518	0.693	0.700	0.715	0.751
	Spec.	0.862	0.850	0.882	0.889	0.897	0.913
	Acc.	0.602	0.576	0.665	0.685	0.708	0.756
SVM	Sens.	0.444	0.381	0.714	0.389	0.377	0.279
	Spec.	0.830	0.807	0.894	0.810	0.805	0.763
	Acc.	0.499	0.428	0.703	0.433	0.418	0.287
RF	Sens.	0.713	0.723	0.875	0.786	0.815	0.844
	Spec.	0.912	0.904	0.950	0.915	0.932	0.939
	Acc.	0.751	0.756	0.860	0.759	0.808	0.829

**Sens.=Sensitivity, Spec.=Specificity, Acc.=Accuracy*

TABLE I: Classification performances of different machine learning approaches (1) Probabilistic Neural Network, (2) Back Propagation Neural Network, (3) Support Vector Machine, (4) Random Forest using different image features.

IV. Results and Discussion

Table I gives the performance of different feature sets in the classification of the ROIs associated with the images obtained from Nashik (Sec. III-A). We show the performance of Random Forest ensemble method with machine learning approaches like Probabilistic Neural Network (PNN) [33], [34], Support Vector Machine (SVM) [35], [36], [37] and Back Propagation Neural Network (BPNN) [34], [37], broadly used for plant disease detection and classification. The average sensitivity, specificity and accuracy over all four classes and 50 iterations for all the different machine learning approaches and different features is also reported.

Results show Random Forest performs better than the other approaches with best classification accuracy 86%. It consistently gives better prediction accuracy for all kind of features used in this study. PNN, BPNN and SVM show poor performances for certain features with very low sensitivity causing large number of mis-classification of disease affected patches or ROIs as background. In case of PNN sensitivity varies between 28.5% to 81.5% for different features, while BPNN and SVM attain a maximum sensitivity of 72.2% and 76.5% respectively. Random Forest shows better classification performance with sensitivity ranging between 71.3% to 87.5% and specificity between 90.4% to 95%. Comparison between different feature sets shows that GLCM performs better than other features for all the machine learning approaches. Local Binary Patterns and Local features show poor sensitivity for classification with values ranging between 28.5% to 72.3% and 57.7% to 71.3% respectively.

Statistical features extracted from R, G, B planes also show good classification accuracy. Table II shows the performance of Random Forest in finding each of the classes using GLCM features.

	c = 0	c = 1	c = 2	c = 3
Sensitivity	0.758	0.954	0.930	0.858
Specificity	0.908	0.990	0.955	0.944

TABLE II: Performance of Random Forest in classifying each of the classes using GLCM features. c = 0 represents ROIs as background and c = 1,2 and 3 represents ROIs affected by Anthracnose, Powdery Mildew and Downy Mildew respectively

Imagica – An online image-based feature recognition system

We have developed a system called *Imagica* to enable image-processing services for agricultural applications. To achieve this, *Imagica* encodes a number of image processing algorithms to address diverse requirements ranging from cleansing - such as identifying a leaf in a random background - to identification of specific features such as detecting a disease within a leaf and assessing its severity. *Imagica* has a generic and flexible RESTful web-service interface to accept raw images and return processed images which allows it to render image processing capabilities to a larger system. The algorithm discussed above is being included as part of *Imagica*'s offerings to allow it to produce results in live scenarios where disease images are streamed from different locations through a variety image-acquisition sources. This would help create impact of the work at scale.

V. Conclusion

In this paper Random Forest algorithm has been proposed for detection and classification of different grapes diseases like Anthracnose, Powdery Mildew and Downy Mildew, from images collected under uncontrolled environment with random background. The algorithm first extracts some initial ROIs from the input images, which are classified as background or leaf area affected by above mentioned diseases using Random Forest algorithm. Performance of Random Forest algorithm has been compared with different machine learning approaches. Performance of different texture features have also been studied. Random Forest achieves best classification accuracy for GLCM features for background separation and disease classification.

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