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Grape Leaves Pathogens Detection using Image Processing Techniques: A Review

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ABSTRACT: Plant pathogens result in significant losses in terms of agricultural product output, economics, quality, and quantity. Pathogens must be controlled because agrarian yields account for 70% of the Indian economy. To prevent infections, plants must be watched since the very beginning of their life cycle. The typical technique of monitoring is naked eye inspection, which is time-consuming, costly, and requires a great deal of knowledge. So, in order to expedite this process, the disease monitoring system must be automated. Image processing techniques can be used to design the illness detection system. Many researchers have created systems based on various image processing approaches. This paper examines the prospects of methods for detecting the disease in grape leaves in order to aid agricultural progress. Image acquisition, image segmentation, feature extraction, and classification are just a few of the phases that are examined in this work.

KEYWORDS: Plant pathogens, Image Processing techniques, Image Acquisition, Image Segmentation, Feature Extraction, Classification

I. INTRODUCTION

India is an agriculture relied country, with agriculture contributing to the biggest economic sector and playing a critical part in the country's socio-economic development, with over 60% of the population relying on it for employment. It also contributes significantly to the Indian economy, accounting for 19.9% of the country's overall GDP [1]. India is one of the world's leading producers of fruits and vegetables. To fulfil the requirements of a huge and rising population, modern agriculture currently aims to produce the maximum amount of output with the least amount of resources, energy, and time. India is one of the world's top ten grape-producing countries. Italy, France, Spain, the United States, Turkey, China, and Argentina are also present among the top grape producers. With an output of 1.21 million tons from 0.05 million hectares, the grape crop ranks fifth among India's fruit crops. India exports over 54,000 tons of grapes worth at 10,000 US dollars, accounting for nearly 1.45% of global grape exports. Grapes are a popular fruit of India, but because of the disease on the grape vine, roughly 10% to 30% of the grapes are lost [2]. Grapes, which are used to manufacture wines and raisins, are one of India's most commercially productive crops. Maharashtra, trailed by Karnataka and Tamil Nadu, are the major contributors to grape cultivation in India, accounting for over 80% of total viticulture [3]. Grape plant pathogens, on the other hand, have a negative influence on the quality and cause a considerable difference in productivity, resulting in a significant deficit for farmers and a negative impact on the economics and wellness. To avoid this, a reliable method for detecting illnesses early is essential.

Downy mildew, powdery mildew, and anthracnose (shown in Figure 1) can cause significant yield loss in grapevine. Especially when downy mildew attacks the clusters before fruit set, the losses are significant. The entire cluster decomposes, dries out, and falls apart. According to a study, even with the use of pesticides and other disease-prevention strategies, infections cause over 45 percent of crop loss each year. Even today, traditionally used skilled examination with the bare eyes is the most common method that is in practice for detecting and identifying these plant pathogens. In big farms, this method is extremely expensive mostly incorrect and time intensive [4]. To maintain the rate of development of the grape, timely diagnosis of diseases in grape leaves and correct inhibition of the proliferation of certain diseases are critical. To address the challenges, researchers have developed a variety of image processing and machine learning-based approaches with varying results and efficiencies.

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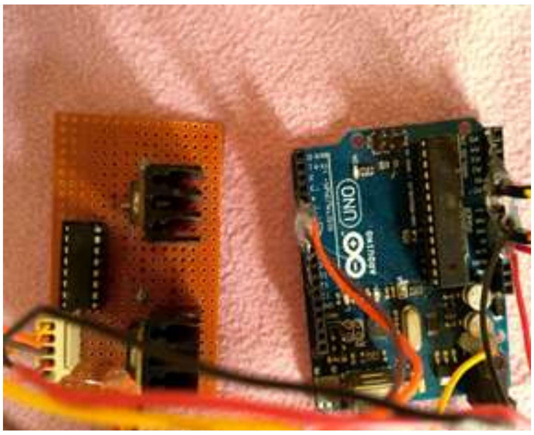
(a) (b) (c)

Figure 1: Common diseases in Grape leaves (a) Downy Mildew (b) Powdery Mildew (c) Anthracnose

II. RELATED WORK



Several studies have suggested image-processing and pattern recognition approaches for precision agriculture such as weed identification in a field, vegetables and fruit sorting, disease monitoring and diagnosis, and so on. Automatic plant pathogens detection is an important area of study because it might help track vast fields of crops and recognize physiological changes as soon as they occur on vegetation. As a result, finding a quick, low-cost, and effective way to detect phytopathogens cases is critical. Extensive chemical that is used to combat plant diseases raises expenses and escalates the risk of hazardous residues on farm produce. This necessitates a precise diagnosis of the disease as well as the stage of the disease. As a result, a model for disease detection and diagnosis that is efficient and economical is necessary.

Cotton Leaf Disease Identification Using Pattern Recognition Techniques was proposed by P. R. Rothe et al. [5] who employed snake segmentation and Hu's moments as a unique property. The back propagation neural network (BPNN) classification technique addressed the various subclass difficulties using an active contour model to restrict the vitality within the infectious area. The average categorization rate was discovered to be 85.52 percent.

Aakanksha Rastogi et al. [6] proposed the disease detection and grading technique in leaves using the CAD and Fuzzy logics. The defective region was segmented using K-means cluster analysis, texture features were extracted using Gray Level Co-occurrence Matrix (GLCM), and illness scoring was done using fuzzy logic. Investigators used an artificial neural network (ANN) as a classification approach, which primarily aids in determining the degree of damaged leaves.

Al Bashish et al. [7] suggested a method for CAD based plant stem and leaf disease detection. The following steps constitute the created methodology, which is predicated on image processing: The data is first segmented using the k-means approach, and then the segments are sent through a trained neural network. The suggested technique accurately and reliably diagnoses leaf diseases, according to the final results.

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Camargo et al. [8] have proposed an approach for employing image processing to identify the sick zone of plants. The image is acquired first, and then the color change is applied. The improvements of the modified images are done using the Gaussian filter. The region of interest is then determined by segmentation. The sectors are split by determining the most appropriate threshold. The separated sections are then categorized and classified as unhealthy or healthy by employing the SVM classifier.

A.Meunkaewjinda et al. [9] developed a hybrid expert system for pathogen detection in grapes, wherein the diseases in leaf tissue were assessed by measuring the ratio of infected region and leaf area. They employed self-organizing mapping BPNN to recognize the color of the grape leaves, which were then used to segregate the grape leaf pixels within the whole image. Following that, illness segmentation is carried out. The segmented image was then filtered with a Gabor wavelet to examine the leaf's color properties. Then after, support vector machines were used to classify the many diseases that affect grape leaves. The Segmentation in this method was adequate, but it had the drawback of being unable to recover ambiguous color pixels from the image's backdrop. There was an uncertainty in knowing how to properly and accurately build an arbitrary mapping technique when using a back propagation neural network.

Al-Hiary et al. [10] have proposed a research study in which they describe an algorithm for detecting and classifying plant illnesses quickly and accurately. The RGB pictures are acquired first by the algorithm. Color transformation is applied to RGB visuals in the next stage. K-means clustering algorithms are then used to classify the images. Gray Level Co-occurrence Matrix is used to extract texture information from a segmented region (GLCM). A neural network is used to classify data. This approach has a 94 percent accuracy rate.

Camargo et al. [11] devised an approach for employing image processing technique to determine plant illnesses. The captured image is first transformed into a color image. After that, the photos are improved with a Gaussian filter. On this altered image, segmentation was carried out in an attempt to isolate the diseased regions by determining the best threshold. The unhealthy regions are then designated on the segmented regions. From the region of interest, different properties such as geometry, texture, grey level, irregular dimension, and distribution of frequencies were collected. The assessment was performed using seven-fold cross validation. The cumulative accuracy of the Support Vector Machine (SVM) employed for classification is 93.1 percent when usable features are included.

Dheeb Al Bashish et al. [12] presented a framework for assessing plant pathogens on the leaves and stems. The suggested work uses the K-Means segmentation approach and uses a neural network to classify the selected features. The classification performance was 93 percent on average.

Wang et al. [13] suggested a principal component analysis and backpropagation networks-based grape disease identification technique. Grape downy mildew and grape powdery mildew are among the diseases in the dataset, and the prediction accuracy was up to 94.29 percent.

Lu J. et al. [14] suggested an in-field wheat disease diagnosis method, which was later integrated as a smartphone app to aid crop diagnostic accuracy. They achieved overall recognition accuracy rate of 97.95 and 95.12 percent, respectively, by adopting two separate architectures, VGG-FCN-VF16 and VGG-FCN-S.

Anthracnose, downy mildew, brown spot, black rot, mites, and leaf blight are six major forms of grape leaf diseases. Liu B et al. [15] suggested an improved convolution neural network-based approach to diagnosis these six types of pathogens. Here they have used a deep decomposed convolution rather than a regular convolution to reduce the number of variables and the Models over-compliance problem. 4023 pictures were taken on the field. 3,646 photos were obtained from public data sets, resulting in overall data set of 107,366 grape leaf images developed by image enhancement algorithms. An inception framework is used to improve the performance of multi-dimensional feature retrieval. To create the first two convolutional layers, a new DICNN model was developed from the ground up and trained. The coefficients of the two convolution layers were lowered in these two layers, which decreased consumption of resources and improved productivity. Relative to those other typical convolutional models, there was a 0.13 percent gain in performance. In comparison to ResNet and GoogLeNet, they attained a precision of 97.22 percent on the test set and provided improved accuracy.

Since the categorization of grape leaf disorders was not up to par, K. Thet et al. [16] set out to address the inadequacy of using the VGG16 Network. As a result, they demonstrated a transfer learning strategy based on upgrading the VGG16 network, a CNN architecture. This technique distinguished healthy leaves from leaves infected with five prevalent grape leaf diseases, including anthracnose, downy mildew, black measles, and others. Myanmar Grapevine Yard provided the data set, which included 6000 photographs. The Global Average Pooling (GAP) layer has been used in place of VGG16's two totally associated layers just before final classification Soft Max layer to increase the accuracy of fine-tuning VGG16 for grapes. When matched to other systems such as VGG16, SVM classifier, and VGG16 fully connected layers, the proposed system outperformed them with 98.4 percent accuracy.

P. Amudala et al. [17] proposed using a United Model to combine multiple CNNs to retrieve relevant discriminating properties. The plant village dataset was used to validate this model. They created a mobile app that could detect and discriminate illness symptoms on plant leaves. The CNN architecture is based on Inception V3, which was utilized by ResNet50 to divide grape leaf diseases into four categories: esca, Arabidopsis leaf mark, black rot, and safe images. The proposed model had a 99.17 percent mean validation accuracy and a 98.57 percent test exactness.

The multi-class SVM is employed as a classifier in the work proposed by Nitish Agarwal et al. [18], and the RGB signal is transformed into LGB form for feature extraction. To save memory and save processing time, image pre-processing involves shrinking, enhancing, and smoothing the image. For image segmentation, the letter K denotes clustering. In evaluating the Black rot, a maximum of 90% accuracy was achieved.

Harshal Waghmare et al. [19] presented a study in which 120 photos were acquired straight from farms using a mobile camera. The accuracy of several approaches such as SVM, BPN, and fuzzy was compared, and then SVM was applied. The image was scaled to 226 × 226 pixels during image preparation. HSV color space has been used to transform RGB images. Background subtraction was used to remove distracting elements from the image and focus on the leaf region. The average level of accuracy was 89.3 percent.

Changjian Zhou, et.al [20] has proposed a new grape leaf spot recognition approach that uses fine-grained data from the local region.

The chosen strategy concentrated on the characteristics of the leaf spot, combining an improved faster R-CNN object detection algorithm with a fixed-size bounding box. This significance detection box would not only decrease the amount of calculation, but also avoid the scale change caused by the classifier.The proposed strategy outperformed existing state-of-the-art models, according to the experimental data. But the number of dataset used for the study was considerably minimal.

Akshai KP et.al [21] proposed a aids in the early detection of plant illnesses, which helps to avoid crop loss and disease transmission.The CNN model is used to accurately predict several plant diseases. The performance of different pre-trained CNN models, such as VGG, ResNet, and DenseNet, is examined, and the DenseNet model is determined to be more accurate based on performance criteria. Performance evaluation parameters including as accuracy, precision, recall, and F1 score are used to test the model.The DenseNet model was the most accurate, with a score of 98.27 percent. The vanishing gradient problem is one of the most common issues in this work. The output of one layer was added to the next layer in the ResNet model, but the output feature maps in the DenseNet model were concatenated with the following future feature maps.The DenseNet model was the most accurate, with a score of 98.27 percent. The vanishing gradient problem is one of the most common issues in this work. The output of one layer was added to the next layer in the ResNet model, but the output feature maps in the DenseNet model were concatenated with the following future feature maps.

V. Singh et.al [22] proposed the genetic algorithm's search capacity was employed to divide unlabeled N-dimension points into K clusters. The texture and color of a picture have been evaluated in the CCM approach. Two techniques, one with k-means clustering and the second with the Genetic algorithm, using the minimal distance criterion. Local homogeneity, contrast, cluster shadow, energy, and cluster prominence were the texture properties that were computed for the H images. With k-mean clustering, the minimum distance criterion had an accuracy of 86.54%, while with SVM, the accuracy was 95.71%. The accuracy was enhanced to 93.63% by combining the Genetic Algorithm with the minimum distance criterion. Here there was no homogeneity seen among the two different approaches that were employed.

E.Kiani et.al [23] proposed a approach consist of five input variables and two outputs in the algorithm. Out of which two of the inputs are about iron deficiency, while the others are about fungal infection. Using the proposed approach, the authors of this paper were able to obtain an overall system accuracy of 96%. Here the input variable that were very minimal.

G.Saradhambal et.al [24] proposed the Otsu algorithm presumes that a picture contains two types of pixels, forming a highly skewed histogram with foreground and background pixels. The morphological and texture oriented features were

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employed to extract features. Area, color axis length, eccentricity, solidity, and perimeter were employed as morphological features, whereas texture-oriented features included contrast, correlation, energy, homogeneity, and mean. This paper just provides an hypothetical understanding of the algorithm used

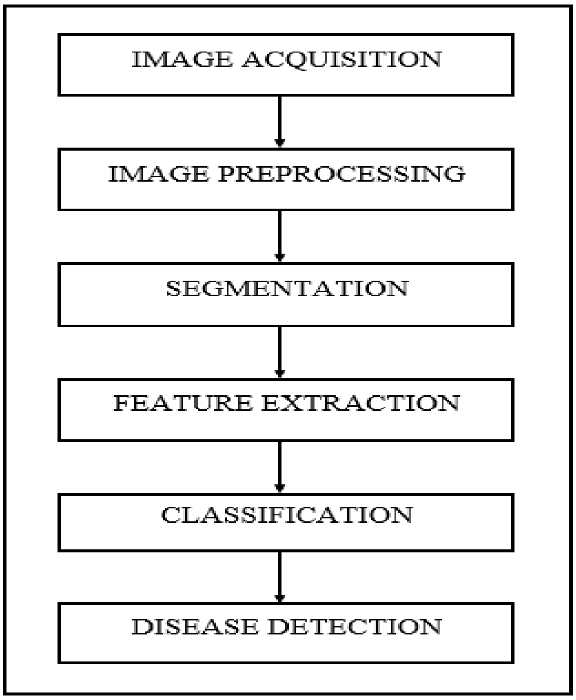

Figure 2: Step-by-Step procedure for disease detection using Image Processing

III. METHODOLOGY

The step-by-step procedure for diagnosis of disease in leaves using image processing techniques is given in the Figure 2 above

A. IMAGE ACQUISITION AND IMAGE PRE-PROCESSING

There are mainly six kinds of grape leaves diseases that hinder the productivity of the crops. In the first stage the pictures of the grape leaves must be captured which would then be used as data set. These data set includes both the diseased plants and the healthy plants leaves. The captured images will have various form and also different dimensions, hence, it becomes essential to pre-process the data and bring all of it to the common form by reducing the noise and distortion.

B. IMAGE SEGMENTATION

This phase seeks to make an image's representation more comprehensible and simpler to examine by simplifying it. This stage is also the essential method to image processing because it is the foundation of feature extraction. Images can be segmented using a variety of approaches, including k-means clustering, Otsu's algorithm, and thresholding, among others [25]. The k-means clustering algorithm divides objects or pixels into K classes based on a set of features. The objects are classified by reducing the sum of squared distances between them and their matching cluster.

C. FEATURE EXTRACTION

The area of interest is the result of the segmentation process. As a result, this stage requires the extraction of characteristics from this region of interest. To establish the significance of a sample image, certain features are required. Color, form, and texture are all possible features. Most scientists are planning to employ textural traits to detect plant illnesses in the near future. Gray-level co-occurrence matrix (GLCM) [25], color co-occurrence method, spatial grey-level dependence matrix, and histogram based feature extraction are just few of the feature extraction approaches that can be used to construct the system. For texture categorization, the GLCM approach is a statistical method.

D. CLASSIFICATION

In the classification phase, you must determine whether the input image is healthy or not. If a diseased image is detected, it has been classified into a number of illnesses by various previous investigations. For classification, a software procedure, also known as a classifier, must be built in MATLAB. K-nearest neighbor (KNN), support vector machines (SVM), artificial neural networks (ANN), back propagation neural networks (BPNN), Nave Bayes, and Decision tree classifiers have all been used by researchers in recent years [25]. The SVM has been shown to be the most often used classifier. Despite the fact that every classifier has advantages and disadvantages, SVM is a simple to use and long-lasting technology.

IV. CONCLUSION

This paper analyses and summarizes numerous image processing-based approaches for plant disease diagnosis which have been used by various researchers in recent years. BPNN, SVM, K-means clustering, Otsu's method, CCM, and SGDM were the main approaches used. These methods are used to determine if the leaves are infected or healthy. The automation of the detecting system employing complicated photos acquired in outdoor lightning and extreme climatic circumstances is one of the obstacles in this approach. Despite significant drawbacks, this review paper indicates that these disease detection techniques are efficient and accurate enough to run the system built for the detection of leaf diseases. As a result, there is still much that may be done to improve existing works in this sector.

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