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A COMPREHENSIVE SURVEY OF GRAPE LEAF DISEASE DETECTION AND CLASSIFICATION USING MACHINE LEARNING BASED MODELS

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Abstract: Plant diseases are becoming a major danger to agricultural productivity as the world's population expands, causing farmers to incur serious consequences. Plant disease can be detected early, which can assist ensure food security and save financial losses. Grape (Vitis Vinifera), a member of the Vitaceae family, is one of India's most important commercial fruit crops. It's a wide-ranging temperate crop that's adapted to the subtropical environment of India's peninsula. Grapefruits and their leaves are more likely to contract illnesses in a grape vineyard. For experts and agronomists, manual observation is impracticable and time-consuming. We conduct a literature study on alternate disease identification and classification methodologies in order to predict disease progression at an early stage. A review of automated classifying and sorting grape leaf disease, including machine learning and deep learning approaches, is also discussed.
Keywords: survey disease comprehensive grape leaf

I. INTRODUCTION

Plant breeders play a critical role in discovering and diagnosing plant diseases. Occasionally, the sickness of manual identification is a time-consuming and tedious process. The attack infection is one of the most significant causes contributing to lower yields. Several studies [1], [2] depict the quality of agricultural products that may be harmed as a result of various plant disease variables. Plant diseases are a major source of agricultural productivity loss and economic losses. Detecting diseases is a challenging task that requires prior experience. Diseases or their symptoms, such as colored spots or streaks, are frequently visible on plant leaves. Plant diseases are frequently caused by microbes such as fungi, bacteria, and viruses. Because of the origin or a etiology of the plant disease, there is a wide range of indications and symptoms[1],[2]. Grape is the most well-known fruit in India, and it is referred to as the "Queen of Fruits." Specifically, Tamil Nadu, Karnataka, Andhra Pradesh (AP), and Maharashtra account for more than 90% of India's grape production and the total area. In the 2012-13 fiscal year, India exported 172.6 thousand MT of grapes. Maharashtra is first in grape production, with 62.7 percent of all grapes produced in the country. The productivity and production of grapes are used to assess the area's and Maharashtra's growth rates [2]. The grape has the best output of any crop in the world, and there is still room for improvement. From 2012/2013 to 2017/2018, this statistic indicates worldwide grape production. Global grape production was around 21.14 million metric tonnes in the marketing year 2015/2016.

Downy Mildew (Plasmoparaviticola), Powdery Mildew (Uncinulanecator), Phylloxera (Daktulosphaira vitifoliae), Vine Trunk Diseases, Pierce's Disease (Xylellafastidiosa), and Anthracnose, among others, cause significant losses in grapes. Downy Mildew, Powdery Mildew, Anthracnose, Grey Mold (Botryotiniafuckelina), and Black Rot (Guignardiabidwellii) are some of the fungal diseases that affect grape leaves in India. As a result, it is critical to identify the disease early on and provide a remedy to the farmer so that harm can be avoided and yield can be maximized [2]. Further part of the paper arranged as follows: Section 2 describes the diverse grapes leaf disease detection methods and classification. Section 3 describes a summary of techniques used in the grapes leaf disease detection and conclusions is discussed in section 4.

II. DIFFERENT GRAPES LEAF DISEASE DETECTION METHODS

The authors proposed an automated approach for segmentation and detection of grape leaf diseases in this study [3]. There are four steps to the recommended model. In order to improve the local contrast of symptoms, a local contrast haze reduction (LCHR) augmentation technique is proposed in the first stage. Following that, in the second phase, LAB colour transformation is performed, and the best channel is chosen based on the pixel information, which is then used in the thresholding function. Color, texture, and geometric properties are extracted and combined using Canonical Correlation Analysis (CCA). Noise is introduced during feature fusion in the form of irrelevant and redundant features, which are eliminated via Neighborhood Component Analysis (NCA). The M-class SVM is then used to classify the resulting reduced features. The proposed method is tested on the Plant Village dataset, which comprises healthy grape leaves along with three types of grape leaf diseases: black measles, black rot, and leaf blight. In comparison to existing techniques, the proposed method achieved an average segmentation accuracy rate of 90% and a classification accuracy rate of above 92 percent. In paper [4] the authors suggested a Faster DR-IACNN model for detecting common grape leaf diseases such as black rot, black measles, leaf blight, and grape mites. First, apply image augmentation and annotation to photos of grape leaf disease in this paper. The INSE-ResNet pre-network, RPN, and Fully linked layers make up the Faster DR-IACNN model. INSE-ResNet contains the residual structure, inception modules, and SE-blocks. Four 1 × 1 convolution layers, one 3 × 3 convolution layer, one 5 × 5 convolution layer, and one 3 × 3 max-pooling layer make up the Inception-v1 model. The SE block is made up of 3 × 3 average pooling layers and two 1 × 1 convolution layers. One convolution layer at the SE block is ReLu, while another convolution layer is signed. 1 × 1 convolution layers are put before or after parallel convolution layers in the Inception ResNet-v2 module. The multiscale feature extraction is improved by using these two inception modules. The dataset in this research includes 16,520 cases of black rot, 19,362 cases of black measles, 15,064 cases of leaf blight, and 11,340 cases of grape mites. There were 62,286 photos of common grape leaf disease in total. The INSE-ResNet model had a recognition accuracy of 99.47 percent. The mAP (mean Average Precision) and FPS (frames per second) were 81.1 and 15.01 percent, respectively.

Using the Inception v3 model and Logistic Regression, the authors [5] suggested to detect and diagnose grape leaf pathogens. The Inceptionv3 model is mostly used to extract features. Pasteurizing convolutions, auxiliary classifiers, grid size reduction, and other optimization strategies are used in the Inceptionv3 model. The features of the grape leaf photos are extracted using these techniques. A logistic regression model was presented after feature extraction to diagnose grape leaf diseases. There are 3209 pictures in the training samples and 853 pictures in the testing samples. A total of 4062 grape leaf photos were sampled. When compared to other models like VGG 16 and VGG 19 with logistic regression, the suggested technique has a classification accuracy of 99.4 percent. The authors [6] used image processing and a machine learning algorithm to construct an autonomous system for detecting illnesses in grape leaves. The proposed approach for detecting grape leaf diseases consists of five steps. Following that, there will be pre-processing, segmentation, diseased part identification, feature extraction, and classification. The grab cut segmentation technique is used to separate the grape leaf portion of the image from the background grape image. The RGB leaf image is then converted to a grayscale image, which is subsequently used to convert the image to a binary image by global thresholding. Energy, homogeneity, contrast, dissimilarity, correlation, and angular second moment are among the six features extracted in this work. After that, different classifiers such as SVM, Random Forest, and AdaBoost are used to apply the extracted features. Finally, separate healthy, black rot, Esca, and leaf blight infestations in grape leaves. There are 5675 grape leaves in the data set. 80 percent of the grape photos were employed in the training set, while the rest were used in the testing set. When compared to Random Forest and AdaBoost, the proposed system achieved 93.035 percent testing accuracy using SVM. The authors [7] suggest an image processing and artificial intelligence based system for the diagnosis of grape leaf diseases. The first step is to use the threshold method to remove the background color component from the input image. Anisotropic diffusion was used to obtain a rejected image during the preprocessing phase. The diseased part of the grape leaf was then divided using the K-Means i.e. clustering algorithm. The morphological features of the fragmented diseased segments were retrieved using the gray scale co-occurring matrix (GLCM). Contrast, homogeneity, maximum probability, homogeneity, inverse variation, differential variation, diagonal variation and entropy are all extracted from the fragmented images in this paper.Finally, the collected traits were used to classify grape leaf diseases such as powdery mildew and downy mildew using feed forwarding propagating neural networks.

This dataset contains 16 powdery mildew and 17 downy mildew images. When color properties are used, the training accuracy is 100 percent. The authors of the research [8] used the DICNN model to identify six common diseases of grape leaves. DICNN consists of three modules: Pre-Network Module, Cascade Dense Startup Module and a mix of two Max-Pooling Layers, One Startup Layer, Global Average Pooling (GAP) Layer and 7-way Softmax. Layer in the third module. The data was reinforced to avoid over-fitting. The Inception module was used to extract features from multiple angles of the grapefruit image. A total of 7,669 grape leaf photographs were used in this study, of which 107,366 images were created using image enhancement. According to the results, the DICNN model outperformed other CNN models, Densnet, Resnet, and Googlenet, as well as BP and United, in detecting anthracnose, brown spot, worms, black rot, downy mildew, leaf blight and healthy leaves. Did. In grape leaves. Precision, recall and F1 scores were used to assess the performance of the indicated method. Brown spot, anthracnose, leaf blight and black rot disease all had recall rates of 96.54 percent, 95.84 percent, 97.05 percent, and 97.29 percent, respectively. Anthracnose, brown spot, mites, black rot, downy mildew, leaf blight and healthy leaves were found with 96.57 per cent, 97.32 per cent, 98.81 per cent, 96.28 per cent, 96.90 per cent, 96.98 per cent and 97.79 per cent purity respectively. In addition, the proposed approach would have a faster convergence speed.

The authors of this paper [9] presented the Convolution Neural Network as an in-depth learning model. Leaf photos are processed using the pre-defined AlexNet architecture for feature extraction and model training. The "National Research Center for Grapes" provided the image dataset (ICAR). These diseases include powdery mildew, downy mildew, rust, bacterial spot and anthracnose. The cell phone's built-in camera module is used to take a picture of the leaf. For powdery mildew bacterial stains, the accuracy is 98.23 percent. Plant diseases cause significant economic and production losses, as well as a decrease in the quantity and quality of agricultural products. There is a high demand these days for systems that detect plant leaf disease to monitor vast fields of crops. The most important thing here is to monitor the health of the plants and look for any infections. According to studies, leaf properties can be used to diagnose most plant diseases. Consequently, leaf-based disease analysis is an attractive new field for plants. The authors [10] use this method to diagnose plant disease using leaf texture analysis and sample identification. The aim of this research is on the system of detecting leaf disease of grape plant. The system accepts the plant leaf as input and divides it after removing the background. The diseased area of the leaf is detected using a high pass filter applied to the split leaf image. The novel fractal-based texture feature is used to retrieve the split leaf texture. Fractal-based features are inherently localized, which makes them a useful design model. Each different disease has a different texture. Multiclass SVM is used to classify the collected texture patterns. Two common diseases found in grape plants are downy mildew and black rot. With an accuracy rate of 96.6 percent, the proposed approach will make the advice of agricultural experts available to farmers with the accuracy of 96.6%.

Grapevine Fanleaf Virus (GFLV) is one of the most serious viral infections of grapes, capable of destroying up to 85% of the crop if not treated promptly. The goal of this project is to use artificial intelligence and an accessible database to identify GFLV-infected leaves. To do so, technical specialists use traditional laboratory methods to classify photographs obtained from infected and healthy grape leaves. The Fuzzy C-mean Algorithm (FCM) is used to highlight the unhealthy areas on each leaf, and the percentages of the first two segments are fed into a Support Vector Machines (SVM) [11] to create an intelligent approach for identifying infected from healthy leaves. The K-fold cross validation approach with k = 3 and k = 5 is used to improve the system's diagnostic reliability. After applying the proposed framework to all pictures using the K-fold validation technique to uncover the True Positive, True Negative, False Positive, and False Negative rates of classification, the average confusion matrix is constructed. The results demonstrate that the algorithm's specificity, or potential to truly detect healthy photos, is 100 percent, and its sensitivity, or ability to correctly detect contaminated images, is around 97.3 percent. The system's average accuracy is roughly 98.6 percent. The results show that the proposed method is more capable than earlier methods.

To recognise several grape leaf diseases such as Black rot, Esca, and Isariopsis leaf spot, the author [12] built a United Model on several CNNs. UnitedModel is a combination of two deep learning architectures, GoogLeNet and ResNet, employed in this paper. The ResNet architecture is piled by many residue modules, whereas the GoogLeNet architecture is stacked by inception modules. UnitedModel is the proposed system with an integration of the powerful InceptionV3 and ResNet50 deepl learning architectures. Using InceptionV3 and ResNet50, feature maps are collected from the testing image and then applied to the GAP layer (Global Average Pooling). Then on to concatenation, a dropout layer, a fully linked layer, dropout layer, and finally classification. The final classification layer in this work is a softmax classifier, which is used to classify grape leaf diseases. There are 171 healthy photos, 476 black rot images, 552 esca images, and 420 isariopsis leaf spot images in this dataset. As a result, the plant village produced a total of 1619 images. UnitedModel's validation and test correctness, according to the results, were 99.17 percent and 98.57 percent, respectively. UnitedModel has a precision, recall, and F1 percentage of 99.05, 98.88, and 98.96, respectively, when compared to other CNN architectures including DenseNet, VGGNet, GoogLeNet, and ResNet. To spot disorders in grapes and grape leaves, the authors [13] introduced the Faster R-CNN and SSD MobileNet designs. The Faster R-CNN is an RPN (Region Proposal Network) that uses a region proposal technique to detect object locations.

The model was pre-trained on the COCO (Common Objects in Context) dataset using the Faster R-CNN model in conjunction with the Inception v2 model, as well as the SSD model using MobileNet. MobileNet is a depthwise separable convolutions-based network. The first input image in MobileNet is applied to a Depth-wise distinct convolutions layer, which is then followed by a 1 x 1 convolutions layer. Batchnorm and ReLu come after these two layers. The dataset for this article consists of 656 photos (201 healthy grape leaves and 195 unhealthy grape leaves) obtained from plant village dataset and the internet. The classification accuracy of the Faster-R-CNN Inception v2 model ranges from 78 to 99 percent. The SSD MobileNet v1 model obtained 90 percent to 99 percent classification accuracy for the input image with less noise, according to the testing findings. For the input image with noise, multiple backgrounds, and resolutions, the classification accuracy of the SSD MobileNet v1 model ranged from 52 percent to 80 percent, indicating poor classification performance. As a result, this model isn't employed to classify objects in real time. In comparison to the SSD MobileNet v1 model, the R-CNN model is faster and better at classifying grape pictures.The author [14] presented a fine-tuning VGG 16 architecture with the Global Average Pooling (GAP) layer to categorise five grape leaf diseases: anthracnose, downy mildew, black measles, Isariopsis leaf spot, and nutrient deficiency. Preprocessing, training, and classification are the three processes in the proposed system. There are thirteen convolution layers and five max pooling levels in the VGG16 architecture. The GAP layer was then used to classify the grape leaf diseases, followed by the SoftMax classification layer. Overfitting is avoided by using a GAP layer, which minimises the dimension. The collection includes 1200 images of anthracnose, 850 photographs of downy mildew, 930 images of nutrient deficiency, 1200 images of black measles, 1020 images of isariopsis leaf spot, and 800 healthy leaf images. As a result, a total of 6000 photos were used. The performance of the VGG16 architecture with GAP layer was compared to that of the VGG16 architecture with fully connected layers and VGG16 with SVM classifier in this paper. The accuracy of fine-tuning VGG16 architecture with GAP layer was 98.9% for training images and 98.4% for testing images, which is higher than the industry average. For training images, the precision, recall, and F1 score of VGG16 with GAP layer were 98.9%, 98.85%, and 98.87 percent, respectively. For testing images, the precision, recall, and F1 score of VGG16 with GAP layer were 98.4%, 98.4%, and 98.4%, respectively.

III. COMPARISON OF DIFFERENT GRAPES LEAF DISEASE DETECTION METHODS

This section examines various leaf disease detection and classification methods that have been used to grapes. We took into account the author's name, publication year, techniques utilised, detection and classification accuracy, dataset size, disease kind, and parameters of their study work in this survey. Table 1 summarises the numerous leaf disease detection techniques utilised in grapes.

TABLE 1- COMPARISON OF DIFFERENT GRAPES LEAF DISEASE DETECTION METHODS

S.No.	Author	Problem	Methodology	Dataset	Parameter	Disease Types
1.	Alishba Adeel et al.	Diagnosis and recognition of grape leaf diseases	Local Contrast Haze Reduction, LAB Color Transformation, Canonical Correlation Analysis, Neighborhood Component Analysis	black measles, black rot, and leaf blight including healthy in plant village data set	An average segmentation saccuracy rate of 90% and classification accuracy is above 92%	black measles, black rot, and leaf blight
2.	Xiaoyue Xie, Yuan Ma et al.	Grape leaf diseases detection	Faster DR-IACNN model	60% of the dataset for the training and 40% for the validation. The number of original grape leaf disease images were 62,286.	mAP (mean Average Precision)-81.1% Speed(FPS)-15.01. The recognition accuracy-99.47%	Black rot, Black measles, Leaf blight, Mites of grape
3.	Nitish Gangwar et al.	Classification of grape leaf diseases	Inception v3 model and Logistic Regression	Training samples of 3209 images and testing samples of 853 images	Classification accuracy: Proposed method -99.4% VGG 16 +Logistic Regression-98.5% VGG 19+ Logistic Regression-98.5%	Black rot, Esca(Black Measles), Leaf Blight and healthy leaf images

4.	S.M. Jaisakthi et al.	Identification of grape leaf disease using image processing and machine learning technique.	Segmentation method (ROI). Further segmentation using global thresholding and semi-supervised technique. Classification using SVM	5675 grapes leaves images and used 80% of the grape leaf images for training and others for testing.	The overall accuracy is 93.035% for 1135 test images using SVM.	Healthy, Black rot, Esca and Leaf blight
5.	Sanjeev S Sannakki et al.	Diagnosis and classification of grape leaf diseases using image processing and artificial intelligence techniques	Anisotropic diffusion and K-means clustering. Feed forward Back Propagation Neural Network for classification	16 images of powdery mildew (class 1) and 17 images of downy mildew. 29 images are used for training and 2 each for testing and validation.	Overall accuracy for training set is 100%	downy mildew and powdery mildew
6.	Bin Liu et al.	Identification of grape Leaf diseases	DICNN model	A total of 7,669 images of grape leaves. 107,366 images were created via image augmentation.	The accuracy of 97.22% compared with DenseNet, ResNet and GoogLeNet architectures. Calculate the precision, Recall and F1 score.	Anthracnose, Brown spot, Mites, Black rot, Downy mildew, Leaf blight and healthy leaves.
7.	Wagh T.A et al.	grape leaf diseases detection	Convolutional Neural Network for prediction Alexnet for training the model	Dataset consist of 1000 images each of Powdery Mildew, Bacterial Spots, Downy Mildew, Anthracnose, Rust and 1500 images of Healthy Leaves	achieves maximum accuracy of 98.23%	Bacterial Spots, Powdery Mildew, Downy Mildew and Rust.
8.	Waghmare, H et al.	Detection and classification of diseases of Grape plant	leaf texture analysis and pattern recognition	Dataset consists of downy mildew & black rot leaves	achieves an accuracy of 96.6%	downy mildew & black rot
9.	Mojtaba Mohammadpoor et al.	Grape Fanleaf Virus Detection	Fuzzy C-mean Algorithm (FCM), Support Vector Machine (SVM)	92 images are collected of healthy and infected leaves	average accuracy of the system is around 98.6%	healthy and infected leaves
10.	Miaomiao Ji et al.	Identification of automatic grape leaf diseases	UnitedModel based on multiple convolutional neural networks (InceptionV3 and ResNet)	Healthy of 171 images, black rot of 476 images, Esca of 552 images and isariopsis leaf spot of 420 images. The total samples of 1619 images.	The average recision (99.05%), Recall 98.88%) and F1-score (98.96%) of UnitedModel. Average validation accuracy of 99.17% and a test accuracy of 98.57%	Black rot, Esca and Isariopsis leaf spot
11.	Shekofa GHOURY et al.	Detection of Grape and Grape leaves diseases	Faster R-CNN and SSD MobileNet Architectures	The total number of 543 images for training and 113 images for testing.	The classification accuracy for Faster-RCNN Inception v2 - 95.57% The classification accuracy for SSD MobileNet-59.29%	Healthy grape, Diseased grape, Healthy grape leaf and Diseased grape leaf

12.	Khaing Zin Thet et al.	Classification of grape leaf diseases detection	Fine-tuning VGG 16 architecture using Global Average Pooling (GAP) layer	The total images are 6000. The dataset was separated into 80% for training samples and 20% for testing samples.	Fine-tuning VGG16 with GAP layers got 98.9% accuracy for the training set and 98.4% accuracy for the testing set.	Anthracnose, Downy mildew, Nutrient insufficient, Black measles, Isariopsis leaf spot and healthy leaf

IV. CONCLUSIONS

The survey of grape leaf disease detection yielded a variety of identification and classification strategies, as detailed above. According to the survey, this report attempts to investigate machine learning approaches utilised by researchers for disease identification and plant classification. These machine learning algorithms assist agricultural professionals in detecting sickness in plants in a timely manner, after which the experts will advise the farmer on early diagnosis. According to agricultural experts' recommendations, the farmer will remove the infected plant as soon as possible, increasing crop production.

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