A SURVEY ON PLANT DISEASE RECOGNITION

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ABSTRACT

Early Detection of Plant Leaf Detection is a major necessity in a growing agricultural economy like India. Not only as an agricultural economy but also with a large amount of population to feed, it is necessary that leaf diseases in plants are detected at a very early stage and predictive mechanisms to be adopted to make them safe and avoid losses to the agri-based economy. This paper proposes to identify the Leaf disease using image processing techniques based on Image segmentation, clustering, and image detectionalgorithms, thus all contributing to a reliable, safe, and accurate system of leaf disease with the specialization.

Keywords: *image processing, android camera, python, algorithm, plant leaf disease, image segmentation*

I. Introduction

India has 157.35 million hectares of agricultural land, second only to the United States. In India, agricultural land accounts for around 60.3% of total land area. Agriculture production is extremely important to India's economy. As a result, in the realm of agriculture, disease detection in plants is critical. The adoption of an automatic disease detection technique is advantageous in detecting a plant disease in its early stages. For example, in India, a disease known as small leaf disease is a dangerous disease that affects plants. The damaged tree's growth is stunted, and it eventually dies. Its influence can be found all over India. Plant disease detection and control are extremely difficult for farmers.As a result, it is critical to diagnose plant diseases at an early stage so that farmers can take appropriate and timely action to avert future losses. Early discovery in such situations could have been beneficial.

Currently, the most extensively used method for plant disease detection is expert naked eye observation, which is used to identify and detect plant diseases. This necessitates a huge staff of experts as well as ongoing expert monitoring, both of which come at a great cost when farms are large. Simultaneously, in other nations, farmers lack adequate facilities or even the knowledge of how to contact professionals. As a result, consulting specialists is both expensive and time-consuming too.In such circumstances, the recommended technique proved to be useful in monitoring huge crop fields. It is easier and less expensive to identify diseases automatically by simply looking at the symptoms on the plant leaves. Plant disease detection by sight is a more time-consuming and inaccurate task that can only be performed in limited locations. Using an automatic detection technique, on the other hand, will need less work, time, and accuracy. Brown and yellow marks on leaves, early and late scorch, and fungal, viral, and bacterial illnesses are all common diseases in plants.Image processing is a technique for measuring the affected region of disease and determining the color difference in the affected area. The technique of dividing or grouping a picture into various portions is known as image segmentation. Picture segmentation can be accomplished in a variety of ways, ranging from simple thresholding to complex color image segmentation approaches. The segmentation process is based on the image's numerous attributes.

This could be color information, image boundaries, or a segment. The study focuses on a method for detecting plant diseases based on image processing. We suggest an Android application in this work that assists farmers in recognizing plant illness by uploading leaf images to the system.The system uses a series of algorithms to determine the disease kind. The user's input photograph is processed via various processes to detect the ailment, and the results are returned to the user via an Android application.

II. Literature Survey

Many researchers have worked tirelessly to discover plant illnesses in order to limit disease damage. Machine learning algorithms have become increasingly popular for identifying plant pests and diseases as technology advances.

Hamuda et al. suggested an automatic crop detection algorithm in (Hamuda et al., 2017). The system was used to detect cauliflowers in video streams shot in natural light under various weather circumstances, and the results were compared to ground-truth data obtained through manual annotation. The sensitivity of this algorithm was 98.91 percent, while the precision was 99.04 percent.

In (Akbarzadeh et al., 2018), Akbarzadeh et al. suggested a support vector machine-based technique for classifying plants.Corn and silver beet spectral reflectance characteristics at 635, 685, and 785 nm, with a pace of 7.2 km/h, were included in the data set. The results of the experiments showed that the proposed algorithm correctly categorized the plants with a 97 percent accuracy.

Zhang et al. developed a visual spectral-based cucumber powdery mildew identification approach in (Wang et al., 2019). The 450- to 780-nm visible light band was chosen as the research range after classification and recognition of spectral properties. The SVM algorithm was then used to create the classification model, which was then optimized using the radial basis kernel function.The results of the studies revealed that this model achieved accuracy of 100 percent for cucumber healthy leaves and 96.25 percent for powdery mildew leaves, with a total accuracy of 98.13 percent.

Waghmare et al. (2016) suggested a technique for identifying grape disease using leaf texture analysis and pattern recognition (Waghmare et al., 2016). The system used a single plant leaf as an input and conducted segmentation after removing the backdrop. The sick section of the leaf was detected using a high pass filter on the segmented leaf image. Finally, a multiclass SVM was given the extracted texture pattern.

Mohammadpoor et al. proposed an intelligent technique for grape fanleaf virus identification in (Mohammadpoor et al., 2020). The area of unhealthy sections of each leaf was highlighted using the Fuzzy C-mean algorithm, and then it was classified using SVM. In addition, the diagnostic reliability of the system was improved using the K-fold cross validation approach with k = 3 and k = 5. The system's average accuracy was roughly 98.6%, according to the results of the experiments.

Machine learning algorithms, on the other hand, necessitate time-consuming image preprocessing and feature extraction (Kulin et al., 2017; Zhang et al., 2018). CNN, on the other hand, can recognize and extract discriminative characteristics for image identification automatically.CNNs have made significant advances in computer vision in recent years.As a result, employing CNN to detect plant diseases has become a hot topic in agricultural information technology research.

Khan et al. (2018) used VGG and AlexNet to extract the properties of infected regions after isolating them from the background (Khan et al., 2018). Experiments on a Plant Village and the CASC-IFW resulted in a classification accuracy of 98.60 percent. The results of the experiments showed that the suggested model surpassed existing approaches in terms of precision and recognition accuracy.

Zhang et al. suggested GPDCNN, a cucumber disease diagnosis method based on AlexNet, in (Zhang et al., 2019). The method efficiently merged contextual information by integrating global pooling layers using dilated convolution, which helped to improve convergence and recognition rate.Six prevalent cucumber leaf diseases were used to train the GPDCNN model, which resulted in a recognition accuracy of 94.65%.

Liang et al. suggested a CNN-based rice blast diagnosis system in (Liang et al., 2019). The model was trained on a data set of 5,808 diseased pictures, including 2,906 positive samples, and achieved acceptable identification accuracy, AUC, and ROC results. The suggested model extracted more discriminative and effective high-level features than the classic techniques of LBPH and Haar-WT, according to the experimental results.

Zhang et al. trained a three-channel CNN model for the identification of tomato and cucumber leaf diseases (Zhang et al., 2019).The method used the three RGB channels separately to employ color information, resulting in the automatic extraction of diseased features using color data. The suggested model outperformed standard approaches in terms of classification accuracy on a data set of tomato and cucumber leaf diseases.

Wagh et al. suggested an automatic grape disease detection system for the recognition of five diseases, including powdery mildew, downy mildew, rust, bacterial spots, and anthracnose (Wagh et al., 2019). The leaf images were subjected to feature extraction and model training using a pre-defined AlexNet architecture. The programme was also able to effectively classify grape illnesses based on experimental results.

Ji et al. suggested a united convolutional neural networks architecture based on an integrated technique in (Ji et al., 2019). United Model, the suggested CNNs architecture, was created to classify common grape leaf diseases. Because of the use of several CNNs, UnitedModel was able to extract complementing discriminative features. UnitedModel had the best performance on multiple evaluation measures, with an average test accuracy of 98.57 percent, according to the trial data.

CNNs have shown satisfactory results in plant disease recognition, according to this research. CNNs, on the other hand, are rarely employed in the diagnosis of leaf disease. Furthermore, most application-oriented picture recognition algorithms are based on well-known transfer learning techniques, and the algorithms have seen little improvement. As a result, this research proposes a CNN-based image identification model leaf diseases.

III. Proposed Methodology

The objective of this system is to concentrate on the plant leaf disease detection for android based on the texture of the leaf. First, the images of various leaves are acquired using a android camera. Then image- processing techniques are applied to the acquired images to extract useful features that are necessary for the analysis.Therefore, looking for exact, fast and low-price method to automatically detect the diseases from the symptoms that come on the plant leaf is of great importance. This enables machine vision that is to provide image based automatic inspection, process control.Following are the system components and the flow of proposed work shown in fig. 1.

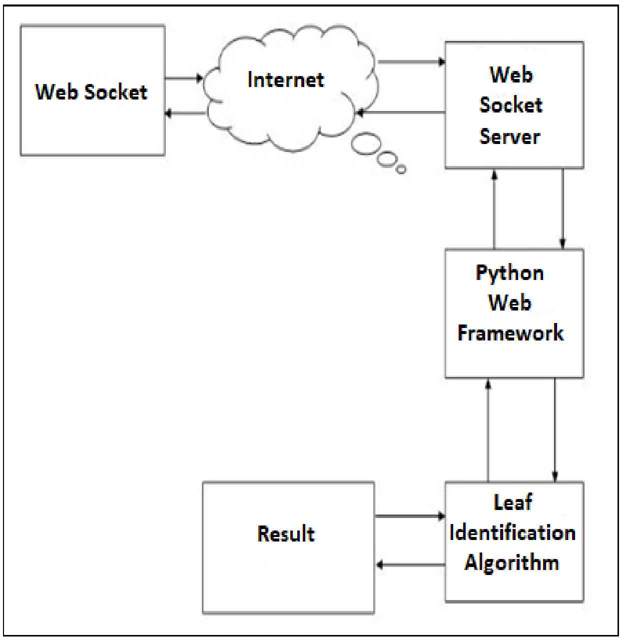

Fig. 1 System Architecture

Web Socket is a computer communication technology that allows for full-duplex communication over a single TCP connection. Send the captured image to the web socket server using a mobile camera.

Python is a high-level computer language for general-purpose programming that is interpreted. Open CV must be installed in Python. One of the libraries used for image processing in Python is the open-source computer vision library. It uses a leaf identification algorithm to detect and identify leaves and illnesses, and then uses the data base to transmit a result back to the sender farmer.

IV. Conclusion

Thus, in this paper leaf disease identification will be done by considering the complete survey, by using image processing techniques based on Image segmentation, clustering, and image detection algorithms, thus all contributing to a reliable, safe, and accurate system of leaf disease with the specialization to identify the disease on the leaf.

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