IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

DETECTION OF MULTIPLE PLANT DISEASE USING DIGITAL IMAGE PROCESSING

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ABSTRACT

For detecting the incidence and quantifying the severity of variability in crops, image-based plant disease detection is one of the most important activities in precision agriculture. Pathogen-caused diseases account for 70 percent to 80 percent of the variabilities, with 60 percent to 70 percent appearing on the leaves compared to the stem and fruits. This study uses leaf image data to conduct a comparative comparison of model implementation for plant disease diagnosis. Until recently, most of these image processing algorithms relied on what some referred to as "shallow" machine learning architectures, and some still do. The DL network is quickly becoming the gold standard for image recognition and pattern analysis research. Regardless, there aren't many research on its use in detecting disease in plant leaves. Thus, we used conventional settings and took into account the three critical elements of architecture, processing capacity, and the amount of training data in our study on a large plant leaf disease picture dataset. In a developing agricultural economy like India, early detection of plant leaf detection is critical. Leaf diseases in plants must be diagnosed at an early stage and predictive techniques implemented to make them safe and avoid losses to the agri-based economy, not only as an agricultural economy but also as one with a big population to feed. This work proposes to identify Leaf disease utilising image processing techniques based on image segmentation, clustering, and image detection algorithms, all of which contribute to a reliable, safe, and accurate leaf disease detection system with specialisation.

I. INTRODUCTION

Plant disease detection is an important aspect of precision agriculture since it focuses on detecting diseases in their early stages [1]. As disease outbreaks become more common around the world, the results of early illness detection can be used for disease diagnosis, control, and damage assessment, particularly since some diseases are exceedingly difficult to control and can result in famine [2-3]. Furthermore, the data can aid in the use of disease-specific remedies or chemical applications such as pesticides and fungicides, which can boost production and prevent billion-dollar losses [4]. According to the literature, plant disease detection include determining the illness's occurrence, severity, and consequences [4]. The proportion of plants in a farm or leaves on a diseased plant is known as disease incidence. The rate at which the disease region of the plant manifests can be described as severity, which is occasionally interchanged with intensity (i.e., relative or absolute area damaged by disease). At the same time, the result is expressed as a percentage of yield lost or a decline in yield quality in the harvest.

Destructive (serology and molecular approaches) and non-destructive (biomarker-based and plant characteristics image processing-based techniques included) methods are used to identify plant diseases [4]. Machine learning-based methods have greatly increased the usage of image-based techniques in precision agriculture. This is due to the increased availability of higher-quality measurements, as well as current algorithms and the capacity to combine numerous image sources. Images from satellite imagery, sensors, or even cameras positioned in fields can all be used to create these images. Earlier imaging approaches, such as hyperspectral imaging, fluorescence imaging, spectroscopy, infrared, and even x-ray imaging, were not cost-effective [5-7]. Image processing approaches, in combination with machine learning classifiers, can now accurately identify such diseases in colour photos at advanced levels [7]. Destructive (serology and molecular approaches) and non-destructive (biomarker-based and plant characteristics image processing-based techniques included) methods are used to identify plant diseases [4]. Machine learning-based methods have greatly increased the usage of image-based techniques in precision agriculture. This is due to the increased availability of higher-quality measurements, as well as current algorithms and the capacity to combine numerous image sources. Images from satellite imagery, sensors, or even cameras positioned in fields can all be used to create these images. Earlier imaging approaches, such as hyperspectral imaging, fluorescence imaging, spectroscopy, infrared, and even x-ray imaging, were not cost-effective [5-7]. Image processing approaches, in combination with machine learning classifiers, can now accurately identify such diseases in colour photos at advanced levels [7].

II. LITERATURE REVIEW

Several research works on image-based plant disease classification using machine learning have been published [1, 7, 20-21]. In conclusion, a substantial amount of the research relied on traditional classification techniques such as SVM, while others focused on DL. Kaur et al. provided a more detailed overview of machine learning approaches used in various plant cultures. Identifying the most popular classifier was one of the foundations for their observations [3]. One of the earliest proposed efforts on pattern recognition using SVM is by Camargo and Smith. Spots, lesions, or stains, as well as strikes, were recognised and segmented, and features were retrieved and supplied into the classifier as inputs [22]. The trained classifier had a 93 percent accuracy rate on a dataset of 117 photos.

They established a precedent for using the extracted features as inputs to the machine learning algorithm to identify plant disease visual symptoms, proving the notion that texture characteristics are valid discriminators for plant disease identification. In separate studies, Camargo and Smith described how illness symptoms areas (ROIs) were preprocessed (filtering and intensity distribution), identified, and segmented using image registration [23]. Using co-occurrence analysis, the characteristics were extracted from the ROI's hue saturation and value (HSV) colour channels. The use of a matrix approach. Although the wavelet transform was utilised as the feature extractor, Bernardes et al. used the SVM for automatic cotton foliar disease classification [24]. There were 420 photos in total in the image dataset, with varied sizes and brightness. However, neither the procedures for preprocessing nor the use of segmentation algorithms were reported in the study. Despite having a total of 216 feature vectors, the claimed classification rate ranged from 80 to 96.2 percent in this regard. Barbedo et al. introduced a pair-wise based classification system that used colour transformations and relevance histograms to find the major features [25]. The image dataset included 82 disorders (74 diseases, four pests, and four abiotic disorders) scattered among 12 plant species, with only 15% of the total photographs obtained under controlled conditions and the remainder in real-world settings from designated experimental areas.
For leaf segmentation, the guided active contour (GAC) approach was used, with two masks constructed depending on discolouration. The suggested method has a poor average accuracy of 58 percent across all

species, owing to the lack of clear similarities between some diseases, sparse image datasets, and input image preprocessing. In a similar manner, Singh and Misra used a genetic algorithm (GA) for the segmentation of sick regions after conducting preprocessing [26]. The SVM classifier was used to partition the data and then identify the presence or absence of disease using texture and colour cues. A total of 106 leaf images were divided into training and testing groups.

When four plant species and five illnesses were examined, the average classification accuracy was determined to be 97 percent. Due to shape fluctuation when diseases progress into severe stages, the research overruled the use of shape parameters such as extent and circularity. The proposed method made the procedure of segmentation and feature extraction less compromising. However, the lack of a comprehensive image dataset restricted the work's relevance.

III. 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.

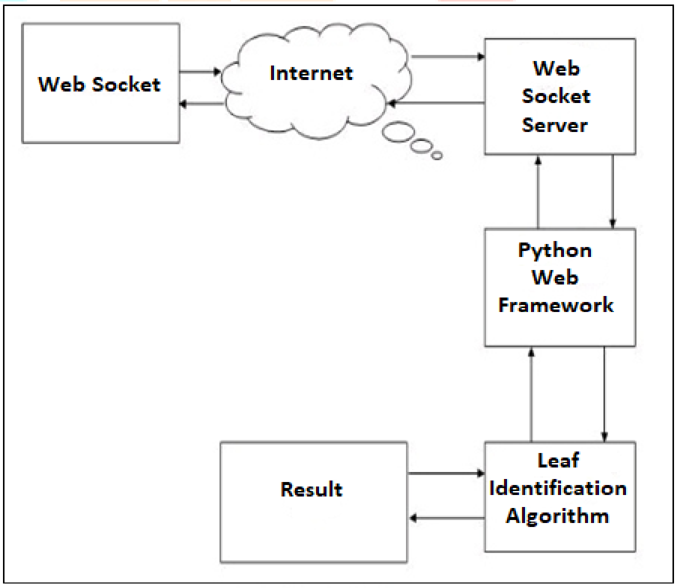

Fig. 1 System Architecture

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. FLOWCHART

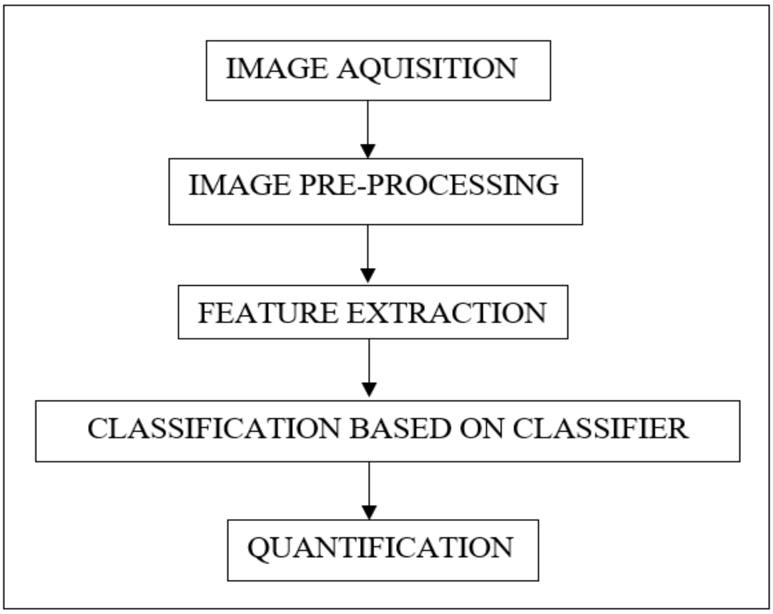

Fig. 2 Flow of Proposed Work

ACQUISITION OF IMAGES

The photos of the leaves are captured using the suitable pixel camera and saved in RGB (Red, Green, and Blue) format. A device agnostic colour space transform is applied when a colour transformation of an RGB leaf image is formed.

IMAGE IMPROVEMENT

The leaf image that was recorded will be resized. The image will then be converted to an appropriate colour space, from which the needed data may be extracted more quickly.

EXTRACTION OF A FEATURE

In picture categorization, feature extraction is a crucial step. It provides for the most accurate representation of the image's content. In feature extraction, phase features are recovered from a segmented image based on their colour, shape, and texture.

Texture Based Feature Extraction is the feature extraction technique utilised for plant leaf diseases. In image processing, the Color Co-occurrence feature extraction approach is a combination of two feature extraction techniques that considers both the colour and texture of an image.

CLASSIFICATION

Artificial neural networks (ANN) and image processing techniques will be utilised to detect plant illnesses early and reliably. For leaf disease classification, the suggested system uses an ANN classifier and a Color Co-occurrence feature extraction method, as well as a Support Vector Machine (SVM).

QUANTIFICATION

The severity of illness discovered on leaves can be assessed using a quantification technique. It's also a crucial aspect of applying image processing techniques to detect diseases.

V. OPPORTUNITIES AND APPLICATIONS

Digital Image Processing Benefits

1. Image processing is quicker and more cost-effective. Processing time, as well as film and other photographic equipment, are reduced.
2. Images with important qualities such as edges can be retrieved and used in industry.
3. Images can be sharpened and given a better aesthetic appearance.
4. Image sizes can be scaled up or down.
5. Images can be compressed and decompressed for speedier network image transmission.
6. Images can be categorised automatically based on the content they contain.
7. Image processing can be used to highlight unfamiliar characteristics.
8. Smoothing images is an option.

Digital Image Processing in Practice

The following are some of the primary fields in which digital image processing is commonly used:

1. Image sharpening and restoration are done via digital image processing.
2. This technique is often employed in agriculture to obtain a high-quality product with precise results.
3. It is employed in the field of remote sensing.
4. It is in the process of transmission and encoding.
5. It's also utilised in colour processing, pattern recognition, and other applications.

VI. RESULT

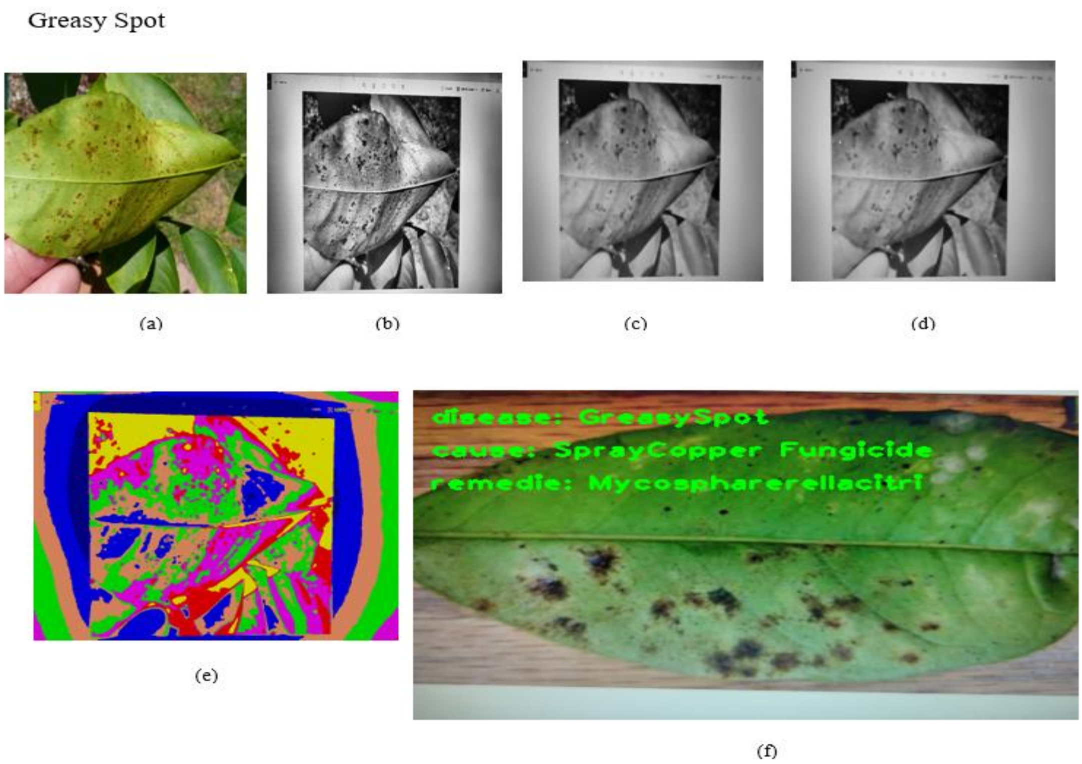

Fig.3- a, b, c, d, e, f:-Greasy Spot original image, enhanced image, gray scale image, blur image, segmented image, final output with disease name, cause and remedy.

Not Infected Leaf

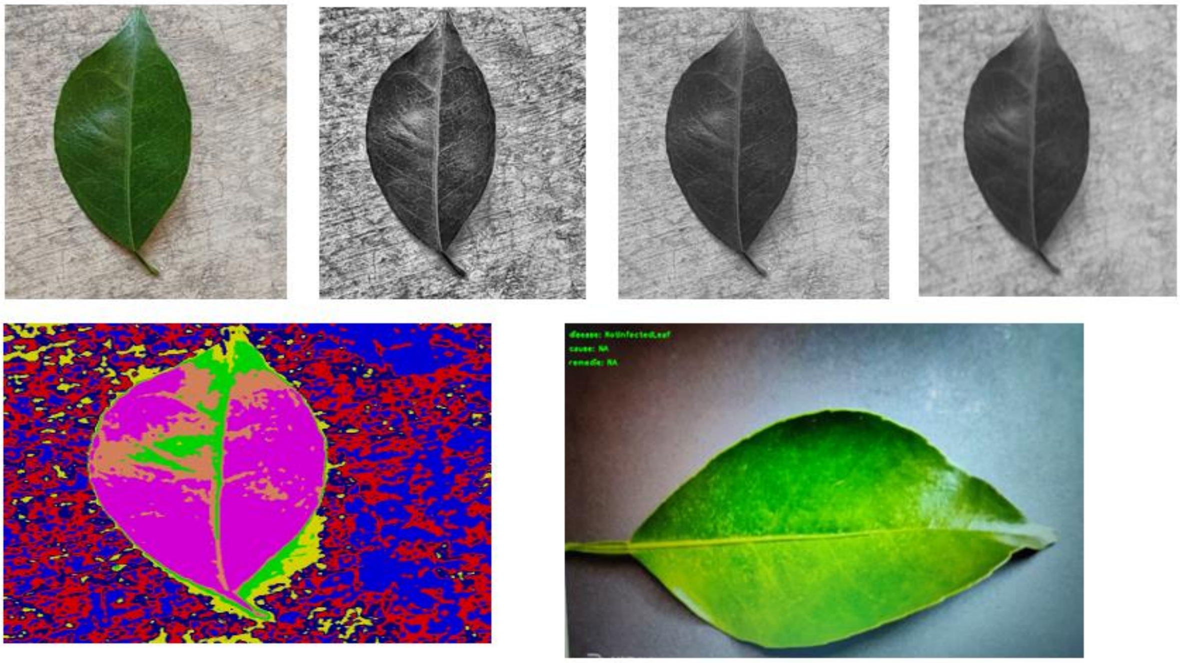

Fig.4- a, b, c, d, e, f:- Citrus Canker original image, enhanced image, gray scale image, blur image, segmented image, final output with disease name, cause and remedy.

VII. CONCLUSION

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 detection algorithms, thus all contributing to a reliable, safe, and accurate system of leaf disease with the specialization. Artificial neural networks (ANN) and image processing techniques will be utilised to detect plant illnesses early and reliably. For leaf disease classification, the suggested system uses an ANN classifier and a Color Co-occurrence feature extraction method, as well as a Support Vector Machine (SVM).

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