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Soft Computing and Image Processing for Detection and Analysis of Plant Infections

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Abstract

We provide a comprehensive evaluation of methods for detecting plant diseases in images taken under normal lighting conditions. The aim of these methods is to use digital image processing to identify plant diseases, rank their severity, and classify them into different categories. Disease symptoms could appear everywhere on a plant, but researchers here focused on the parts of the plant that could be seen by the human eye, such the leaves and stems. This was done for two reasons: (a) to keep the essay at a manageable length, and (b) to provide a more in-depth explanation of the subtleties involved in dealing with roots, seeds, and fruits. Taking these factors into account was crucial to making this decision. There are three broad classes into which the consensus standards fall: detection, severity measurement, and classification. The algorithm's preliminary technical response serves as a basis for subsequent breakdown of each class. Experts in the fields of vegetable pathology and pattern recognition may find this study's comprehensive overview to be useful.

Keywords:- Crop disease recognition, Sum and difference histogram (SADH), Internet of things (IoT), Crop disease monitoring system.

I. INTRODUCTION

Farmers are greatly reliant, not only for their own survival but also for the financial support that their agricultural activities provide. However, despite the fact that farmers have a great deal of leeway in selecting which crops to cultivate, one of the most constant concerns is the spread of infectious diseases. Plant diseases are one of the most significant contributors to the loss of life in the plant world. Plant diseases have the potential to reduce harvests by as much as 95 percent if they are allowed to proliferate. The application of pesticides, the use of

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mechanical cultivation, and the removal of affected plants by hand are just a few of the many strategies that can be utilized in the process of curing plant diseases. Talking to a farmer can be a quick and easy way to figure out what's wrong with your plants if you're looking for an explanation. When carried out manually, however, this method of determining a patient's disease requires a significant investment of both time and effort. The use of pesticides is the next feasible alternative; these chemicals hasten the maturation of plants, but at the sacrifice of their quality. However, increasing the use of pesticides without first determining the exact quantity that is necessary for a particular crop can have a detrimental impact not only on the environment but also on the health of humans. We are able to identify the overall health of a plant through the utilization of a method known as machine learning in conjunction with digital image processing. This approach to determining the requirements of individual plants results in lower overall expenses as well as more effective application of various pesticides. Automatic plant disease diagnosis is a significant undertaking because it might be helpful for farmers to monitor a large field of plants and recognize any signs of illness using a machine learning approach. This is why it is important to have this capability. Despite this, there is still a lot of work to be done before plant diseases can be automatically identified. The manual diagnosis of an illness takes a significant amount of time and effort, and it is prone to errors.

II. RELATED WORK

In this work, we present a strategy for efficiently locating the sonomammogram's Region of Interest (RoI) [1]. To improve the image quality, filtering is performed first. Second, a 3D plot of each bin is obtained by binning the original image. The number of peaks may be calculated from the 3D plots of the binned images.

An approach using a multi-SVM classifier is proposed in this research for identifying and categorizing breast cancer masses in digital mammograms [2]. The focus of this study is on optimizing the classification of breast pictures to distinguish between malignant and benign anomalies in the mass region, with the hope of improving diagnostic accuracy.

In order to pinpoint the source of the plant's disease, scientists are reviewing work conducted by Ghaiwat et al. [6]. This research provides a comprehensive overview of the various approaches that can be taken to classify plant diseases. Based on the provided test data, the k-nearest-neighbor method appears to still be the simplest of all methods for sophistication prediction.

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Researchers looked at the work of Mrunalini et al., who suggest a system for classifying and identifying the various plant illnesses, to make a prognosis about the nature of the illness that was precipitated by the reference to [7]. In this article, we discuss the color co-occurrence methodology that may be utilized to extract feature sets. Disease detection in leaves may now be done automatically using neural networks. The expected method will make a sizable contribution to the precise detection of leaves, and it appears to be a vital way, just in case of steam and root diseases, which will putt less work into calculation.

A method for the early and accurate identification of plant diseases employing a mistreatment artificial neural network (ANN) and several image processing techniques is presented in the paper by Kulkarni et al., which was the subject of the research. The goal of creating this approach was to detect diseases quickly and accurately. [5] The Kulkarni et al. An ANN classifier is used for classification, and a Gabor filter is used for feature extraction in the proposed method, which together produce excellent results, with a recognition rate of up to 91%. The numerous plant diseases are classified using a classifier that is largely ANN-based. This disease classifier uses a number of features, including color, texture, and pattern, to establish diagnoses. North Borneo Bashir published an article titled "Unwellness Detection in Malus domestica Using Efficient Techniques Such as K-mean Bunch, Texture, and Color Analysis," and this study set out to categorize it. [9] In order to classify this work, it has to be analyzed. To characterize and recognise the many forms of agriculture, it makes use of texture and color possibilities typically seen in traditional and affected areas. The K-means cluster, the Thomas Bayes classifier, and the principal element classifier are all viable options for classification that may be used in the near future.

Mrunalini et al. [3] detail a method for categorizing and diagnosing plant diseases. In the Indian economy, it has been shown that a machine-learning-based recognition system can reduce costs and improve efficiency. As a method for identifying patterns in a dataset, the co-occurrence of colors is proposed. This is only one example of how: [For example:] In order to automatically identify leaf diseases, neural networks are used. The proposed method requires less time spent in front of a computer, but it can considerably aid in the correct identification of illnesses affecting the plant's leaves, stems, and roots. Useful segments are obtained by sequentially performing the following procedures: (1) obtaining a color transformation structure for the input RGB image; (2) masking and removing the green pixels using a specific threshold value; (3) performing the segmentation process; and (4) computing the texture statistics. The publication [4] lays out each of these stages in detail. Finally, a

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classifier is applied to the retrieved features to determine the disease classification. Using experimental findings collected from a database of roughly 500 plant leaves, the validity of the suggested approach is demonstrated. Kulkarni et al. provide a method for rapid and precise diagnosis of plant diseases. Artificial neural networks (ANNs) are used in this method with conventional approaches to image processing. The proposed technique improves recognition rates by as much as 91% thanks to the employment of an ANN classifier for classification and a Gabor filter for feature extraction. It has been shown that a classifier based on an artificial neural network (ANN) can distinguish between different plant diseases by using a mix of parameters, including texture, color, and characteristics [5].

III. CHARACTERISTICS OF A LEAF IMAGE

Spots or blemishes cluster on the leaves of diseased plants, and this is a common symptom of many different diseases. A crucial diagnostic marker [20] for identifying plant diseases, leaf spots are an indicator of the presence of the illness itself. In Figure 1, we present a variety of alternate spots that can be utilized to classify and identify individual sick leaves. These marks can be used in the identification and classification of diseased leaves.

Fig. 1. Samples of Diseased Leaf image

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Pathology tissue specimens There are a number of different ways that leaves can be represented aesthetically, which are explored in this article. To extract the possible targets from the image, we employ an established and true method of image processing.

1. **Length and ratio of principal axes:** The magnitude relation of the lengths of the primary axes is the length of each axis divided by its own length.
2. **Solidity:** Solidity, also known as compactness, is measured as a price between zero and one; if an area has a solidity price of up to one, this indicates that the area is completely compacted. It is the magnitude relation between the gibbose space and the space of the spot, which may be computed as follows:

$$\frac{Spot\ Area}{Convex\ Area}$$

3. **Extent:** The percentage of the total number of pixels contained within the bounding box that are located within the spot is also referred to as the oblongness magnitude relation. It has a value between zero and one, and once this magnitude relation of spot has the value one, its form is as follows:

$$\frac{Spot\ Area}{Bounding\ Box\ Area}$$

4. **Hydraulic Radius:** it's calculated by dividing the spot space by the spot perimeter:
5.

$$\frac{4 \times \pi \times Spot\ Area}{(Spot\ Perimeter)^2}$$

6. **Complexity:** It is also known as the dispersion index, and it indicates the perimeter of the unit spot space. The higher the price, the more involved the spot form is, and the reverse is also true. It is calculated as follows:

$$\frac{(Spot\ Perimeter)^2}{Spot\ Area}$$

7. **Euler Number:** It gives a concise explanation of a topologically invariable property of spot. It is calculated as the number of objects that are contained inside the region minus the total number of holes that are present in those objects.

IV. METHODOLOGY AND RESULTS DISCUSSION

In this part, the principles of using image processing for diagnosing and classifying plant diseases are demonstrated (Fig. 2).

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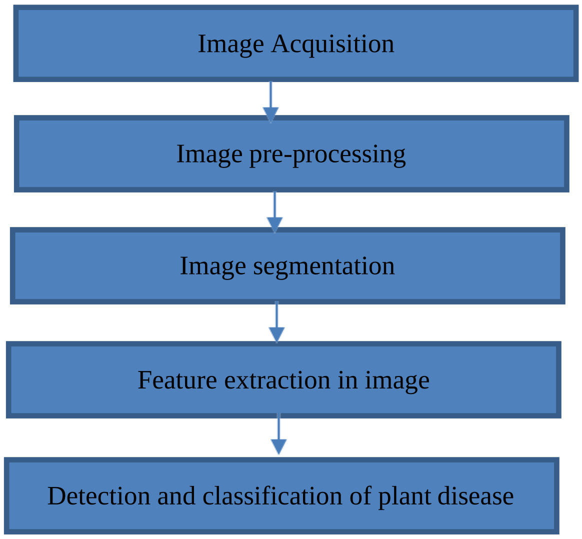

Fig. 2. Fundamental procedures for the identification and classification of plant diseases

A. Image acquisition

The camera was able to snap pictures of the leafy canopy of the plant, which can be seen down below. This picture was constructed by utilizing the RGB color space, which is comprised of red, green, and blue. First, a color house transformation is performed on the color transformation structure, and then the structure is used to build a color transformation structure for the RGB leaf image. This procedure is carried out independently of the device that is being used to view the image.

B. Image Pre-processing

Numerous other pre-processing methods are considered for eradicating image noise and selectively erasing specific objects. The image of the leaf was clipped, or cropped, so that just the relevant part of the picture would be seen. Ultimately, the smoothing filter is what's used to complete the process of making an image more refined. Giving out better quality images helps businesses stand out from the crowd. This is the equation for transforming RGB photos into monochrome ones (1).

$$f(x) = 0.2989 * R + 0.5870 * G + 0.114 * B \qquad (1)$$

To further emphasize the disease depictions, a bar graph effort is applied to the image, which evenly balances the image intensities. Intensity levels are often dispersed using the accumulative distribution function.

C. Image Segmentation

When you segment an image, you separate it into multiple pieces that all have the same characteristics or options, or that are comparable in some other way. The process of

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segmentation can be carried out via a wide number of techniques, such as the otsu' approach, the k-means clump method, changing the RGB image into an HIS model, and many more.

D. Feature Extraction

Feature extraction plays a crucial role in the identification process. Feature extraction is widely used in many different types of image processing tasks. Diseases in plants can be diagnosed using visual cues such as color, texture, morphology, edges, and more.

E. Classification

When employing this technique, the hue, saturation, and texture of each individual pixel all play a part in the production of an original quality for the image. For the purposes of this endeavor, the RGB image is thus reborn in the form of an HSI representation.

1. Choose Image

Fig. 3. Choose Image

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2. The result of Pre-processing and Segmentation

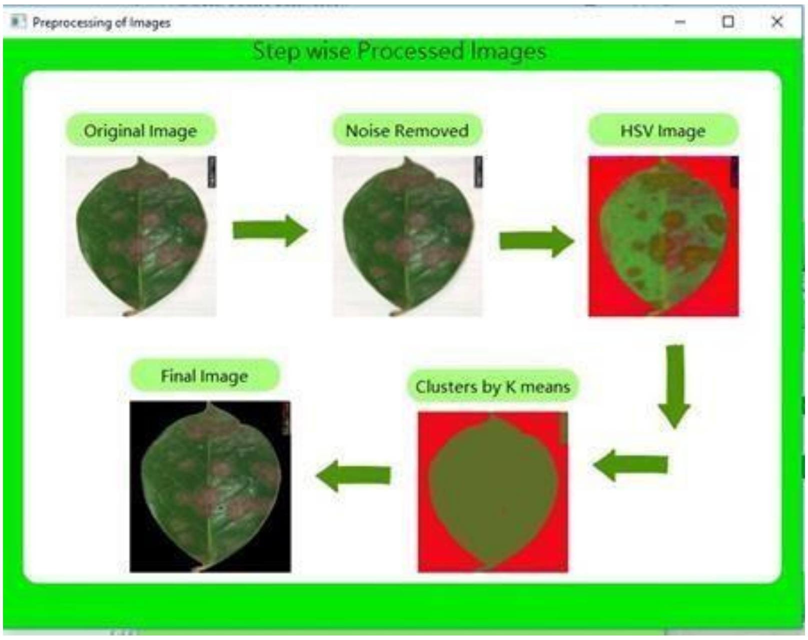

Fig. 4. Pre-processing and Segmentation Steps

3. The result of Prediction

Fig. 5. Prediction - whether the leaf is healthy or not?

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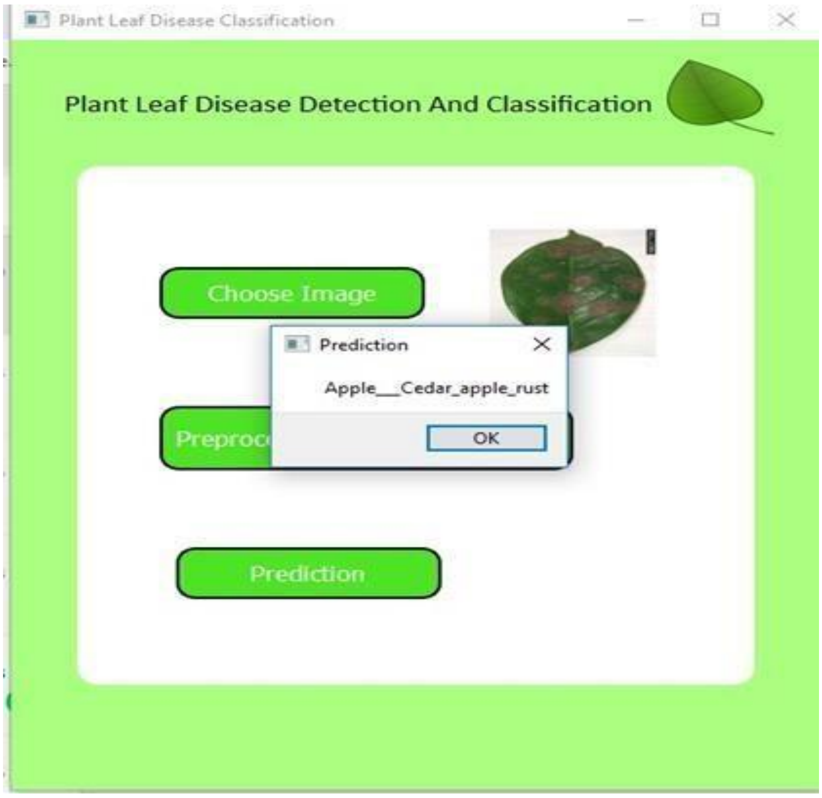

Fig. 6. Prediction of the Disease

Difference between the time an algorithm is started and the time it finishes running is used to characterize its execution time. Time to execute an algorithm is defined as: finish time minus start time Figure 6shows that the accuracy of the proposed method is higher than that of the current system. In comparison to the predicted approach's 97% accuracy, the already available method only achieves 95% accuracy. The presented algorithm is compared to the available algorithm in terms of the amount of time it takes to implement. It is found that the implementation time for the envisioned method is smaller than that of the available algorithm.

Table 1 Comparison of results

Disease samples	No. of images used for training	No. of images used for testing	Detection accuracy/%		
			MDC withK mean	MDC with Proposed algorithm	SVM with Proposed algorithm
Banana	15	10	80.00	91.00	91.00
Beans	15	14	92.85	92.85	92.85
Lemon	15	10	90.00	100.00	100
Rose	15	12	83.33	91.66	100

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	Overall accuracy	86.54	94.63	96.71

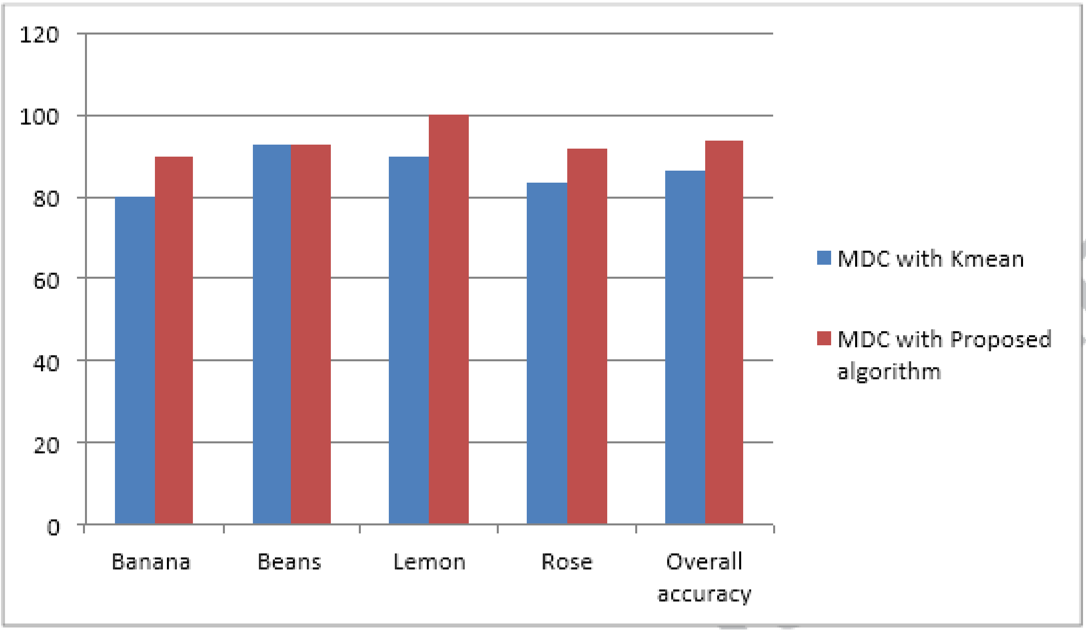

Fig. 7 Comparison of results

The number of samples of leaf disease that were classified to each of the five classes of leaf disease by making use of the technique that was provided can be found displayed in Table 1 and Figure 7. According to the findings, an inaccurate diagnosis was made for a very small percentage of the leaf samples that were afflicted by frog eye leaf spot or bacterial leaf spot. Only two of the leaves are affected by the bacterial leaf spot disease, and of those two, only one of the leaves is affected by the frog eye leaf spot illness. The suggested method has an average classification accuracy of 97.6, which is significantly higher than the figure of 92.7 that is reported in [17].

V. CONCLUSION

The agricultural disease monitoring system that has been described has the potential to successfully solve the problem of human-computer interaction at every stage of the deductive reasoning process. During the crop disease monitoring reasoning process, the field disease fact image is utilized as the major human-computer interface technique. This makes it possible to visually watch the data being collected. Due to the fact that the function of the users in the monitoring process is comparable to that of plant protection specialists out in the field, training for both the specialists and the farmers is incorporated into the monitoring technique. On the other hand, the system is able to deliver prospective diagnostic results to users in the form of real-world photos of diseases that are found in the field. This

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could lead to an increase in the monitoring system's overall efficiency. The capability to record user monitoring and subsequently conduct analysis of that data within the context of actual diseases is one of the features of the system. You can utilize it to streamline the studying and testing procedures that you have to go through. One of the most appealing aspects of the system is the interactive monitoring format that it offers, which integrates real-time graphics with input from both humans and computers. This is the primary selling point of the system. The software not only has the potential to be useful as a tool for illness monitoring, but it also provides a form of multimedia training that is friendly, genuine, and participatory. In addition to this, it has the potential to serve as a tool for monitoring the development of certain diseases. The fact that this method can be easily included into the current computer infrastructure also helps to the significant improvement in the reliability of the data gathered for the purpose of disease surveillance. It has the potential to serve as an excellent instructional tool for multimedia, and it also has the potential to assist with the challenge of monitoring and treating diseases in the industrial industry. In subsequent research, new environmental parameters will be incorporated into the algorithm used for disease recognition and prediction, which will ultimately lead to greater accuracy. This study will contribute to the development of modern agriculture by laying the groundwork for the eventual replacement of the traditional empirical agricultural production mode with the large-scale and automatic modern agricultural production mode. This will be accomplished by laying the groundwork for the eventual replacement of the traditional empirical agricultural production mode. This is what will take place as the number of people working in agriculture continues to decrease and scientific and technical advancement continues hand in hand.

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