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Plant IVRNet- A deep transfer Learning Model with stacked pre-trained models for plant leaf disease detection

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Abstract

To increase food production and spare farmers from expensive spraying processes, Plant leaf diseases must be identified early on. Because the afflicted and healthy portions of plant leaves are so similar, accurately and promptly identifying a number of plant leaf diseases is a challenging undertaking. Furthermore, the presence of noise and blurring on the photos, as well as variations in light, color, and brightness, add to the intricacy of the detecting process. Automatic disease detection through neural network based digital image processing tech nique is proposed in this paper. The Otsu segmentation is used for proper segmentation and the modified co-occurrence of gray levels Accurate texture feature extraction from matrices is used to create feature sets that are used to precisely diagnose illness. The proposed algorithm can detect disease correctly with 95.51% accuracy which is quite high compared with existing algorithm.

Keywords: *Leaf Classification, Neural Network, K-means clustering, Image Processing.*

1. INTRODUCTION

As per research released by the Food and Agriculture Organization (FAO) of the United Nations, there will be a significant surge in the global human population to reach 9.1 billion by 2050. The need for food will rise in tandem with this expansion in the human population. In farming and plantation different kind of diseases are common and needs to take proper action which keeps the plant healthy. Generally, most of the plant disease affect its leaf and generate some kind of unique pattern on the leaf through which the disease can be detected and proper action can be taken depending upon the detection. But in real time there are many type diseases present which makes it different for the human for manual detection, which rise in the automatic detection of the plant disease through various computer-based processing technique, digital image-based processing technique are generally used for the plant disease detection efficiently in lesser time than other techniques. In this study, we offer an efficient neural network-based image processing-based plant disease classification system that can accurately identify the illness based on its characteristic.

2. LITERATURE REVEIW

Monu Bhagat et al [1] proposed “Plant Leaf Disease Classification Using Grid Search Based SVMThe authors of this work suggested a computationally efficient approach for determining whether plant leaves are healthy or unwell and for identifying plant leaf diseases when unhealthy. So in proposed paper they used the SVM algorithm, a system for classifying and identifying plant diseases will be created. With minimal computational work, this strategy will assist farmers in obtaining a helpful technique for precise disease identification. Literature Review

Surampalli Ashok et al. [2] were proposed “Tomato Leaf Disease Detection Using Deep Learning Techniques”. The methods of image processing applied in this paper to identify the tomato plant leaf disease included picture segmentation, clustering, and open-source algorithms. With an emphasis on tomato plants, these techniques worked together to provide a trustworthy, safe, and accurate leaf disease system. The suggested approach maps picture pixel intensities into hierarchical features, which are then extracted using CNN and compared to images from the training dataset.

N Nandhini and R Bhavani [3] proposed “Feature extraction for diseased leaf image classification using machine learning”. In the present study, they used K-Nearest Neighbor, Decision Trees, and Support Vector Machines to analyze the efficacy of the classification based on the obtained characteristics. Thus, identification of the leaf-based illness is crucial for managing crop disease. The approach suggested uses the color characteristics of diseased leaf images to classify the image of the lesion. S. Yogeshwar Yadhav et al. [4] proposed "using CNN model with optimized activation function for plant disease detection and classification." In this study, they addressed the optimal real-time identification of plant illnesses and the afflicted region through the application of convolutional neural network (CNN) algorithms. This allows for the use of suitable fertilizers to avoid additional harm to plants caused by pathogenic viruses. In order to determine the proportion of the affected region, the K-means clustering technique was applied in MATLAB, and the optimal fertilizer dosage was recommended in order to increase crop output.

Minu Eliz Pothen and Maya L Pai [5] proposed “detection of rice leaf diseases using image processing”. To characterize the approaches used for rice leaf disease categorization, they put out a number of distinct approaches. Otsu's approach is utilized to segment images of brown spot disease, bacterial leaf blight, and leaf smut. Consequently, the suggested approach helps farmers salvage their crops at an early stage by identifying the illness that damages the leaves of rice plants.

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Divyanshi Tiwari et al. [6] proposed “potato leaf diseases detection using deep learning”. The authors of this paper suggested a model that extracts relevant properties from the dataset by fine-tuning (transfer learning) pre-trained models, such VGG19. Researchers have therefore developed an automated system that can recognize and classify diseases in potato leaves, such as late blight, blight, and healthy with creative treatment, by utilizing the concept of transfer learning.

Rudresh Dwivedi et al. [7] proposed “Grape disease detection network based on multi-task learning and attention features”. The authors of this research worked on a Grape leaf disease detection network (GLDDN) that evaluates, detects, and classifies features using dual attention techniques. Hence, testing conducted on a benchmark dataset during the assessment stage demonstrates that a disease detection network may be more appropriate than the current techniques.

S Gayathri et al. [8] proposed “Image analysis and detection of tea leaf disease using deep learning”. To identify the tea plant illness from a set of leaf picture data, the authors used a deep CNN known as LeNet. Consequently, LeNet became the ideal CNN model that was applied in different contexts to enhance the diagnostic assessment of tea and other plant leaves. Thus, the suggested approach greatly reduces the computational complexity needed to use a typical neural network.

Pushkara sharma et al. [9] proposed “classification of plant leaf diseases using machine learning and image pre-processing techniques”. The authors of this research suggested using artificial intelligence to automatically detect and categorize plant leaf diseases in order to quickly and easily identify the illness, classify it, and carry out the necessary treatments to cure it.

Jiang Huixian [10] proposed “the analysis of the plants image recognition based on deep learning and artificial neural network”. This paper's primary goal is to use image analysis to extract plant leaf attributes and identify different plant species. Plant leaf pictures are first segmented using a variety of techniques. Following this, feature extraction algorithms are employed to extract the texture and form data from leaf sample photos. To get reconstruction errors, the learning model receives image samples from the test set.

The CNN framework was utilized by the authors of Vickers (2017) for classification tasks, whereas the VGG network was employed for sickness localization. In comparison with the authors' statistics (Sharma et al., 2022), this model achieved a respectable degree of accuracy. The authors of (Kumari and Singh, 2018) used the VGG16 framework for data segmentation and the AlexNet framework for data classification. However, this approach's classification accuracy is subpar.

Education and Kaur (2021). Various pattern-based techniques, such as the LBP, SIFT, and GLCM, were applied to feature vector estimation. Then, to complete the classification task, a number of well-known machine learning classifiers, including the SVM and RF, were trained on the computed features. The RF classifier produced the best results, while the classification accuracy required improvement. Against the most advanced models currently in use for recognizing and categorizing plant diseases.

Ramesh et al. (2018) suggested a computer-aided technique for the automatic identification and categorization of different plant leaf flaws. The input samples were subjected to the HOG filter for feature estimation, while the Random Forest (RF) technique was employed for illness classification.

Kuricheti and Supriya's (2019) classification results for plant leaf diseases were superior. However, for photos with significant brightness variations, detection performance suffered.

3. GOALS AND RESEACH QUESTION

The results of the literature review highlight issues, challenges, and research needs that are worthwhile to investigate from the standpoint of leaf diagnosis, detection, and classification, this study seeks to make a significant contribution to the comprehensive analysis of the most recent literature. Our primary research question for the literature study is: Which K-Nearest Neighbor (KNN) algorithm has been used to identify and categorize leaf diseases.

The following are the study's main contributions:

- We created an effective modified KNN algorithm model to enhance the classification of plant illnesses by automatically identifying diseases in different stages of distinct plants.
- We compared the suggested method's efficacy with cutting-edge methods for recognizing and categorizing plant diseases.
- In order to precisely categorize and identify plant diseases, the novel modified KNN algorithm framework automatically extracts the most discriminative properties.

4. PLANT DISEAESE CAUSATION FACTORS

Numerous plant diseases can damage a plant's growth at various stages of its life, which could have a negative impact on crop productivity as a whole. Plant diseases can be attributed to a wide range of variables during different phases of plant development. Abiotic and biotic variables make up the two primary groups of causes that cause crop diseases shown by Figure 1. Water, temperature, radiation, and a lack of nutrients are examples of abiotic variables that hinder plant growth, whereas microbial infection in plants leads to the development of biotic factors such viruses, fungus, bacteria, mites, and slugs.

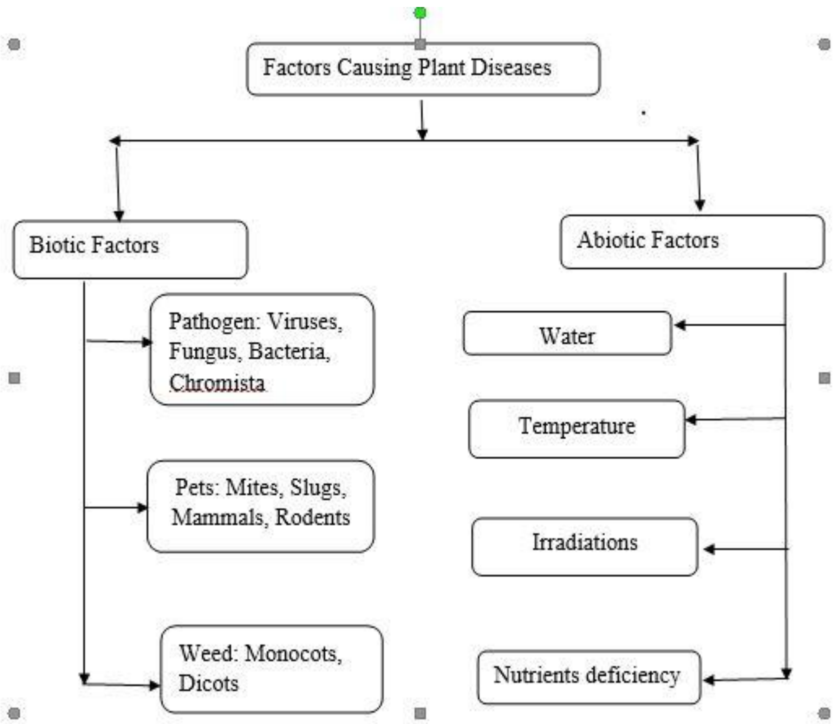

Fig 1: Plant disease-causing variables

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Contribution: In this research, we extract accurate texture features using the modified grey level co-occurrence matrix.

5. CLASSIFICATION OF PLANT DISEASES:KEY ISSUES

In our research we outlined a few challenges to crop disease identification and categorization so that the scientific community can examine the root reasons, which could have a pertinent to influence on developing methods for diagnosing and identifying plants in real time. Temperature, radiation, and dietary deficiencies are only a few of the problems and elements that might influence the diagnosis and categorization of diseases.

1) Plant disease characteristics, their extraction, and the kind of classifiers employed are the primary determinants of the effectiveness of plant disease detection systems.

2) The detection model's performance is greatly impacted by complex backgrounds in real-field photos, so it is imperative to remove them from the background and segment the diseased area from leaf data.

3) As most disease symptoms are illusory and mix in with normal tissue, it can be challenging to tell what sections are healthy and those that are sick.

4) It will be challenging to distinguish, isolate, or merge distinct diseases' simultaneous presentations into hybrid symptoms (coexistence of many diseases on the same leaf).

5) The selection of relevant qualities, polluted regions, and homogeneity of illness traits present substantial hurdles for disease recognition systems.

6. MATERIALS AND METHODS

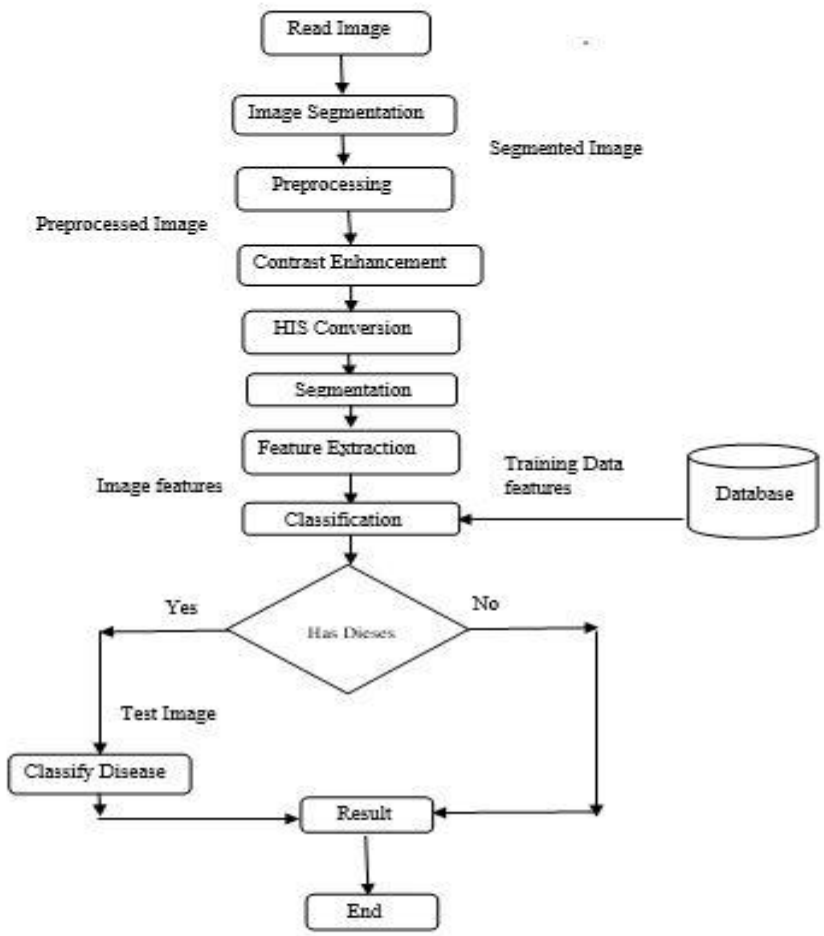

Fig 1: Proposed Leaf Classification Algorithm

A. Read Image

Step1: The captured leaf image is first read by the tool which is generally in the form of JPEG, PNG or similar format and converts them into generic pixel-based format. The image processing toolboxes present in the MATLAB tool [11] used for this purpose.

Step2: An image can be divided into several sections or regions using the read image analysis, frequently depending on the properties of the individual pixels in the image.

B. Pre-processing

Step3: Pre-processing is an enhancement of the image data that reduces undesired distortions or brings out certain aspects of the image that are crucial for additional processing, though geometric image modifications (rotation, scaling, translation, etc.)

C. Contrast Enhancement

Step4: The RGB component of the pre-processed image will fall between 0 and 255. Divide the picture by 255 to represent it in the [0 1] range. Determine the components of hue, intensity, and saturation (H, I, S). To extract the effective features, it is essential to convert the RGB colour model image into corresponding the HIS model using below equations [11].

$$h(i) = \sum_{x=1}^{N} \sum_{y=1}^{M} 1 \quad (1)$$

Where, N and M are image dimensions.

The cumulative distribution function of the pixel values are then

$$DF(j) = \sum_{i=1}^{j} h(i) \quad (2)$$

To produce the enhanced output image, scale the input image using the cumulative distribution function as

$$g(x, y) = \left\{\frac{CDF\,[f\,(x,y) - CDF_{min}]}{(N \times M) - CDF_{min}}\right\} \times (L - 1) \quad (3)$$

Where, CDF_{min}. is the cumulative distribution function.

The Fig. 4 shows the enhanced image's histogram,which spreads throughout the x-axis. It shows the efficient colour distributions of the image.

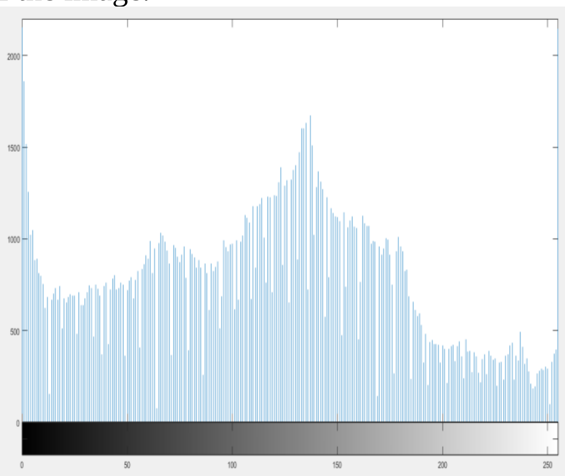

Fig 4: Histogram of the Enhanced Leaf Image.

$$\theta = \left\{ \frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{\frac{1}{2}}} \right\} \quad (4)$$

$$H = \{\theta; \quad if\ B \le G\ 360-\theta; if\ B > G \quad (5)$$

$$S = 1 - \frac{3}{(R+G+B)^2}[(R,G,B)_{min}] \quad (6)$$

$$I=1/3(R+G+B) \quad (7)$$

Where, R is the red pixel values
G is the green pixel values
B is the blue pixel values

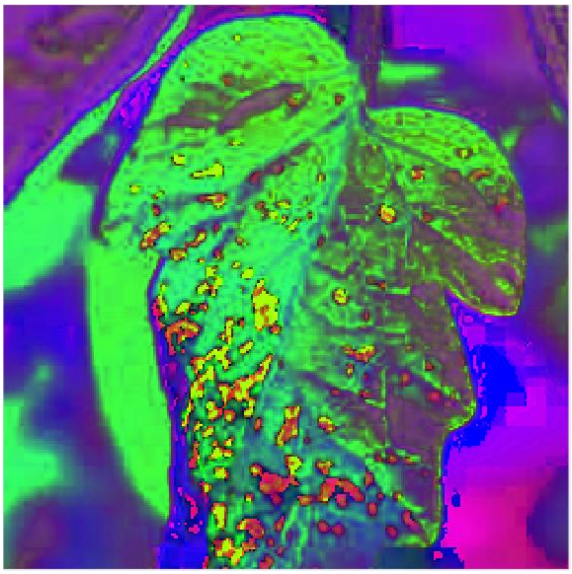

Fig 5: HIS colour model of the leaf image.

D. Segmentation

Step5: Now the enhanced image is segmented depending upon the similarities of the feature present in that image. It helps the feature extraction block to generate the accurate feature which helps in proper diagnostics of the leaf condition. The Otsu's segmentation [11, 12] technique is used to perform the segmentation of the input image. In the case of Otsu's method, the algorithm searches the variances which is defined as

$$\sigma_w^2(t) = w_0(t)\sigma_0^2(t) + w_1(t)\sigma_1^2(t) \quad (8)$$

Where,

w_1 and w_2 are represents, the probabilities of the two classes separated by a threshold t
σ_0 and σ_1 are represents the variances of these two classes.
The L bins of the histogram is defined as two classes of probabilities as

$$w_0(t) = \sum_{i=0}^{t-1} p(i) \quad (9)$$

$$w_1(t) = \sum_{i=t}^{L-1} p(i) \qquad (10)$$

In the case of two classes, maximizing inter-class variance is equal to reducing intra-class variation.

$$\sigma_b^2(t) = w_0(t)w_1(t)[\mu_0(t) - \mu_1(t)]^2 \qquad (11)$$

E. Feature Extraction

Step6: In feature extraction a dataset's amount of redundant data is decreased through image processing. Here to enhance the visual quality of the input image which enhanced the features present in it. The histogram-based enhancement [11, 12] technique is used for the enhancement. Each pixel values of f (x,y) is mapped into L uniformly spaced pixels h(i) which is given in Equation (1) Once features are extracted then these features are applied to classification. In image processing, the Gray Level Co-occurrence Matrix is mostly utilized for extracting texture features [13]. The GLCM technique is mostly utilized in image processing applications, such as biomedical. The GLCM techniques are able to display the position of each grey level pixel.

Fig 6: Leaf Image Labelled by Cluster Index

In this work, a total of 11 texture features are identified using the GLCM algorithms [13]. The attributes extracted from GLCM include Mean Standard Deviation, Energy, Entropy, Skewness, Variance, Kurtosis, Smoothness, Contract, and Correlation. The properties and formulas of the GLCM are displayed in Table I.

$$mean(\mu) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} p(i,j) \qquad (12)$$

$$standard\ deviation(a) = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(p(i,j)-\mu)^2} \qquad (13)$$

$$Energy(E) = \sum_{(i,j)} p(i,j)^2 \qquad (14)$$

$$Entropy(h) = -\sum_{k=0}^{l-1} prk(prk)$$

$$keroness(S) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}((p(i,j)-\mu^2)/a) \qquad (16)$$

$$Variance(var) = (S.D)^2 \qquad (17)$$

$$Kartosis(k) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}((p(i,j)-\mu^2)/a) - 3 \qquad (18)$$

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$$Smoothness(R) = 1 - 1/(1 + a^2) \quad (19)$$

$$Contrast(e) = \sum_{i=1}^{M} \sum_{j=1}^{N} (i,j)^2 p(i,j) \quad (20)$$

$$orrelation(Corr) = \sum_{i=1}^{M} \sum_{j=1}^{N} ((i-\mu)(j-\mu)p(i,j))/(a_1 a_2) \quad (21)$$

F. Load Disease Database

Step7: The standard leaf disease features [14] load in the program to train the algorithm for detecting the different diseases. The Alternaria, anthracnose, bright feat, carpospore feat etc., diseases are used as the database.

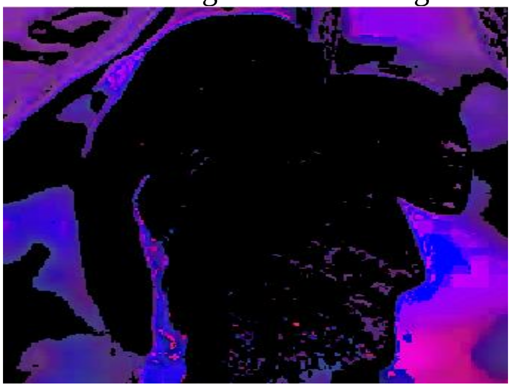
G. Compare and Decision

Step8: The Euclidean distance [12] is used for compare the test feature with database features and makes proper decision which indicates the proper disease

Fig 7: The result dialog

7. Result and Discussion

The suggested approach is put into execution with MATLAB, a tool that uses a common programming language. [11]. The input and enhanced leaf image is shown in figure 2.



(a). Cluster 1

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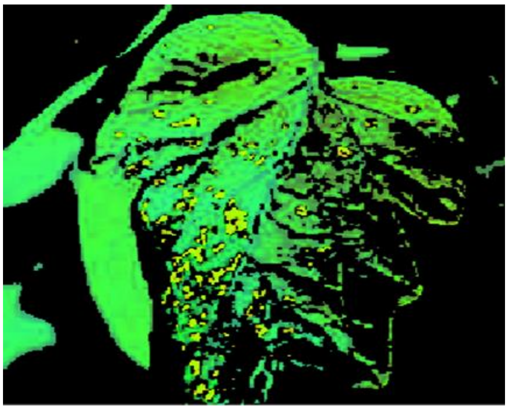
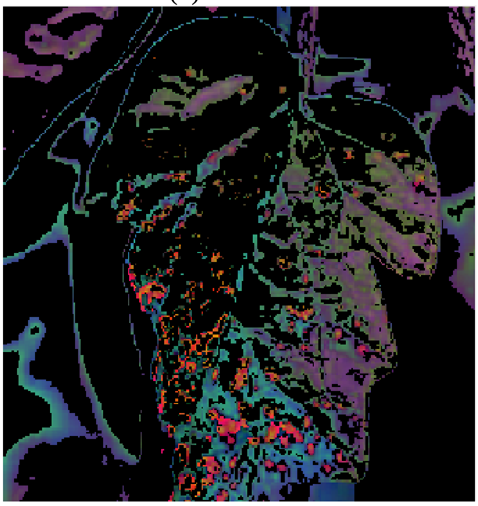


(b). Cluster 2



(c). Cluster 3

Fig 8: Leaf Image Labelled by Cluster Index

The standard disease feature for leaf presented in [15] are used in the program which shows 98.11% disease detection accuracy for standard leaf database [14] using the proposed algorithm.

Table I: Detection Accuracy Of The Proposed Algorithm.

Sl. No	Image	Disease	Accuracy
1	Sample-1	Anthracnose	98.11 %
2	Sample-2	Anthracnose	96.77 %
3	Sample-3	Bacterial	95.45 %
4	Sample-4	Citrus Canker	97.28 %
5	Sample-5	Gray Mold	96.82 %
6	Sample-6	Powdery Mild	98.08 %
7	Sample-1	Anthracnose	98.11 %

8. COMPARISON WITH EXISTING TECHNIQUES

The detection accuracy is compared with the existing technique and plotted in Table II which shows that the proposed method is more effective in detecting the proper disease than existing techniques.

Table Ii: Comparisons with Existing Techniques.

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S.N	Authors	Techniques	Accuracy
1	Anshul Bhatia et el. [16]	Complex Decision Tree	89.5%
2	Syafiqah Ishak et al. [17]	Neural Network Classifier	91.7%
3	Mohammed Hussein and Amel H. Abbas [18]	Quadratic SVM	90.7%
4	Kaur and Education,	SIFT, LBP, GLCM + SVM	82.12
5	Ramesh et al.	HOGs + RF	70.14
6	Kuricheti and Supriya,	GLCM + SVM	91
7	Proposed	Modified KNN	95.11%

CONLUSION

In this work, we developed a novel approach to detect the disease from the leaf image accurately. The uses of Otsu's segmentation and modified feature extraction technique help to achieve higher disease detection accuracy than existing techniques. The comparison table proves our approach.

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