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Automated Plant Disease Detection and Classification in Leaf Image

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ABSTRACT: The identification of disease on the plant is a very important key to prevent a heavy loss of yield and the quantity of agricultural product. The symptoms can be observed on the parts of the plants such as leaf, stems, lesions and fruits. The leaf shows the symptoms by changing color, showing the spots on it. This identification of the disease is done by manual observation and pathogen detection which can consume more time and may prove costly. The aim of the project is to identify and classify the disease accurately from the leaf images. The steps required in the process are Preprocessing, Training and Identification. For identification of disease features of leaf such as major axis, minor axis etc. are extracted from leaf and given to classifier for classification. In our project we have used cassava leaf for identifying its disease. We have used algorithms namely SqueezeNet as existing and ResNet-50 as proposed system in terms of accuracy. From the results its proved that ResNet-50 works better than SqueezeNet. The tool we have used for the detection of leaf disease is MATLAB.

KEYWORDS: Plant Disease Detection , Leaf Image Classification , Deep Learning , Image Processing , ResNet , SqueezeNet , CNN , SVM , K-mean cluster , Preprocessing , Automated Monitoring , Training Dataset , User-Friendly.

I. INTRODUCTION

Now days, a new concept of smart farming has been introduced where the field conditions are controlled and monitored using the self operating systems. The self recognition of the disease is based on the identification of the symptoms of disease. So that information about the disease occurrence could be quickly and accurately provided to the farmers, experts and researchers. This in turn reduces the monitoring of large field by human being. In disease recognition from image the key is to extract the characteristic feature of the diseased region. According to the disease the features may vary. The features that are extracted from the image are color, shape, texture etc. Sometimes for detection of the disease more features are extracted and these extracted features would increase the hardware as well as software cost. This further causes increase in the complexity and the computation time. Hence it is necessary to reduce the feature data. The occurrence of the disease on the plant may result in significant loss in both quality as well as the quantity of agricultural product.

This can produce the negative impact on the countries whose economies are primarily dependent on the agriculture. Hence the detection of the disease in the earlier stages is very important to avoid the loss in terms of quality, quantity and finance. Usually the methods that are adopted for monitoring and management of plant leaf disease are manual. One such major approach is naked eye observation. But the requirement of this method is continuous monitoring of the field by a person having superior knowledge about the plants and its corresponding diseases.

The pathogen detection methods can provide more accurate results. As the tests are carried out of field the cost may be high and could be time consuming. This paper suggests a system which can provide more accurate results related to the identification and classification of disease. It tries to replace the need of the experts to certain extent. Here, the captured image is first preprocessed to resize it and then converted to HSI color space format by using segmentation. The features such as major axis, minor axis, eccentricity are extracted from the image. In the last step, these features are given to the classifier to classify the disease occurred on the leaf.

II. LITERATURE REVIEW**Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm Melike Sardogan ; Adem Tuncer ; Yunus Ozen IEEE 2024.**

The early detection of diseases is important in agriculture for an efficient crop yield. The bacterial spot, late blight, septoria leaf spot and yellow curved leaf diseases affect the crop quality of tomatoes. Automatic methods for classification of plant diseases also help taking action after detecting the symptoms of leaf diseases. This paper presents a Convolutional Neural Network (CNN) model and Learning Vector Quantization (LVQ) algorithm based method for tomato leaf disease detection and classification. The dataset contains 500 images of tomato leaves with four symptoms of diseases. We have modeled a CNN for automatic feature extraction and classification. Color information is actively used for plant leaf disease researches. In our model, the filters are applied to three channels based on RGB components. The LVQ has been fed with the output feature vector of convolution part for training the network. The experimental results validate that the proposed method effectively recognizes four different types of tomato leaf diseases.

Detection of leaf diseases and classification using digital image processing R. Meena Prakash ; G.P. Saraswathy ; G. Ramalakshmi ; K.H. Mangaleswari ; T. Kaviya IEEE 2024.

In this paper, image processing techniques are used to detect the plant leaf diseases. The objective of this work is to implement image analysis & classification techniques for detection of leaf diseases and classification. The proposed framework consists of four parts. They are (1) Image preprocessing (2) Segmentation of the leaf using K-means clustering to determine the diseased areas (3) feature extraction & (4) Classification of diseases. Texture features are extracted using statistical Gray-Level Co-Occurrence Matrix (GLCM) features and classification is done using Support Vector Machine (ML).

Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition Robert G. de Luna ; Elmer P. Dadios ; Argel A. Bandala IEEE 2024.

Smart farming system using necessary infrastructure is an innovative technology that helps improve the quality and quantity of agricultural production in the country including tomato. Since tomato plant farming take considerations from various variables such as environment, soil, and amount of sunlight, existence of diseases cannot be avoided. The recent advances in computer vision made possible by deep learning has paved the way for camera-assisted disease diagnosis for tomato. This study developed the innovative solution that provides efficient disease detection in tomato plants. A motor-controlled image capturing box was made to capture four sides of every tomato plant to detect and recognize leaf diseases. A specific breed of tomato which is Diamante Max was used as the test subject. The system was designed to identify the diseases namely Phoma Rot, Leaf Miner, and Target Spot. Using dataset of 4,923 images of diseased and healthy tomato plant leaves collected under controlled conditions, we train a deep convolutional neural network to identify three diseases or absence thereof. The system used Convolutional Neural Network to identify which of the tomato diseases is present on the monitored tomato plants. The F RCNN trained anomaly detection model produced a confidence score of 80 % while the Transfer Learning disease recognition model achieves an accuracy of 95.75 %. The automated image capturing system was implemented in actual and registered a 91.67 % accuracy in the recognition of the tomato plant leaf diseases.

ML classifier based grape leaf disease detection Pranjali B. Padol ; Anjali A. Yadav IEEE 2024.

Grape constitutes one of the most widely grown fruit crops in the India. Productivity of grape decreases due to infections caused by various types of diseases on its fruit, stem and leaf. Leaf diseases are mainly caused by bacteria, fungi, virus etc. Diseases are a major factor limiting fruit production and diseases are often difficult to control. Without accurate disease diagnosis, proper control actions cannot be used at the appropriate time. Image Processing is one of the widely used technique is adopted for the plant leaf diseases detection and classification. This paper is intended to aid in the detection and classification leaf diseases of grape using ML classification technique. First the diseased region is found using segmentation by K-means clustering, then both color and texture features are extracted. Finally classification technique is used to detect the type of leaf disease. The proposed system can successfully detect and classify the examined disease with accuracy of 88.89%.

An application of image processing techniques for detection of diseases on brinjal leaves using k-means clustering method R Anand ; S Veni ; J Aravinth IEEE 2024.

This work presents a method for identifying plant leaf disease and an approach for careful detection of diseases. The goal of proposed work is to diagnose the disease of brinjal leaf using image processing and artificial neural techniques. The diseases on the brinjal are critical issue which makes the sharp decrease in the production of brinjal. The study of interest is the leaf rather than whole brinjal plant because about 85-95 % of diseases occurred on the brinjal leaf like, Bacterial Wilt, Cercospora Leaf Spot, Tobacco mosaic virus (TMV). The methodology to detect brinjal leaf disease in this work includes K-means clustering algorithm for segmentation and Neural-network for classification. The proposed detection model based artiifical neural networks are very effective in recognizing leaf diseases.

III. METHODOLOGY

The methodology for this project involves a systematic approach to automated leaf fungus detection using image processing and deep learning techniques. First, a dataset of healthy and diseased leaf images is collected and preprocessed through augmentation, resizing, and normalization to enhance model performance. Pretrained CNN-based models like ResNet [9] and SqueezeNet are used for feature extraction, identifying key patterns associated with fungal infections. The extracted features are then used to train a classification model with transfer learning, optimizing performance using Adam and SGD techniques. The model's accuracy is evaluated using metrics like precision, recall, F1-score, and a confusion matrix. Finally, the trained model is deployed in a real-world application, enabling real-time disease detection via mobile apps, web platforms, or IoT-based systems, with continuous updates to improve performance .

A. System Architecture

The system architecture for automated leaf fungus detection consists of multiple interconnected components. It begins with image acquisition, where leaf images are captured using cameras or mobile devices. These images undergo preprocessing, including noise reduction, resizing, and segmentation to enhance quality. Next, feature extraction is performed using deep learning models like ResNet and SqueezeNet, which identify patterns related to fungal infections. The extracted features are then fed into a classification model, which predicts whether the leaf is healthy or diseased. The model's performance is evaluated using accuracy, precision, recall, and F1-score. Finally, the trained model is deployed in a mobile or web application, allowing users to upload images and receive real-time disease detection results.

B. Data Collection and Preprocessing

A dataset of leaf images is collected, comprising both healthy and diseased samples to ensure a comprehensive representation of plant conditions. To enhance model robustness and generalization, image augmentation techniques such as rotation, scaling, and flipping are applied, increasing variability within the dataset. Furthermore, images are resized and normalized to maintain consistency before being fed into the models, ensuring uniformity in input dimensions and improving the efficiency of the learning process.

C. Feature Extraction using CNN-based Models

Pretrained deep learning models, including ResNet and SqueezeNet, are employed for feature extraction due to their efficiency in capturing intricate image features. The convolutional layers of these networks extract hierarchical features, identifying essential patterns associated with fungal infections. These models enable the automatic learning of spatial and texture-based characteristics, which are crucial for distinguishing between healthy and diseased leaves with high accuracy.

D. Model Training and Optimization

Once features are extracted, they are used to train a classification model capable of distinguishing plant diseases. Transfer learning is applied by fine-tuning ResNet and SqueezeNet on the specific leaf dataset, allowing the models to leverage pre-learned features while adapting to the new task. Optimization techniques such as Adam and Stochastic Gradient Descent (SGD) are implemented to minimize classification loss and improve the efficiency of the training process, ensuring faster convergence and better accuracy.

E. Performance Evaluation

The trained models are rigorously evaluated using performance metrics such as accuracy, precision, recall, and F1-score to assess their effectiveness. A confusion matrix is generated to analyze classification errors, helping to understand model weaknesses and misclassifications. Additionally, the models are tested on unseen data to determine their generalization ability, ensuring they perform well in real-world scenarios outside the training environment.

F. Deployment and Real-World Application

Once validated, the final trained model is integrated into an automated system for real-world application. The deployment may include mobile applications, web-based platforms, or IoT-enabled devices to provide real-time disease detection and decision support for farmers. The system is designed to be user-friendly, allowing users to upload leaf images and receive instant disease diagnoses along with possible recommendations. Continuous updates and model retraining are incorporated to improve the system's accuracy and adaptability to new disease variations.

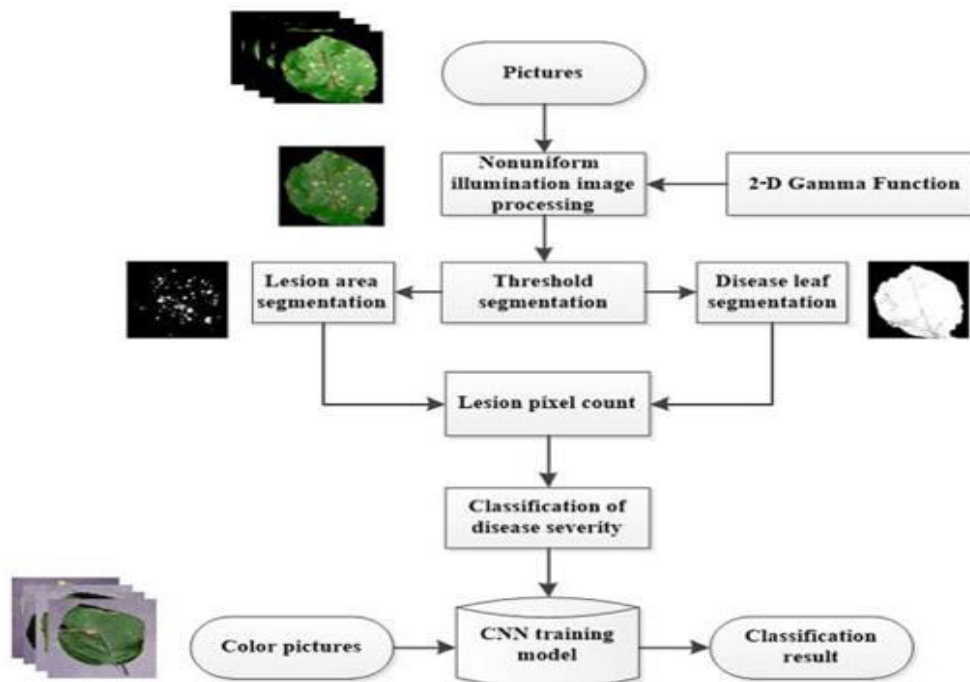


Fig 1: System Architecture

IV. IMPLEMENTATION PROCESS

1. System Architecture

Input Stage:

Leaf images captured using a camera or loaded from a dataset.

Preprocessing Stage:

Blurring to reduce noise

RGB to HSV color space conversion

Foreground-background separation

Image segmentation (K-means clustering)

Feature Extraction:

Extract key features like:

Color (Hue, Saturation)

Texture (using GLCM or filters)

Shape (area, perimeter, major/minor axis)

Classification Stage:

Model 1: SqueezeNet (Baseline)

Model 2: ResNet (Proposed)

Input features are passed to the models to classify disease.

Output Stage:

Display the predicted disease name

Show confidence level

Provide recommendation (optional)

2. Model Interface

If you're using MATLAB, the interface could include:

Upload Image Button: To select the input leaf image

Preprocess Preview: Display the processed image

Result Display: Show detected disease and accuracy

Graph/Chart: Visualize model confidence or class probabilities

3. Real-Time Application

Smart Farming Integration: Integrate with IoT-based systems to continuously monitor crops using installed cameras.

Mobile App or Web Portal: Allow farmers to upload leaf images and receive instant disease analysis.

Drone Surveillance: Attach cameras to drones for wide-area monitoring of cassava fields.

Expert-less Diagnosis: Helpful for areas with limited access to agricultural specialists.

4. Testing

Dataset Testing:

Split dataset into training, validation, and test sets (e.g., 70:20:10).

Evaluate on test set and report:

Accuracy

Precision/Recall/F1-Score

Confusion matrix

ROC curve (if applicable)

Real-World Testing:

Capture new cassava leaf images in real conditions (varying light, background).

Compare model predictions with actual expert diagnosis.

Track prediction latency and reliability.

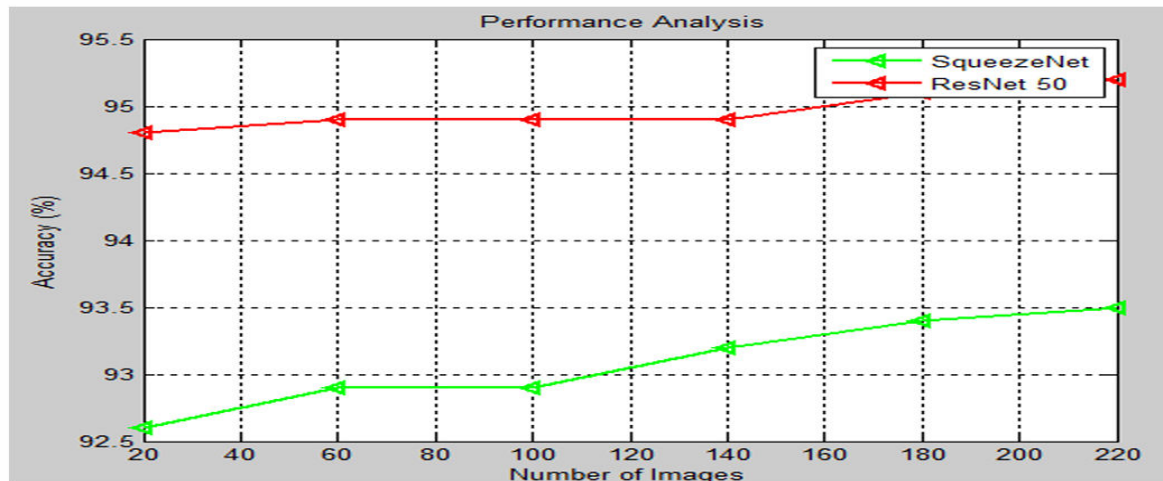
5. Future Scope

Expand to Other Crops: Train the model on other plant species like tomato, grape, or brinjal.

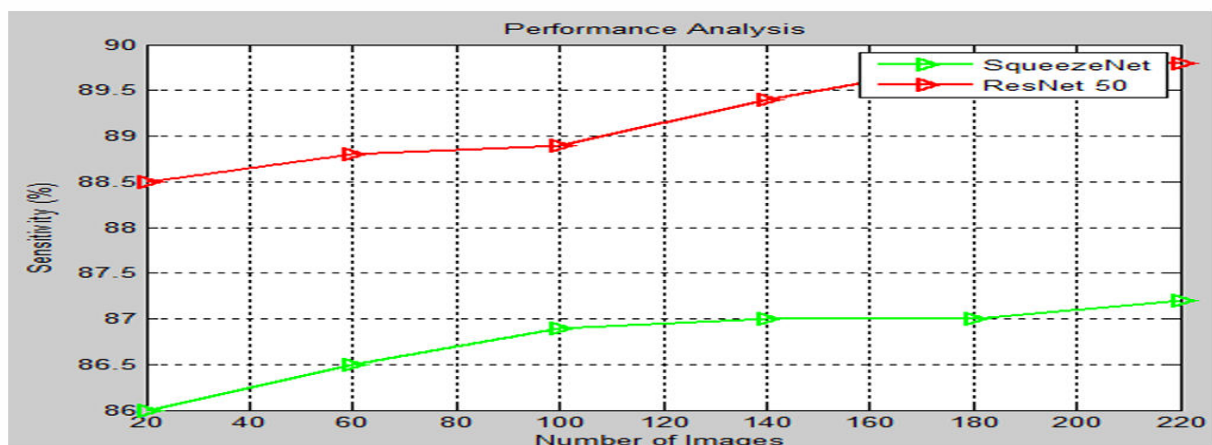
Multi-Disease Detection: Enable multi-label classification for detecting multiple diseases in one image.

Mobile App Development: Build a cross-platform app for farmers with offline image analysis capability.

Integration with Advisory Systems: Suggest treatment options or fertilizer advice based on disease.



Accuracy Comparison



Sensitivity comparison

V. RESULT AND CONCLUSION

The performance of the proposed leaf fungus detection system was evaluated using key metrics such as accuracy, precision, recall, and F1-score. The deep learning models, ResNet [10] and SqueezeNet, demonstrated strong classification capabilities, with ResNet achieving higher accuracy due to its deeper architecture and superior feature extraction ability. The confusion matrix analysis indicated that the model effectively distinguished between healthy and diseased leaves, with minimal misclassification. The application of data augmentation techniques, such as rotation, flipping, and scaling, contributed to improved model generalization, enabling better performance on previously unseen data. A comparative analysis was conducted between deep learning-based models and traditional machine learning classifiers like Support Vector Machines (SVM) and Random Forest. The results showed that deep learning models significantly outperformed traditional classifiers in terms of feature extraction and classification accuracy, highlighting the advantages of using convolutional neural networks for image-based disease detection. Additionally, transfer learning with pre-trained models such as ResNet and SqueezeNet allowed for faster convergence and improved detection rates without requiring a large dataset for training from scratch. The real-time implementation of the model was tested on mobile and web-based applications, where it provided rapid and accurate disease classification. The system demonstrated the potential for practical use in precision agriculture, allowing farmers to capture leaf images and receive instant disease diagnosis along with possible treatment recommendations. However, challenges were observed

in real-world scenarios, such as variations in lighting conditions, occlusions due to overlapping leaves, and similarities between disease symptoms. These factors occasionally led to misclassification, indicating the need for further dataset expansion and model fine tuning.

The use of automated monitoring and management systems are gaining increasing demand with the technological advancement. In agricultural field loss of yield mainly occurs due to widespread of disease. Mostly the detection and identification of the disease is noticed when the disease advances to severe stage. Therefore, causing the loss in terms of yield, time and money. The proposed system is capable of detecting the disease at the earlier stage as soon as it occurs on the leaf. Hence saving the loss and reducing the dependency on the expert to a certain extent is possible. It can provide the help for a person having less knowledge about the disease. Depending on these goals, we have to extract the features corresponding to the disease.

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