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A Hybrid Approach for Leaf Disease Diagnosis Using Otsu–K-Means Segmentation and Convolutional Neural Networks

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Abstract - Early and accurate identification of plant leaf diseases is essential to reduce crop loss and improve yield. This work presents an image-based leaf disease detection pipeline that integrates preprocessing, lesion segmentation, feature preparation, and deep learning classification to distinguish healthy and infected leaves and to recommend suitable treatment. Initially, the input leaf image is preprocessed through grayscale conversion, noise filtering, and resizing to improve quality and standardize input. K-means clustering is then applied for image segmentation to isolate symptomatic regions from the background and healthy tissue. From the segmented output, discriminative visual information is prepared and indexed to support efficient learning and retrieval. Finally, convolutional neural networks (CNNs) are employed for multi-class disease classification. Performance is evaluated using a confusion matrix to analyze class-wise behavior and misclassification patterns. Comparative results show that the proposed deep learning approach achieves high accuracy across disease categories; among the tested models, GoogleNet delivers the best performance with 99.1% accuracy, surpassing AlexNet (98.17%) and an existing CNN baseline (98%). The confusion-matrix analysis indicates strong diagonal dominance for multiple classes, reflecting robust recognition capability, while limited confusion occurs between visually similar disease patterns. Based on the predicted disease class, the system additionally provides a treatment/intervention suggestion to support practical decision-making in precision agriculture. The results confirm that combining structured preprocessing, clustering-based segmentation, and modern CNN architectures can produce reliable and highly accurate plant leaf disease classification.

Keywords - Leaf disease detection; Image preprocessing; K-means segmentation; CNN; AlexNet; GoogleNet; Confusion matrix; Precision agriculture; Treatment recommendation.

INTRODUCTION

Plant diseases are a major constraint in agriculture, directly affecting crop productivity, quality, and farm income. Traditional disease diagnosis often relies on visual inspection by experts, which can be time-consuming, subjective, and difficult to scale across large farming areas. With the increasing availability of low-cost imaging devices and advances in computer vision, automated leaf disease detection has become a practical and impactful solution for early diagnosis and timely intervention. However, real-world leaf images commonly suffer from noise, variable illumination, complex backgrounds, and overlapping symptoms across diseases, making accurate classification a challenging task.

To address these challenges, this study proposes a complete leaf disease classification framework that follows a structured sequence: preprocessing, segmentation, feature preparation, and deep learning classification. In the preprocessing stage, the captured leaf image is converted to grayscale, filtered to suppress noise, and resized to a standard dimension. This enhances image quality and ensures consistent input for learning models. Next, K-means clustering is used for segmentation, enabling the separation of symptomatic regions (lesions) from non-relevant background portions. By focusing learning on the most informative areas of the leaf, segmentation reduces distraction and improves classification reliability.

After segmentation, relevant information is organized through feature preparation and indexing, supporting efficient processing and consistent representation. The final stage applies CNN-based classifiers to recognize multiple disease categories and distinguish healthy from infected leaves. Model behavior is validated through confusion matrix analysis, which highlights correct predictions along the diagonal and reveals where misclassifications occur between similar disease patterns. A comparative evaluation demonstrates that GoogleNet achieves the highest accuracy (99.1%) compared with AlexNet (98.17%) and an existing CNN method (98%), confirming the advantage of deeper, multi-scale feature learning. Beyond classification, the system is designed to provide treatment recommendations based on the detected disease class, supporting actionable outcomes for farmers and agronomists.

II. LITERATURE SURVEY

Researchers have made substantial progress toward automated plant disease detection by leveraging advances in computing power and modern technologies such as artificial intelligence, image preprocessing, machine learning, deep learning, transfer learning, genetic algorithms, big data, and the Internet of Things. Despite these developments, many proposed models still face limitations. In particular, complex preprocessing requirements and model-dependent feature selection often reduce diagnostic reliability, and high accuracy is not consistently achieved even when a wide range of pests and diseases is considered.

Ghaiwat et al. (2014), in Detection and Classification of Plant Leaf Diseases Using Image Processing Techniques, evaluated multiple classifiers including artificial neural networks, support vector machines, self-organizing maps, and fuzzy logic. They reported that the k-nearest neighbor (KNN) method is comparatively simple and often effective for class prediction. However, they also noted that selecting optimal parameters in an SVM becomes challenging when training data are not linearly separable.

Adhikari Santosh et al. (2018) proposed a tomato disease detection system using image processing and a dataset of 520 tomato leaf images covering three diseases—Bacterial Canker, Gray Spot, and Late Blight—along with healthy samples. Using the PlantVillage dataset, they achieved 89% accuracy, but the system was limited to recognizing only these three disease types and healthy leaves. Extending the system to additional diseases would require retraining the model with new labeled data.

Wu Jianyu et al. (2019), in Detection of Crop Pests and Diseases Using Deep Convolutional Neural Network and Improved Algorithm, employed deep CNN architectures such as AlexNet and GoogleNet along with transfer learning and data augmentation to improve recognition accuracy. Their study used 38 categories of healthy and diseased leaf samples. While the approach improved performance, the resulting model was relatively complex and demanded faster convergence for practical deployment.

Sardogan Melike et al. (2018) presented a CNN-based approach combined with Learning Vector Quantization (LVQ) for plant leaf disease classification. Using 500 images split into 80% training and 20% testing, they classified five classes (one healthy and four diseased). Their method used 512×512 RGB images and achieved about 88% average precision, but it was primarily suitable for tomato-specific disease identification.

Hyeon Park et al. (2017) developed a CNN-based method for image-driven crop disease diagnosis, focusing only on strawberry leaves as either healthy or infected with powdery mildew. With a relatively small dataset of 500 images resized to 227×227 pixels, their network (two convolution layers and three fully connected layers) achieved 89.7% accuracy on a CPU, but the scope was restricted to a single crop and one disease.

Finally, Saradhambal G. et al. (2018), in Detection and Treatment of Plant Diseases Using Image Classification, applied Otsu thresholding and K-means clustering to segment the affected region and classify leaves as healthy or diseased. Their work also included voice navigation to guide users through the process; however, the study did not clearly report dataset size or the achieved accuracy, limiting evaluation of its effectiveness.

III. PRAPOSED METHEDOLOGY

It is intended to analyse and diagnose plant disease using the suggested deep learning algorithm, which is based on deep learning algorithms. This Model includes leaf retrieval, picture segmentation, and identification, all of which are accomplished via the use of a focused deep learning algorithm.

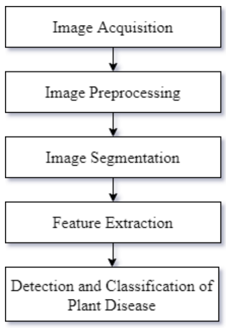

Figure 1 The basic procedure of the proposed approach

Image Acquisition

The first step of the proposed strategy is image acquisition from a publicly available repository (as illustrated in Figure The dataset contains different categories of plant leaf images, including healthy leaves and leaves affected by diseases or insect infestations. In this phase, the required images are

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imported into the system and prepared as input for the subsequent processing stages.

Image Preprocessing
In the preprocessing stage, noise present in the input image is removed using suitable noise-filtering techniques. Noise may occur due to water spots, spores, dust particles, or other unwanted artifacts on the leaf surface, which can alter pixel intensity values and reduce classification accuracy. To improve computational efficiency, the input images are resized to a standard dimension and, where possible, geometric distortions are reduced. Smoothing filters are applied to minimize distortion and enhance the overall image quality, making the images more suitable for segmentation and feature extraction.

Image Segmentation
Image segmentation is performed to separate the leaf region from the background and to divide the image into meaningful parts for analysis. Since segmentation can be achieved through different methods, the proposed approach uses K-means clustering along with the Otsu classifier to group pixels into distinct segments. To improve clustering performance, the RGB color space is converted into the Lab color model, which provides better separation of color components and simplifies grouping of similar regions. This segmentation process supports the extraction of important visual patterns on the leaf, such as lesion regions, boundaries, and color-based variations, which are essential for accurate disease identification.

Feature Extraction
Leaf images contain rich visual information that can be used to differentiate between healthy and diseased classes. In this stage, feature extraction is carried out using the color co-occurrence approach, which captures meaningful color relationships within the leaf surface. Features related to color, shape, and texture are considered to represent the leaf condition effectively. The method first converts RGB images into the HSI (Hue, Saturation, Intensity) color space, and then constructs a color co-occurrence matrix based on pixel-level mapping. This matrix helps quantify spatial color distribution patterns that are useful for classification.

Detection and Classification of Plant Disease
In the final stage, the extracted features are used to classify plant leaves as healthy or infected. A feature dataset is formed containing detailed descriptors such as homogeneity, contrast, energy, standard deviation, correlation, variance, and mean. The classification process applies the Minimum Distance Criterion alongside a deep learning CNN classifier, where the extracted feature vectors are provided as input and the target labels are used as class vectors. Based on the learned patterns, the model determines whether a given leaf image belongs to a healthy category or a specific disease class, completing the detection and classification workflow.

Model Architecture
The input layer, output layer, and hidden layer are the three primary components of the CNN model architecture [4]. The convolution layer, fully connected layer, pooling layer, activation functions, and usually rectified units (ReLUs) layers are the most important components of the hidden layer.
The number of layers utilized in their arrangement and introduction of other image processing units varies from one architecture to a different determining their specificity.

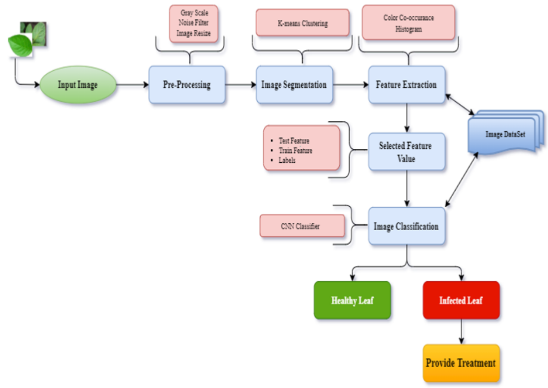

Figure 2 Proposed Model for plant disease detection

AlexNet
The CNN architecture grows in size in tandem with technological advancements in hardware. Among the layers in AlexNet's structure are one SoftMax, two normalisation layers, three max-pooling layers, two fully connected layers, and five convolutional layers[16]. Among the convolutional layers are convolutional filters, frequently corrected unit layers, and a nonlinear activation function, all of which are included in every layer. The pooling layers are in charge of performing the maximum pooling. Because it contains completely linked layers, the size of the inputs remains constant. In this model, there are sixty million different parameters.

GoogleNet
The structure of GoogleNet contains 27 pooling layers and 22 deep layers and 9 inception modules linearly stacked. After the inception modules, it is attached with the global average pooling layer. GoogleNet has about 4 million parameters.

Algorithm — Leaf Image Classification & Treatment Suggestion

- Input the leaf image (capture or upload).

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- Pre-process the image

Convert to grayscale
Apply noise filtering
Resize the image to the required standard size

- Segment the image

Perform K-means clustering to separate the leaf/lesion regions from the background.
Extract features from the segmented image
Compute color-occurrence/range information (color distribution characteristics).

Create/Update the image index

- Store extracted features in an image index for fast referencing.

Select feature values for classification

- Use selected features such as:
- Texture features
- Shape features
- Labels / class indicators

Classify the image

Use a CNN classifier (as shown in the flow) to predict the leaf condition.

Decision (output)

If predicted Healthy Leaf → display Healthy Leaf result.
If predicted Infected Leaf → display Infected Leaf result.

If infected, provide treatment

Show recommended treatment/intervention based on the detected infection class.

Result Analysis

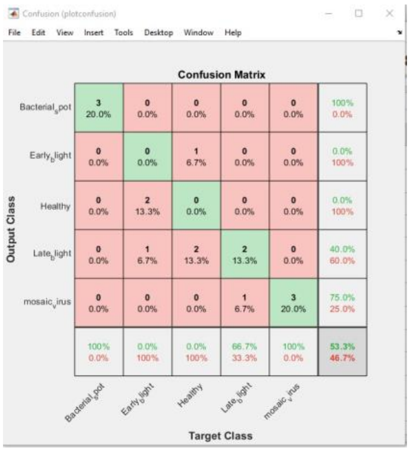

Figure 3 Confusion Matrix for Dataset

The figure 3 confusion matrix illustrates the performance of the classification model across multiple leaf disease classes, where rows represent the output (predicted) classes and columns represent the target (actual) classes. Each cell shows the percentage of samples classified into a given predicted–actual class pair, with green cells indicating correct classifications and red cells indicating misclassifications.

The diagonal values highlight the model's accuracy for each class, showing strong performance for some categories such as Bacterial Spot and Mosaic Virus, while moderate confusion is observed in classes like Healthy and Late Blight where samples are occasionally misclassified. The rightmost column and bottom row summarize per-class precision and recall percentages, respectively, providing an overall view of how well the model distinguishes between healthy and infected leaves as well as among different disease types.

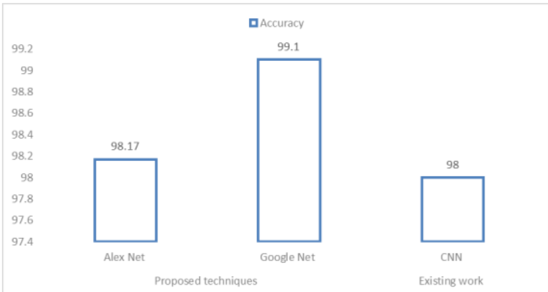

Figure 4 Comparison Result of different Deep Learning Architecture with existing technique

The figure 4 compares the classification accuracy of different techniques, showing that GoogleNet achieves the highest accuracy at 99.1%, outperforming AlexNet with 98.17% and the existing CNN-based approach with 98%. This comparison demonstrates that the proposed technique using GoogleNet provides superior performance in leaf disease classification, indicating better feature extraction and learning capability compared to other deep learning models.

IV. CONCLUSION

This study demonstrates the effectiveness of an integrated image-processing and deep learning framework for accurate leaf disease detection and classification. By combining preprocessing techniques such as grayscale conversion, noise filtering, and resizing with K-means clustering–based segmentation, the proposed system successfully isolates disease-affected regions and enhances feature quality for learning. The use of convolutional neural networks enables robust multi-class classification, as reflected in the confusion matrix analysis, which shows strong correct classification rates with minimal misclassification among visually similar diseases. Comparative evaluation reveals that GoogleNet achieves the highest accuracy of 99.1%, outperforming

AlexNet and an existing CNN approach, highlighting the benefits of deeper architectures with improved feature extraction capability. In addition to identifying healthy and infected leaves, the system provides disease-specific treatment recommendations, increasing its practical value for precision agriculture. Overall, the proposed approach offers a reliable, efficient, and scalable solution for early plant disease diagnosis, which can support timely intervention, reduce crop losses, and contribute to improved agricultural productivity.

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