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PLANTAIN LEAF DISEASE DETECTION USING MULTICLASS CLASSIFICATION

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Abstract

Plantain (banana) is among the most significant plantation crops, yet its production has been severely affected by leaf diseases. Traditional manual inspection by specialists is not only time-intensive but also prone to inaccuracies. While earlier research primarily targeted one or two specific leaf diseases or relied on a single convolutional neural network (CNN) architecture, this study introduces a deep learning approach designed to identify eight distinct categories of plantain leaf conditions—seven disease types and one healthy category. Multiple CNN models, including those leveraging transfer learning, were assessed for classification performance. The study compares the effectiveness of EfficientNetB0, ResNet-50, DenseNet-121, and Inception-V3 in detecting these diseases, with all models fine-tuned on the collected dataset. EfficientNetB0 outperformed the others, reaching a testing accuracy of 98.37%. Detailed evaluation metrics—accuracy, precision, recall, and F1-score—for each class are provided through classification reports and confusion matrices. These findings suggest that modern CNN architectures offer a robust solution for early and accurate detection of plantain leaf diseases.

Index Terms: CNN Models, EfficientNetB0, ResNet-50, DenseNet-121, Inception-V3, Fine-Tuning, Precision, Recall, F1-Score.

I. INTRODUCTION

Plantain is a vital staple crop, supplying both nutrition and livelihoods to millions, particularly in tropical and subtropical regions. Its cultivation plays a key role in ensuring global food security and sustainable agriculture. However, plantain yields face significant risks from various leaf diseases that, if not detected and managed quickly, can severely impact fruit quality and quantity. These diseases impair photosynthesis and hinder plant development, leading to substantial economic losses for farmers.

Early detection of such diseases is therefore crucial to minimize yield loss and support the sustainability of smallholder plantain farming. Traditionally, diagnosis relies on manual inspection by agricultural experts, a process that is labour-intensive and difficult to scale. Furthermore, access to qualified specialists is often limited in remote rural areas, resulting in delayed responses. Compounding the challenge, many leaf diseases display similar early symptoms, making visual identification prone to error.

Recent advances in artificial intelligence (AI) have led to the growing use of automated image-based detection systems, which offer a promising alternative to conventional methods. Among AI techniques, deep learning (DL) excels in visual recognition tasks,

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with convolutional neural networks (CNNs) proving especially effective. CNNs can automatically extract complex, hierarchical features from raw images without human guidance. In agricultural applications, they have achieved impressive results—exceeding 97% accuracy in some plant disease classification tasks. Research has also shown that leveraging pre-trained CNN models on large image datasets enhances performance and reduces training time, enabling robust disease detection systems even with limited data.

This study presents a multi-class CNN-based DL model designed to automatically detect and classify plantain leaf diseases. Using transfer learning, the model is trained on a specialized plantain leaf dataset to distinguish among seven disease types and healthy leaves, totalling eight categories.

The research contributes in the following ways:

- **Multi-class classification framework:** A CNN-based system is developed for eight-class disease classification, incorporating data augmentation and pre-processing to improve accuracy and address challenges associated with small datasets.
- **Model comparison:** The study evaluates four prominent CNN architectures—EfficientNetB0, ResNet50, DenseNet121, and InceptionV3—under identical experimental conditions to assess their effectiveness in classifying plantain leaf diseases.
- **Comprehensive evaluation:** Model performance is measured using standard metrics such as accuracy, precision, recall, and F1-score. Detailed analysis through confusion matrices and classification reports provides insights into per-class performance and identifies potential limitations.
- **Top-performing model:** Among the models tested, EfficientNetB0 achieves the highest test accuracy at 98.37%, establishing it as the most effective for this task.

These findings highlight the strong potential of deep learning with CNNs for accurate, automated detection of plantain leaf diseases. The results affirm the suitability of these models for agricultural disease identification and lay a foundation for future research. They also open avenues for developing more advanced solutions, such as hybrid models and real-time diagnostic tools.

II. RELATED WORK

In recent years, numerous studies have explored deep learning techniques for detecting plant diseases. Convolutional Neural Networks (CNNs) have shown greater effectiveness compared to traditional machine learning methods, primarily because they eliminate the need for manual feature extraction.

Initial research applied CNN models to classify diseases in crops like tomato, rice, maize, and in some cases, banana. However, identifying multiple disease types in banana leaves remains difficult due to high similarity within the same class and notable variations across different classes.

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To enhance classification accuracy with limited training data, some researchers have adopted transfer learning using pre-trained CNN architectures such as VGG, ResNet, and Inception. While these approaches have shown promise, many of the existing studies either evaluated only a single method or lacked comprehensive comparisons across multiple models, limiting their ability to draw broader conclusions not been applied and evaluated by succeeding methods.

This study is different from other research works in that it involves an in-depth comparison of current CNN model designs that can be applied for multi-class classification of a banana leaf disease image dataset.

III. METHODOLOGY

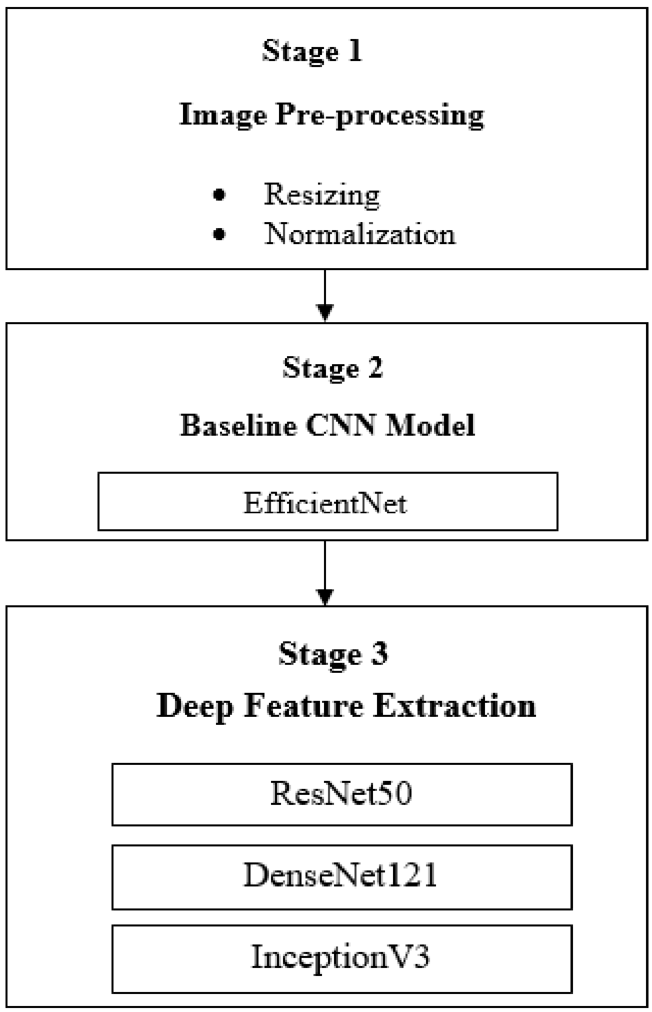

Figure 1: Proposed Architecture

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A. Dataset Preparation

The dataset employed in this paper has a total of **5,711 images** of plantain leaves. These images are divided into eight categories:

1) Healthy Leaf

Figure 2: Healthy Leaf of Plantain Tree

In South Tamil Nadu, a "healthy" banana leaf (Vaazhai ilai) is characterized by specific qualities, such as the way it looks, or appears aesthetically, is structurally sound and contains the right amount of nutrients, and may include items traditionally eaten with this produce in feasts and celebrations. This is considered a major part of healthy, sustainable and safe nutrition; the primary reason people choose to utilize banana leaves for food preparation is because they improve the taste of food when eaten warm.

2) Banana Sigatoka

Banana Sigatoka is a fungal disease caused by the Mycosphaerella species of fungus. The conditions in which Sigatoka occurs are warm and moist in a humid environment.

Figure 3: Sigatoka Disease of Plantain Tree

The Banana Sigatoka Disease is referred to as the Banana Leaf Spot Disease and comes in two types, the Yellow Sigatoka Disease and the Black Sigatoka Disease. The first occurrence of the Banana Sigatoka Disease was in Java, Indonesia, in 1902, and then in 1912 was found to be in an epizootic state in the Sigatoka Valley of Fiji. The disease has been documented in many areas of the world that produce bananas other than India,

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including Colombia, Mexico, Uganda, and Venezuela. For India, the disease is of serious concern to all banana-producing regions, which comprise a total of nine states; Andhra Pradesh, Assam, Bihar, Gujarat, Karnataka, Kerala, Maharashtra, Tamil Nadu and West Bengal.

3) Insect Pests

Insect pests consist of living organisms such as beetles, aphids, and caterpillars which consume or damage the plant and/or deposit their eggs on the plant.

Figure 4: Insect Pest Disease of Plantain Tree

Common insect pests found on banana plants are banana weevils, aphids, thrips, and leaf-eating caterpillars. These pests cause symptoms such as small holes, chewing damage, streaks, and discoloration of leaves. Infestations weaken the banana plant's photosynthetic capacity, increasing its vulnerability to secondary infections. In addition to direct harm, certain pests also transmit viruses that negatively affect the plant's growth and development.

4) Pestalotiopsis

Pestalotiopsis infects plantain plants through leaf wounds or natural openings. The pathogen spreads directly to plant tissues when spores germinate under warm, humid conditions, or through contact with already infected plants.

Figure 5: Pestalotiopsis Disease of Plantain Tree

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The fungal pathogens of Banana Plant leaves are Pestalotiopsis, which cause development of greyish brown Leaf Blight spots on leaves with dark margins. As the spots expand and begin to merge, they eventually destroy the leaves, causing them to wither and dry out.

The fungus thrives and spreads quickly in wet, muddy environments, moving from plant to plant via wind and rain. Implementing sound agricultural practices and ensuring sufficient spacing between banana plants can effectively help manage Pestalotiopsis Leaf Blight.

5) Cordana

Cordana Leaf Spot is a fungal disease that affects plantain leaves, caused by Cordana musae (also known as Neocordana musae). The pathogen spreads via spores carried by wind and water, particularly thriving in warm, humid conditions commonly found during summer. It primarily infects leaf tissues that have already been damaged, taking advantage of the favorable environment to establish infection.

Figure 6: Cordana Disease of Plantain Tree

Cordana musae fungus is responsible for creating Cordana leaf spot on plant leaves. The upper side of the leaf shows oval or elongated brown spots with pale grayish centers. Unlike many other plant diseases, this condition progresses slowly. However, under conditions of high moisture and low light, Cordana can cause severe damage.

Infected leaves are unable to produce enough sugars via photosynthesis, impairing plant health, so they require careful attention. Effective prevention includes adequate plant spacing, good drainage, and watering at appropriate times.

6) Moko disease

Moko disease in plantains is caused by the bacterium Ralstonia solanacearum. The pathogen spreads through contaminated farming equipment, insects that feed on flower parts, and damaged roots that allow bacterial entry. Once infected, plants rapidly show symptoms, including wilting and yellowing.

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Figure 7: Moko Disease of Plantain Tree

Moko disease is a severe bacterial infection that affects banana plants, caused by the bacterium Ralstonia solanacearum. Typical symptoms include leaf wilting and yellowing, along with reduced crop yield. When the pseudostems of infected plants are cut open, they often show yellowish bacterial exudate and brown discoloration inside. The fruit bunches that develop are typically misshapen, underdeveloped, and ripen irregularly. The pathogen spreads between plants via contaminated soil, tools, and insect vectors. Once a plant is infected, it cannot be saved, making early detection crucial. Identifying the presence of the disease and eliminating its source are key steps in managing its spread.

7) Banana bract mosaic virus (BBrMV)

Banana bract mosaic virus (BBrMV) causes bract mosaic disease in plantains. The virus spreads via insect vectors—specifically Pentalonia nigronervosa and Aphis gossypii—in a non-persistent manner, as well as through the use of infected planting material.

Figure 8: Bract Mosaic Virus Disease of Plantain Tree

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Bract Mosaic Virus (BBrMV) infection can be characterized by prominent bright reddish/purple mosaic patterns on the Upper and Lower Extrusions, along with mottled spots on the Pseudostems and occasionally leaf veins. Following plant infection, typical symptoms include various forms of streaking, mottling and distortion of young leaves as they develop; plant growth is severely stunted, and bunch development is significantly compromised. BBrMV is spread through infected plant material (primarily by way of aphid vectors) and disease control measures utilize both Virus-Free Suckers and strict field sanitation practices.

8) Panama disease

Panama disease, also known as Fusarium wilt, occurs when the soil-borne fungus, Fusarium oxysporum, infects plantain through the root system and invades the plant's vascular system, blocking water and nutrient transport. As a result, the older leaves of plantain plants turn yellow along their margins, wilt, and eventually collapse.

Figure 9: Panama Disease of Plantain Tree

The disease known as Panama disease (Fusarium wilt), attacks the plantain leaf by beginning with a yellowing effect at the edges of the lower leaves. Infected leaves become dry and shriveled, gradually turning yellow, and as the disease progresses, the entire plant shows yellowing. When the Water-Blocking Fungus obstructs the stem, the pseudostem develops splits and ultimately collapses. Panama Disease, also known as Fusarium wilt, poses a serious threat to plantations due to its destructive nature. The Fusarium oxysporum pathogen enters through the roots and spreads upward, causing discoloration in the vascular system and forming reddish-brown tissue. This disease can persist in the soil for long periods.

The dataset was split using stratified sampling into 70% for training, 15% for validation, and 15% for testing.

B. Data Pre-processing and Augmentation

All images were resized to 224×224 pixels, which aligns with the standard input dimensions required by most convolutional neural networks. To expand and diversify the training dataset, we employed several data augmentation techniques, including rotation, flipping, zooming, and brightness adjustments. Data normalization was performed using

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pixel values to ensure consistent input scaling. For model-specific pre-processing—particularly to enhance performance and minimize overfitting in the EfficientNet architecture—we implemented targeted augmentation strategies using the TensorFlow tf.keras.layers API. These included:

- Random horizontal flipping, to simulate varied leaf orientations;
- Random brightness adjustment (factor of 0.1), to reflect differing lighting conditions encountered in real-world environments;
- Random contrast adjustment (factor of 0.1), to improve the visual distinction within image features.

C. Deep Learning Models

This study employs state-of-the-art convolutional neural network (CNN) architectures—ResNet50, InceptionV3, DenseNet121, and EfficientNetB0—for the automated classification of plantain leaf diseases. These models are selected based on their proven performance in image classification tasks, where they have demonstrated strong capabilities in extracting meaningful visual features.

Their effectiveness stems from well-established feature learning mechanisms that perform reliably across various computer vision applications. To enhance classification performance while reducing the need for large training datasets, transfer learning is utilized.

Each model is pre-trained on the ImageNet dataset, which provides extensive visual data necessary for robust network initialization. This process equips the CNNs with optimized weights, enabling them to detect basic visual patterns such as edges, textures, and object shapes efficiently.

Input images are resized to 224 × 224 pixels before being fed into the networks. The original classification layers at the end of each CNN—designed for ImageNet's categories—are replaced with new fully connected layers and a softmax activation function. These modified layers contain eight output units, corresponding to the seven disease categories and one healthy leaf class, allowing the models to specialize in plantain leaf diagnosis. Finally, fine-tuning is performed on both the newly added layers and selected lower layers to further refine the network's accuracy in identifying specific plantain leaf conditions.

Mathematical Description of the Proposed CNN-Based Classification Model

This section presents the mathematical framework of the proposed convolutional neural network (CNN) model, designed for multi-class classification of plantain leaf diseases. Each equation is clearly explained to ensure transparency and enable accurate replication of the methodology.

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1) Dataset Representation:

The Dataset Representation Equation provides a representation for the whole plantain image dataset and is described as follows:

$$\boxed{D = \{(x_i, y_i)\}_{i=1}^{N}} \quad \rightarrow \textbf{Equation 1}$$

The dataset representation equation is a mathematical expression of images that contain plantain leaves that we have acquired in this study. This representation can be expressed in terms of:

- **X_i:** The i-th input RGB image of a plantain leaf resized to **224 x 224 x 3**.
- **Y_i:** The ground-truth class label for the i-th input RGB image from one of the 8 categories.
- **N= 5711** images in the dataset

This structure is done during the preparation of the dataset, labelling the dataset with class labels, and creating the stratified split of the dataset into training, validation, and test datasets. (70%–15%–15% split ratio).

2) Deep Neural Network Formulation:

This formula shows how the deep neural network processes the image to extract the features and produce the raw scores.

$$\boxed{Z_i = f(x_i; \theta)} \quad \rightarrow \textbf{Eq. 2}$$

- **Z_i:** The output vector (logits) from the final fully connected layer.
- **F:** The non-linear mapping function expressed via the CNN model (for example, ‘EfficientNetB0’)
- **θ:** The learnable parameters of the network (the weights and the bias).

In this framework, the above equation will be utilised in the forward propagation stage. During this process, image data from a plantain leaf will be taken as input and will be propagated through the pre-trained convolutional neural network to obtain appropriate features for classification and output score distribution across classes.

3) Probability Transformation (SoftMax):

SoftMax applies the SoftMax function on raw values to produce probabilities that sum up to 1.

$$\boxed{\hat{Y}_{ik} = e^{z_{ik}} / \Sigma_{j=1}^{8} e^{z_{ij}}} \quad \rightarrow \textbf{Eq. 3}$$

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This Equation transforms the Logit values produced by the CNN into what are referred to as class probabilities. These probabilities are computed as follows

- **$\hat{Y}_{ik}$:** The calculated conditional probability that input i belongs to class k.
- **e^{zik}:** The exponential of the logit for class k.
- **Σ:** The sum of all class scores (normalization).

This equation is used to predict disease status for both training data and testing data.

4) Loss Function (Categorical Cross Entropy)

This gives us the error between what is predicted and what is actually true and this is what our model tries to minimize.

$$\boxed{L = -(1/N) \Sigma_{i=1}^{N} \ \Sigma_{k=1}^{8} \ y_{ik} \cdot \log(\hat{y}_{ik})} \quad \rightarrow \textbf{Eq. 4}$$

The loss function compares the predicted probabilities to true class labels. The loss function is optimized while training the CNN.

- **L:** The total loss (error) value.
- **y_{ik}:** 1 if the actual label corresponds to the correct disease. Otherwise, 0.
- **$\log(\hat{y}_{ik})$:** Logarithm of the predicted probability.

The logits produced by the CNN will be converted into class probabilities through this formulation.

5) Optimization (Adam Algorithm)

This is the mathematical expression of the weight adjustment in the Adam optimizer to reduce the loss.

$$\boxed{\theta_{t+1} = \theta_t - \alpha \cdot \hat{m}_t / (\sqrt{\hat{v}_t} + \varepsilon)} \quad \rightarrow \textbf{Eq. 5}$$

- **θ_t:** The vector of parameters at step t.
- **α:** Learning rate
- **$\hat{m}_t$:** The bias-corrected estimate of the first moment (mean) of gradients.
- **$\sqrt{\hat{v}_t}$:** Bias-corrected estimate of second moment (variance) of gradients.
- **ε:** A small constant for numerical stability.

The Adam Optimizer has been selected for optimizer use in this work, with the initial learning rate set to 10−3, then gradually decreased through the process of fine-tuning so as to achieve optimal performance results.

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6) Performance Evaluation Metrics: These metrics measure the performance of the classifier on the confusion matrix values of True Positives **(TP)**, True Negative **(TN),** False Positives **(FP),** and False Negative **(FN).**

- **Accuracy:** The proportion of the total predictions that were correct.

$$\boxed{\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)} \quad \rightarrow \text{Eq. 6}$$

- **Precision:** "Quality" of positive predictions. Of all images that the model is called 'Sigatoka', how many were 'Sigatoka'?

$$\boxed{\text{Precision} = TP / (TP + FP)} \quad \rightarrow \text{Eq. 7}$$

- **Recall:** "Coverage" of actual positives. Of all the 'Sigatoka' images present, how many did the model find?

$$\boxed{\text{Recall} = TP / (TP + FN)} \quad \rightarrow \text{Eq. 8}$$

- **F1-Score:** The harmonic mean of Precision and Recall. This is the best single metric when you need to balance quality and coverage.

$$\boxed{\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})} \quad \rightarrow \text{Eq. 9}$$

D. Training:

We trained all models using the Adam optimizer with the categorical cross-entropy loss function. A batch size of 32 and max 10 epochs were used, including early stopping based on the validation loss. Learning rates were adjusted per model (initial training used 1e-3 and reduced during fine-tuning).

IV. EXPERIMENTAL RESULTS

Accuracy Comparison

The following were the respective test accuracies of each of these models after fine-tuning:

- **EfficientNetB0:** 98.37% (best performance)
- **ResNet50:** 63.22% (the baseline); after **fine-tuning**, it is 88.51%.
- **DenseNet121**: 80.27% (the baseline); after **fine-tuning**, it is 86.07%
- **Inception V3:** 55.22% (the baseline); after **fine-tuning**, it is 78.53%

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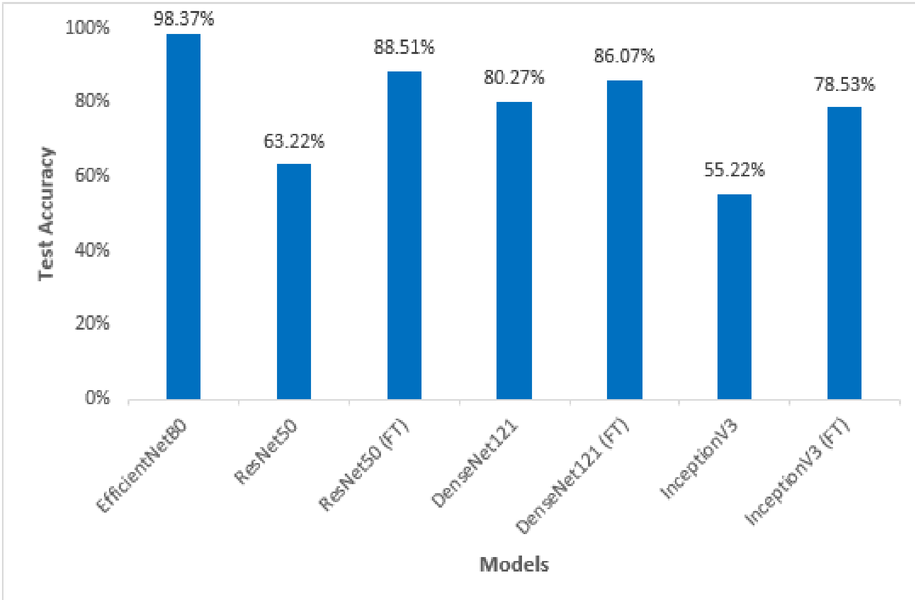

Figure 10: The comparison of test accuracy of baseline and fine-tuned models of different CNN architectures for recognizing banana leaf diseases

Clearly, EfficientNetB0 has outperformed the others on our dataset, and this is in line with the literature evidence that modern architectures attain very high accuracy. We plotted a bar graph of these accuracies for visual comparison.

Classification Report and Confusion Matrix

We then created classification reports for each model, listing precision, recall, and F1-score per class. EfficientNetB0's report showed all classes having more than a 98.37% precision and recall, reflecting almost perfect predictions. Several other models showed notably lower recall for certain classes, with values close to their overall accuracy. Additionally, the confusion matrix for EfficientNetB0 indicates that the majority of predictions fall along the diagonal, representing correct classifications, while false positives remain relatively infrequent. Misclassifications primarily occur among diseases with similar visual features—such as Cordana leaf spot and Pestalotiopsis leaf spot, as previously noted. This analysis confirms the model’s ability to effectively differentiate between various leaf spot types, though minor overlap persists due to the closely resembling traits of some diseases.

Discussion:

The experimental findings showed that state-of-the-art convolutional neural networks are well-suited for multi-class classification of banana leaf diseases. By utilizing transfer learning, model performance improved through the use of pre-trained feature representations. A comparative evaluation indicated that EfficientNet delivered the highest accuracy, benefiting from its balanced scaling of depth, width, and resolution.

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Overall, this research lays a strong foundation for future advancements, as integrating hybrid methods and optimization strategies.

V. CONCLUSION

In this paper, we have successfully developed a deep learning system that automatically detects different types of diseases manifesting in plantain leaves. Experiments are carried out on an aggregate dataset of 5,711 images divided into eight classes: healthy and seven specific diseases like Sigatoka and Moko. For the purpose of improving the learning ability of computers from these images, "transfer learning" utilizes pre-trained knowledge, and "data augmentation" is considered to increase the variety of training examples. We compare four famous advanced models such as EfficientNetB0, ResNet50, DenseNet121, and InceptionV3 to find which one is better. It is crystal clear that EfficientNetB0 is the best model among all the checked ones, achieving a very high accuracy of 98.37%. Comparing it with the rest of the models, ResNet50 scored an accuracy of 88.51%, DenseNet121 scored an accuracy of 86.07%, and InceptionV3 scored 78.53%. When investigating the errors, we see that the model is very reliable; just a few minor confusions between diseases that are somehow similar, such as Cordana and Pestalotiopsis. The result of this research proves that using the EfficientNetB0 model will be highly accurate and effective for early disease detection rather than the time-consuming manual checking over all Enhancement percentage used to be discussed.

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