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Efficient Net-Based Deep Learning Framework for Banana Leaf Disease and Nutrient Deficiency Classification

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Abstract
Traditional banana disease identification methods rely heavily on manual inspection, which is time-consuming, error-prone, and dependent on expert knowledge. Furthermore, similar visual symptoms between banana leaf diseases and nutrient deficiencies make accurate classification challenging under real-field conditions. This research proposes a deep learning framework for classification of banana leaf diseases and nutrient deficiencies using leaf images. The proposed model utilizes a pre-trained EfficientNet architecture for automatic feature extraction and multi-class classification of disease and nutrient deficiency categories. The dataset consists of approximately 3272 banana leaf images collected from Kaggle, including healthy leaves, diseased leaves, and nutrient-deficient samples across 21 classes. Images were preprocessed using resizing, normalization, and data augmentation techniques to improve model robustness under varying environmental conditions. In addition, feature map visualization of convolutional layers was performed to analyze internal CNN activations and understand the visual patterns learned by the model during classification. Experimental results demonstrate that the proposed approach achieves 79% classification accuracy and 91% top-k accuracy under real-field conditions. The visualization of intermediate convolutional activations improves interpretability by showing how the CNN extracts disease-related and nutrient-deficiency-related features from banana leaf images. The proposed framework can support early disease diagnosis, reduce crop losses, and assist farmers in efficient banana crop management systems.

Keywords: *Deep Learning, Banana Leaf Disease, Nutrient Deficiency, EfficientNet, CNN, Feature Map Visualization, Image Classification, Smart Agriculture*

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I. Introduction

Banana is one of the most important and widely cultivated fruit crops in tropical and subtropical regions across the world. It serves as a staple food and a major source of nutrition for millions of people while also contributing significantly to the agricultural economy of developing countries such as India, Brazil, China, and Philippines. India is among the leading producers of bananas globally, where banana cultivation provides employment opportunities and financial support to a large farming population. In addition to its economic importance, bananas are rich in carbohydrates, vitamins, minerals, and dietary fiber, making them an essential component of human nutrition and food security. Due to the high market demand and export potential of banana crops, maintaining healthy banana production has become increasingly important in modern agriculture.

Despite its agricultural significance, banana cultivation is highly vulnerable to various environmental and biological challenges. Among these, leaf diseases and nutrient deficiencies are major factors responsible for significant reductions in crop quality, productivity, and yield. Banana plants are susceptible to multiple diseases such as Black Sigatoka, Panama disease, Fusarium wilt, bacterial wilt, and leaf spot diseases, which directly affect photosynthesis and plant development. Similarly, nutrient deficiencies including magnesium deficiency, calcium deficiency, iron deficiency, potassium deficiency, and nitrogen deficiency negatively impact leaf structure, fruit quality, and overall plant growth. If these conditions are not identified and treated at an early stage, they can spread rapidly across plantations and cause severe economic losses to farmers.

Traditionally, banana disease diagnosis and nutrient deficiency identification are performed through manual visual inspection by agricultural experts or farmers. However, this approach is time-consuming, labor-intensive, subjective, and often inaccurate under real-field conditions. Accurate diagnosis requires expert-level knowledge and experience because many diseases and nutrient deficiencies exhibit visually similar symptoms such as yellowing, spotting, curling, and discoloration on leaves. Furthermore, environmental factors including lighting variations, shadows, complex backgrounds, dust, moisture, and different camera angles make manual identification even more challenging. Small-scale farmers in rural areas may also lack access to agricultural specialists, leading to delayed treatment and increased crop damage. Therefore, there is a strong need for automated, reliable, and intelligent systems capable of accurately identifying banana leaf diseases and nutrient deficiencies at an early stage.

In recent years, advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have significantly transformed the field of precision agriculture. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in various image classification and computer vision applications because of their ability to automatically extract complex visual features from images. Several researchers have applied CNN-based models for plant disease detection using leaf images and achieved promising classification performance. Transfer learning approaches using pre-trained deep learning architectures such as VGGNet, ResNet, MobileNet, InceptionNet, and EfficientNet have further improved classification accuracy while reducing training complexity and computational cost.

Although previous research has shown encouraging results in agricultural disease detection, several limitations still exist in current approaches. Most existing systems focus only on single-task classification, where the model detects either plant diseases or nutrient deficiencies independently. As a result, separate models are often required for different agricultural problems, increasing computational overhead and reducing system efficiency. Furthermore, many deep learning models operate as black-box systems, where predictions are generated without clear understanding of how the model extracts features from leaf images. This lack of interpretability reduces transparency and user trust, especially in agricultural applications where farmers and agricultural experts require understandable predictions before taking corrective actions.

To overcome these limitations, this research proposes a deep learning framework for classification of banana leaf diseases and nutrient deficiencies using image-based analysis. The proposed framework utilizes a pre-trained EfficientNet architecture because of its strong performance, efficient scaling capability, and reduced computational complexity. Transfer learning is applied to improve feature extraction efficiency and reduce training time. The EfficientNet model automatically learns hierarchical visual features such as edges, textures, discoloration patterns, and disease spots from banana leaf images captured under real-field conditions.

In addition to classification performance, feature map visualization is incorporated into the proposed system to analyze the internal activations of convolutional layers during prediction. Feature maps generated from convolutional layers help visualize how the CNN extracts important visual patterns associated with banana diseases and nutrient deficiencies. Lower convolutional layers capture simple image features such as edges and textures, while deeper layers learn more complex disease-related and nutrient-deficiency-related structures. This visualization improves interpretability by providing insight into the hierarchical feature learning behavior of the CNN model.

The proposed research uses a banana plant image dataset collected from Kaggle consisting of healthy leaves, diseased leaves, and nutrient-deficient leaf samples captured under real-field conditions. The images are preprocessed using resizing, normalization, and augmentation techniques to improve model robustness against environmental variations. Experimental evaluation demonstrates that the proposed approach achieves effective classification performance and strong generalization capability under practical agricultural conditions. The developed framework can assist farmers, agricultural researchers, and smart farming systems in early disease diagnosis, reducing crop losses, improving productivity, and supporting sustainable agricultural practices.

Healthy ***Black Sigatoka*** ***Panama Disease***

Magnesium Deficiency **Iron Deficiency** **Calcium Deficiency**

Fig. 1. Examples of healthy, diseased, and nutrient-deficient banana leaf samples used in the dataset.

II. Literature Review

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have significantly improved image-based plant disease detection systems in smart agriculture. Several researchers have applied Convolutional Neural Networks (CNNs) and transfer learning techniques for automated crop disease identification because of their strong capability in extracting discriminative visual features from leaf images. Deep learning approaches reduce dependency on manual inspection and improve classification accuracy under complex environmental conditions.

Many studies have focused on plant disease classification using pre-trained deep learning architectures such as VGGNet, ResNet, InceptionNet, MobileNet, and EfficientNet. These models have demonstrated promising results in identifying diseases in crops including tomato, potato, rice, maize, and banana plants. Transfer learning techniques further improve classification performance by utilizing pre-trained weights from large-scale image datasets, thereby reducing training time and computational complexity.

Several researchers specifically investigated banana leaf disease classification using image-based deep learning approaches. Amara et al. proposed a CNN-based framework for banana leaf disease recognition and achieved high classification accuracy for major banana diseases. Similarly, Selvaraj et al. applied deep learning techniques for banana disease identification under field conditions and highlighted the importance of automated agricultural monitoring systems. However, most of these studies focused only on disease detection and did not address nutrient deficiency classification simultaneously within a unified framework.

In addition to disease detection, nutrient deficiency analysis has also gained attention in precision agriculture. Researchers have used image processing and machine learning approaches to identify nutrient deficiencies in crops based on leaf discoloration and texture variations. However, nutrient deficiency detection remains challenging because deficiency symptoms often resemble disease symptoms, leading to high inter-class similarity and increased misclassification.

Several studies have also explored visualization techniques for understanding the internal behavior of deep learning models in agricultural image analysis. Convolutional feature map visualization is commonly used to analyze activation patterns learned by CNN architectures during image classification tasks. Feature maps generated from convolutional layers help identify important textures, edges, color variations, and disease-related structures captured by the model. These visualization techniques improve interpretability and provide insights into hierarchical feature extraction mechanisms within deep neural networks. In agricultural applications, feature map analysis supports understanding of how CNN models differentiate between healthy leaves, diseased regions, and nutrient-deficient patterns.

Although existing research demonstrates strong performance in agricultural disease classification, several limitations remain unresolved. Most existing systems are designed for single-task classification and focus only on either disease detection or nutrient deficiency analysis independently. Furthermore, limited research has explored deep learning frameworks capable of simultaneously classifying banana leaf diseases and nutrient deficiencies under real-field conditions while also providing visualization of internal CNN feature extraction behavior. Therefore, there is a need for an efficient deep learning framework capable of accurate banana leaf disease and nutrient deficiency classification along with feature map visualization for improved interpretability in practical agricultural applications.

TABLE I: **COMPARISON OF EXISTING METHODS**

Author	Method Used	Dataset	Accuracy	Limitation
Amara et al.	CNN	BananaLeaf Dataset	92%	Only disease classification
Selvaraj et al.	Transfer Learning	Field Images	89%	No explainability
Zhang et al.	ResNet50	PlantVillage	90%	Controlled environment only

		Dataset		
Kumar et al.	MobileNet	Banana Dataset	87%	Nutrient deficiencies not included
Proposed Work	EfficientNet + Feature Map Visualization	Real-field Banana Dataset	91%Top-k Accuracy	Improved visualizationandmulti-class classification

III. DATASET DESCRIPTION

Banana leaf diseases and nutrient deficiencies exhibit significant visual complexity under real agricultural conditions, making the availability of a diverse and representative dataset essential for developing an effective deep learning-based classification framework. In this research, a publicly available banana plant image dataset collected from Kaggle was utilized for training and evaluating the proposed deep learning model. The dataset contains banana leaf images belonging to healthy, disease-infected, and nutrient-deficient categories captured under natural environmental conditions.

Unlike laboratory-controlled datasets, the images used in this study were collected under real-field agricultural environments containing variations in illumination, shadows, background clutter, leaf orientation, camera distance, and environmental noise. These variations increase the complexity of classification tasks and make the dataset more suitable for evaluating the robustness and practical applicability of the proposed system in real-world farming conditions. The use of real-field images ensures that the developed framework can generalize effectively across different agricultural environments and assist farmers in practical disease diagnosis applications.

The dataset consists of approximately 3272 banana leaf images categorized into 21 different classes representing healthy leaves, multiple banana diseases, and various nutrient deficiency conditions. The disease classes include common banana leaf diseases such as Black Sigatoka, Panama disease, bacterial wilt, anthracnose fungal infection, Cordana leaf spot disease, insect pest infections, and chewing insect damage. Similarly, the nutrient deficiency categories include calcium deficiency, magnesium deficiency, iron deficiency, potassium deficiency, sulfur deficiency, and zinc deficiency. These diseases and nutrient deficiencies were selected because they commonly affect banana cultivation and significantly reduce crop productivity, fruit quality, and overall agricultural yield.

One of the major challenges associated with banana leaf analysis is the high visual similarity between disease symptoms and nutrient deficiency symptoms. Several classes exhibit overlapping characteristics such as yellowing, spotting, discoloration, curling, necrotic patches, and texture changes on the leaf surface. This high intra-class and inter-class similarity increases classification difficulty and makes accurate prediction more challenging under practical conditions. Furthermore, environmental factors such as varying lighting intensity, shadows, occlusions, and complex field backgrounds further contribute to classification complexity. Therefore, the dataset provides a realistic and challenging benchmark for evaluating deep learning-based agricultural diagnosis systems.

To ensure reliable model training and unbiased performance evaluation, the dataset was divided into training, validation, and testing subsets. The training dataset was used to learn feature representations and optimize network parameters, while the validation dataset was utilized for monitoring model performance and tuning hyperparameters during training. The testing dataset was finally used to evaluate the classification capability of the proposed framework on previously unseen images. This dataset splitting strategy improves generalization capability and reduces the risk of overfitting during model training.

Prior to model training, several preprocessing operations were applied to improve input consistency and model performance. All images were resized to 256 × 256 pixels to match the input dimensions required by the EfficientNet architecture. The images were converted into RGB format and normalized using EfficientNet preprocessing functions to improve feature extraction efficiency and training stability. In addition, data augmentation techniques including horizontal flipping, rotation, zooming, shifting, and brightness adjustment were applied to artificially increase dataset diversity and improve model robustness against environmental variations. These augmentation techniques also help reduce overfitting and improve the model’s ability to generalize across different field conditions.

The dataset contains a balanced combination of healthy, diseased, and nutrient-deficient banana leaf samples, enabling the proposed framework to effectively learn multiple disease and nutrient deficiency categories within a unified deep learning architecture. Furthermore, the dataset supports feature map visualization analysis by enabling observation of convolutional layer activations during classification. These visualizations help analyze how the CNN model extracts and learns important disease-related and nutrient-deficiency-related features from banana leaf images under real-field conditions.

Overall, the selected dataset provides a comprehensive and realistic representation of banana leaf conditions under practical agricultural environments. Its diversity, complexity, and real-field characteristics make it highly appropriate for evaluating the effectiveness, robustness, and interpretability of the proposed deep learning framework for banana leaf disease and nutrient deficiency classification.

TABLE II: DATASET DISTRIBUTION

Class Category	**Number of Images**
Healthy Leaves	332
Disease Classes	1621
Nutrient Deficiency Classes	1319
Total Images	3272

IV. Proposed Methodology

4.1 Overview of Proposed Framework

The primary objective of the proposed research is to develop an efficient deep learning framework capable of identifying banana leaf diseases and nutrient deficiencies using image-based analysis under real-field agricultural conditions. In practical farming environments, banana crops are frequently affected by multiple diseases and nutritional disorders that exhibit visually similar symptoms such as yellowing, necrotic patches, curling, spotting, chlorosis, and discoloration on leaf surfaces. Manual diagnosis of these conditions requires expert agricultural knowledge and continuous monitoring, which is often difficult, time-consuming, labor-intensive, and economically expensive for farmers, particularly in rural agricultural regions. Therefore, there is a strong requirement for intelligent automated systems capable of providing accurate and reliable predictions for early crop health monitoring.

To address these challenges, the proposed research introduces a deep learning framework that integrates transfer learning, EfficientNet-based feature extraction, classification, and feature map visualization into a unified architecture. The proposed framework is specifically designed to improve classification performance while simultaneously enhancing interpretability and practical usability in smart agriculture applications.

The overall workflow of the proposed framework consists of several major stages including image acquisition, preprocessing, data augmentation, deep feature extraction, classification, feature map visualization, and final prediction generation. Initially, banana leaf images are collected from a publicly available Kaggle dataset containing healthy leaves, diseased leaves, and nutrient-deficient samples captured under natural environmental conditions. Unlike laboratory-controlled datasets, the images used in this research contain real-field complexities such as varying illumination conditions, shadows, background clutter, occlusions, environmental noise, different camera angles, and inconsistent leaf orientations. These factors increase classification difficulty and make the dataset more representative of real agricultural scenarios.

In the preprocessing stage, all images are resized into fixed dimensions to ensure input consistency for deep learning model training. Image normalization is applied to stabilize pixel intensity distributions and improve optimization performance during network training. To improve dataset diversity and minimize overfitting, multiple data augmentation operations including rotation, flipping, zooming, translation, and brightness adjustment are applied. These augmentation techniques help the model learn robust visual representations and improve generalization capability under varying field conditions.

After preprocessing, the images are passed through a pre-trained EfficientNet backbone network which functions as the primary feature extractor within the proposed framework. EfficientNet was selected because of its strong classification performance, efficient compound scaling mechanism, reduced parameter complexity, and improved computational efficiency compared to conventional convolutional neural network architectures. The EfficientNet backbone automatically extracts hierarchical visual features including edges, color variations, lesion patterns, texture abnormalities, and structural distortions present on banana leaves.

The extracted deep features are then utilized for multi-class classification of banana leaf diseases and nutrient deficiency categories. The classification layer predicts the corresponding banana leaf condition using learned feature representations extracted by EfficientNet. The deep learning model is trained to optimize classification accuracy while improving generalization capability under practical agricultural conditions.

In addition to classification performance, feature map visualization is incorporated into the proposed framework to analyze the internal activations of convolutional layers during prediction. Traditional deep learning models generally operate as black-box systems where predictions are generated without understanding how image features are extracted internally. To improve interpretability, feature maps generated from convolutional layers are visualized to observe how the CNN captures important visual patterns associated with diseases and nutrient deficiencies.

Lower convolutional layers capture simple image structures such as edges, textures, and color gradients, while deeper layers learn more complex disease-related and nutrient-deficiency-related features including lesion regions, discoloration patterns, and abnormal leaf textures. The feature map visualization helps analyze hierarchical feature learning behavior within the CNN architecture and provides insights into how the model differentiates between healthy leaves, diseased regions, and nutrient-deficient leaf structures.

The visualization of convolutional activations improves interpretability and assists researchers in understanding the internal learning process of the EfficientNet model. The proposed framework therefore combines effective classification performance with feature visualization capability, making it suitable for practical deployment in precision agriculture systems, automated crop monitoring platforms, and smart farming applications.

Overall, the proposed methodology aims to provide an intelligent and computationally efficient solution for early banana leaf disease diagnosis and nutrient deficiency identification. The framework contributes toward reducing crop losses, improving banana yield quality, minimizing delayed treatment risks, and supporting sustainable agricultural practices through AI-driven agricultural monitoring technologies.

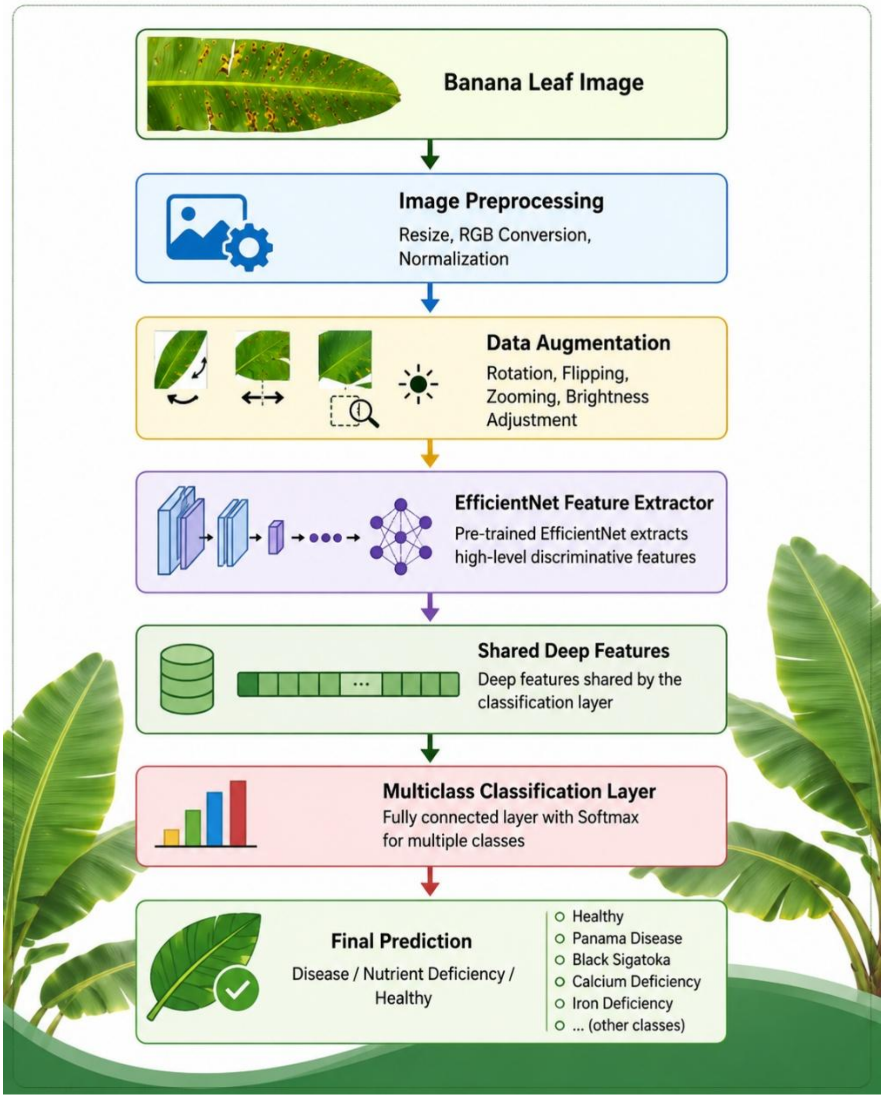

Fig. 2. Proposed workflow for banana leaf disease and nutrient deficiency classification using EfficientNet.

4.2 Image Acquisition and Dataset Preparation

The dataset used in this research was collected from Kaggle and contains approximately 3272 banana leaf images belonging to healthy, diseased, and nutrient-deficient categories. The dataset includes 21 different classes representing various banana leaf diseases and nutrient deficiency conditions captured under real agricultural environments. The collected images contain variations in illumination, shadows, background complexity, leaf orientation, camera angle, and environmental noise, making the dataset suitable for evaluating the robustness of the proposed deep learning framework under practical field conditions.

The disease categories include common banana leaf diseases such as Black Sigatoka, Panama disease, bacterial wilt, anthracnose fungal infection, Cordana leaf spot disease, and insect-related infections. Similarly, the nutrient deficiency categories include calcium deficiency, magnesium deficiency, iron deficiency, potassium deficiency, sulfur deficiency, and zinc deficiency. Healthy banana leaf images were also included to improve classification diversity and model generalization capability.

To ensure reliable model training and unbiased performance evaluation, the dataset was divided into training, validation, and testing subsets. The training dataset was utilized for learning deep feature representations and optimizing network parameters, while the validation dataset was used for monitoring model performance during training. The testing dataset was finally used for evaluating classification accuracy on previously unseen banana leaf images. This dataset splitting strategy helps improve generalization performance and reduces overfitting during model training.

4.3 Image Preprocessing and Data Augmentation

Before training the deep learning model, several preprocessing operations were applied to improve input consistency and classification performance. All banana leaf images were resized to 256 × 256 pixels to match the input dimensions required by the EfficientNet architecture. Image resizing ensures uniform input dimensions and improves computational efficiency during model training.

The images were converted into RGB format and normalized using EfficientNet preprocessing functions to stabilize pixel intensity distributions and improve feature extraction capability. Normalization also improves optimization stability and accelerates convergence during network training.

To improve dataset diversity and reduce overfitting, multiple data augmentation techniques were applied to the training images. The augmentation operations included horizontal flipping, rotation, zooming, width shifting, height shifting, and brightness adjustment. These augmentation techniques artificially increase dataset variability and help the model learn robust visual features under different environmental conditions.

Data augmentation also improves the generalization capability of the proposed framework by enabling the CNN model to learn disease-related and nutrient-deficiency-related patterns from multiple transformed versions of banana leaf images. This helps improve classification robustness under real-field agricultural conditions containing varying lighting conditions, shadows, occlusions, and background clutter.

Section 5 — Experimental Results and Discussion

5.1 Training Performance Analysis

A) Accuracy Graph

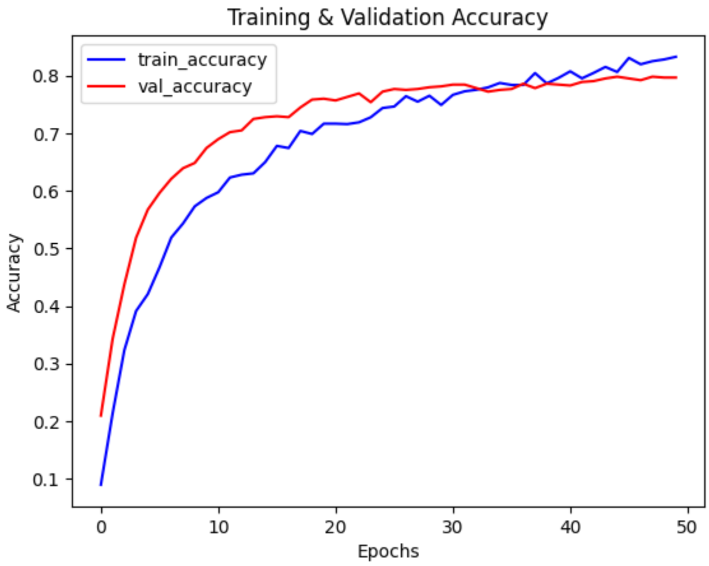

Fig. 3. Training and validation accuracy of the proposed EfficientNet-based model during training epochs.

The training and validation accuracy graph illustrates the learning performance of the proposed EfficientNet-based deep learning model during the training process. Initially, the model achieved lower accuracy values because the network was still learning basic visual features from banana leaf images. As the number of epochs increased, both training and validation accuracy gradually improved, indicating effective feature learning and optimization. The validation accuracy closely followed the training accuracy with only minor fluctuations, demonstrating good generalization capability and reduced overfitting. The final validation accuracy of approximately 79% indicates that the proposed framework successfully learned discriminative visual patterns associated with banana leaf diseases and nutrient deficiencies under real-field agricultural conditions.

B) Loss Graph

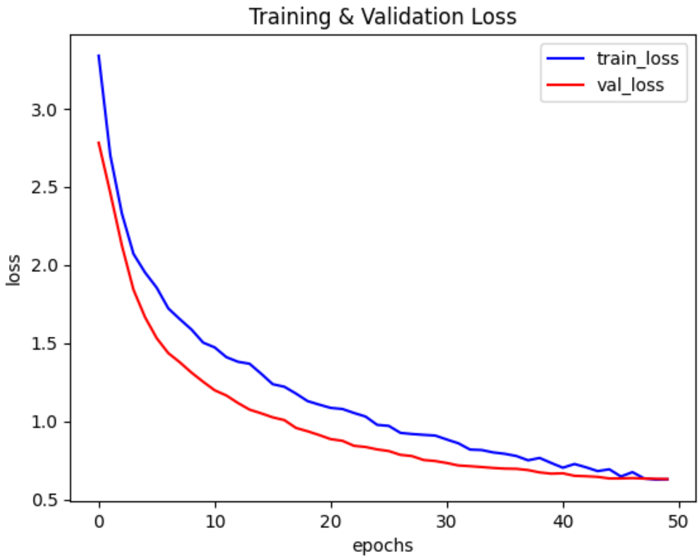

Fig.4.Training and validation loss of the proposed EfficientNet-based model during training epochs.

The training and validation loss graph represents the optimization behavior of the proposed deep learning model during training. Initially, both training and validation loss values were relatively high because the model parameters were randomly initialized. As the training progressed, the loss values gradually decreased, indicating improved classification capability and stable convergence of the network. The validation loss consistently decreased along with the training loss, demonstrating that the proposed model generalized effectively to unseen banana leaf images while minimizing classification errors. The smooth convergence behavior also indicates reduced overfitting and stable model training performance.

5.2 Classification Performance

The proposed EfficientNet-based deep learning framework achieved effective classification performance on the banana leaf dataset collected under real-field agricultural conditions. Experimental evaluation demonstrated that the proposed model achieved approximately 79% classification accuracy and 91% top-k accuracy across healthy, diseased, and nutrient-deficient banana leaf categories. The obtained results indicate that the EfficientNet architecture successfully learned discriminative visual representations associated with multiple banana leaf conditions.

The proposed framework effectively classified various disease categories including Black Sigatoka, Panama disease, bacterial infections, fungal diseases, and insect-related damage, along with multiple nutrient deficiency conditions such as calcium deficiency, magnesium deficiency, potassium deficiency, and iron deficiency. The classification results demonstrate that the model was capable of distinguishing visually similar disease and nutrient deficiency symptoms despite high inter-class similarity.

The use of transfer learning with EfficientNet significantly improved feature extraction capability and enhanced classification efficiency under complex agricultural conditions. The model successfully captured important visual patterns such as discoloration, lesion regions, texture abnormalities, chlorosis, and leaf damage patterns from banana leaf images. The achieved top-k accuracy further indicates that the correct class predictions were frequently present among the top predicted categories generated by the model.

Although the dataset contained real-field challenges including varying illumination conditions, shadows, complex backgrounds, environmental noise, and inconsistent leaf orientations, the proposed framework demonstrated stable generalization performance. The experimental results confirm that the EfficientNet-based framework can effectively support automated banana leaf disease diagnosis and nutrient deficiency identification for practical smart agriculture applications.

1. Prediction Output Figure

Fig.5 .Sample prediction outputs generated by the proposed EfficientNet-based framework for banana leaf classification.

The prediction outputs demonstrate the practical classification capability of the proposed EfficientNet-based deep learning framework for banana leaf analysis. The model successfully predicts the corresponding banana leaf disease or nutrient deficiency category along with a confidence score indicating prediction certainty and classification reliability. The obtained prediction results confirm that the proposed framework can effectively identify multiple banana leaf conditions under real-field agricultural environments. The generated confidence scores for prediction outputs were observed in the range of approximately 79% to 95% for correctly classified banana leaf samples, indicating stable prediction capability and effective feature extraction performance of the EfficientNet architecture.

1. Confusion Matrix

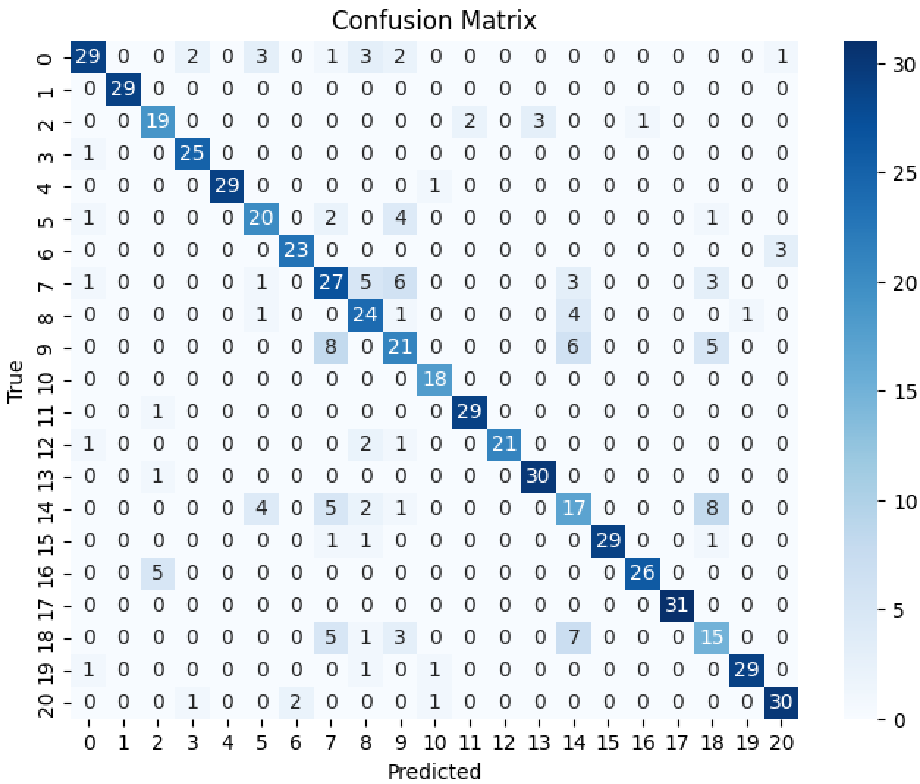

Fig.6.Confusion matrix representing classification performance of the proposed EfficientNet-based framework across multiple banana leaf classes.

The confusion matrix illustrates the class-wise classification performance of the proposed EfficientNet-based deep learning framework for banana leaf disease and nutrient deficiency identification. Most classes achieved high prediction accuracy, as indicated by the strong concentration of values along the diagonal region of the confusion matrix. This demonstrates that the proposed model successfully learned discriminative visual features associated with healthy leaves, disease-infected leaves, and nutrient-deficient banana leaf samples.

Several classes achieved high true positive prediction counts, indicating effective class-wise classification capability and stable generalization performance under real-field agricultural conditions. Minor misclassifications were observed between visually similar disease and nutrient deficiency categories because of overlapping symptoms such as discoloration, chlorosis, spotting, and texture abnormalities on banana leaf surfaces. Certain nutrient deficiency classes and fungal disease categories exhibited inter-class similarity, leading to limited prediction confusion.

Despite the presence of environmental challenges including varying illumination conditions, shadows, background complexity, and inconsistent leaf orientations, the proposed framework maintained reliable classification performance across multiple categories. The confusion matrix analysis confirms that the EfficientNet architecture effectively extracted hierarchical visual features and achieved robust multi-class classification capability for practical smart agriculture applications.

5.3 Feature Map Visualization Analysis

Fig A — Early Layers

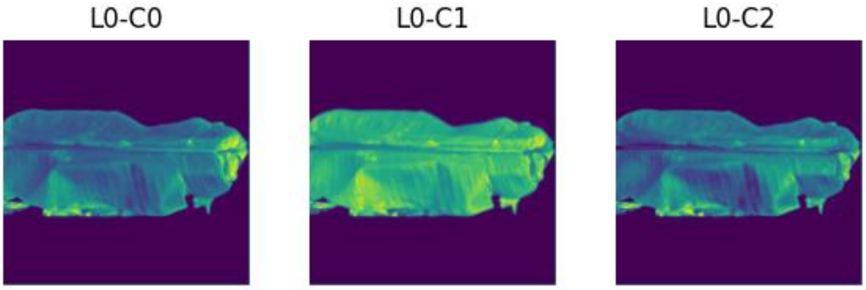

Fig.7.Feature maps generated from early convolutional layers capturing low-level visual features.

Fig B — Intermediate Layers

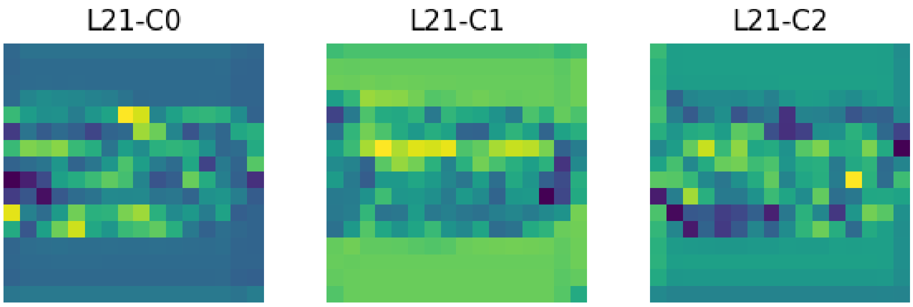

Fig. 8. Intermediate convolutional feature maps highlighting texture abnormalities and disease-related structures.

Fig C — Deep Layers

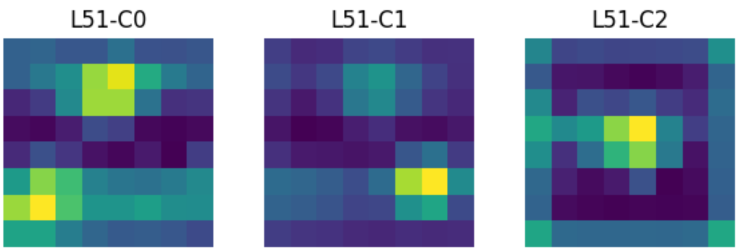

Fig.9. Deep convolutional feature maps representing high-level abstract visual features learned by the EfficientNet architecture.

The feature map visualizations illustrate the internal activations generated by convolutional layers within the EfficientNet-based deep learning framework. Early convolutional layers primarily captured low-level visual features such as edges, textures, and leaf boundaries, while intermediate layers extracted disease-related texture patterns and discoloration regions. Deeper convolutional layers learned more abstract and high-level representations associated with banana leaf diseases and nutrient deficiencies. These visualizations demonstrate the hierarchical feature extraction capability of the CNN model and provide insight into the internal learning behavior of the EfficientNet architecture during classification.

VI. Conclusion

The proposed research presented an EfficientNet-based deep learning framework for automatic classification of banana leaf diseases and nutrient deficiencies using image-based analysis under real-field agricultural conditions. The developed framework utilized transfer learning and convolutional neural network techniques for automatic feature extraction and multi-class classification of healthy leaves, diseased leaves, and nutrient-deficient banana leaf samples. The dataset used in this research consisted of approximately 3272 banana leaf images collected under practical agricultural environments containing variations in illumination, shadows, background complexity, and environmental noise.

Experimental evaluation demonstrated that the proposed framework achieved approximately 79% classification accuracy and 91% top-k accuracy across multiple banana leaf categories. The EfficientNet architecture successfully learned discriminative visual representations associated with disease symptoms and nutrient deficiency patterns such as discoloration, spotting, chlorosis, texture abnormalities, and damaged leaf structures. The obtained results confirm that the proposed framework can effectively support automated banana leaf disease diagnosis and nutrient deficiency identification under complex agricultural conditions.

In addition to classification performance, feature map visualization was performed to analyze the internal activations generated by convolutional layers within the EfficientNet architecture. The generated feature maps demonstrated the hierarchical feature extraction capability of the CNN model, where lower convolutional layers captured low-level image features such as edges and textures, while deeper layers extracted high-level disease-related and nutrient-deficiency-related visual patterns. The visualization analysis improved interpretability and provided insights into the internal learning behavior of the deep learning model during classification.

The proposed framework can assist farmers and agricultural monitoring systems in early disease diagnosis, reducing crop losses, improving banana crop productivity, and supporting smart farming applications. Overall, the research demonstrates that deep learning-based agricultural monitoring systems can provide efficient, reliable, and scalable solutions for automated banana leaf disease and nutrient deficiency classification under practical field conditions.

Future Work

In future work, the proposed framework can be extended by integrating disease treatment recommendation systems capable of providing fertilizer suggestions, pesticide recommendations, spraying guidance, and preventive agricultural measures based on the predicted banana leaf condition. Additional improvements may include real-time mobile application deployment, IoT-enabled smart farming integration, and larger multi-environment agricultural datasets to further improve classification accuracy and practical usability in precision agriculture applications.

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