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PREDICTION AND DETECTION OF BANANA LEAF DISEASES USING DEEP LEARNING

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ABSTRACT
The detection and classification of Banana Leaf Diseases is a critical aspect of modern agriculture. Plant health directly influences crop yield and quality. In traditional identification methods, manual inspection is undertaken which is time-consuming and prone to human error. So, the study suggests a deep learning-based technique for banana leaf disease detection using a Convolutional Neural Network (CNN). This model is trained technically using a large dataset of banana leaf images, each comprising a variety of disease categories such as Sigatoka, Bacterial Wilt, among other common fungal and bacterial infections. Deep learning has been employed in this framework to increase the accuracy and hence the early detection of disease, consequently increasing the chances for timely treatment. The experiments conducted show that the deep learning model surpasses conventional image processing techniques by giving the highest accuracy, the most effective performance and robustness in real-world agricultural applications. It is also believed that the presented method could be a major innovation tool in precision farming to help farmers optimize their practices and prevent damage to their crop due to disease

Keywords:
Disease Detection, Deep Learning, Convolutional Neural Networks (CNN), Image Classification.

I. Introduction

Bananas are more than a staple commodity for millions—they're a backbone of world agriculture and an integral force behind the global economy. One of the most extensively cultivated fruits, bananas particularly in tropical and subtropical countries, offer incomes for millions of farmers. But for all their prominence, banana farms are ever-under siege from disease that can annihilate production and cause massive economic losses to producers and farmers. Historically, disease identification in banana plants has depended on expert visual checks. Although effective in its own right, the process is not flawless. It is labor intensive, requires expert skills and is highly prone to human error. These problems inevitably result in delay giving diseases a chance to spread and are harmful to the plants. Deep Learning technologies can be helpful in this way. Deep learning offers automatic and reliable disease diagnosis by processing large volumes of image data and identifying subtle visual patterns. It can make agricultural sensors more effective and help farmers identify problems early on and respond in time before the damage is irreversible. This leads to reduced losses, healthier harvests and a step towards sustainable farming. Bananas are not merely a favourite fruit of the world—they are a vital crop for millions of farmers in tropical and subtropical regions. Beyond being a nutritious and delicious food bananas are also a major source of income and employment. In fact bananas are grown in over 130 countries and rank as the fourth most important food crop globally. However bananas are highly susceptible to diseases that mainly target their leaves, posing serious challenges for farmers and the agricultural industry as an entire.

Banana leaf diseases can have a devastating impact on crops. The leaves are essential for photosynthesis the process through which the plant produces the energy needed to grow and bear fruit. When leaves are affected by diseases and their growth is diminished from plants, their ability to photosynthesize is compromised and reduces yields and poor fruit quality. For farmers who rely on bananas for their livelihood this can mean significant financial losses and food insecurity in regions where banana is a staple food.

Among the most harmful banana leaf diseases are Sigatoka (yellow and black), Bacterial Wilt, Fusarium Wilt and Typhoid Wax. Sigatoka caused by fungal pathogens is particularly destructive. It reduces the lifespan of banana leaves and limits plant's ability to produce energy. Over time this may lead to early leaf death and poor fruit production. Similarly Bacterial Wilt causes the plant to wilt, eventually killing it and Fusarium Wilt attacks the plant' internal systems. This causes it to collapse completely. These diseases spread rapidly, making it difficult for farmers to control outbreaks without early detection.

1.1 Impact of Banana Diseases

Diseases of bananas include Black Sigatoka (by Mycosphaerella fijiensis), Panama disease (by Fusarium oxysporum), and Banana Bunchy Top Virus (BBTV) that know no bounds and cause considerable yield losses around the world. These diseases reduce both the quantity and the quality of banana production and also increase management and disease control costs. For example, untreated Black Sigatoka is responsible for losses of up to 50% in yield. Plus, the fast spread of diseases like Panama disease has led to the abandonment of large plantation areas, particularly in regions purely dependent on monoculture farming practices. There, therefore, is a compelling need for efficient means of disease detection and timely reporting.

1.2 Challenges in Traditional Disease Detection

Traditional methods of disease detection usually depend on the manual inspection done by trained agronomists or farmers. Some drawbacks of these techniques are: Was laborious: Disease scouting across vast swaths of land takes time and energy and is expensive. Personally subjective: Accuracy is dependent on inspector expertise, which could lead to inconsistent results, especially in complex cases that involve overlapping symptoms. Delayed Diagnosis: Late identification results in less effective control action, resulting in rousing crop losses and economic costs. Compared to other modalities, this manual approach offers limited scalability across vast plantations or distant areas. As with banana leaf disease farmers can impact the entire economy. Since bananas are a major export crop for many developing countries widespread disease outbreak can disrupt trade, increase farming costs and even threaten food supplies in regions that depend on banana as a staple. One of the biggest problems with banana leaf diseases is that they don't get caught in their early stages. Even with these challenges, advancements in farming technology are offering hope. Artificial intelligence and deep learning are now being used to detect banana leaf diseases early and accurately. By analyzing images of banana leaves, these systems can quickly identify the type of disease. This enables farmers to take targeted actions, such as removing infected plants or applying specific treatments, to stop the disease from spreading further. Addressing banana leaf diseases is important not just for farmers but for the global agricultural community. These diseases emphasize the need for sustainable farming practices, better disease management, and technological innovation. Tackling them effectively can lead to healthier crops, reduced economic losses, and a steady food supply for millions of people. Banana leaf diseases go beyond being a farming issue they threaten food security, farmer livelihoods, and economic stability. That's why investing in research, technology, and sustainable practices is so critical to protecting this essential crop. With the right solutions, we can help farmers manage these challenges and secure a brighter, more sustainable future for banana farming.

II. Background and Related Work

Traditional ways of detecting diseases within banana leaves include manual inspection and chemical analysis. The farmer and agricultural expert have to manually observe the leaves for signs of infection, which may include discoloration, spots, or wilting. Though a widely accepted means for years, it suffers from many challenges: it's time-consuming, thus needs specially trained personnel and in relation to someone or something. large-scale farming operations prone to human error. On the other hand, chemical analysis is expensive, time-consuming, and usually impractical, yet very efficient. Recent advances in machine learning and deep learning have inspired novel techniques in the way diseases of plants are classified. These techniques provide an automatic classification scheme for diseases on the basis of images of infected leaves, bringing about a major improvement in both accuracy and speed of diagnosis. Another well-known and successful technique that uses deep learning is convolutional neural networks (CNNs). CNNs have demonstrated superior performance at identifying and classifying plant diseases by grasping complex patterns within image data. Techniques such as transfer learning further the advances of CNNs. Transfer learning draws upon previously trained models to classify diseases; it is especially successful when working with limited datasets. Furthermore, hybrid models that integrate different algorithms became popular due to their ability to strike a balance between accuracy and computation efficiency. The comparison of these methods has conclusively proven the superiority of deep learning techniques: CNNs and transfer learning use traditional approaches on the part of precision and scalability. In the same breath, hybrid models are an avenue that amalgamates the strength of different approaches that, together, ensure more robust and adaptable solutions in the detection of banana leaf diseases.

III. Problem Statement

Banana leaf diseases are a serious threat for farmers and the agricultural industry. These diseases spread rapidly attack the leaves that the plant relies on to produce energy through photosynthesis. When the leaves are damaged the plant’s growth slows down and fruit production falls. Overall yields suffer from falling leaves and disease-causing bacteria. For farmers who depend on bananas for their food and income it can lead to major financial losses and even food shortages. Making this issue even tougher is the difficulty of catching infectious diseases early. Most farmers look for visible signs like spots or discoloration on leaves to detect infections. Unfortunately, by the time these signs appear in the landscape they often spread to other parts of the plant or nearby crops. At that stage control of the outbreak becomes more difficult and costly. Without a clear diagnosis many farmers turn to broad-spectrum pesticides in an attempt to save their crops. While this might seem like a quick fix, it can harm the environment, raise costs and lead to pesticide resistance over time. This makes it even harder to manage future outbreaks and threatens the long-term sustainability of farming. This paper proposes a CNN-based deep learning approach for early, affordable, and scalable detection of banana leaf diseases. The real challenge is finding the tools farmers need for managing their crops effectively. It’s time to move beyond the banana crisis and save the banana. But it'll also help protect farmers' livelihoods, ensuring food security and supporting the economies that depend on this important crop.

IV. Literature Survey

The application of deep learning in banana leaf disease detection has emerged as a vital research area, driven by the urgent need to safeguard global banana production, a staple crop critical to food security and rural economies. Over the past decade, researchers have increasingly turned to convolutional neural networks (CNNs) to automate the identification of diseases such as Sigatoka, Fusarium wilt, and Black Leaf Streak, which collectively cause billions of dollars in annual crop losses. Early studies, like the work by Amara [1], demonstrated the feasibility of using basic CNN architectures like LeNet to classify banana leaf diseases with promising accuracy, setting the stage for more sophisticated approaches. Subsequent research has leveraged advanced pre-trained models such as ResNet, VGG-16, Inception-v3, and Efficient Net, often enhanced through transfer learning. For instance, Poojary [2] fine-tuned ResNet-50 on the Plant Village dataset, achieving over 97% accuracy in distinguishing healthy leaves from those infected by Sigatoka or Fusarium. These models excel in controlled

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environments with curated datasets but face challenges when deployed in real-world field conditions, where factors like uneven lighting, occlusions and complex backgrounds degrade performance.
To address these limitations, researchers have adopted multi-stage pipelines combining segmentation, augmentation, and hybrid architecture. Segmentation techniques, such as Mask R-CNN and U-Net, have been employed to isolate diseased regions from healthy tissue, as seen in Rahman [8], who improved detection precision by focusing on localized lesions. Data augmentation strategies including rotation, flipping, and synthetic image generation using generative adversarial networks (GANs) have been critical in expanding small, imbalanced datasets. For example, Mohanty [5] highlighted the scarcity of field-collected images in public repositories like Plant Village, which primarily feature lab-condition photos, necessitating synthetic data to mimic real-world variability. Hybrid models, integrating CNNs with traditional machine learning classifiers like support vector machines (SVMs) or attention mechanisms, have further improved robustness. A study by Chen [3] combined Efficient Net with an attention module to prioritize disease-specific features, achieving 98.3% accuracy on a dataset spanning multiple banana cultivars.

V. Proposed system

5.1 Dataset Preparation

Banana leaf images were collected from multiple sources, including publicly available datasets, research institutions, and local farms. Efforts were made to ensure diversity in the dataset, capturing images from different regions, under varying lighting conditions, and at various stages of disease progression. The dataset comprised seven primary classes: Black Sigatoka Disease, Bract Mosaic Virus Disease, Healthy Leaves, Insect Pest Damage, Moko Disease, Panama Disease, Yellow Sigatoka Disease

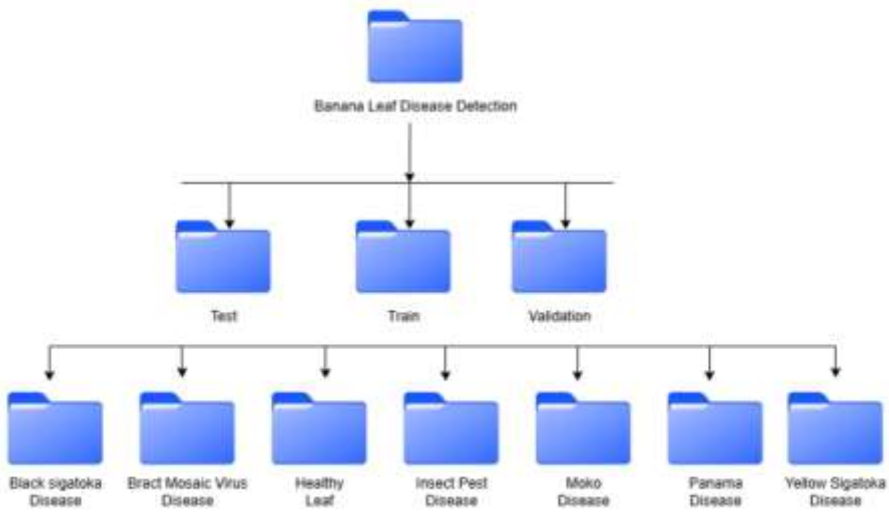

Figure 5.1.1 Banana Disease Classes Dataset

5.1.2. Dataset Description

The database consists of a total of 3,265 images, of which 2,615 are for training and 650 are for validation. The resolution of the Images was resized to 128x128 pixels for compatibility with the model architecture. The Color Format of images was RGB format to capture intricate leaf patterns and color differences.

5.1.3. Data Augmentation

To improve model robustness and address class imbalance, the following augmentation techniques were applied: Flipping for Horizontal and vertical flips to simulate diverse leaf orientations. Rotation for Random rotations between ±15° to account for varying camera angles. Scaling for Random zoom in and out to replicate different distances of image capture. Brightness Adjustment for Modifications to replicate lighting conditions from natural settings. Noise Injection for Addition of Gaussian noise for model resilience to noisy data.

5.2 Image Preprocessing

5.2.1 Resizing and Normalization

All images were resized to 128x128 pixels and normalized to a [0, 1] range by dividing by 255. This standardization ensures faster convergence during training and prevents vanishing gradients.

Figure 5.2.1 Image Normalization

5.2.2 Sobel Edge Detection

Edge detection filters, such as Sobel, were applied to enhance features like disease-specific leaf patterns. Sobel images were generated to test the model's ability to classify using enhanced structural details.

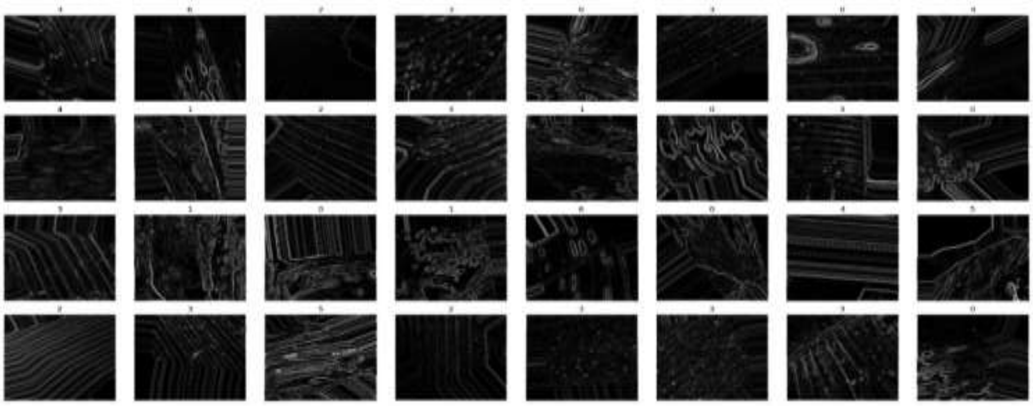

Figure 5.2.2 Sobel Edge Detection Filter

5.2.3. Model Architecture (Based on LeNet)

The model architecture was adapted to suit the dataset's complexity. Key layers include: Convolutional Layers: Feature extraction with ReLU activation and Batch Normalization learning. Pooling Layers: Down-sampling with MaxPooling to reduce dimensionality. Dropout Layers: Added after convolutional blocks to prevent overfitting. Global Average Pooling: To reduce spatial dimensions without overfitting. Fully Connected Layers: Dense layers with Batch Normalization and Dropout for classification into seven classes.

5.2.4. Training Configuration

Optimiser: Adam with default learning rate for adaptive optimization. Loss Function: Categorical cross-entropy, suitable for multi-class classification. Metrics: Accuracy, precision, recall, and F1-score. Class Weights: Computed to handle class imbalance, ensuring fair contribution from underrepresented classes

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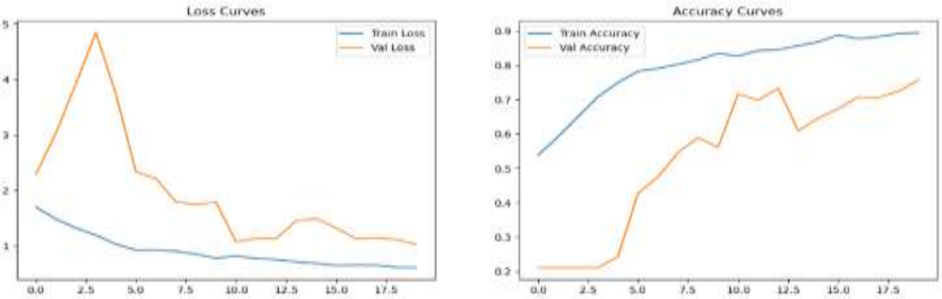

Figure 5.2.3 Model Training Accuracy Graph

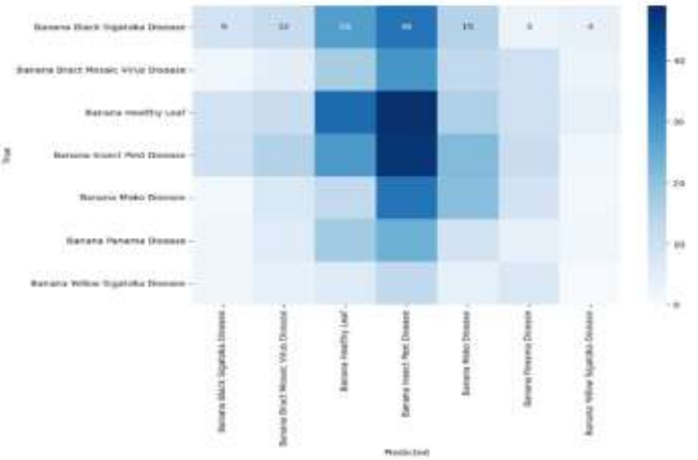

Figure 5.2.4 Model Confusion Matrix

5.2.5. Model Evaluation and Performance Analysis

The performance of the deep learning model was evaluated using a comprehensive set of visual and quantitative metrics. The confusion matrix (Figure 5.2.4) reveals the classification effectiveness across the seven banana leaf categories, including both healthy and disease-affected classes. While the model shows strong prediction tendencies toward the "Banana Insect Pest Disease" and "Banana Healthy Leaf" classes, some degree of misclassification is evident, particularly among visually similar disease categories such as "Banana Black Sigatoka Disease" and "Banana Yellow Sigatoka Disease." This overlap suggests the potential need for more refined feature extraction or the inclusion of additional data to reduce inter-class confusion.

The loss and accuracy curves (Figure 5.2.3) provide insight into the training dynamics over 20 epochs. The training loss consistently decreases, indicating effective learning, while the validation loss initially increases before gradually declining, suggesting that the model undergoes some overfitting before stabilizing. The training accuracy steadily improves, nearing 90%, while the validation accuracy rises to approximately 75%, reflecting decent generalization performance, albeit with room for improvement. The model demonstrates strong classification capability across most classes, as supported by quantitative metrics such as precision, recall, and F1-score. These metrics further validate the model's effectiveness, especially when paired with the use of class weights to handle class imbalance during training.

VI. Result

Figure 6.1 Final Model Predicted Output

VII. Conclusion

Primarily affecting the banana plant, banana leaf disease is also an indicator for other agricultural practices and environmental health. It must be said that there are several factors causing banana leaf diseases: improper farming techniques, changing climate and pests. Early detection and good care should stop the virus from spreading and result in better harvests. This study highlights the importance of early detection of banana leaf diseases, which are influenced by both biotic and environmental factors. Deep learning models, as demonstrated, offer promising results for scalable disease diagnosis and sustainable agriculture. From these strategies, it retches safe management that combines sustainable purposes of agricultural production, dealing with ecosystem protection, and securing public health. Future research can explore real-time deployment on edge devices, integration with mobile apps for field use, and testing under real-world environmental variability.

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