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RESEARCH ARTICLE

DETECTION OF DISEASES ON BANANAS (MUSA SP.) USING IMAGE PROCESSING AND MACHINE LEARNING TECHNIQUES

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Abstract

Bananas, whose demand is very high in the global market, are considered one of the best agricultural export products in the Philippines — a country where agriculture plays a significant role in economic development. However, diseases in bananas have caused significant losses to farmers over the years due to low yields, as it significantly affects the growth and quality of the fruits. To solve the problem, studies have shown that early detection of diseases in bananas is essential for the local farmers to determine a cost-effective control measure to perform which helps reduce the infestation, if not eradicate it. Since image processing has proven to be an effective tool for classification and analysis, it was used as the focus of the study. A total of 3000 images of common banana diseases, divided into training, validation, and testing datasets, and whose symptoms are mostly found on the leaves, were collected, preprocessed, and loaded into the four (4) pre-trained convolutional neural network model architectures namely, VGG19, InceptionV3, ResNet50 and EfficientNet which adopted the same optimization and model parameters. To determine the model with the best performance when used in a test dataset, accuracy results and the confusion matrix and classification report were utilized as performance evaluation metrics. The results have shown that among the identified model architectures, the EfficientNet model obtained the highest accuracy of 91%.

Introduction:

Agriculture plays a significant role in the development of the economy in the Philippines, contributing an average of 19 percent to the country's Gross Domestic Product (GDP) (De Asis, 2003). According to the Philippine Statistics Authority (2020), crop cultivation was the leading agricultural enterprise in the country in 2020, with a total output of 54.9 percent, surpassing other agricultural operations such as livestock, poultry production, and fisheries, which made up 17.9 percent, 14.3 percent, and 12.8 percent, respectively. Approximately 9 million hectares of the country's 30 million hectares of land were dedicated to agriculture (Tolentino et al., 2015). In 2005, the agriculture sector contributed 19 percent to the country's GDP, making the Philippines one of the leading exporters of various agricultural products in high demand in the global market, including rice, maize, sugarcane, coconut, rubber, pineapple, coffee, and notably, bananas (Altoveros et al., 2007).

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Fresh bananas are one of the best agricultural products and major export commodities for the Philippines, contributing about 200 million US dollars annually (PCAARRD, 2013). According to Voora et al. (2020), bananas were one of the most traded fruits in the world in 2017, with 22.7 million tons, representing 20 percent of global production. Bananas have consistently been a top dollar earner for the country, becoming the second most important export commodity. The Philippine banana export industry is highly competitive, contributing 29.3 percent to agricultural export earnings in 2019, according to Mapa et al. (2020), thereby establishing the country as a dominant banana exporter in the Asian market (Huang, 2024).

However, diseases in bananas pose a significant threat to banana production, leading to substantial problems in the Philippines and East and Central Africa (ECA) (Vanlauwe et al., 2013). Based on the findings of Viljoen et al. (2017), the presence of diseases and their harmful effects, such as loss of yields, can destabilize food security, production, and household income by up to 25 percent. In the Philippines, over 2,000 hectares in Mindanao were lost to Panama disease and the effects of El Niño in 2015, causing a drop in production volumes (Azman et al., 2020). The situation led the Pilipino Banana Growers and Exporters Association (PBGEA) to seek government support to help recover the banana industry, especially since more than 5,000 hectares were abandoned in the Davao region due to the severe loss caused by Panama disease.

As noted by Puig (2014), the management of banana diseases in the region can be attributed to strategies such as early detection and containment, disease management techniques, and the development of long-term strategies through research. Common problems for banana farmers include the late identification of diseases and lack of knowledge in dealing with unsuitable conditions. The introduction of information technology in agriculture has paved the way for more effective solutions to agricultural problems, including using image processing and expert systems to support decision-making and improve crop yields.

Related Works:

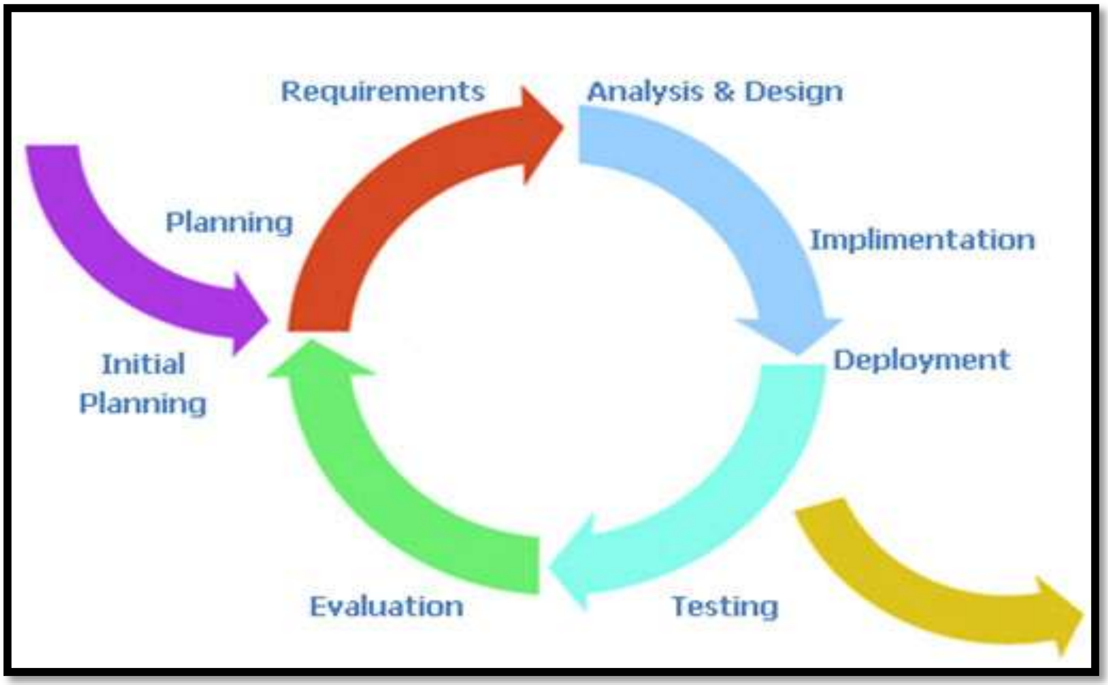
Many studies have utilized machine learning algorithms and image classification in agriculture. Kumar et al. (2020) developed an expert system integrating image processing to determine pest and disease attacks in rapeseed-mustard. Chen Lai et al. (2010) applied a similar approach in corn. Other studies, such as those by Lehri et al. (2008), and Kaur (2014), incorporated textual data alongside images. El-Helly et al. (2003) and Sharma et al (2022) developed systems for detecting leaf diseases like Downy mildew, Leafminer, and Powdery mildew. Ganesan (2007) created Crop-9-DSS, a decision support system for crop management in Kerala, India, focusing on various crops, including bananas. Prathibha G. et al. (2014) used image processing for early detection of borers in tomatoes. Tigadi et al (2016) proposed an automatic plant disease detector for bananas using HOT feature extraction and Artificial Neural Network-based training and classification. Anasta et al. (2021) used multilevel thresholding methods for banana disease detection, while Raut et al. (2017) employed digital image processing with K-means clustering and a multi-SVM algorithm. Kumar et al. (2010) used the KNN classifier and texture features for flower image classification. Panchal et al. (2016) utilized image processing for pomegranate leaf disease detection using K-means clustering and SVM for classification. Sladojevic, et al. (2016) applied a deep neural network for leaf disease classification with high accuracy. Abu et al. (2019) used deep learning and Tensorflow for flower classification, achieving high accuracy rates. Kumar, P. et al. (2020) demonstrated advanced CNN with Tensorflow for image classification, with over 95 percent accuracy. Kumbhar et al. (2019) developed "Farmer Buddy," a web-based cotton leaf disease detection system using CNN. Karol (2019) implemented CNN for plant disease detection and remedy recommendation, with applications in drone-based crop surveillance. Mohanty et al. (2016) used CNN for leaf disease identification, emphasizing texture and color features for high accuracy. Akter et al. (2021) introduced attention architecture for classifying Bangladeshi medicinal plants using deep learning techniques.

The primary objective of this study was to identify the most effective model for classifying banana diseases, a tool that can assist in the early detection of diseases and inform appropriate prevention and control strategies based on integrated disease management standards. By leveraging TensorFlow and CNN-based models, including EfficientNetV2, VGG-19, InceptionV3, and ResNet50, we trained and tested these models on an extensive image dataset containing images of various banana diseases, such as Moko disease, Panama disease, Bunchy Top, and Black Leaf Streak (BLS). The model that achieved the highest accuracy from each experiment was selected as the foundation for a disease classification system designed to provide critical insights and decision support to banana growers. This system aims to enhance productivity by enabling timely disease diagnosis, thereby facilitating more effective disease management practices. This research aligns with the objectives of the Philippine Council for Agriculture, Aquatic, and Natural Resources Research and Development (PCAARRD), which seeks to improve agricultural practices and productivity through the adoption of innovative technologies in banana farming (Philippine Council for Agriculture, Aquatic and Natural Resources Research and Development, 2013).

Methodology:-

The Iterative and Incremental Model

Figure 1:- The Iterative and Incremental Model.



The Iterative and Incremental Development Model (IIDM), as shown in **Figure 1**, was employed in this study, offering a cyclical process that allows flexibility across its phases. Unlike the linear Waterfall model, IIDM progresses through iterations, each with clearly defined objectives that must be achieved before moving to the next phase. This iterative process ensures that with each cycle, the project incrementally progresses toward the desired outcome (Azman et al., 2020). The methodology adopted for this research follows this iterative and incremental approach, with phases completed sequentially throughout the project's development. In addition, a machine learning pipeline was integrated into the methodology to structure activities related to image processing and the development of the machine learning model, ensuring a systematic and comprehensive approach from the project's inception to its completion.

The Machine Learning Pipeline

The proposed method in this study aimed to determine the most effective convolutional neural network (CNN) model for classifying banana diseases. The research utilized four well-known pre-trained CNN models for image classification to distinguish between common banana diseases: Bunchy Top disease, Fusarium Wilt disease, Moko Bacterial Wilt, and Sigatoka. These models were trained on the same banana image datasets using consistent image and batch sizes, epoch numbers, augmentation processes, activation functions, and optimization parameters. The overall results and performance metrics of each model were compared and discussed. The model that demonstrated the highest performance and accuracy was ultimately selected. The entire process of the proposed methodology is best described by a machine learning pipeline. This pipeline consists of a series of complex data processing steps arranged sequentially, starting from data acquisition, preprocessing, feature extraction, model training, and culminating in deploying the model to generate predictions on test data (Atoum, 2018). It provides a detailed procedure on how the workflow was codified and automated to produce the machine learning model (Makihara et al., 2003).

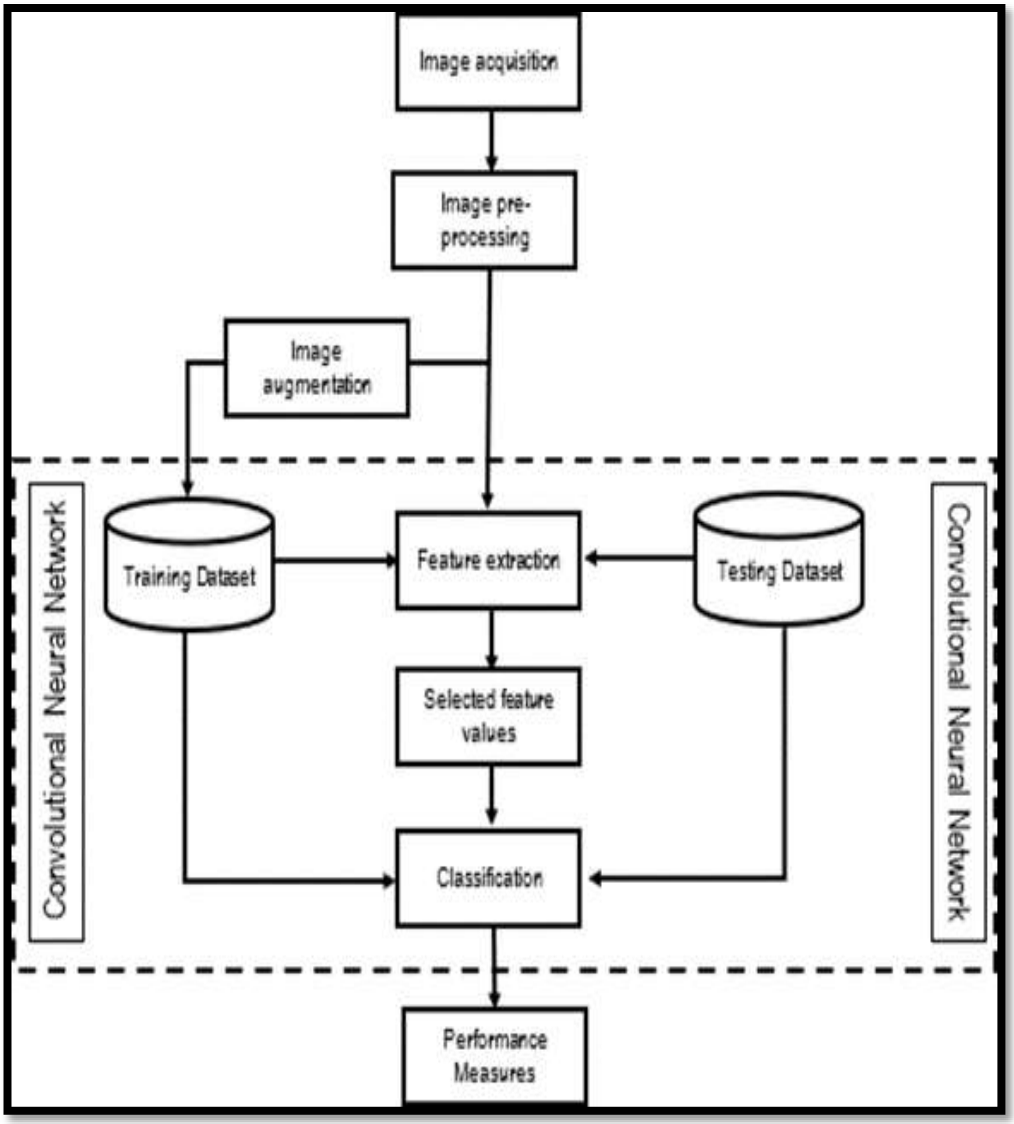


Figure 2:- The Machine Learning Pipeline.

The machine learning pipeline began with the collection of images of the various banana plant diseases specified in the study's scope. **Figure 2** illustrated the process flow of the system's disease detection, which underwent several phases of image processing and dataset training for classification.

Image Acquisition

The images of banana diseases used in this system were acquired using two methods. The first method involved capturing images with a digital camera and a mobile phone during visits to banana farms in Davao City, Cateel, and the City of Mati, Davao Oriental. The second method of data collection involved downloading images from various reliable sources. As the study focused on disease classification based on symptoms manifested on the leaf, images were captured specifically targeting the disease-affected portions of the leaf's front view. This approach aligns with the findings of Haque et al. (2022), indicating that disease symptoms must be visibly apparent on the leaves, as shown in **Figure 3**. During the image acquisition process, the researcher collaborated with banana experts to accurately identify and validate the diseases present in the banana images. These methods ensured a comprehensive and reliable dataset for training the CNN models, facilitating accurate disease classification and contributing to the robustness of the research findings.

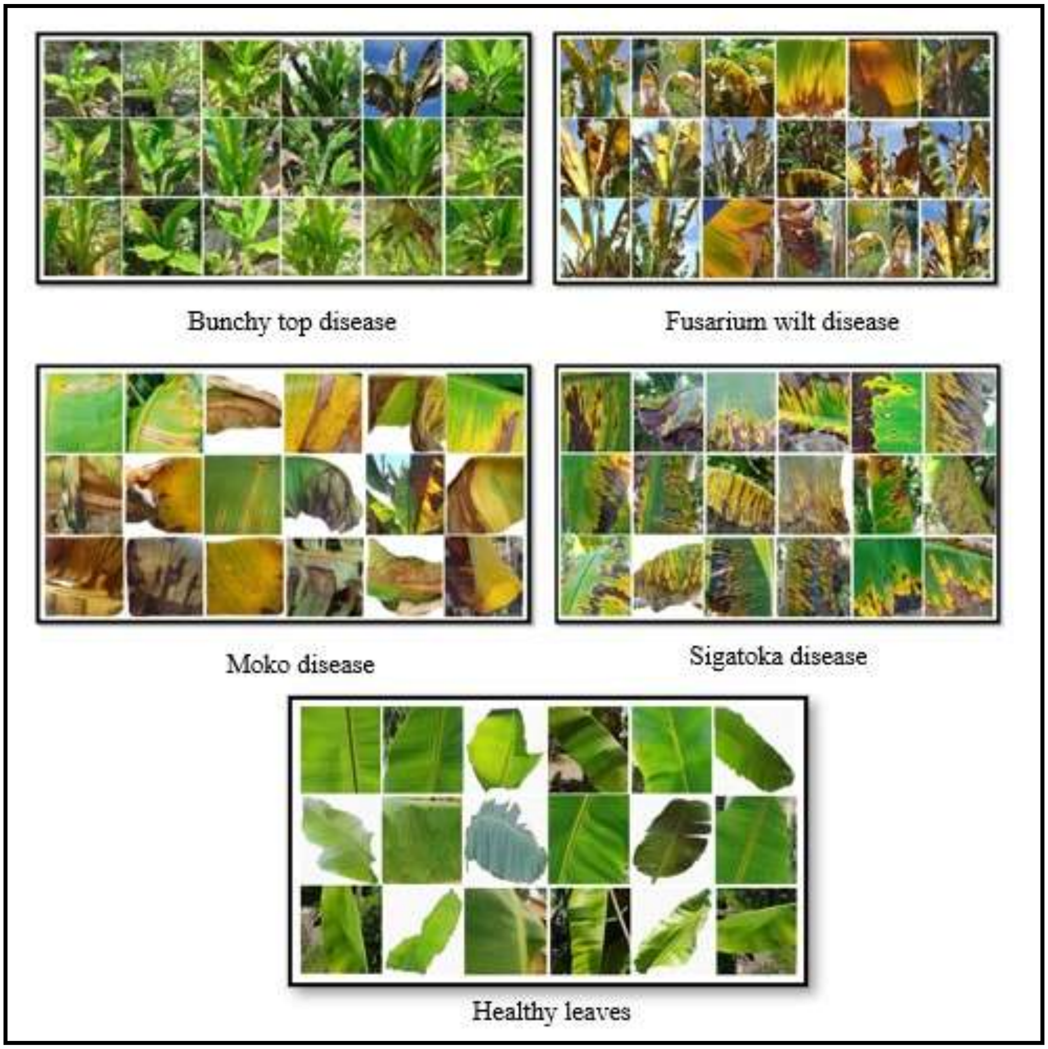


Figure 3:- Sample Image Dataset.

In this study, to replicate real-world conditions and address the challenges of using an image-based detection system, the researcher adopted an approach without a standardized method for capturing images. This approach aligns with the study by Alessandrini et al. (2021), which emphasized using accurate and representative sample images of banana leaves acquired under real-time conditions without controlling lighting, backgrounds, or angles. Images were taken from various perspectives, with most captured from short distances and some from higher vantage points. Additionally, the camera's zoom capability was utilized to focus on disease-infected banana leaves taken from greater distances. This practice was necessary because, as advised by banana experts, entering areas of banana farms contaminated with Fusarium Wilt (Panama disease) is prohibited to prevent the disease's spread. The images were captured using natural backgrounds, with lighting conditions reflecting the actual environment at the time of data collection. This method ensured that the dataset realistically represented the variability and unpredictability encountered in real-world scenarios, thereby enhancing the robustness and applicability of the image-based detection system developed in this study.

Dataset Preparation

Image datasets consisting of banana leaf images were created and analyzed for the web application. The dataset, stored in a repository, comprises 3,000 images representing the four (4) common banana diseases (Philippine Council for Agriculture, Aquatic and Natural Resources Research and Development, 2013).Additionally, a class containing images of healthy leaves was included to distinguish diseased leaves from healthy ones. Each class comprised 600 images, forming the comprehensive image dataset used in this study. All images were accurately classified, properly labeled, and stored in JPG format in the RGB color space model. The dataset was divided into three parts: 80% of the images were used for training, 10% for validation, and 10% for testing. This division ensured a robust evaluation of the model's performance. The distribution of images per class is detailed in **Table 1**. This structured approach to dataset creation and division facilitated the development of a reliable image-based detection system, providing a strong foundation for accurate disease classification in banana leaves.

Table 1:- Total Number of Banana Images and Splitting of the Image Dataset.

Classes	No. of Training Images	No. of Testing Images	No. of Validation Images	Total No. of Images per Class
Bunchy Top Disease	480	60	60	600
Fusarium Wilt Disease	480	60	60	600
Sigatoka Disease	480	60	60	600
Moko Disease	480	60	60	600
Healthy Leaves	480	60	60	600
Total	**2400**	**300**	**300**	**3000**

Image Pre-processing

The images used in this study underwent pre-processing to enhance their quality for analysis. This process included resizing the images to a standard 224 x 224 dimension, as the original images varied in size (Chithra & Bhavani, 2019).

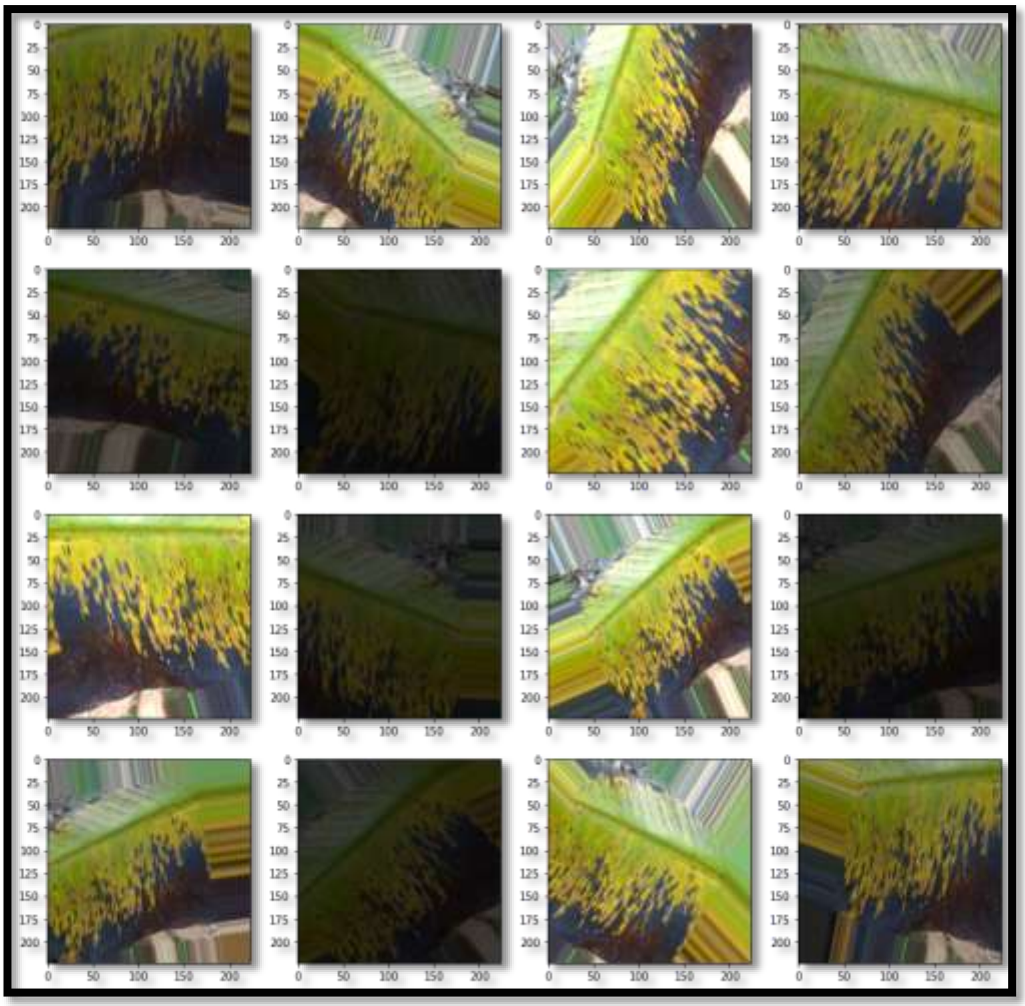


Figure 4:- Result of augmentation on a sample image.

To improve model performance and outcomes, image augmentation techniques were applied to the training data. The `preprocessing_function` was used to instruct the data generator to apply `preprocess_input` to each training image before it was sent to the model, ensuring that the images met the specific requirements of each model. Various image augmentation techniques were employed to generate new and diverse examples of image inputs. These techniques included randomly flipping images vertically and horizontally (horizontal_flip and vertical_flip), randomly shifting image inputs within a range of 0.2 (height_shift_range and width_shift_range), randomly rotating images up to 45 degrees (rotation_range), and randomly zooming in on image inputs within a range of 0.3 (zoom_range). Additionally, brightness adjustments were made to train the model on images taken under different lighting conditions, using a brightness range from 0.2 (dark) to 1.2 (bright). These augmentation techniques created a more robust training dataset by simulating various real-world conditions and scenarios. A sample image of Sigatoka disease, shown in **Figure 4**, illustrates the results of these augmentation techniques. This comprehensive pre-processing and augmentation approach ensured that the model was trained on a diverse set of images, enhancing its ability to accurately classify banana leaf diseases under varying conditions.

Feature Extraction and Classification

In this study, pre-trained convolutional neural networks (CNNs) were utilized to extract robust and informative features from training images for disease classification. The CNN models employed were EfficientNetV2, VGG-19, InceptionV3, and ResNet50. These pre-trained models were evaluated and compared to determine which network achieved the highest accuracy rate in classification relative to their prediction time.

Model Training

The study evaluated the identified convolutional neural network architectures—each chosen for its established capabilities in feature extraction and classification accuracy. Optimization of the models employed the Adam optimization technique, renowned for its ability to deliver effective results rapidly in deep learning tasks. All input images were resized to a standardized 224 x 224-pixel format and preprocessed before being fed into the models, which were updated using a batch size of 32. For multi-class classification of banana leaf diseases and healthy leaves, categorical cross-entropy served as the appropriate loss function. Training protocols included a default of 50 epochs, complemented by a callback list featuring ModelCheckpoint for saving model weights, ReduceLROnPlateau for dynamically adjusting the learning rate based on validation performance, and EarlyStopping to halt training when no improvement was detected over ten epochs. These methodologies were meticulously documented and detailed in **Table 2**, ensuring transparency and reproducibility in the optimization and parameter setup for achieving robust classification results in the study.

Table 2:- Optimizer and Model Parameter Setup Applied to all CNN Models.

Optimizer and Model Parameters Setup	
Batch size	32
Image size (height, width)	224, 224
Optimizer	Adam
Learning rate	0.0001
Loss function	Categorical Cross-entropy
Epoch size	50
Steps per epochs	75
Validation steps	10

Model Evaluation

Measuring the performance of a model is necessary and is considered an essential part of image classification. This will help understand and evaluate the parameters in the image dataset that affect the classification results (Ashaari et al., 2013). In this research, each pre-trained convolutional neural network model architecture was evaluated and compared according to five (5) performance evaluation metrics, including the confusion matrix, accuracy, precision, recall, and f1-score. The result was noted and used as the basis for determining the model that showed the best performance. The performance evaluation metrics were discussed as follows:

Confusion Matrix

This performance evaluation method is usually used in multiclass classifications and is done after classification. It consists of the four values; namely, T.P. (True Positive), which are values that have been appropriately classified, T.N. (True Negative) are values that were predicted to be negative and are correctly classified as negative, F.P. (False

Positive) refers to the values predicted to be positive but is negative, and F.N. (False Negative) are positive values that were negatively predicted. The accuracy, precision, recall, and f1-scores are the frequently used performance metrics based on the values represented in the confusion matrix as indicated by Sharma et al. (2022) with the equations presented.

Accuracy. This performance evaluation metric provides the proportion of the total number of correctly predicted values (Demir, 2022). The formula used to calculate accuracy is shown in (1).

$$Accuracy = (TP+TN)/(TP+TN+FP+FN) \quad (1)$$

Precision. As stated by Demir (2022), this performance evaluation metric, also called the positive predictive value, refers to the proportion of the correctly predicted positive values out of the total predicted positive values and can be calculated using (2).

$$Precision = TP/(TP+FP) \quad (2)$$

Recall. This performance evaluation metric, whose formula is shown in (3), is also known as sensitivity or the T.P. rate; recall refers to the proportion of the actual positive values that were correctly identified as a positive value out of the total actual positive occurrences (Demir, 2022).

$$Sensitivity = TP/(TP+FN) \quad (3)$$

F1-Score. The F1 score, also known as the F score, as the "harmonic mean of precision and sensitivity it gives importance to both factors" (Demir, 2022). The f1 score can be derived using the formula in (4).

$$F1\ Score = 2 \times (Precision \times Sensitivity) / (Precision + Sensitivity) \quad (4)$$

Analysis and Results:-

Training and Validation Accuracy and Loss

To assess and compare the performance of pre-trained convolutional neural network (CNN) models in classifying banana leaf diseases, their training and validation accuracies and losses are summarized in **Table 3**. ResNet50 achieved the highest training accuracy at 95.17% and the lowest training loss at 16.35%, highlighting its strong ability to learn and accurately classify disease-affected banana leaf images. EfficientNet followed with a training accuracy of 91.42% and a training loss of 24.81%, demonstrating robust learning performance. InceptionV3 achieved a training accuracy of 87.29% with a loss of 34.27%, while VGG-19 recorded the lowest training accuracy at 83.33% and the highest training loss at 47.57%, indicating its challenges in effectively learning from the training data.

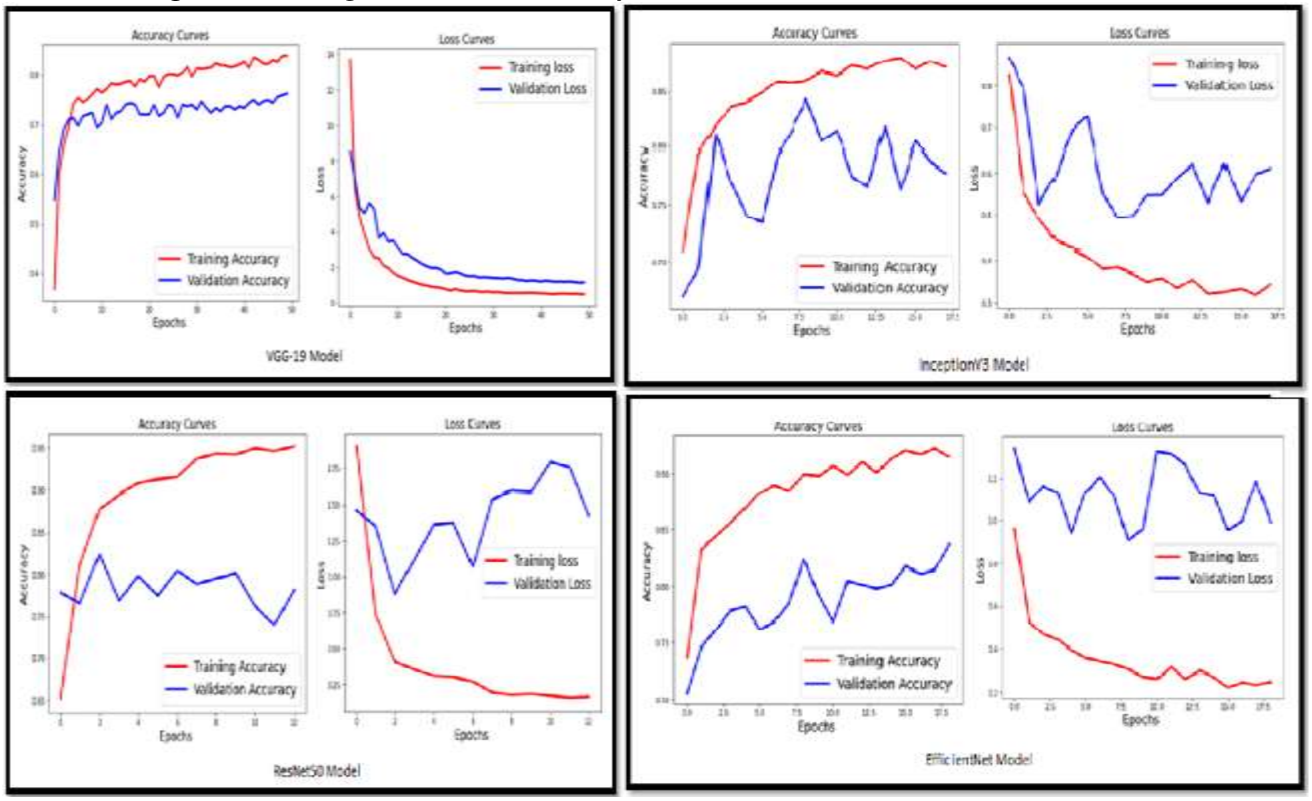
In terms of generalization to unseen data, EfficientNet outperformed other models, achieving the highest validation accuracy at 83.71% and a validation loss of 85.17%, showcasing its ability to generalize well. InceptionV3, despite ranking third in validation accuracy at 77.85%, demonstrated the lowest validation loss at 61.12%, indicating effective prediction with minimal errors on unseen data. ResNet50, while excelling in training performance, struggled with generalization, as reflected by its validation accuracy of 78.18% and a high validation loss of 142.81%. Similarly, VGG-19, which showed the weakest training performance, also displayed limited generalization with a validation accuracy of 76.22% and a validation loss of 114.02%.

Table 3:- Training and Validation Accuracy and Loss Results for Each Classifier.

Model	No. of Epochs	Training Accuracy (%)	Training Loss (%)	Validation Accuracy (%)	Validation Loss (%)
VGG-19	50	83.83	47.57	76.22	114.02
ResNet50	50	95.17	16.35	78.18	142.81
InceptionV3	50	87.29	34.27	77.85	61.12
EfficientNet	50	91.42	24.81	83.71	98.97

Validation loss reflects the total errors generated from each image input in the validation dataset. All models exhibited signs of overfitting, fitting well on the training dataset but not generalizing effectively to unseen data. This overfitting may be attributed to the complexity of the models relative to the dataset or the duration of the training period. A detailed comparison of training accuracy and loss curves for each model is presented in **Figure 5** offering further insights into their learning behavior and generalization capabilities.

Figure 5:- Training and Validation Accuracy and Loss Curvesfor Each Model Classifier.



Testing Accuracy and Loss

To assess how effectively the model classifiers generalize to unseen data, they were evaluated using a dedicated test dataset in this study. The results, presented in **Table 4**, reveal key insights into the banana disease classification performance based on test accuracy and loss metrics. EfficientNet emerged as the top performer, achieving the highest testing accuracy at 90.67% and the lowest testing loss of 44.59% among the four model classifiers. This highlights EfficientNet's robust capability to accurately classify disease-affected banana leaf images that were previously unseen during training and validation phases. ResNet50 followed closely with the second-highest testing accuracy of 88.67%, albeit with a higher test loss of 68.74%. VGG-19 demonstrated an 85.33% testing accuracy and a test loss of 60.3%, indicating reliable performance but with slightly higher error rates compared to EfficientNet and ResNet50. InceptionV3, while achieving an 81.33% testing accuracy, exhibited a test loss of 53.44%, positioning it with the lowest accuracy among the models tested on the test dataset.

Table 4:- Testing Accuracy and Loss Results for Each Classifier.

Model	Test Accuracy	Test Loss
VGG-19	85.33	60.3
ResNet50	88.67	68.74
InceptionV3	81.33	53.44
EfficientNet	90.67	44.59

These findings underscore EfficientNet's effectiveness in generalizing to new, unseen data, demonstrating superior accuracy and minimized errors in classifying banana diseases. The comparative analysis provided in Table 5 and Figure 11 offers clear insights into each model's performance metrics, aiding in the selection and optimization of CNN models for practical applications in agricultural disease detection.

Despite achieving high accuracy rates on the training dataset, the validation performance of the four model classifiers in this study revealed significantly higher losses compared to their training phases, indicating potential overfitting issues. This disparity suggests that while the models effectively learned the training data patterns, they struggled to generalize to unseen validation data. To mitigate overfitting, strategies such as ModelCheckpoint, ReduceLROnPlateau, and EarlyStopping callbacks were employed, halting training when validation loss improvements ceased. Notably, ResNet50 ceased training at Epoch 13, EfficientNet at Epoch 19, and InceptionV3 at Epoch 18, underscoring the complexities of model optimization in real-world applications like banana disease classification. Addressing these challenges, insights from Ashaari et al.(2013) advocate for a holistic approach beyond accuracy, emphasizing the utility of metrics like confusion matrices and classification reports to comprehensively evaluate model performance, as applied in the analysis of test datasets in this study.

Performance Evaluation

The results derived from the confusion matrix and classification reports offer a detailed performance summary of the pre-trained convolutional neural network (CNN) models used for banana leaf disease classification. The evaluation focuses on four key performance metrics: accuracy, precision, recall, and f1-score. These metrics provide an in-depth understanding of model behavior on a class-by-class basis, allowing for a granular analysis of the strengths and limitations of each model.

The confusion matrices (as seen in **Figure6**) and classification reports (as seen in **Table 5**) were presented for each model classifier generated from the images in the test dataset.

Table 5:- Classification Report for Each Model Classifier.

Model		**Precision**	**Recall**	**F1-Score**	**Support**
	Bunchy Top	0.88	0.98	0.93	60
	Fusarium Wilt	0.91	0.88	0.90	60
	Moko	0.88	0.70	0.78	60
	Sigatoka	0.88	0.70	0.78	60
Resnet50	Healthy	1.00	0.98	0.99	60
	Accuracy			0.89	300
	Macro AVG	0.89	0.89	0.88	300
	Weighted AVG	0.89	0.89	0.88	300
	Bunchy Top	0.92	0.95	0.93	60
	Fusarium Wilt	0.87	0.90	0.89	60
	Moko	0.88	0.87	0.87	60
	Sigatoka	0.88	0.82	0.84	60
EfficientNet	Healthy	0.98	1.00	0.99	60
	Accuracy			0.91	300
	Macro AVG	0.91	0.91	0.91	300
	Weighted AVG	0.91	0.91	0.91	300
	Bunchy Top	0.89	0.97	0.93	60
	Fusarium Wilt	0.80	0.85	0.82	60
	Moko	0.79	0.68	0.73	60
	Sigatoka	0.82	0.83	0.83	60
VGG19	Healthy	0.97	0.93	0.95	60
	Accuracy			0.85	300
	Macro AVG	0.85	0.85	0.85	300
	Weighted AVG	0.85	0.85	0.85	300
	Bunchy Top	0.81	0.93	0.87	60
	Fusarium Wilt	0.83	0.72	0.77	60
	Moko	0.88	0.60	0.71	60
	Sigatoka	0.68	0.83	0.75	60
InceptionV3	Healthy	0.91	0.98	0.94	60
	Accuracy			0.81	300
	Macro AVG	0.81	0.81	0.81	300

Weighted AVG	0.81	0.81	0.81	300

EfficientNet emerged as the top-performing model, achieving the highest overall accuracy of 91%. This model exhibited consistently strong performance across disease classes, underpinned by its ability to generalize effectively to unseen data. Precision rates for healthy leaves (98%), Bunchy Top disease (92%), Fusarium Wilt (87%), and Sigatoka disease (88%) reflect its precise classification capabilities. Moreover, recall scores were particularly impressive for healthy leaves (100%) and Bunchy Top disease (95%), indicating high sensitivity in detecting these classes. These metrics culminated in exceptional f1-scores, with healthy leaves achieving 99% and Bunchy Top disease reaching 93%. EfficientNet's balanced performance across precision, recall, and f1-score underscores its robustness and adaptability in handling the inherent complexity of banana leaf disease classification.

ResNet50 closely followed EfficientNet, achieving an overall accuracy of 89%. The model excelled in identifying healthy leaves, with perfect precision (100%), high recall (98%), and an f1-score of 99%. For Bunchy Top disease, ResNet50 demonstrated robust metrics with 88% precision, 98% recall, and a 93% f1-score. Fusarium Wilt also recorded strong performance with 91% precision, 88% recall, and 90% f1-score. However, the model faced challenges with Moko disease, achieving a lower recall (70%) and f1-score (78%), which indicates potential difficulties in distinguishing this disease from other categories. These results highlight ResNet50's overall strength in disease classification, particularly for less ambiguous cases, while pinpointing areas requiring refinement for more complex disease presentations.

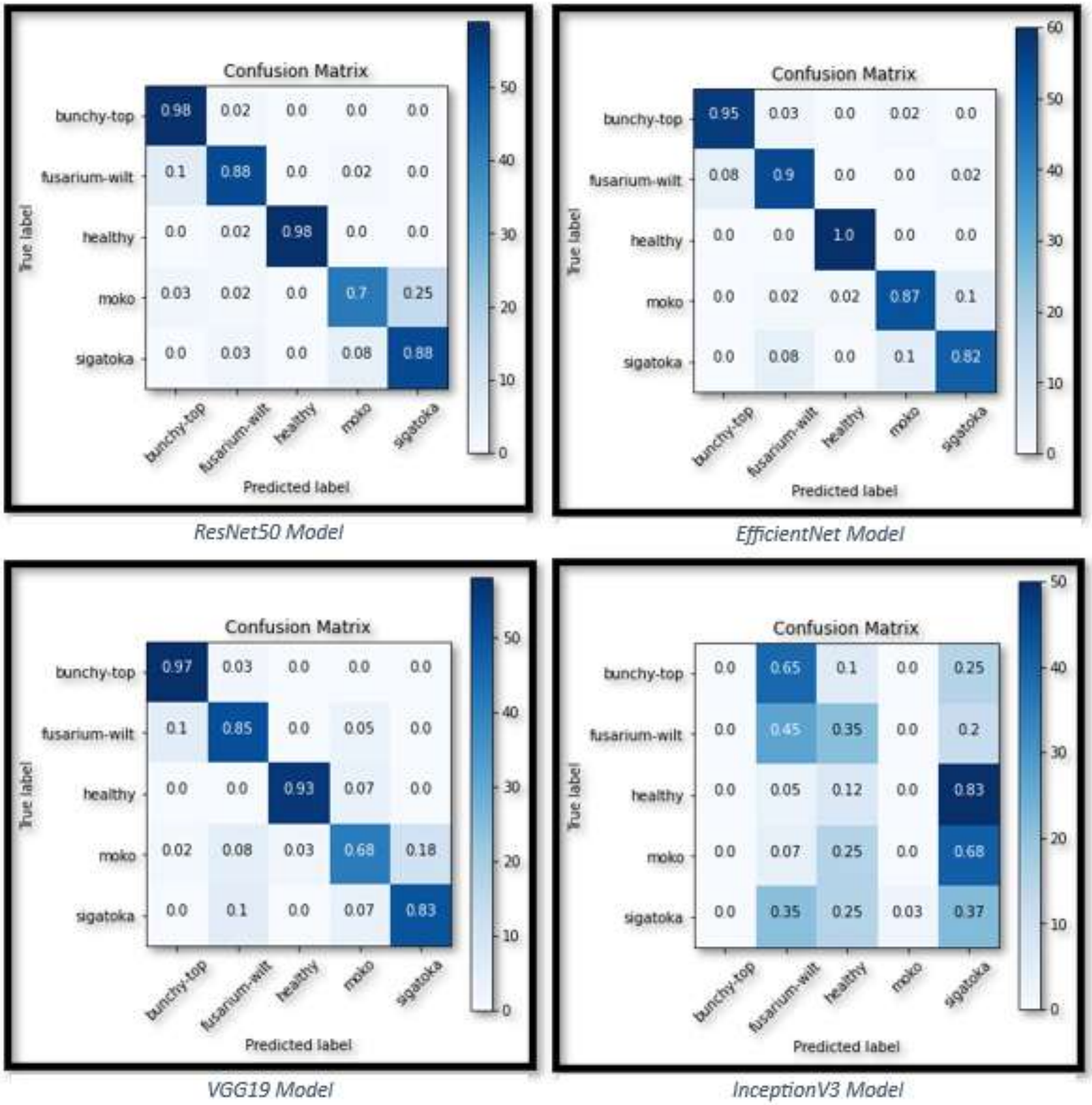
VGG19 exhibited comparatively lower performance, with an overall accuracy of 85%. While it achieved high precision for healthy leaves (97%) and Bunchy Top disease (89%), its precision scores for Fusarium Wilt (80%), Sigatoka (82%), and Moko disease (79%) were less consistent. Recall metrics were strongest for Bunchy Top disease (97%) and healthy leaves (93%), but declined for Moko disease (73%) and Sigatoka (79%), resulting in lower f1-scores for these categories. These results suggest that VGG19 struggles to achieve consistent classification across all disease types, particularly for more challenging classes like Moko disease. However, its solid performance in detecting non-diseased and straightforward cases indicates its utility in simpler classification scenarios.

InceptionV3, with an overall accuracy of 81%, demonstrated variable performance across disease classes. Healthy leaves achieved the highest precision (91%), recall (98%), and f1-score (94%), showcasing the model's strong capability in identifying non-diseased samples. Bunchy Top disease also performed well, with an f1-score of 87%, supported by 81% precision and 93% recall. However, the model struggled with Moko disease, achieving lower precision (88%) and recall (60%), resulting in an f1-score of 71%. Sigatoka disease exhibited similar variability, with moderate precision (82%) and recall (78%). These metrics underscore InceptionV3's potential for classifying certain diseases effectively but highlight the need for enhancements to handle challenging cases with greater reliability.

The classification reports for all models provided weighted averages across precision, recall, and f1-score, offering a holistic view of their performance. EfficientNet led with a weighted average of 0.91, indicating a superior balance between accuracy, sensitivity, and specificity. ResNet50 followed with weighted averages of 0.89 for precision and recall, and 0.88 for f1-score, demonstrating strong overall performance. In contrast, VGG19 and InceptionV3, with weighted averages of 0.85 and 0.81, respectively, reflected weaker and more inconsistent performance across the dataset. These findings suggest that EfficientNet and ResNet50 are more suitable for complex disease classification tasks, while VGG19 and InceptionV3 may benefit from further fine-tuning or augmentation to improve performance, particularly for more challenging disease classes.

Overall, these results highlight the effectiveness of EfficientNet and ResNet50 for banana leaf disease classification. Despite their strong overall performance, challenges remain, particularly with the classification of Moko disease, which exhibited lower recall and f1-scores in most models. Future work could focus on addressing these challenges by augmenting the training dataset, fine-tuning the models, and exploring techniques such as transfer learning, data augmentation, and ensemble modeling. These strategies could improve model generalization and further enhance classification accuracy, particularly for underrepresented or complex disease classes. The findings from this evaluation provide a robust foundation for deploying CNN-based models in practical applications, such as precision agriculture and disease monitoring systems, where accurate disease detection is critical for improving crop management and productivity.

Figure 6:- Confusion Matricesfor Each Model Classifier.



Conclusion:-

Banana diseases pose significant challenges to farmers, potentially leading to substantial losses in the banana industry if left unchecked. This research addresses these issues by developing a web-based banana disease detection system using Python, TensorFlow, and Streamlit. The system classifies common banana diseases—Bunchy top, Fusarium wilt, Moko, Sigatoka—and identifies healthy banana leaves from uploaded images. A dataset of 3,000 banana leaf images was utilized, divided into training, validation, and test sets, resized to 224 x 224 pixels, and trained using four convolutional neural network architectures: VGG19, InceptionV3, ResNet50, and EfficientNet. Optimization was performed using the Adam optimizer across 50 epochs. Evaluation metrics showed EfficientNet achieving the highest accuracy of 91% among the models. Thus, EfficientNet was implemented in the web application, providing farmers with disease classification and preventive measures to manage banana plant health effectively.

Recommendations:-

Future studies aiming to enhance model accuracy should standardize image capture methodologies. Images should be captured in controlled environments with high-resolution cameras (≥15 megapixels) (Bindushree& Sivasankari, 2015), preferably against a plain white background [51], maintaining optimal distances (9 – 12 inches)(Zhang, 2020; Bindushree& Sivasankari, 2015;Concepcion et al., 2022) or at most 11 – 24 inches(Li et al., 2022; Radha et al., 2017). Consideration of various lighting conditions—natural light, flash on/off, backlighting—can further enrich the dataset, as suggested by Rzannyet al. (2017). Including images at different angles (0°, 45°, 60°, 90°) based on a study by Wang et al. (2022) and employing data augmentation techniques will increase dataset diversity, reducing overfitting and enhancing model generalization. Optimization strategies such as larger image sizes, batch sizes (e.g., 64, 128), additional layers, and extended epochs should be explored to refine model learning capabilities. Integration of negative images during validation can strengthen models' ability to distinguish non-banana objects. However, it's noted that CNNs may struggle with negative image recognition due to inherent limitations in semantic understanding of objects. Nevertheless, in the study conducted by Hosseini et al. (2017), it is revealed that even though CNN has been considered impressive in terms of its performance in identifying similar images used in training, it showed that it has limitations in recognizing negative images wherein the results turned out poorly with much lower accuracy. Hosseini et al.(2017) observations after the study indicate that when CNN is trained in raw data, it cannot recognize the semantics of the objects. With this, it could be a good starting idea to focus on for future researchers who wish to conduct similar but more advanced studies on bananas. Furthermore, usability testing of the web application is recommended to assess its performance and user-friendliness, ensuring practical utility in agricultural settings.

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