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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

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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. As a solution to the problem, research highlights the importance of identifying banana diseases at an early stage, enabling local farmers to implement cost-efficient control methods that can minimize, or even eliminate, the spread of infestations. Given the effectiveness of image processing in classification and analysis tasks, this study centered on its application hence, a dataset of 3,000 images depicting common banana diseases, primarily manifesting on the leaves, was compiled and divided into training, validation, and testing subsets. These images underwent preprocessing before being input into four pre-trained convolutional neural network architectures—VGG-19, InceptionV3, ResNet50, and EfficientNet—all of which were configured with identical optimization techniques and model parameters.Performance evaluation metrics such as accuracy results, confusion matrix, and classification report were used to identify the model with the highest performance in a test dataset.The results have shown that among the identified model architectures, the EfficientNet model obtained the highest accuracy of 91%.

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Introduction:-

The agricultural sector is a key driver of economic growth in the Philippines, accounting for approximately 19 percent of the nation's Gross Domestic Product (GDP) on average (De Asis, 2003). As reported by the Philippine Statistics Authority (2020), crop cultivation emerged as the top agricultural activity in the Philippines in 2020, contributing 54.9 percent to the sector's total output. This exceeded the contributions of livestock at 17.9 percent, poultry production at 14.3 percent, and fisheries at 12.8 percent. Additionally, around 9 million hectares out of the country's total 30 million hectares of land were allocated for agricultural purposes (Tolentino et al., 2015). In 2005, the agriculture sector contributed 19 percent to the country's GDP, making the Philippines one of the leading

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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).

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). Voora et al. (2020) noted that bananas ranked among the most widely traded fruits globally in 2017, with a trade volume of 22.7 million tons, accounting for 20 percent of the world's total production. In the Philippines, bananas have remained a significant source of export revenue, securing their position as the country's second most valuable 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, as reported by Vanlauwe et al. (2013), banana diseases present a major challenge to production, causing significant issues in both the Philippines and East and Central Africa (ECA). Viljoen et al. (2017) also found that the impact of diseases, including yield losses, can disrupt food security, agricultural output, and household income by as much as 25 percent. In the Philippines, more than 2,000 hectares of farmland in Mindanao were rendered unusable in 2015 due to Panama disease and the El Niño phenomenon, leading to a decline in production levels. The Pilipino Banana Growers and Exporters Association (PBGEA) called for government intervention to aid in reviving the banana industry. This plea was driven by the abandonment of over 5,000 hectares in the Davao region, where Panama disease had caused devastating losses (Cheshire, 2016).

Puig (2014) highlighted that the control of banana diseases in the region relies on approaches such as early detection and containment, disease management methods, and the formulation of sustainable strategies through research. Banana farmers often face challenges, such as delayed disease identification and insufficient knowledge on handling unfavorable conditions. The integration of information technology into agriculture has facilitated more efficient solutions to these issues, including the use of image processing and expert systems to aid in decision-making and enhance crop productivity. Hence, this study aims to address these challenges.

Related Works:

Numerous studies have explored the use of machine learning algorithms and image classification in agriculture. Kumar et al. (2020) developed an expert system that combines image processing to identify pest and disease infestations in rapeseed-mustard crops. A similar approach was applied by Chen Lai et al. (2010) in corn. Other researchers, such as Lehri et al. (2008) and Kaur (2014), integrated textual data with images for enhanced analysis. El-Helly et al. (2003) and Sharma et al. (2022) created systems to detect leaf diseases, including Downy mildew, Leafminer, and Powdery mildew. In Kerala, India, Ganesan (2007) developed Crop-9-DSS, a decision support system for crop management that also focuses on bananas. Prathibha G. et al. (2014) applied image processing to detect borers in tomatoes at an early stage. Tigadi et al. (2016) proposed an automated plant disease detection system for bananas, using HOT feature extraction and an Artificial Neural Network (ANN) for classification. Anasta et al. (2021) employed multilevel thresholding techniques for banana disease detection, while Raut et al. (2017) utilized digital image processing with K-means clustering and a multi-SVM algorithm. Kumar et al. (2010) explored the use of KNN classifiers and texture features for flower image classification. Panchal et al. (2016) applied image processing techniques to detect leaf diseases in pomegranates, combining K-means clustering and SVM for classification. Sladojevic et al. (2016) used deep neural networks for accurate leaf disease classification. Abu et al. (2019) applied deep learning with TensorFlow for flower classification, achieving high accuracy. Kumar, P. et al. (2020) demonstrated the effectiveness of advanced CNN models with TensorFlow for image classification, achieving accuracy rates above 95 percent. Kumbhar et al. (2019) introduced "Farmer Buddy," a web-based cotton leaf disease detection system utilizing CNN. Karol (2019) employed CNN in plant disease detection and recommendation systems, including applications for drone-based crop surveillance. Mohanty et al. (2016) focused on using CNN for leaf disease identification, emphasizing texture and color features to improve accuracy. Akter et al. (2021) presented a deep learning-based attention architecture for classifying Bangladeshi medicinal plants.

The goal of this study was to identify the most effective model for classifying banana diseases, aiming to support early detection and inform appropriate prevention and control strategies based on integrated disease management principles.Using TensorFlow and CNN-based models, including EfficientNet, VGG-19, InceptionV3, and ResNet50, these models were employed to train and evaluate a comprehensive image dataset that included images of various banana diseases, such as Moko disease, Fusarium Wilt (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 study is in line with the goals of the Philippine Council for Agriculture, Aquatic, and Natural Resources Research and Development (PCAARRD), which aims to enhance agricultural practices and increase productivity by promoting the use of innovative technologies in banana farming (Philippine Council for Agriculture, Aquatic and Natural Resources Research and Development (PCAARRD), 2013).

Methodology:-

The Iterative and Incremental Model

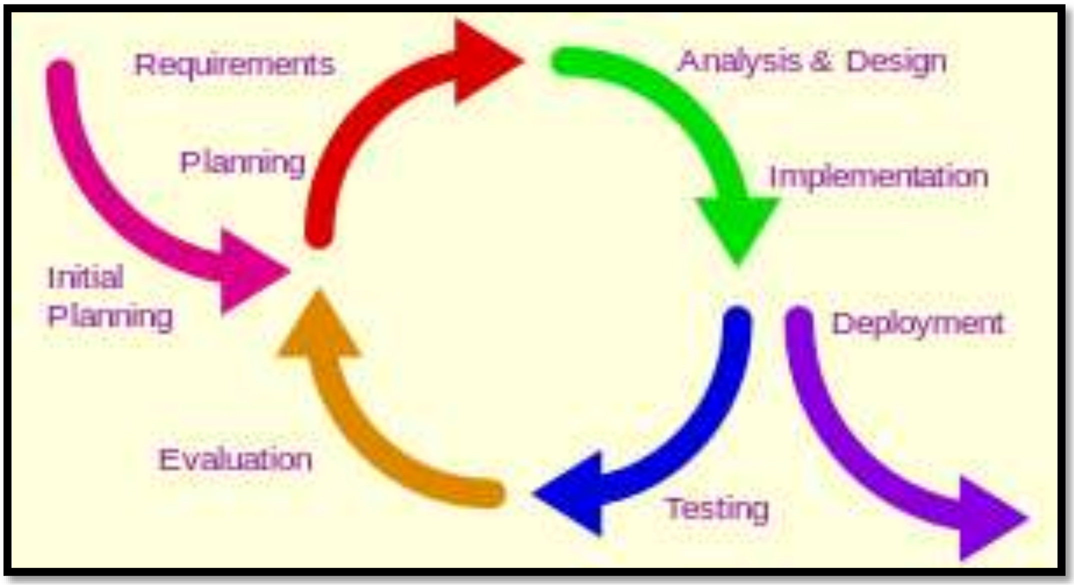


Figure 1:-The Iterative and Incremental Model(Chowdhury, Bhowmik, Hasan, & Rahim, 2017).

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 (Chowdhury, Bhowmik, Hasan, & Rahim, 2017). The methodology adopted for this research follows this iterative and incremental approach, with phases completed sequentially throughout the project's development. Furthermore, a machine learning pipeline was incorporated into the methodology to organize the processes associated with image processing and model development, providing a structured and thorough approachfrom the project's inception to its completion.

TheMachine Learning Pipeline

In this study, a methodology was proposed and adopted which aimed to identify 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 (Panama 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 selected. The entire workflow can be characterized by a machine learning pipeline, which involves a sequence of intricate data processing stages. These stages include data collection, preprocessing, feature extraction, model training, and finally, deploying the model to make predictions on test data (Atoum, 2018). This pipeline outlines the process through which the workflow was systematically structured and automated to develop the machine learning model (Makihara et al., 2003).

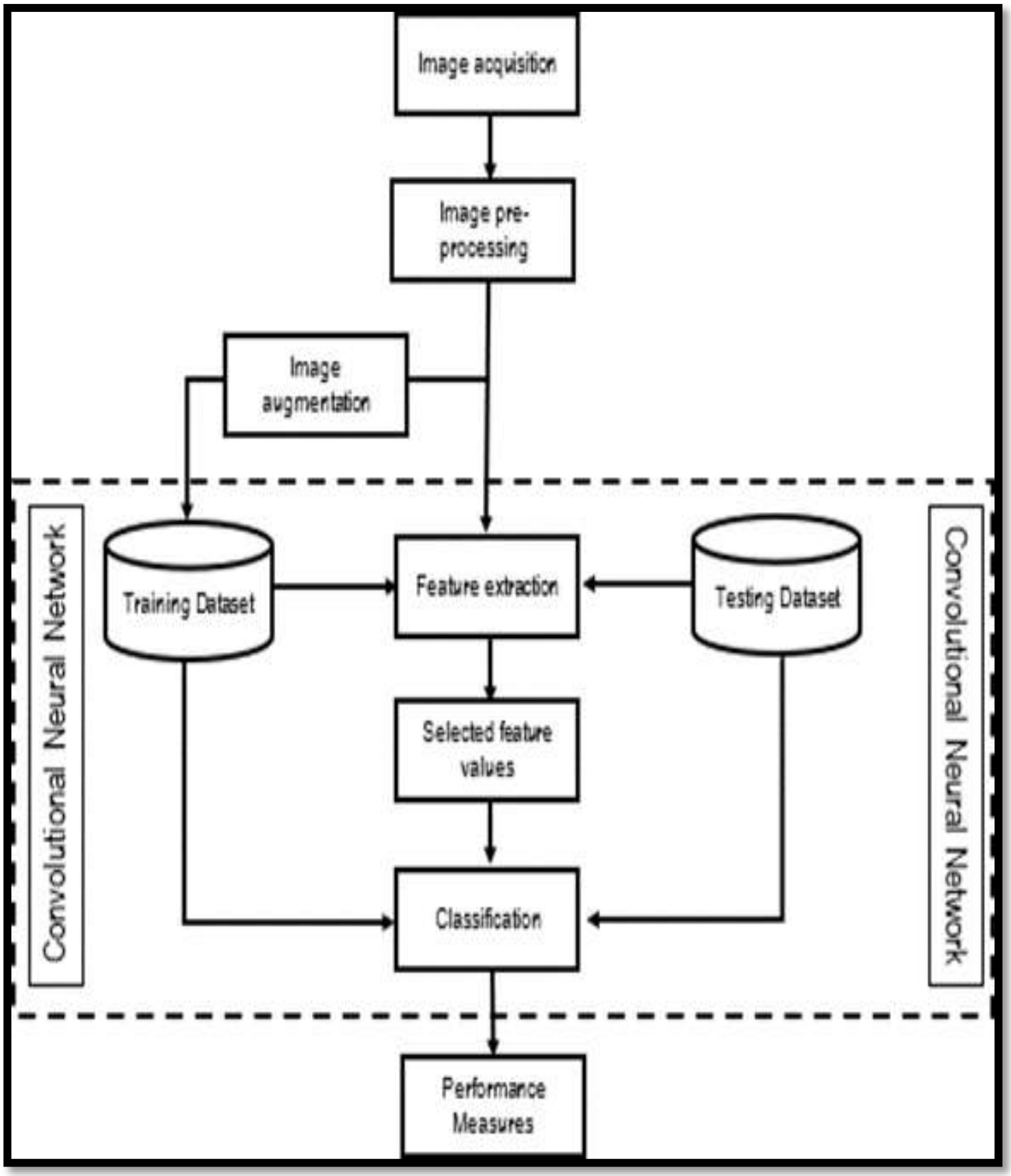


Figure 2:- The Machine Learning Pipeline.

The machine learning pipeline commenced with the gathering of images representing the different banana plant diseases covered within the scope of the study. **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 strength of the research findings.

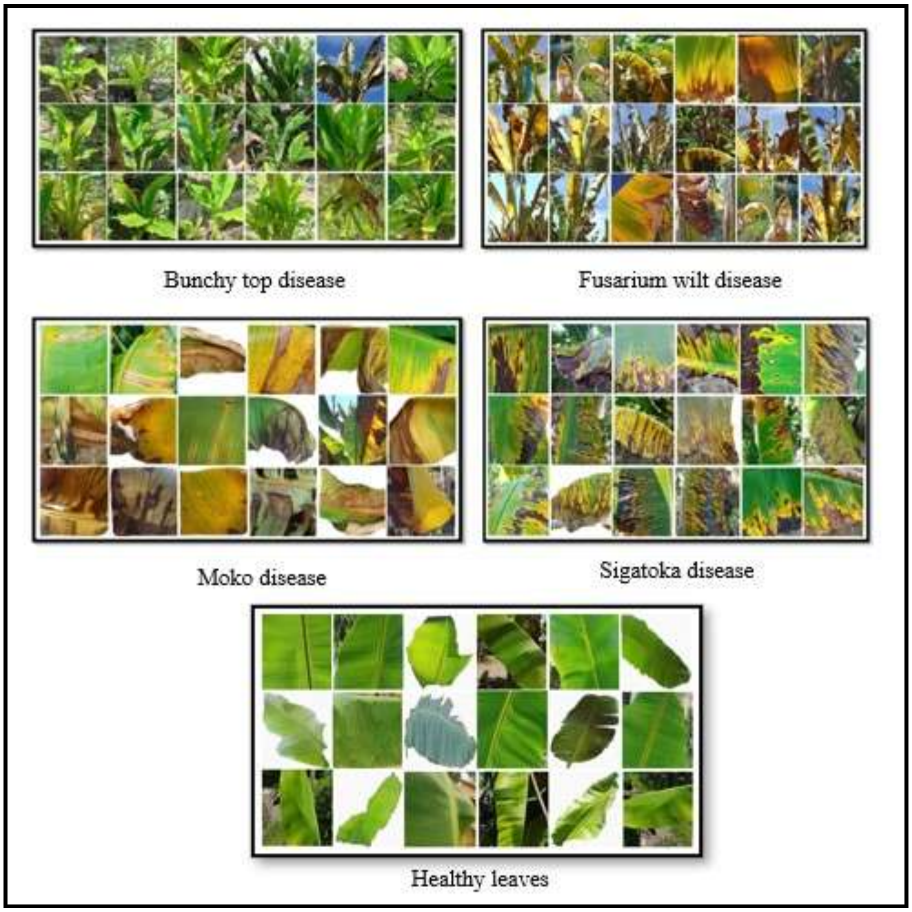


Figure 3:-Sample Image Dataset.

In this study, to replicate real-world conditions and address the challenges of using an image-based disease classification 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 approach guaranteed that the dataset accurately reflected the variability and uncertainty typical of real-world situations, thereby improving the validity and practical relevance of the image-based disease classification system developed in this research.

Dataset Preparation

A collection of 3,000 banana leaf images was created and examined, representing four common banana diseases (Philippine Council for Agriculture, Aquatic and Natural Resources Research and Development (PCAARRD), 2013). Moreover, a class of images representing healthy leaves was incorporated to differentiate between diseased and healthy leaves. 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 assigned to training, 10% to validation, and 10% to testing. This allocation allowed for a comprehensive evaluation of the model's performance. The distribution of images across the classes is presented in Table 1. This structured approach to dataset creation and division facilitated the development of a reliable image-based disease classification system, providing a strong foundation for accurate disease classification in banana leaves.

Table 1:-Total Count of Banana Images and Dataset Division.

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).

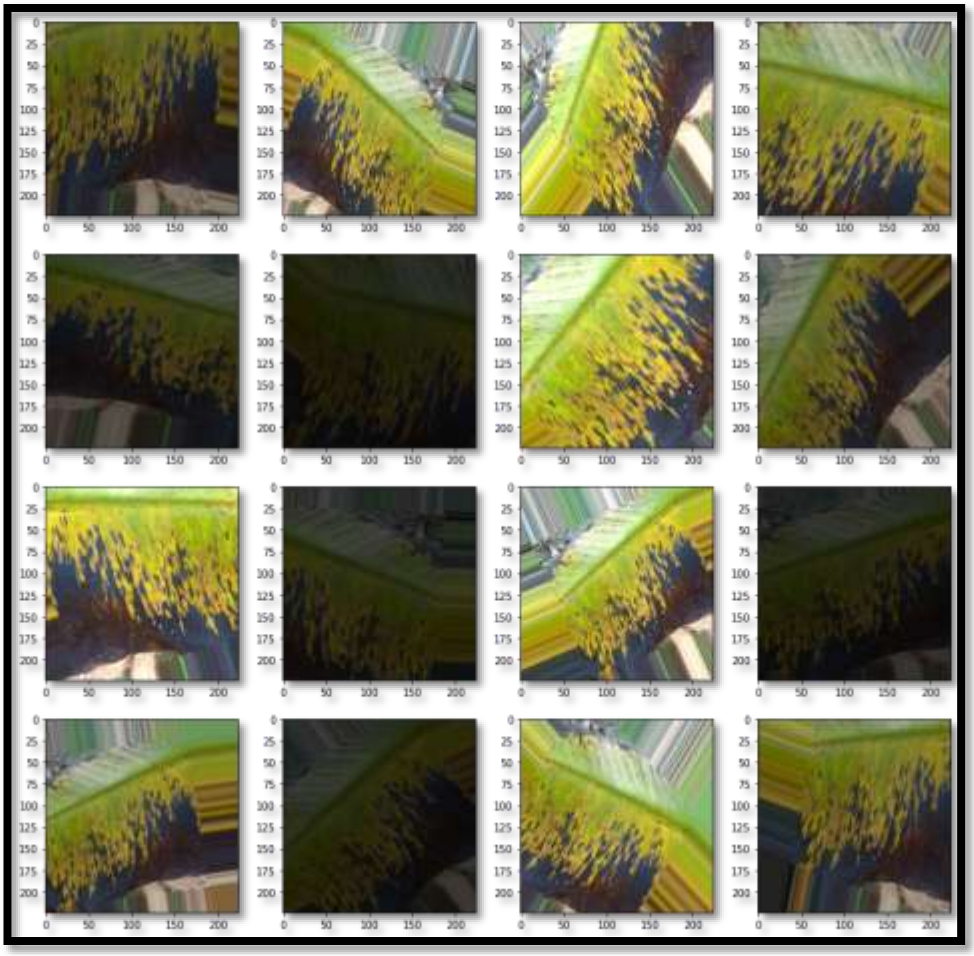


Figure 4:-Result of augmentation on a sample image.

To enhance model performance and results, image augmentation techniques were applied to the training data. The *preprocessing_function* was utilized to guide the data generator in applying *preprocess_input* to each image before feeding it into the model, ensuring compatibility with the specific requirements of the model. A variety of augmentation methods were implemented to create diverse training examples. These included random horizontal and vertical flipping, random height and width shifts in image position within a 0.2 range, random rotations up to 45 degrees, and zooming in of images within a 0.3 range. Furthermore, brightness adjustments were made to simulate different lighting conditions, with brightness values ranging from 0.2 (dark) to 1.2 (bright), allowing the model to learn from images captured under varying light conditions. These augmentation techniques created a wellmadetraining 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 thorough pre-processing and augmentation strategy guaranteed that the model was trained on a wide range of images, improving its capacity to accurately identify banana leaf diseases across different conditions.

Feature Extraction and Classification

In this research, pre-trained convolutional neural networks (CNNs) were used in extracting meaningful and powerful features from the training images for disease classification. The CNN models tested included EfficientNet, VGG-19, InceptionV3, and ResNet50. These models were assessed and compared to identify which network delivered the best classification accuracy in relation to 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 exemplary 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 study, each pre-trained convolutional neural network model architecture was assessed and compared using five performance evaluation metrics: 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 evaluation method is commonly applied in multiclass classifications and is conducted after the classification process. It involves four key values: T.P. (True Positive), which refers to correctly classified positive values; T.N. (True Negative), which are correctly classified negative values; F.P. (False Positive), indicating values predicted as positive but are actually negative; and F.N. (False Negative), which are positive values incorrectly predicted as negative. Accuracy, precision, recall, and F1-score are standard performance metrics derived from these values in the confusion matrix, as outlined by Sharma et al. (2022), with the corresponding equations provided.

Accuracy. This performance evaluation metric indicates the proportion of correctly predicted values out of the total (Demir, 2022). The formula for calculating accuracy is presented in equation (1).

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

Precision. According to Demir (2022), this performance metric, known as the positive predictive value, represents the ratio of correctly predicted positive values to the total predicted positive values, and it can be computed using equation (2).
Precision = TP/(TP+FP) (2)

Recall. This performance metric, also referred to as sensitivity or the true positive rate, measures the proportion of actual positive values that were correctly identified as positive out of the total actual positive cases. Its formula is presented in equation (3) (Demir, 2022).
Sensitivity = TP/(TP+FN) (3)

F1-Score. The F1 score, also referred to as the F score, is the harmonic mean of precision and sensitivity, emphasizing the importance of both metrics (Demir, 2022). The F1 score can be calculated using the formula in equation (4).
F1 Score = 2 x (Precision x Sensitivity) / (Precision + Sensitivity) (4)

Analysis and Results:-

Accuracy and Loss during Training and Validation

To evaluate and compare the performance of pre-trained convolutional neural network (CNN) models in classifying banana leaf diseases, the training and validation accuracies and losses of each model are summarized in **Table 3**. ResNet50 achieved the highest training accuracy at 95.17% and the lowest training loss at 16.35%, demonstrating its strong capability in learning and accurately classifying banana leaf disease images. EfficientNet followed closely with a training accuracy of 91.42% and a training loss of 24.81%, indicating strong performance. InceptionV3 reached 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%, suggesting difficulties in learning effectively from the training data.

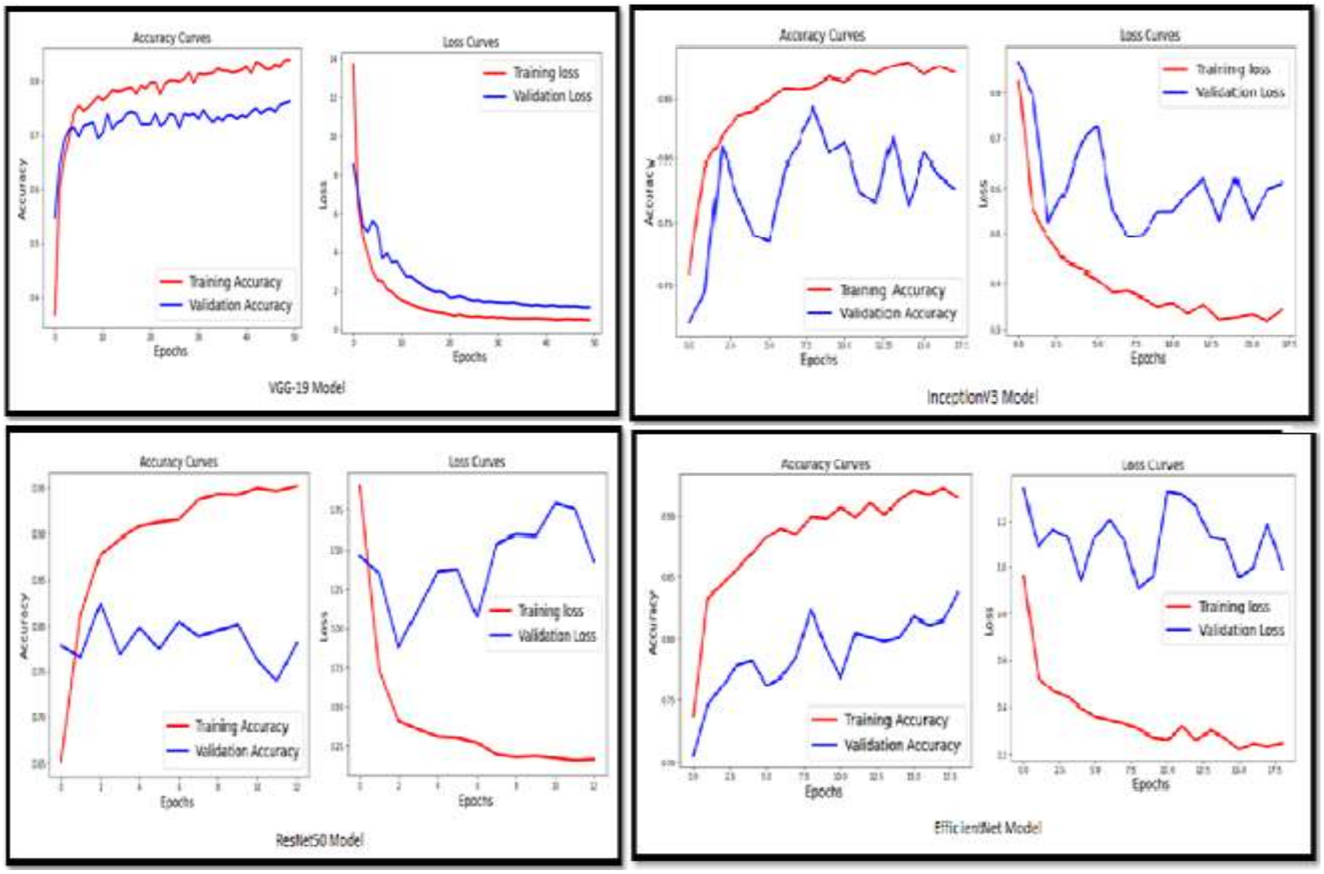
When assessing the models' ability to generalize to new data, EfficientNet outperformed the others, achieving the highest validation accuracy at 83.71% and a validation loss of 85.17%, highlighting its strong generalization ability. InceptionV3, although third in validation accuracy at 77.85%, showed the lowest validation loss at 61.12%, indicating effective predictions with minimal errors on unseen data. ResNet50, despite excelling in training, faced challenges in generalization, reflected by its validation accuracy of 78.18% and a high validation loss of 142.81%. Similarly, VGG-19, which exhibited the weakest training results, also showed limited generalization with a validation accuracy of 76.22% and a validation loss of 114.02%.

Table 3:-Accuracy and loss resultsoccured during training and validation 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 sum of errors generated from each image in the validation dataset, indicating that all model classifiers exhibited signs of overfitting, as they performed well on the training dataset but failed to generalize to unseen data, such as the images in the validation set (Goodfellow, Bengio, & Courville, 2016; Chollet, 2018). This overfitting could be due to the complexity of the models in relation to the dataset size or the length of the training process. A comprehensive comparison of the training accuracy and loss curves for each model is provided in **Figure 5**, offering deeper insights into their learning patterns and ability to generalize.

Figure 5:- Accuracy and loss curvesoccured during training and validationforeach classifier.



Accuracy and Loss during Testing

To evaluate the models' ability to generalize to new, unseen data, a separate test dataset was used in this study. The findings, summarized in **Table 4**, provide valuable insights into the performance of the banana disease classification models based on their test accuracy and loss. EfficientNet outperformed the other models, achieving the highest test accuracy of 90.67% and the lowest test loss of 44.59%. This highlights EfficientNet'spowerful 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:-Accuracy and loss resultsoccured during testing 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.

Although the four model classifiers demonstrated high accuracy on the training dataset, their performance on the validation set showed considerably higher losses, indicating possible overfitting. This difference suggests that while the models successfully captured patterns in the training data, they faced challenges in generalizing 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 Ashaariet 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 outcomes from the confusion matrix and classification reports provide a comprehensive performance overview of the pre-trained convolutional neural network (CNN) models employed for banana leaf disease classification. The evaluation emphasizes four critical performance metrics: accuracy, precision, recall, and f1-score. These metrics offer a detailed view of each model's performance on a per-class basis, enabling a thorough analysis of their strengths and weaknesses.

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
VGG-19	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
InceptionV3	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

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 was identified as the highest-performing model, reaching the best 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 consistent performance in precision, recall, and f1-score highlights its effectiveness and versatility in managing the complexities associated with banana leaf disease classification.

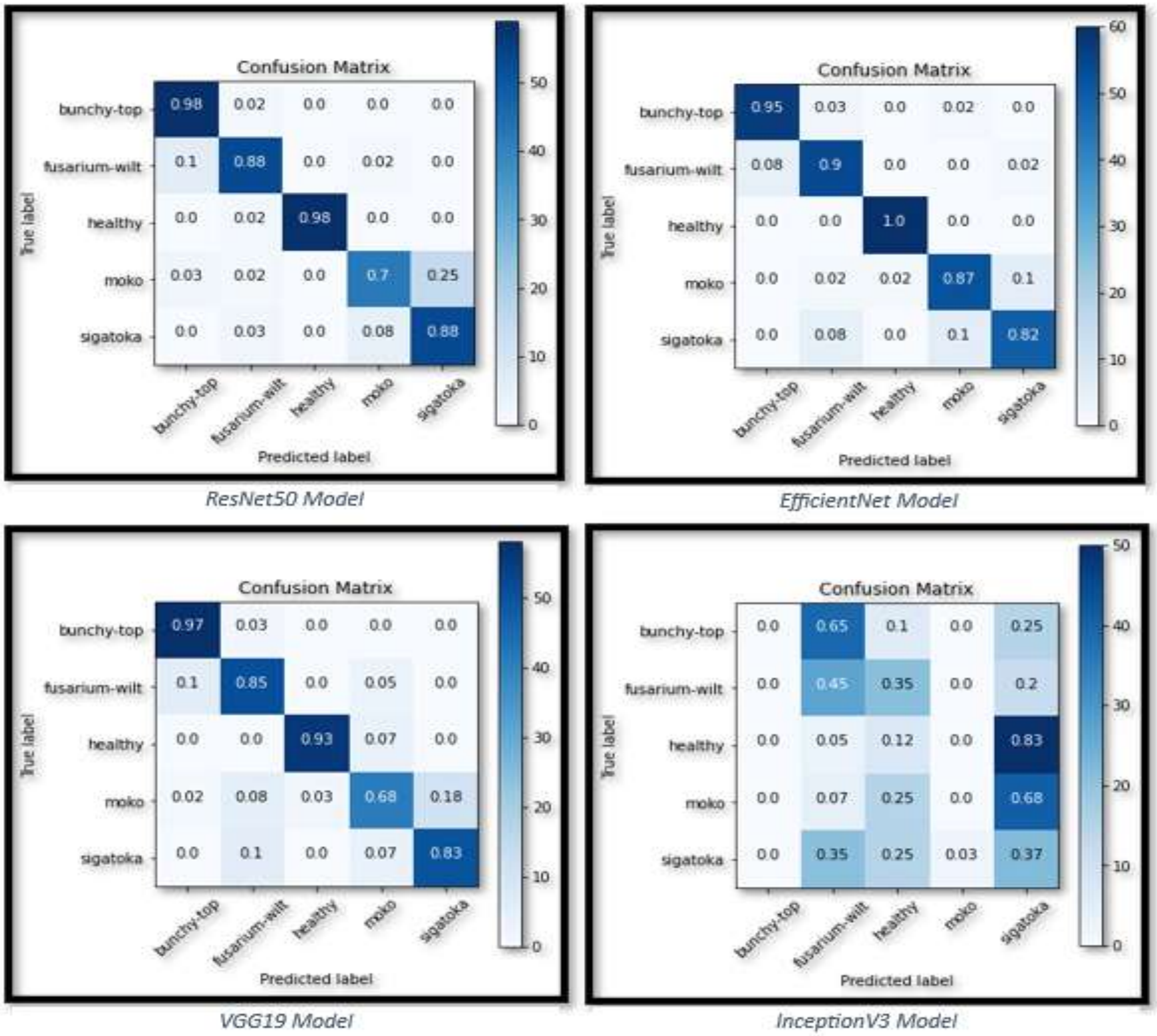
ResNet50 closely followed EfficientNet, achieving an overall accuracy of 89%. The model performed exceptionally well in detecting healthy leaves, attaining perfect precision (100%), high recall (98%), and an f1-score of 99%. For Bunchy Top disease, ResNet50 showed strong results with 88% precision, 98% recall, and a 93% f1-score. Fusarium Wilt also showed solid performance, with 91% precision, 88% recall, and 90% f1-score. However, the model struggled with Moko disease, displaying a lower recall (70%) and f1-score (78%), suggesting challenges in accurately differentiating this disease from others. 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.

VGG-19 demonstrated relatively lower performance, attaining an overall accuracy of 85%. Although 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 stable. 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 VGG-19 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 encountered challenges with Moko disease, showing reduced precision (88%) and recall (60%), which resulted in an f1-score of 71%. A similar trend was observed with Sigatoka disease, where precision (82%) and recall (78%) were moderate. 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 presented weighted averages for precision, recall, and f1-score, giving a comprehensive overview of their performance. EfficientNet topped the results with a weighted average of 0.91, reflecting an excellent balance between accuracy, sensitivity, and specificity. ResNet50 ranked second, with weighted averages of 0.89 for precision and recall, and 0.88 for f1-score, indicating solid overall performance. In contrast, VGG-19 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 VGG-19 and InceptionV3 may benefit from further fine-tuning or augmentation to improve performance, particularly for more challenging disease classes.

Figure 6:- Confusion matrix results for each model classifier.



In summary, these findings demonstrate the the effectiveness of EfficientNet and ResNet50 in classifying banana leaf diseases. 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 strong 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.

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 an image-based disease classification 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: VGG-19, 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 image-based banana disease classification system, 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 is noted that CNNs may struggle with negative image recognition due to inherent limitations in semantic understanding of objects. However, the research by Hosseini et al. (2017) revealed that while CNNs have demonstrated strong performance in identifying images similar to those seen during training, they struggle to recognize negative images, leading to significantly lower accuracy. Their findings suggest that when CNNs are trained on raw data, they fail to grasp the semantics of the objects, limiting their ability to effectively recognize unseen instances.With this, it could be a good starting point for future researchers who aim to conduct similar but more advanced studies on bananas.Furthermore, usability testing of the image-based banana disease classification system is recommended to assess its performance and user-friendliness, ensuring practical utility in agricultural settings.

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