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A Deep Learning Approach To Multi-Class And Multi-Label Cassava Leaf Disease Detection Using Mobilenetv2 And Image Augmentation

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Abstract: This paper presents the development of a deep learning model using pre-trained models to detect multiple cassava leaf diseases using simultaneous multi-class and multi-label classification. Cassava diseases often occur as single or mixed infections, complicating visual diagnosis critical to food security in tropical regions. Existing models, designed primarily for single-label classification, struggle with overlapping symptoms. To address this, a dataset of 10,000 expert- annotated cassava leaf images was compiled from Plant Village. The MobileNetV2 model, optimized for mobile deployment, was trained using binary cross-entropy loss with Sigmoid activation for Multi-label classification and Categorical cross-entropy loss with Softmax activation. The model achieved 95% accuracy, outperforming NasNet, demonstrating effective real-time, in-field disease diagnosis. This research advances agricultural AI applications by enabling scalable, mobile-compatible cassava disease detection.

Keywords: Cassava leaf disease detection, Multi-class and Multi-label classification, MobileNetV2, Lightweight deep learning

I. INTRODUCTION

In recent years, cassava leaf disease detection has become a critical focus for ensuring food security and sustainable agriculture in tropical regions [1-3]. Traditional methods for identifying diseases on cassava leaves rely heavily on expert visual inspection, which is subjective, time-consuming, and often unavailable to smallholder farmers in remote areas [2,3]. Early approaches used handcrafted image features such as color, texture, and shape descriptors extracted through techniques like color histograms, Local Binary Patterns (LBP), and Gray Level Co-occurrence Matrices (GLCM) [5,6,7]. These features were then input into machine learning classifiers including Support Vector Machines (SVM), k-means clustering, and neural networks to perform disease classification [5,6]. However, the accuracy of such traditional methods largely depends on the quality of feature engineering, which is labor-intensive and requires domain expertise. Additionally, the performance is often limited by the difficulty of designing universal features that generalize well across varying leaf conditions and disease symptoms.

With the rise of deep learning, convolutional neural networks (CNNs) using pre-trained models have gained prominence as they automatically learn hierarchical feature representations directly from raw images without manual feature design [1,2].

Figure 1: Diseased Cassava Leaf Symptoms.

Convolutional Neural Networks (CNNs) have shown superior performance in image recognition by leveraging convolution and pooling layers to extract spatial features [1]. Tewari [1] proposed a lightweight CNN for cassava disease detection using depth-wise separable convolutions and attention mechanisms, achieving high accuracy with low computational cost. Thaiyalnayaki and Joseph [2] showed that deep learning models like multi-layer perceptrons (MLP's) outperform traditional classifiers such as SVM's. Earlier methods by Al Hiary et al. [5] and Al Bashish et al. [6] used image segmentation and handcrafted features, while Tang et al. [7] improved performance by combining CNN's with texture descriptors.

Although most research focuses on multi-class classification, real-world cassava leaves often show multiple diseases, requiring multi-label approaches [8], [9]. This study uses MobileNetV2 with transfer learning to extract features for both multi-class and multi-label classification. The goal is to support real-time, mobile-based cassava disease diagnosis for improved farm-level decision-making.

The rest of the paper is organized as follows: Section 2 briefly reviews the related studies. In Section 3, we provide our methodology. The experimental results and quality discussion are presented in Section 4. Finally, the conclusion is made in Section 5.

II. LITERATURE REVIEW

Riaz et al. [1] proposed a deep learning-based approach for the diagnosis and classification of cassava leaf diseases using the EfficientNetB3 architecture. The dataset, obtained from a Kaggle competition, comprised 21,397 images categorized into five classes: Cassava Bacterial Blight (CBB), Cassava Brown Streak Disease (CBSD),Cassava Green Mottle (CGM), Cassava Mosaic Disease (CMD), and healthy leaves. Due to class imbalance, data augmentation techniques such as flips, rotations, and shears were applied to ensure equal representation across categories.The model employed transfer learning with pre-trained ImageNet weights and was trained using TensorFlow and Keras, achieving an overall test accuracy of 83.03% and over 90% accuracy for individual classes. Comparative analysis showed that EfficientNetB3 outperformed models like ResNet50 and MobileNetV2 in terms of accuracy and computational efficiency.Additionally, a graphical user interface was developed using PyQt5 to support real- time predictions in field settings.The study highlighted challenges related to overlapping visual features among diseases and noted the potential for mobile deployment in future work.

Liu and Wang [2] provides a comprehensive review of plant disease and pest detection using deep learning techniques. They highlight that deep learning methods outperform traditional image processing by integrating feature extraction into an end-to-end framework. The authors classify existing work based on network architectures which includes classification, detection, segmentation and also analyzed their strengths and limitations. They emphasize challenges such as the limited generalizability of models trained on laboratory datasets due to seasonal, regional, and growth-stage variations in plant symptoms. Additionally, they note that most studies focus on visible spectrum images, advocating for multi-spectral and fused data approaches to enhance detection accuracy. Early diagnosis remains difficult due to subtle symptoms and environmental factors affecting image quality.The review also stresses the need for large, diverse, real-world datasets,improved unsupervised learning methods, reduced model complexity for mobile deployment, and interdisciplinary integration of agronomic knowledge to advance practical applications.

Hassan and Maji [3] developed a lightweight convolutional neural network combining inception modules, residual connections, and depthwise separable convolutions for plant disease identification. Evaluated on PlantVillage, Rice, and Cassava datasets, their model achieved accuracies of 99.39%, 99.66%, and 76.59%, respectively, while reducing parameters by 70% compared to InceptionV3. The lower accuracy on the Cassava dataset was attributed to data imbalance and complex backgrounds. Their model outperformed popular pre-trained networks like VGG16 and ResNet50 in both accuracy and training time. Five-fold cross- validation confirmed model robustness, suggesting its suitability for real-world deployment with further optimization.

Nisha P. and Vijayakumar J. [4] proposed a hybrid approach for cassava leaf disease recognition and classification using image processing and machine learning techniques. The system applies CLAHE for contrast enhancement, K-means clustering and GLCM for feature extraction, and an SVM classifier to distinguish between healthy and diseased leaves. Their method achieved 100% classification accuracy on a dataset of cassava leaf images.Additionally, fuzzy logic was employed to grade disease severity based on the infected leaf area, facilitating efficient disease diagnosis and aiding farmers and pathologists by automating and speeding up the grading process.

Ma, Wang, Zhang, Wang, Jia, Gao, and Su [5] developed a two-stage deep transfer learning method for maize leaf disease identification, addressing gray leaf spot, common rust, and northern leaf blight. They pre-trained eight deep and four lightweight CNN models on the Plant Village dataset, with ResNet and MobileNet achieving 99.48% and 98.69% accuracy, respectively.These models were fine-tuned on a smaller,field-collected maize leaf dataset from mobile phone images. The fine-tuned MobileNet attained the highest accuracy of 99.11%, highlighting transfer learning's effectiveness on small datasets and its potential for mobile application in real-time field diagnosis.

Alirezazadeh, Schirrmann, and Stolzenburg [6] investigated the use of the Convolutional Block Attention Module (CBAM) to improve plant disease classification performance in CNN's under limited training data. They applied CBAM to five well-known CNN architectures: EfficientNetB0, MobileNetV2, ResNet50, InceptionV3, and VGG19 fine-tuning them on the DiaMOS Plant dataset of pear tree foliar diseases. The addition of CBAM improved classification accuracy for all tested models except VGG19, with EfficientNetB0+CBAM achieving the highest accuracy of 86.89%, outperforming baseline EfficientNetB0 by 1.07%. The study showed CBAM enhances discriminative feature extraction with minimal computational overhead, helping CNN's better focus on disease-relevant image regions. Statistical tests confirmed significant performance improvements, especially for lightweight models suitable for deployment on low-end devices.

Hasan, Yusuf, and Alzubaidi [7] conducted an extensive review of recent deep learning advancements in plant disease detection and classification. Their analysis covered developments from 2017 to 2020, evaluating model architectures, data augmentation strategies, transfer learning, feature visualization, and classification accuracy. They emphasized the effectiveness of shallow models on small datasets and highlighted the role of advanced augmentation and generative approaches, such as CycleGAN and ProGAN, to over come dataset limitations. The authors stressed that dataset diversity and suitable backbone selection significantly impact model performance more than sample volume alone. Additionally,the integration of hyperspectral imaging and salience map techniques was recommended to enhance disease localization and feature extraction. Future directions include automated labeling using GANs, early disease detection via hyperspectral data, and training deep models on visually similar disease symptoms for improved robustness.

Abayomi-Alli, Damaševičius, Misra, and Maskeliūnas [8] developed a deep learning-based cassava disease recognition model designed to perform well on low quality images, common in real-world agricultural settings. They proposed a novel data augmentation technique by transforming image color histograms using Chebyshev orthogonal functions, thereby improving the model's ability to generalize under image degradation effects such as resolution loss, blurring, and overexposure. Using MobileNetV2, the augmented model achieved significant accuracy improvements up to 20.6% compared to the baseline. Their results highlight the importance of robust training strategies for deployment on low-end devices used by rural farmers.

Satoto, Syarief, and Khotimah [9] proposed a Region Proposal Convolutional Neural Network (RPCNN) combined with data augmentation to improve cassava disease classification from leaf images. They applied a convex hull-based segmentation to isolate leaf regions, minimizing background interference. Data augmentation was used to increase dataset diversity and reduce class imbalance. The model achieved an average classification accuracy of 99.00% with minimal training error (MSE: 0.0080), outperforming traditional CNN architectures such as AlexNet, VGG16, and ResNet50. The integration of region proposal enhanced the model's focus on diseased areas, making it suitable for early disease detection in cassava farming.

John [10] developed a cassava disease detection model using a pre-trained DenseNet169 Convolutional Neural Network, addressing real-world challenges like class imbalance and image noise. The study utilized a dataset of 21,397 cassava leaf images, representing four disease classes and one healthy class, sourced from Ugandan farms. To manage class imbalance, a modified weighted cross-entropy loss function was implemented, ensuring equal importance to minority and majority class samples. Data augmentation and early stopping were applied to enhance generalization and prevent overfitting. The model achieved high sensitivity (92.05%) and specificity (90.98%), with an average AUC score of 0.9614, demonstrating strong classification performance.

Zhou, Chen, Wang, and Huan [11] reviewed recent advancements in lightweight convolutional neural networks (CNNs) suitable for mobile deployment. The study evaluated models such as MobileNet, ShuffleNet, MixNet, and EfficientNet on the ImageNet 2012 dataset. EfficientNet demonstrated thehighest accuracy (77.3%) with relatively low parameters and FLOPs. Key design strategies include depthwise separable convolutions, group convolutions, 1×1 convolutions, residual connections, and channel shuffle techniques. The authors highlighted the growing importance of neural architecture search and reinforcement learning in optimizing lightweight models. The paper concludes that efficient structural design significantly enhances model deployment on resource-limited platforms.

Tewari [12] proposed a lightweight convolutional neural network (CNN) model for cassava leaf disease classification, addressing four diseases: cassava mosaic disease, cassava green mottle, cassava bacterial blight, and cassava brown streak leaf disease. The model utilizes depthwise separable convolutions and incorporates both channel and spatial attention mechanisms to focus on disease regions while suppressing background noise. Experimental results show the model outperforms established architectures such as VGG16, ResNet50, EfficientNet, MobileNetV1, and MobileNetV2, achieving 77% test accuracy with fewer parameters (1.4 million) and lower FLOPs, making it suitable for mobile deployment in real- world farming conditions.

Thaiyalnayaki and Joseph [13] proposed a soybean disease classification approach using Support Vector Machine (SVM) and a deep learning multi-layer perceptron (MLP) model. The dataset consisted of 683 instances with 36 plant attributes classified into 19 disease classes. The SVM classifier achieved an accuracy of 88.73%, while the deep learning MLP model reached a higher accuracy of 94.14%. The deep learning model used multiple hidden layers with ReLU activation and softmax output, optimized via stochastic gradient descent with negative log-likelihood loss. The authors noted that further optimization of the deep learning architecture's layers could improve classification accuracy. The study emphasizes the importance of accurate disease detection to reduce pesticide misuse and crop loss.

Arsenovic, Karanovic, Sladojevic, Anderla, andStefanovic [14]addressed the limitations of deep learning models for plant disease detection in real-world conditions by introducing a large dataset of 79,265 leaf images with varied backgrounds, angles, and lighting. They applied traditional and GAN-based augmentation techniques to reduce overfitting. A novel two-stage neural network architecture, PlantDiseaseNet,was proposed, achieving 93.67% accuracy on the Plant Disease dataset. The model demonstrated robustness in complex environments and potential for integration into mobile apps. Future work includes detecting diseases across different plant parts and growth stages to enhance decision support systems.

III. MATERIALS AND METHODS

3.1 Dataset Description

To build this lightweight deep learning model capable of detecting multiple cassava leaf diseases, this research placed strong emphasis on thorough data collection and proper organization. Two major datasets were used: a primary dataset and a secondary one. The primary dataset was crowd sourced from cassava farms located around the Federal University of Technology Owerri, University of Port Harcourt, and the National Root Crops Research Institute in Umudike. Undergraduate students helped in collecting 4,000 high-quality images using smartphones and digital cameras, capturing both healthy and diseased cassava leaves in natural farm conditions. The secondary dataset was sourced from Kaggle, containing 9,436 labeled images across five disease categories. This publicly available data complemented the primary dataset and helped in creating a more diverse and comprehensive collection. To ensure accuracy, all images were annotated by plant pathology experts using annotation software. Each image was labeled as either healthy, affected by a single disease, or showing multiple disease symptoms overcoming the limitation of previous datasets that only identified one disease per leaf.

3.2 Data Preprocessing

The dataset used in this research consists of 4,000 high-quality cassava leaf images. An Expert plant pathologists annotated the dataset into 13 distinct classes, covering both single-disease and multi-disease cases. As shown in table1, these include healthy leaves(400),Cassava Mosaic Disease (360), Cassava Bacterial Blight (500), Cassava Green Mite Disease (650), and Cassava Brown Streak Disease (360). Multi-disease classes such as CMD/CBBD (120), CGMD/CMD (430), and CGMD/CBBD/CMD (280) were included to reflect real-world cases where leaves exhibit symptoms of multiple infections.After applying pre-processing techniques such as resizing, normalization, and data augmentation, the number of image instances increased to 4,630, enhancing the dataset's diversity and robustness for model training.

Table1:Data Processing Statistics

S/N	ClassLabel	Classification Type	Description	Count
1	Healthy	Single-label	Leaves without any visible disease Symptoms	400
2	Cassava Bacterial Blight (CBBD)	Single-label	Leaves affected by CBBD only	500
3	Cassava Brown Streak Disease(CBSD)	Single-label	Leaves affected by CBSD only	360
4	Cassava GreenMite Disease(CGMD)	Single-label	Leaves affected by CGMD only	650
5	CassavaMosaic Disease(CMD)	Single-label	Leaves affected by CMD only	360
6	CBBD/CBSD	Multi-label	Leaves showing symptoms of Both CBBD and CBSD	300
7	CGMD/CBBD	Multi-label	Leaves showing symptoms of Both CGMD and CBBD	340
8	CMD/CBBD	Multi-label	Leaves showing symptoms of Both CMD and CBBD	120

9	CGMD/CBSD	Multi-label	Leaves showing symptoms of Both CGMD and CBSD	370
10	CGMD/CMD	Multi-label	Leaves showing symptoms of Both CGMD and CMD	430
11	CGMD/CBBD/CMD	Multi-label	Leaves showing symptoms of CGMD,CBBD and CMD	280
12	CMD/CBSD/CBBD	Multi-label	Leaves showing symptoms of CMD,CBSD,andCBBD	270
13	CMD/CGMD/CBSD	Multi-label	Leaves showing symptoms of CMD, CGMD, and CBSD	250

Table2:Split Ratio

TrainingSet(70%)	ValidationSet(20%)	Test Set(10%)
3241	926	463

In this research, 70% of the 4000 dataset was allocated for training, 20% for validation and the remaining 10% for testing as shown in table 2.The training set was utilized to train the model, the validation set aided in tuning the hyper parameters to prevent overfitting, and the test set was used to provide an unbiased evaluation of the final model's performance.

Table 3:Summary of selected models base design and training considerations

Hyper-parameter	MobileNetV2 Range	NASNet Range
Dropout Rate	0.2-0.5	0.2-0.5
L2 Regularization	$1e^{-4}$-$1e^{-5}$	$1e^{-4}$-$1e^{-5}$
Epochs	50-100	50-150
Optimizer	Adam	Adam
BatchSize	16-32	16-32
LearningRate	$1e^{-3}$-$1e^{-4}$	$1e^{-3}$-$1e^{-4}$

Table 3 illustrates the training considerations of the selected models. Both MobileNetV2 and NASNet models were trained under identical conditions.

3.3 Mathematical Approach for the Considered Procedure

The development of a deep learning model for detecting cassava leaf diseases using multi-class and multi-label classification is fundamentally grounded in mathematical principles and techniques. This approach enabled us to construct efficient algorithms tailored to agricultural diagnostics, where the simultaneous presence of multiple diseases on a single leaf poses a unique challenge.

At the core of this mathematical framework lies the formulation of the learning task as an optimization problem. The primary objective is to determine the model parameters that minimize a defined loss function suited for multi-label classification. To detect cassava leaf diseases using the MobileNetV2 model in combination with binary cross-entropy loss and Sigmoid activation, the process can be broken down into the following key mathematical components.

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+F)} \tag{3.1}$$

$$\text{Precision} = \frac{TP}{(TP+FP)} \tag{3.2}$$

$$\text{Recall} = \frac{TP}{TP/(TP+FN\ \ )} \tag{3.3}$$

$$\text{F1 Score} = \frac{2*(\text{Precision}*\text{Recall})}{(\text{Precision}+\text{Recall})} \tag{3.4}$$

AUC can be computed by calculating the area under the ROC curve using the trapezoidal rule.

If $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$ are points on the ROC curve, AUC can be approximated as:

$$AUC = \sum_{i=1}^{n-1} . (x_{i+1} - x_i). \left(\frac{yi+yi+1}{2} \right) \tag{3.5}$$

3.4 Model Architecture

Figure 2 below illustrates the proposed architecture of the deep learning model for cassava leaf disease detection, beginning with data collection and pre-processing followed by dataset splitting into training, validation, and test sets. Pre-trained models (MobileNetV2 and NasNet) are used for classification, then evaluated using performance metrics (accuracy, recall, precision, F1-score) to select the best-performing model for both multi-class and multi-label predictions.

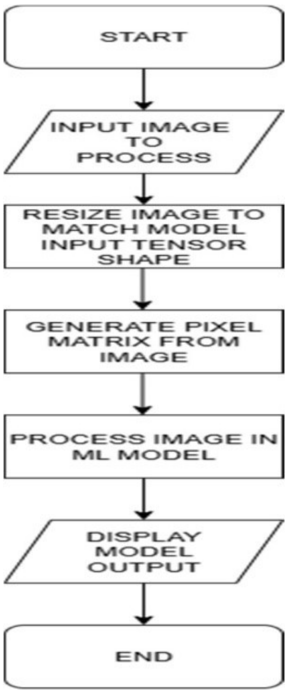


Figure 2:Mobileappflowchart

Figure 2, presents a flowchart outlining the image processing pipeline for cassava disease detection. It illustrates the sequential steps from image input, resizing, pixel matrix generation, and model inference to the final display of the model's prediction output.

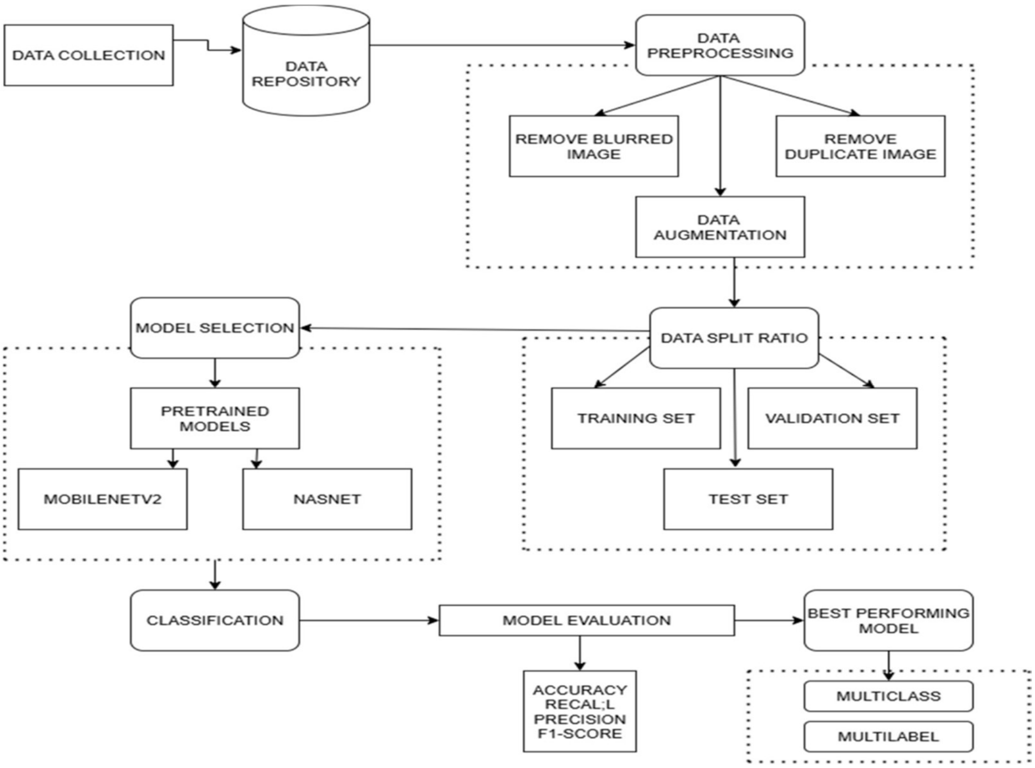


Figure 3: Architecture of the proposed system

IV. RESULTS AND DISCUSSIONS

4.1 Model Performance Evaluation

Table 4 below, shows the proposed MobileNetV2 model evaluation at training and testing stage. At test stage it achieved 95% accuracy in detecting cassava leaf diseases, indicating its potential for real-time diagnosis in tropical regions. Its precision is 98%, effectively reducing false positives,while a recall of 100% highlights its capacity to capture a significant portion of actual disease instances. The balanced F1-score of 98% further demonstrates the model's competence in this area. However, adapting the model to diverse field conditions is essential. Fine-tuning with region-specific data and mixed infection patterns can enhance performance. Additionally, addressing potential biases is critical for equitable outcomes. By leveraging the model's strengths and incorporating context-specific considerations, an improved classifier for cassava disease was developed to effectively tackle related challenges in agriculture's digital landscape. Figure 5, shows a mobile app scan result for both multi-class and multi-label disease detection.

Table 4: Proposed Model Evaluation

	Accuracy	**Precision**	**F1-Score**	**Recall**
TrainingStage	0.98	0.95	1.00	0.97
TestingStage	0.95	0.98	1.00	0.98

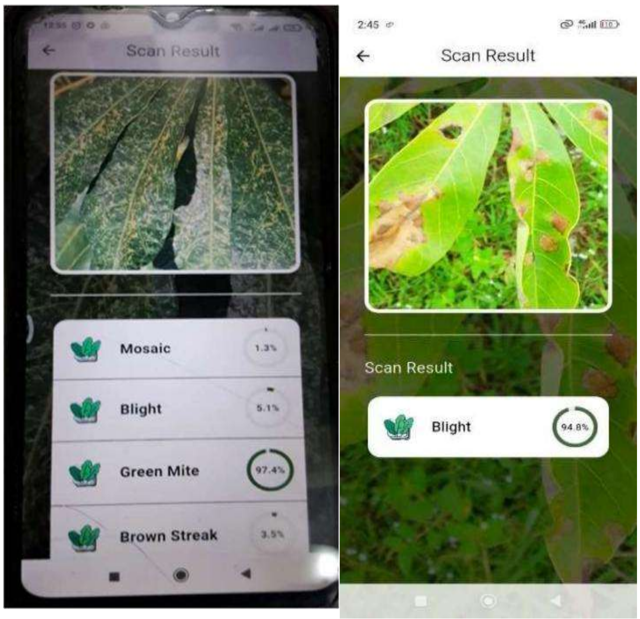


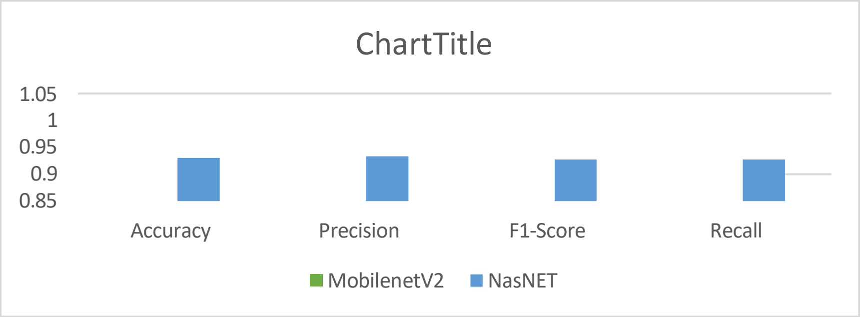
Figure 4:MobileApp Scan Result

4.2 Comparison Evaluation with NasNET

This section presents a comparison of deep learning models used in the experiments, specifically MobileNetV2 and NasNet. As shown in Table 2, the MobileNetV2 classifier demonstrated superior performance in detecting cassava leaf diseases, achieving 95% accuracy, 98% precision, 100% recall, and an impressive F1 score of 98%. This indicates a robust capability in identifying both single and mixed infections with minimal false positives or missed cases. In contrast, the NasNet model attained 93% accuracy, with 93.3% precision, 92.7% recall, and a lower F1 score of 92.7% as seen in Table 5 below. While these results still reflect strong performance, NasNet's comparatively reduced recall suggests a higher likelihood of missing disease cases, which could have critical implications in agricultural diagnostics. Additionally, its lower F1 score indicates less balance between precision and recall compared to MobileNetV2.

Table 5: Comparison evaluation with other machine learning techniques

	Accuracy	**Precision**	**F1-Score**	**Recall**
MobilenetV2	0.95	0.98	1.00	0.98
NasNET	0.93	0.933	0.927	0.927



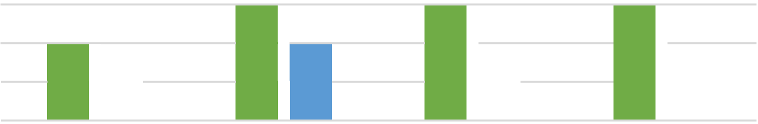


Figure 5.Comparison Evaluation Chart

ROC_AUC Graphical Results

The Receiver Operating Characteristic (ROC) curve for the cassava disease detection classifier provides valuable insights into the model's diagnostic performance. This curve illustrates how effectively the model distinguishes among multiple cassava leaf disease classes, including Mosaic, Blight, Brown-streak, and Green-mite, as well as healthy samples. The ROC curves being well-separated from the diagonal line which represents random guessing demonstrate the classifier’s strong discrimination ability across all categories.

The Area Under the Curve (AUC) further quantifies this performance. With AUC scores of 1.00 for Mosaic, Blight, Green-mite, and the micro-average, and 0.99 for Brown-streak, the model exhibits near-perfect capability in identifying each disease class. Interpreting the ROC AUC alongside metrics such as accuracy, precision, recall, and F1-score provides a comprehensive understanding of the classifier's reliability.

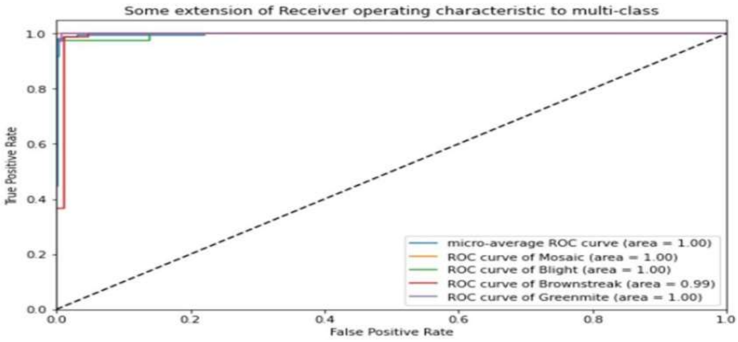


Figure 6: ROC_AUC-Graph

Figure 4, demonstrates the model's effectiveness in distinguishing between cassava leaf disease classes by employing a MobileNetV2 architecture designed for multi-class and multi-label classification, achieving strong performance levels with an AUC of 1.00 for most classes and 0.99 for Brown-streak. Although the classifier performs exceptionally well overall, a few cases of Brown-streak may still be misclassified as other diseases due to symptom overlap, highlighting the need for ongoing refinement and domain-specific tuning in real-world deployment.

MobileAppIntegration

Table 6: System Development Requirements

Configuration	Parameters
Displayresolutioninpixels	FHD(1920x1080)
Memory(RAM)	16GB
OperatingSystem	android iOS MacOS
DevelopmentLanguage	Dart Kotlin Swift python
DevelopmentTools	colab android studio Flutter

Table 6, outlines the system development requirements necessary for building and deploying the cassava disease detection model and its associated mobile application. The cassava disease detection model was successfully integrated into a mobile application to facilitate real-time diagnosis directly from farmers' mobile devices. The initial model was developed and trained using Keras. For deployment within a mobile environment, especiallyone built using Flutter, the model was converted into TensorFlow Lite format.The Python script used for the conversion is hosted on Google Colab. The mobile application was builtusing Flutter, Google's cross-platform software development framework that allows a single codebase to run on both Android and iOS devices. The app serves as the frontend interface, capturing cassava leaf images from the user, sending the image input to the embedded ML model, and displaying the predicted disease output. Converting the Keras model toTensorFlow Lite ensured compatibility with Flutter and enabled efficient offline inference, making the system accessible and practical for use in rural and low-connectivity farming environments.

V. CONCLUSION

In conclusion, this research addresses the critical issue of detecting cassava leaf diseases, particularly in cases of single and mixed infections. The primary goal was to develop aclassifier that accurately identifies multiple diseases, overcoming the limitations of single-label models. By using MobileNetV2 with image augmentation and multilabel classification, the study built a robust and efficient model. The results showed high accuracy, proving its effectiveness in field conditions. Future research should explore early disease detection, test across diverse environments, and consider models like Vision Transformers for improved agricultural diagnostics.

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