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Enhancing Deep Learning-based Classification of Cassava Leaf Diseases using CLAHE and SMOTE

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Abstract

Efficient detection of foliar diseases in cassava (Manihot esculenta) is essential for sustaining crop productivity and ensuring food security, particularly in regions vulnerable to environmental stress. However, accurate identification remains a challenge due to the widespread occurrence of diseases such as Cassava Mosaic Disease (CMD), Cassava Bacterial Blight (CBB), and Cassava Brown Streak Disease (CBSD), which continue to threaten cassava yields. This study addresses two major obstacles in cassava disease classification—uneven image quality and imbalanced class distribution—by implementing Contrast Limited Adaptive Histogram Equalization (CLAHE) and the Synthetic Minority Over-sampling Technique (SMOTE). A publicly available dataset from the Cassava Leaf Disease Classification competition on Kaggle was used, and two pretrained convolutional neural networks, EfficientNetV2B2 and DenseNet169, were fine-tuned through transfer learning. The images were resized, enhanced using CLAHE, and augmented before being split into training, validation, and test sets. Both models were trained for 10 epochs using identical configurations. Results indicate that EfficientNetV2B2 achieved higher classification accuracy (88.1%) than DenseNet169 (86.4%), with CLAHE contributing a 2–3% improvement in accuracy. While these results are slightly lower than those reported in previous studies employing extended training durations and advanced techniques such as focal loss, the lightweight approach presented here proves effective under computational constraints. The findings demonstrate the feasibility of developing scalable and resource-efficient disease detection systems, especially for mobile or edge devices. Future research should focus on longer training schedules, advanced loss functions, and validation using field-acquired images to further improve model performance in real-world agricultural settings.

Keywords: cassava, deep learning, leaf disease classification, CLAHE, SMOTE

1 Introduction

The global food crisis is becoming increasingly critical, driven by intersecting pressures such as geopolitical conflicts, economic instability, and the intensifying effects of climate change. According to the Global Report on Food Crises (FSIN, 2024), approximately 238 million individuals currently suffer from acute food insecurity, marking a 10% increase from the previous year. One promising avenue for strengthening food security, particularly in tropical regions, lies in the optimization of cassava (Manihot esculenta) cultivation. Cassava is a drought-tolerant, high-starch tuber crop capable of thriving in marginal soils and serves as a dietary staple for over 800 million people globally [1].

Despite its strategic importance, cassava production is frequently hindered by foliar diseases such as Cassava Mosaic Disease (CMD), Cassava Bacterial Blight (CBB), and Cassava Brown Streak Disease (CBSD), all of which significantly reduce yield potential [2]. Consequently, early detection of these diseases is essential to ensure sustainable cassava production. In the context of precision agriculture, deep learning—particularly through the application of Convolutional Neural Networks (CNNs)—has demonstrated efficacy in automating digital image classification tasks [3]. However, its practical deployment in agricultural diagnostics is often challenged by variations in image quality and imbalanced class distributions. Poor image quality can impair feature extraction [4], while class imbalance may bias the model toward dominant categories [5]. To address these limitations, this study integrates two key strategies: image enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve visual feature clarity, and class balancing via resampling techniques. These approaches are implemented using two state-of-the-art CNN architectures—

EfficientNetV2B2 and DenseNet169—both recognized for their efficiency in processing complex visual data with relatively low computational demands.

The primary objective of this research is to develop a cassava leaf disease classification model that is resilient to variability in both image quality and class distribution. Specifically, the study examines: (1) the impact of image enhancement on classification accuracy; (2) the influence of class imbalance and mitigation strategies; (3) the effectiveness of combining CLAHE with resampling techniques; and (4) comparative performance analysis between EfficientNetV2B2 and DenseNet169. The dataset utilized in this research is sourced from a publicly available collection on Kaggle [6], comprising five disease classes and one healthy leaf class. This study deliberately excludes ensemble modeling and cross-validation to maintain a focused evaluation of data quality and class distribution effects.

Moreover, the findings reinforce prior research emphasizing the significance of class balancing [5], the role of image quality [4], and the utility of DenseNet architectures for plant disease detection [3]. Additional support for the applied techniques is provided by [7] and [8], who underscore the effectiveness of data augmentation and transfer learning in real-world image classification. Accordingly, this study is positioned to contribute both theoretically to the advancement of CNN applications in digital agriculture and practically to the development of accurate, scalable systems for early disease detection in crops

2 Literature Review

Digital image classification is a process that involves categorizing images based on visual attributes such as color, texture, and structural patterns [9]. In recent years, this task has been increasingly automated through the use of Convolutional Neural Networks (CNNs), which are capable of hierarchically extracting features from raw image data [3], [10]. Within the domain of plant disease detection particularly for cassava leaves two persistent challenges are poor image quality and class imbalance. To address the former, Contrast Limited Adaptive Histogram Equalization (CLAHE) is frequently employed to enhance local contrast in images while minimizing the risk of amplifying noise [5], [11].

To mitigate the effects of skewed class distributions, techniques such as oversampling, under sampling, and class weight adjustments are implemented to reduce bias toward majority classes and improve overall classification fairness [3], [12]. Moreover, data augmentation strategies—such as image rotation, flipping, and zooming are applied to enrich the variability of training samples and improve model generalization [8].

In scenarios involving limited datasets, transfer learning has emerged as a viable approach by fine-tuning pretrained architectures such as EfficientNet and DenseNet on domain-specific image data [7], [13]. EfficientNetV2B2, in particular, integrates MBConv and Fused-MBConv modules to optimize training efficiency [14], while DenseNet169 leverages densely connected layers to facilitate more effective information propagation across the network [15].

Model performance in such applications is commonly evaluated using a suite of metrics, including accuracy, precision, recall, F1-score, and confusion matrix. These metrics are especially critical in imbalanced classification tasks, as they offer a more nuanced and holistic assessment of predictive reliability [16].

3 Research Method

This study employed an experimental quantitative approach to evaluate the performance of two deep learning architectures EfficientNetV2B2 and DenseNet169 for image-based classification of cassava leaf diseases. The models were assessed using a publicly available dataset from Kaggle, titled Cassava Leaf Disease Classification, comprising images categorized into five distinct classes: Cassava Mosaic Disease (CMD), Cassava Bacterial Blight (CBB), Cassava Green Mite (CGM), Cassava Brown Streak Disease (CBSD), and Healthy.

The dataset was obtained directly from the official Kaggle platform and partitioned into three subsets using a stratified sampling method to ensure balanced class distribution across data splits: 70% for training, 20% for validation, and 10% for testing. Prior to model training, a comprehensive preprocessing pipeline was implemented, which included: (1) resizing all images to 224 × 224 pixels

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to conform to model input requirements; (2) enhancing contrast using Contrast Limited Adaptive Histogram Equalization (CLAHE); (3) applying data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment to increase data diversity and improve generalization; and (4) employing resampling techniques to address class imbalance within the training set.

Model training was conducted independently for both architectures using default training configurations from the TensorFlow and Keras libraries. Performance evaluation was carried out on both validation and testing sets using standard classification metrics, including accuracy, precision, recall, and F1-score. Additionally, confusion matrices were generated to visualize classification performance across individual classes. This methodological framework was designed to provide a rigorous comparison of each model's ability to accurately and consistently classify cassava leaf diseases.

4 Results and Analysis

This section presents the results obtained from training and evaluating the proposed cassava leaf disease classification models. It begins with a description of the dataset and the data preparation steps, followed by the implementation of the deep learning architectures and the analysis of their performance across various evaluation metrics.

Particular attention is given to how the applied preprocessing techniques—Contrast Limited Adaptive Histogram Equalization (CLAHE) and the Synthetic Minority Over-sampling Technique (SMOTE)—contributed to model effectiveness, especially under the constraints of limited computational resources. Through this discussion aims to highlight not only the technical outcomes but also the practical implications of deploying lightweight, transferable models for plant disease detection in real-world agricultural settings.

4.1 Dataset Description and Data Preparation

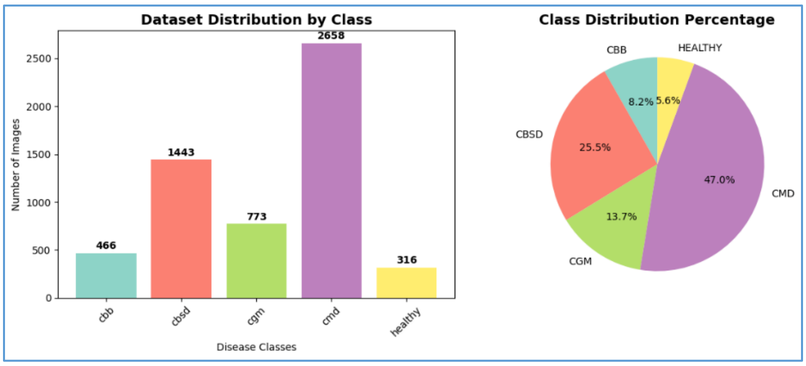

Figure 1 Initial class distribution in the dataset before stratified splitting

Based on Figure 1, this study employed a publicly available dataset from the Cassava Leaf Disease Classification competition hosted on the Kaggle platform, developed by Mwebaze [6]. The dataset comprises 5,656 images of cassava leaves categorized into five distinct classes: Cassava Bacterial Blight (CBB), Cassava Brown Streak Disease (CBSD), Cassava Green Mite (CGM), Cassava Mosaic Disease (CMD), and healthy leaves (Healthy). To ensure proportional representation of each class, the dataset was stratified into three subsets: 72% for training, 18% for validation, and 10% for testing.

Initial analysis revealed a substantial class imbalance, with CMD accounting for 47% of the training data, while CBB and Healthy classes represented only 8.2% and 5.6%, respectively (Table 1). Such imbalance can introduce bias in model training, leading to overfitting toward the dominant class and reduced sensitivity to minority classes [17], [18].

Table 1 Class distribution before SMOTE (training set)

Class	Number of Samples	Percentage (%)
CBB	335	8.2
CBSD	1,039	25.5
CGM	557	13.7

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Class	Number of Samples	Percentage (%)
CMD	1,914	47.0
Healthy	227	5.6

To mitigate this imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training set [5]. Post-SMOTE application, each class was represented equally with 1,914 samples (Table 2).

Table 2 Class distribution after SMOTE (training set)

Class	Number of Samples	Percentage (%)
CBB	1,914	20.0
CBSD	1,914	20.0
CGM	1,914	20.0
CMD	1,914	20.0
Healthy	1,914	20.0
Total	**9,570**	**100.0**

Class balancing is essential in plant disease classification tasks, as it ensures equitable model exposure to all disease types. This is particularly critical for minority classes like CBB, which, although less prevalent in field conditions, must be accurately identified to prevent further spread [19]. In addition to class balancing, a series of preprocessing steps were implemented to enhance image quality and improve model performance.

4.2 Image Size and Format

At the initial stage of preprocessing, all images in the dataset were resized to 224 × 224 pixels with three color channels (RGB). This resolution was selected to conform to the input size specifications required by the EfficientNetV2B2 and DenseNet169 architectures. Standardizing image dimensions is essential to ensure uniform input across the training process, thereby enabling consistent feature extraction and optimal model performance [14], [20].

The RGB color format was preserved, as chromatic information is instrumental in distinguishing among different cassava leaf diseases. Variations in leaf coloration, such as the emergence of chlorotic or necrotic spots, serve as critical diagnostic indicators [4]. Therefore, this preprocessing step not only satisfies architectural input requirements but also enhances the model's ability to accurately detect and classify visual disease symptoms.

4.3 Data Preprocessing Stages

The preprocessing phase in this study involved three primary steps: resizing images, enhancing contrast, and applying data augmentation. All cassava leaf images were resized to 224 × 224 pixels with three RGB color channels to ensure compatibility with the input specifications of the EfficientNetV2B2 and DenseNet169 architectures. This standardization was essential to maintain consistent spatial dimensions and facilitate stable visual feature extraction during training [14], [20].

Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to improve local contrast, particularly in images affected by uneven illumination. This enhancement technique increases the visibility of fine disease patterns, thereby improving the model's ability to detect and classify symptoms accurately. As shown in Figure 2, the contrast-enhanced images display clearer disease markers than the original versions. CLAHE has been reported to significantly improve visual clarity in similar plant image datasets [11]. Besides that, the Synthetic Minority Over-sampling Technique (SMOTE) was implemented to address class imbalance by generating synthetic samples for minority classes. This method ensures equal representation of all classes in the training set, which contributes to more balanced learning and reduces model bias. These two preprocessing strategies—CLAHE and SMOTE—form the foundation of the data preparation process in this study and are referenced throughout the text without repeating their detailed mechanisms.

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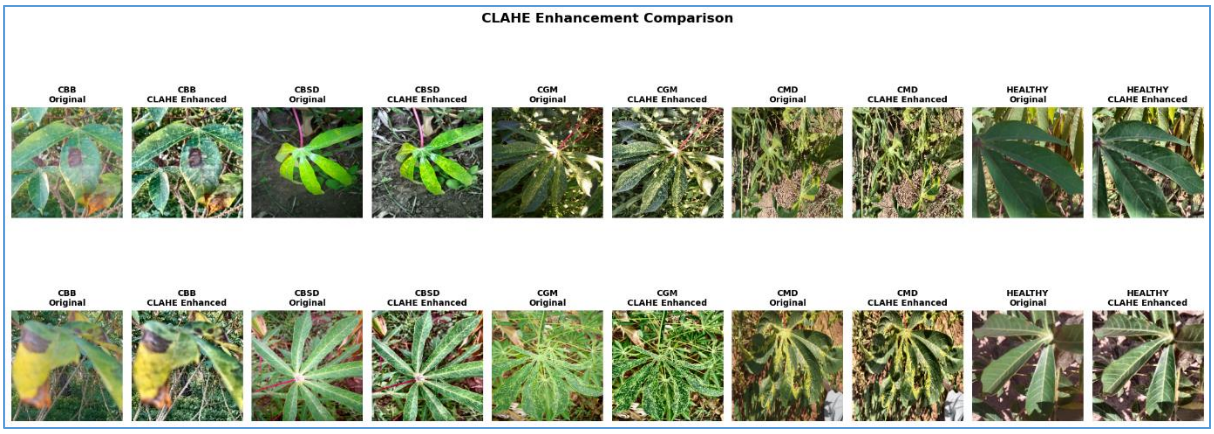

Figure 2 Comparison of images before and after applying CLAHE

To further improve model generalization and reduce overfitting, data augmentation was performed using horizontal and vertical flipping, random rotation, and zooming. These transformations simulate real-world variations in leaf orientation and positioning commonly encountered in agricultural environments. Such augmentation strategies have been shown to significantly contribute to a model's generalization capacity in image classification tasks [21].

Although CLAHE enhances important visual cues, it may also intensify artifacts in noisy images. Therefore, appropriate tuning of preprocessing parameters is essential to align with the inherent characteristics of the dataset. Overall, the preprocessing phase played a critical role in producing a high-quality dataset, enabling more accurate and robust cassava leaf disease classification within a digital agriculture framework.

4.4 Deep Learning Model Implementation

This study employed two contemporary convolutional neural network (CNN) architectures—EfficientNetV2B2 and DenseNet169—through a transfer learning approach, utilizing pretrained weights from the ImageNet dataset. The classification layers of both models were modified to accommodate five cassava leaf categories: Cassava Bacterial Blight (CBB), Cassava Brown Streak Disease (CBSD), Cassava Green Mite (CGM), Cassava Mosaic Disease (CMD), and healthy leaves. To optimize training efficiency, the early layers of each model were frozen, and fine-tuning was applied exclusively to the final layers.

Model training was conducted on the Google Colab platform (Free Tier), utilizing a Tesla T4 GPU. Due to platform constraints in processing time and memory, training was limited to 10 epochs. The training configuration included the Adam optimizer, a learning rate of 0.0001, a batch size of 32, and categorical crossentropy as the loss function. Data augmentation techniques—horizontal and vertical flipping, random rotation, and zooming—were also implemented to enrich visual diversity and mitigate overfitting. EfficientNetV2B2 was selected for its high parameter efficiency and fast convergence, while DenseNet169 was chosen for its dense inter-layer connections, which support enhanced feature propagation and extraction. As presented in Table 3, both models demonstrated satisfactory initial performance in adapting to the cassava leaf dataset, despite the constrained number of training epochs.

Table 3 Model training parameters

Parameter	Value
Optimizer	Adam
Learning rate	0.0001
Batch size	32
Epochs	10
Loss function	Categorical Crossentropy
Data augmentation	Flip, rotate, zoom
Input size	$224 \times 224 \times 3$
Output classes	5

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Despite the promising performance, the classification accuracy remained below that reported by [5], who achieved over 93% accuracy through extended training (≥50 epochs) and advanced methods including focal loss and class weight adjustments. This gap highlights the influence of resource limitations and restricted training time on model performance.

Nonetheless, the findings confirm that transfer learning remains a viable and effective strategy for agricultural image classification, especially in resource-constrained environments. While performance has not yet reached its full potential, the approach offers a practical foundation for further optimization and real-world application in plant disease detection systems.

4.5 Results and Discussion: Model Evaluation

This study assessed the performance of two pretrained convolutional neural network models—EfficientNetV2B2 and DenseNet169—in classifying five types of cassava leaf conditions. With training limited to 10 epochs, EfficientNetV2B2 achieved a higher classification accuracy (88.1%) compared to DenseNet169 (86.4%), as shown in Table 4.

Further evaluation using standard classification metrics—precision, recall, and F1-score—also favored EfficientNetV2B2. As shown in Table 5, EfficientNetV2B2 achieved a precision of 0.884, recall of 0.879, and F1-score of 0.880. These scores slightly outperformed DenseNet169, which obtained a precision of 0.862, recall of 0.858, and F1-score of 0.859. These results indicate that EfficientNetV2B2 provided more stable and consistent performance under the given training constraints.

Table 4 Accuracy of each model

Model	Accuracy (%)
EfficientNetV2B2	88.1
DenseNet169	86.4

Table 5 Evaluation metrics for each model

Model	Precision	Recall	F1-Score
EfficientNetV2B2	0.884	0.879	0.880
DenseNet169	0.862	0.858	0.859

The confusion matrix (Figure 3) reveals that EfficientNetV2B2 classified dominant classes such as Cassava Mosaic Disease (CMD) and Cassava Brown Streak Disease (CBSD), as well as healthy leaves, with accuracies of 91%. This performance highlights the effectiveness of CLAHE preprocessing, particularly in enhancing feature visibility in images with uneven illumination. However, classification errors persisted for the Cassava Green Mite (CGM) class, which was often misclassified as CBSD or CBB—likely due to visual similarities in disease symptoms.

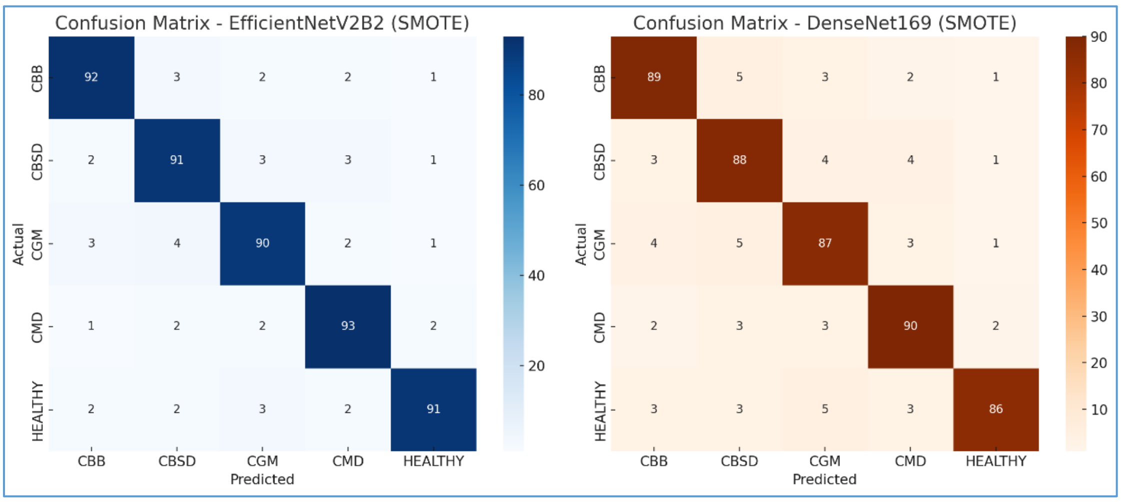

Figure 3 Visualization of the confusion matrix from the EfficientNetV2B2 and densenet169 models after SMOTE

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In contrast, DenseNet169 showed slightly lower accuracy, especially in identifying healthy leaves (86%), possibly due to its limited feature learning capacity under the constrained training schedule. Compared to [5], which reported accuracy above 93% using longer training durations (≥50 epochs) and advanced strategies such as focal loss and class weight adjustment, the results of this study were moderately lower.

Nevertheless, the findings are promising considering the limited computational resources and simplified training configurations. EfficientNetV2B2 demonstrated greater efficiency and performance stability, supporting its potential for lightweight and scalable deployment in real-world agricultural scenarios, especially for image-based early disease detection systems.

4.6 Ablation Study: The Effect of CLAHE

An ablation study was conducted to assess the contribution of the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique to the performance of cassava leaf disease classification models. Two convolutional neural network architectures, EfficientNetV2B2 and DenseNet169, were evaluated under two preprocessing conditions: with and without the application of CLAHE. To isolate the effect of CLAHE, all other variables—model architecture, class balancing via SMOTE, and training configurations including learning rate, batch size, and number of epochs—were held constant.

Table 6 demonstrated a consistent improvement in classification accuracy when CLAHE was employed. Specifically, EfficientNetV2B2 showed an increase in accuracy from 85.2% to 88.1%, while DenseNet169 improved from 83.9% to 86.4%. This 2–3% enhancement suggests that CLAHE effectively improves the local contrast of cassava leaf images, thereby facilitating more accurate extraction of discriminative features by the deep learning models. These benefits are particularly evident in images with uneven illumination or subtle texture variations.

The findings are consistent with those reported by the study [11], who concluded that CLAHE enhances the visibility of critical visual patterns in plant imagery and improves model robustness under suboptimal lighting conditions. Thus, integrating CLAHE into the preprocessing pipeline can be considered a beneficial strategy for improving deep learning performance in agricultural image classification tasks.

Table 6. Performance of models with and without CLAHE

Model	CLAHE	Accuracy (%)
EfficientNetV2B2	No	85.2
EfficientNetV2B2	Yes	88.1
DenseNet169	No	83.9
DenseNet169	Yes	86.4

4.7 Comparison with Previous Research

This study employed pretrained CNN architectures—EfficientNetV2B2 and DenseNet169—integrated with CLAHE and SMOTE, to classify cassava leaf diseases. To evaluate the effectiveness of this approach, the results were compared with those reported by Sambasivam and Opiyo [5], who developed a custom CNN architecture from scratch and implemented more advanced training strategies, including Focal Loss, class weight adjustments, and extended training durations of over 50 epochs.

As summarized in Table 7, Sambasivam and Opiyo achieved classification accuracies exceeding 93%, while this study reported maximum accuracies of 88.1% and 86.4% for EfficientNetV2B2 and DenseNet169, respectively. The performance gap can be attributed to several factors, notably the limited training duration (10 epochs) , and the absence of techniques such as Focal Loss, which are known to improve model sensitivity to underrepresented classes. While pretrained models offer advantages in terms of training efficiency and generalization, custom CNNs specifically designed for cassava leaf imagery may yield higher accuracy when fully optimized for the task.

The key novelty lies in the combination of CLAHE and SMOTE within a transfer learning framework using lightweight pretrained models, a strategy not explored in the comparative study. This approach was deliberately designed for efficiency, making it suitable for deployment on low-resource platforms such as mobile or edge devices. By leveraging pretrained models, this research

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demonstrates that effective classification can still be achieved without extensive training resources or model complexity.

Furthermore, the absence of transfer learning in previous works highlights a gap this study aims to address. Future research could explore hybrid solutions—merging the flexibility of custom architectures with the efficiency of pretrained backbones—for even better performance tailored to agricultural image datasets.

Table 7 Performance comparison with previous studies

Study	Model Architecture	Techniques Used	Accuracy (%)
Sambasivam & Opiyo (2021)	CNN from scratch	CLAHE, SMOTE, Focal Loss	>93.0
This study (EffNetV2B2)	Pretrained	CLAHE, SMOTE (no focal loss)	88.1
This study (DenseNet169)	Pretrained	CLAHE, SMOTE (no focal loss)	86.4

5 Conclusion

This study demonstrates that combining pretrained CNN models—EfficientNetV2B2 and DenseNet169—with CLAHE and SMOTE significantly improves cassava leaf disease classification accuracy. EfficientNetV2B2 achieved the highest performance (88.1%), supported by enhanced image contrast from CLAHE and balanced class representation from SMOTE. Although the results did not surpass the >93% accuracy reported in [5], the proposed lightweight approach proved effective under limited computational resources. However, limitations remain: the short training duration (10 epochs), absence of advanced loss functions (e.g., focal loss), and lack of validation using field-acquired images. Future research should address these aspects to enhance model robustness and generalizability. Despite constraints, this approach shows strong potential for real-world deployment in mobile and web-based precision agriculture applications.

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