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Enhancing Coffee Leaf Rust Detection with DenseNet201Plus and Transfer Learning

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Abstract

Coffee leaf rust (CLR) is a disease of coffee leaves caused by the fungus Hemileia Vastatrix, posing a major threat to global coffee production. Early and accurate detection is crucial for sustainable farming practices and disease management. This study proposes a novel deep learning approach that integrates DenseNet201Plus, an enhanced version of DenseNet201, with transfer learning to improve the accuracy and efficiency of CLR detection. DenseNet201Plus incorporates fine-tuned layers and optimized hyperparameters designed for plant disease classification, while transfer learning utilizes pre-trained weights from large-scale image datasets, enabling the model to adapt the characteristics of CLR images with limited training data. The model was evaluated on two datasets: the newly collected, high-quality Mbozi CLR dataset and the publicly available ImageNet CLR dataset, using accuracy, precision, recall, and F1-score. Results demonstrate that DenseNet201Plus achieved an accuracy of 99.0% on the Mbozi dataset, surpassing 97.78% obtained by the ImageNet Public dataset, with corresponding gains across all performance metrics. Results confirm that integration of DenseNet201Plus with transfer learning on the high-quality dataset significantly enhances CLR detection. The method outperformed several other baseline methods. The proposed approach offers a scalable, real-time detection solution for field deployment, supporting precision agriculture, enabling timely and targeted interventions.

Keywords: Coffee Leaf Rust, Transfer Learning, DenseNet201Plus, High-Quality Image, Precision Agriculture

1. INTRODUCTION

Coffee leaf rust (CLR) poses one of the most serious threats to global coffee production. The effectiveness of Artificial Intelligence (AI) driven diagnostic tools relies not only on advanced modeling methods but also on the quality of the dataset [1][2]. Poorly annotated, unbalanced, or low-resolution data can significantly reduce the ability of the model to generalize, leading to a reduction of diagnostic accuracy and an increase in incorrect predictions in real-world settings [3]. As a

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result, establishing a high-quality representation of well-curated datasets is essential in building robust models capable of ensuring timely and effective disease control practices[4]. Furthermore, although progress has been made in plant disease detection, CLR remains challenging due to its variable symptom expression, susceptibility to environmental conditions such as lighting and humidity, and the presence of similar visual patterns in other leaf diseases[5]. These factors make automated detection more complex and emphasize the need for an architecture capable of capturing fine-grained disease-specific features.

Traditional approaches for the diagnosis of CLR primarily focus on manual inspection for detecting CLR and have largely relied on manual inspection and chemical analysis, which results in subjectivity, cost, and time-consuming [6]. As human experts may miss or late detect subtle symptoms of infections, misdiagnosis of disease by using these methods may occur due to a delay in response and variations in appearance [7]. Decreasing the reliance on manual labor and lowering the risk of future spread, the great demand for significant automation of systems that can detect rust leaves correctly and quickly [8].

According to the author [9], deep learning has been seen as a breakthrough technology in the field of image processing, ranging from medical diagnostics to agriculture. [10] explained how transfer learning is used to reuse a model built for a particular task and reuse it as a starting point for another related task, which demonstrates good performance when few datasets are used. These methods adapt the learned features of a large dataset, such as ImageNet, and use them to build specialized tasks like detecting CLR. This technique leverages the learned features of large-scale datasets, which enhances diagnostic accuracy and model development [11].

This study introduces an adapter transfer learning approach built on the DenseNet201plus architecture, an improved version of DenseNet201. DenseNet201Plus utilizes the use of attention mechanisms and modules, and dense connectivity, in which subtle features of disease are detected on coffee leaves [12]. Compared to widely used architectures such as ResNet50 and VGG16, DenseNet201Plus offers superior feature reuse and stronger gradient flow [13]. The integration of attention modules enables precise localization of disease symptoms, even under challenging symptoms such as background noise and uneven lighting [14]. This makes it particularly well-suited for CLR detection as the symptom pattern may be small, irregular, or partially obscured.

However, this study relies on two distinct datasets: the Mbozi dataset with high-quality images and the diverse ImageNet public dataset. The Mbozi dataset was curated for CLR detection through a standardized field protocol, capturing high-resolution images under controlled lighting conditions to ensure consistent visual

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quality. This curation process minimizes background noise and enhances the visibility of disease features and making it special valuable for model training and in real-world applications [15].

The main objective of this study is to demonstrate that a high-quality dataset is a critical factor in achieving robust model performance in CLR diagnosis. By conducting a comparative analysis between the high-resolution Mbozi dataset and a diverse and broader public dataset, this study aims to give empirical evidence that the quality of the input dataset significantly affects the outcome of the model performance [2][16]. The results contribute to the development of more useful, reliable, and interpretable diagnostic systems, and they also guide image collection protocols that promote best practices in precision agriculture.

2. RELATED WORKS

Early efforts in plant disease detection using deep learning were pioneered by [17], who demonstrated the potential of transfer learning with well-known architectures such as AlexNet and GoogLeNet on standardized datasets like PlantVillage. Their work set high benchmarks for accuracy despite the limited scope of available training data, laying the foundation for subsequent research in plant pathology and automated image-based diagnostics [18]. These studies highlighted the scalability of deep neural networks in agricultural applications, inspiring numerous studies to adopt similar approaches.

Early accomplishments encourage researchers to experiment with various CNN architectures, such as VGG16, ResNet50, and InceptionV3, to address the issue of early disease detection in different plants [19]. The study conducted by [20], leveraging transfer learning to enhance performance and capture fine-grained disease features using images. The study also identifies limitations in addressing real-world variations in image quality and differing environmental conditions.

To address these challenges, attention mechanisms have been integrated into deep learning models to focus on disease-specific regions and mitigate issues related to illumination variation, occlusion, and complex backgrounds [16]. Modified CNNs with attention modules have shown improved accuracy in distinguishing between healthy and diseased leaves, particularly when symptoms are subtle [21] [17]. DenseNet-based architectures, in particular, have drawn interest for their dense connectivity pattern, which promotes feature reuse and efficient gradient flow[22]. While ResNet50 and VGG16 remain popular choices, DenseNet's ability to preserve and combine multi-scale features makes it especially suitable for tasks requiring high sensitivity to small, localized visual cues, an essential requirement for CLR detection.

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Despite these advancements, many prior works have relied on synthetic or low-quality public datasets, which often contain background noise, inconsistent resolution, and variable lighting conditions [18]. These limitations reduce model robustness and hinder deployment in real agricultural environments [20]. This gap underscores the need for high-quality, field-collected datasets that accurately represent real-world disease conditions[21].

This study addresses these issues by employing the DenseNet201Plus architecture, an enhanced version of DenseNet201 that incorporates attention modules for precise symptom localization, combined with a robust transfer learning framework [23]. It evaluates performance on two datasets: the Mbozi dataset, curated through standardized field protocols to ensure high-resolution, noise-free images, and a diverse public dataset. This dual-dataset evaluation not only validates the effectiveness of DenseNet201Plus but also provides empirical evidence that dataset quality is a decisive factor in achieving reliable, interpretable, and scalable CLR detection in precision agriculture [10][24]. The results of our study add value to the body of knowledge, underlining the importance of algorithms and dataset quality in advancing disease detection methods

3. METHODS

To efficiently identify CLR disease, the study follows the workflow shown in Figure 1. Notably, it utilizes the Mbozi dataset and a larger public dataset, which demonstrate that higher image quality significantly contributes to the development of trustworthy and robust models.

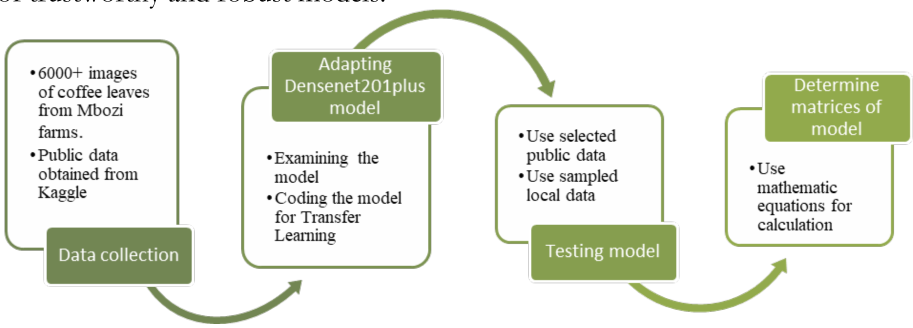

Figure 1. Methodology flow diagram

3.1 Data Collection

The newly collected Mbozi dataset contains high-resolution images captured directly from a variety of Mbozi coffee farms. These images were taken in controlled conditions that minimize motion blur, maintain consistent lighting, and provide detailed leaf textures as shown in Figure 2. Each image was inspected and annotated by experts to ensure labeling accuracy, and samples were balanced across

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healthy and rust-affected leaves to reduce bias. This dataset includes a variety of symptom stages, from early spots to severe infections, ensuring robust representation. By utilizing this curated dataset, results from this study demonstrated improved performance compared to models trained on publicly available datasets. The Mbozi dataset thus serves as the gold standard in our approach, underscoring the significance of high-quality, real-field data in practical agricultural applications.

Figure 2. Mbozi datasets samples of coffee leaves.

The public dataset, collected from multiple sources for CLR detection, provides greater diversity in geographical and environmental conditions. However, image quality varies, with some samples exhibiting low resolution, inconsistent lighting, and distracting backgrounds. The comparison between these two datasets highlights the role of image quality in model performance.

3.2 Data Preprocessing and Augmentation

Both datasets undergo rigorous preprocessing and augmentation steps to ensure compatibility with DenseNet201Plus. All images were resized to 224 × 224 pixels to match the input dimensions of the model, and pixel values were normalized to the range of 0- 1 to enhance training stability. Data augmentation was applied to both datasets, although with slightly different intensities: (1) Mbozi dataset: Rotations ±20°, horizontal/vertical flips, and minor zoom adjustments were applied to preserve fine texture details while increasing sample variability. (2) Public dataset: In addition to the above, more aggressive zoom up to 20% and shearing were used to simulate diverse real-world capture conditions and compensate for lower baseline quality. Augmentation mimics real-world conditions, allowing the model to generalize beyond Mbozi scenarios. Table 1 presents the distribution of images across classes in each dataset.

Table 1. Class distribution in each dataset

Class distribution	Mbozi Dataset	Public Dataset
Training	4208	3778
Validation	902	810
Test	904	812

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3.3 DenseNet201Plus Model Architecture

The DenseNet201Plus model in Figure 3 is a modified version of DenseNet201, where each layer in which each layer receives feature maps from all preceding layers, as expressed in Equation (1).

$$x_i = C_i([C_0, C_1 \ldots\ldots\ldots\ldots C_{i-1}]) \quad (1)$$

Where:
x_i is the output of the i^{th} transfer learning layer
C_i is a Combined function of Batch Normalization, ReLU, and convolutions.
$C_0, C_1 \ldots \ldots \ldots \ldots C_{i-1}$ are concatenated features from the preceding layers 0 to i-1

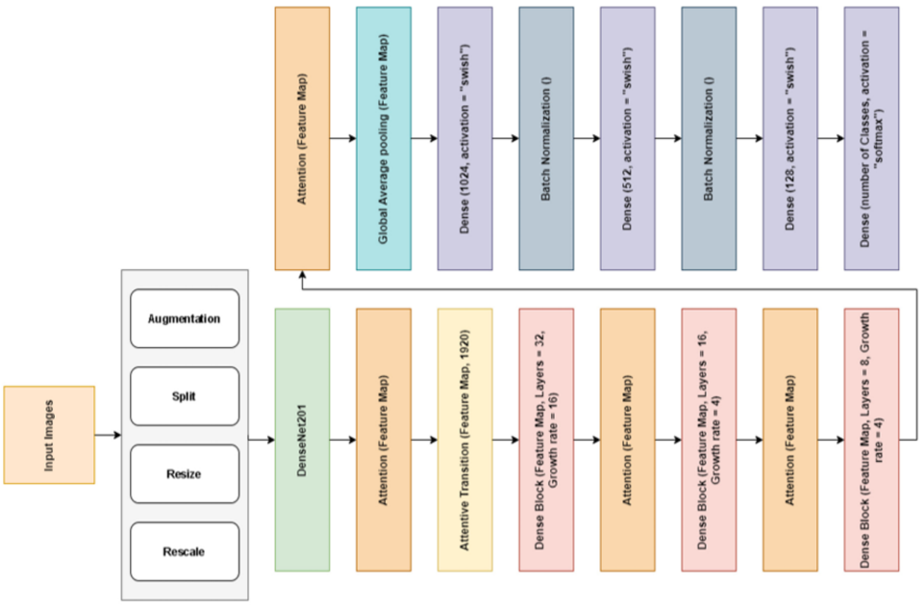

Figure 3. DenseNet201Plus architecture [12].

Key enhancements over the original DenseNet201 include: An additional CNN block with a 3×3 filter and dropout to prevent overfitting the model. Fully connected layers (1024, 512, 256, 128 units) with batch normalization. Global average pooling followed by an attention-weighted dense layer to focus on the infected region dynamically. The SoftMax layer in the final classification is used to distinguish between rust-affected and healthy leaves, as shown in equation 2

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$$z = w^T f + b$$
$$\hat{y} = SoftMax(z) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (2)$$

Where:
w is the weight matrix
b is a bias term
f represents the final feature representative
$\hat{y}$ represents the probability distribution over classes

3.4 Transfer Learning Technique

DenseNet201Plus was initialized using pre-trained weights from ImageNet, as shown in Figure 4. The first convolutional layers were frozen to preserve low-level feature extraction, while the deeper layers were fine-tuned on CLR datasets.

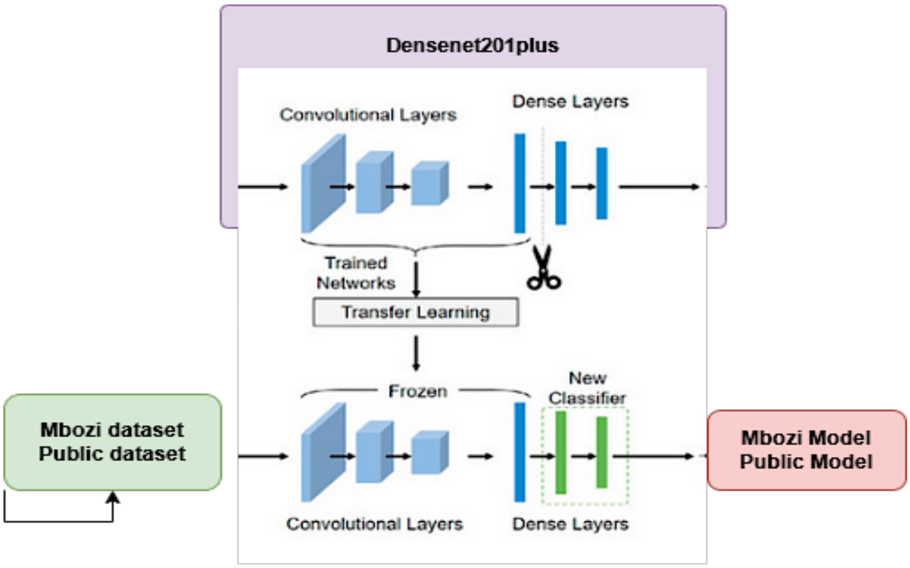

Figure 4. Transfer learning workflow

Categorical cross-entropy was used as a loss function, as shown in equation 3, for its effectiveness in multi-class and binary classification problems, providing stable optimization when classes are balanced. This choice was made over alternatives such as focal loss because both datasets have relatively balanced class distributions. The primary challenge lies in capturing subtle visual differences rather than correcting severe imbalances.

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$$L=\sum_{I=1}^{N}\sum_{c=1}^{C} y_{ic} \log(\hat{y}_{ic}) \quad (3)$$

Where:
N is the number of samples
C is the number of classes
y_{ic} is the actual label (1 if sample i belongs to class c, otherwise 0)
$\hat{y}_{ic}$ is the predicted probability for class c of sample i

3.5 Experimental Setup

3.5.1 Dataset

The Mbozi dataset includes two balanced classes, healthy and rust-affected leaves, captured in varying growth stages and controlled environmental conditions. High-resolution images ensure detailed leaf texture visibility. The Public dataset from Kaggle includes a more diverse environment, but with inconsistent image quality.

3.5.2 Model Training

Hyperparameters were selected through empirical testing on the validation set. the Adam optimizer with a learning rate of 1×10^{-4} was chosen for its fast convergence and ability to handle sparse gradients. A batch size of 32 was chosen to balance GPU memory efficiency with gradient stability. Training ran for 50 epochs, with early stopping to prevent overfitting. The summary of the model training approaches is depicted in Table 2.

Table 2. Summary of Training Procedure

Parameter	Value / Description
Optimizer	Adam
Initial Learning Rate	1×10^{-4}
Batch Size	32
Early Stopping	Enabled (used to prevent overfitting)
Loss Function	Categorical Cross-Entropy
Epochs	50

3.5.3 Model Evaluation

The model was evaluated using accuracy, precision, recall, and F1-score evaluation metrics. Accuracy assesses the overall model correctness, determining the correct

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prediction proportion as expressed in equation 4. The F1-score measures the harmonic mean of precision and recall, hence providing a balanced metric that is very important when using datasets that are not balanced. These metrics provide deep information about model categorization performance, emphasizing limitations in the real-world environment and the strength of the model.

$$Accuracy=\frac{TP+TN}{TP+FP+TN+FN} \quad (4)$$

Precision assesses the ability of the model to identify only true positive meaningful cases while reducing false positive cases. TP stands for true positive, FP for false positive, and FN for false negative. Equation (5) defines Precision, which is the positive value that combines specificity and accuracy of the model performance.

$$Precision=\frac{TP}{TP+FP} \quad (5)$$

Recall or sensitivity in equation 6 was used to calculate the ability of the model to detect all true positive instances and reduce false negatives. The Recall, also known as the likelihood of detection, was calculated by dividing the number of correctly identified positive outcomes by the total number of positive outcomes, as expressed in Equation 6. TP stands for true positive, FP for false positive, and FN for false negative.

$$Recall=\frac{TP}{TP+FN} \quad (6)$$

The F1-score in equation 7 indicates the misclassification of all positive samples from the model performance. In contrast, the most excellent score of the model was achieved when there were no false negatives (FN) or false positives (FP), which indicates that the categorization was great.

$$F1\text{-}score=\frac{2 \times TP}{2 \times TP+FP+FN} \quad (7)$$

4. RESULTS AND DISCUSSION

4.1. Performance Evaluation

The model achieves significant results when comparing the newly collected Mbozi and Public datasets. The Mbozi dataset demonstrates a higher precision of approximately 99.33% and an overall accuracy of around 99.0%, as shown in Figure 5, indicating its ability to accurately detect healthy and diseased leaves with minimal false positives. In contrast, the model trained on the public dataset shows

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slightly lower precision at about 96.63%, but slightly higher recall of 99.01%. this reflects an increased sensitivity to identifying rust infections with more false alarms. Both models attained high F1 scores of 99.00% for Mbozi and 97.79% for the Public dataset, making them suitable for a variety of deployment scenarios.

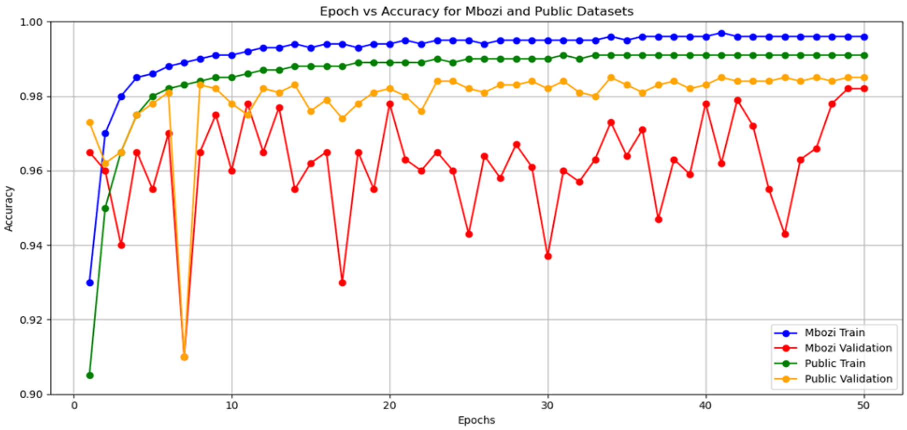

Figure 5. Accuracy on all datasets.

The confusion matrices in Figure 6 further confirm that the Mbozi-trained model made fewer false positives and false-negative errors, supporting the conclusion that dataset quality plays an important role in enhancing classification robustness. This goes with our preprocessing strategy, where Mbozi images underwent normalization, resizing to 224×224 pixels, and carefully controlled argumentation to simulate realistic field variability without degrading image clarity. The Public dataset underwent similar augmentation, though lower baseline image quality limited its benefit.

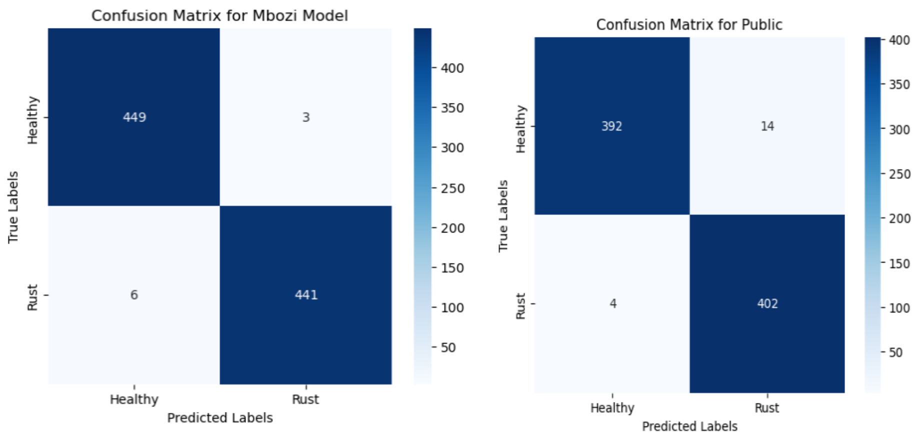

Figure 6. Confusion Matrices.

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The performance metrics in Table 3 reinforce the advantage of the Mbozi dataset with consistently higher accuracy and precision even under similar hyperparameter settings. The selection of categorical cross-entropy loss for final layers was deliberate, as it is well-suited for a two-class problem and ensures stable gradient behavior during fine-tuning. Hyperparameters such as the learning rate of $1{\times}10^{-4}$, batch size of 32, and 50 training epochs were determined using grid search, balancing convergence speed and preventing overfitting.

Table 3. Performance metrics for CLR detection across the datasets

	Metrics				
Dataset	**Accuracy**	**Test Accuracy**	**Precision**	**Recall**	**F1-score**
Mbozi	99.00	98.34	99.33	98.67	99.00
Public	97.78	98.52	96.63	99.01	97.79

The training loss curve in Figure 7 indicates that the Mbozi-trained model converged faster and reached a lower minimum loss than the Public dataset, showing that high-quality images enable more efficient learning.

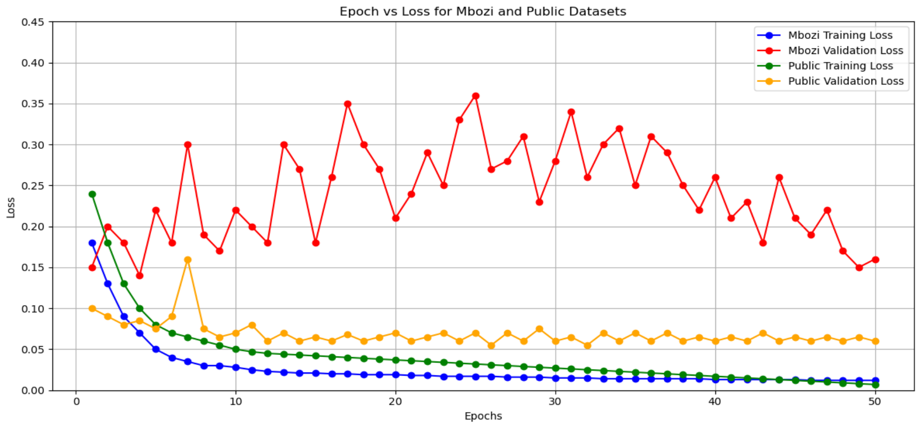

Figure 7. Loss graph on all datasets.

4.2. Discussion

The comparative analysis presented in Table 4 and Figure 8 underscores the superior performance of DenseNet201Plus, which achieved the highest classification accuracy of 99.0%, outperforming all state-of-the-art models including CNN (98.89%), SUNet (98.45%), CoffNet (98.0%), and even its baseline variant DenseNet201 (98.72%). This notable improvement is attributed to the synergy between three critical factors: enhanced architectural design, strategic use of transfer learning, and the use of the high-quality, domain-specific Mbozi dataset.

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Unlike traditional approaches that often emphasize model complexity alone, this study illustrates that data quality plays an equally pivotal role in achieving high-performance outcomes. The Mbozi dataset, collected under a rigorously controlled image acquisition process—including consistent lighting, diverse disease stages, and real-world leaf conditions—has proven crucial in enabling the model to generalize effectively and minimize misclassifications. This is evident in the remarkably low false positive and false negative rates shown in Figure 6, and the faster convergence behavior visualized in Figure 7.

In real-world applications such as precision agriculture, these findings are particularly impactful. Models trained on noisy or inconsistent public datasets, while still performing respectably, tend to exhibit slightly reduced precision and greater variability in learning curves. The Mbozi dataset not only led to faster convergence (Figure 7) and higher precision (99.33%) but also allowed DenseNet201Plus to maintain a high F1-score of 99.0, indicating both high sensitivity and specificity.

Moreover, the deliberate selection of categorical cross-entropy loss, optimized hyperparameters (learning rate = 1×10^{-4}, batch size = 32, 50 epochs), and targeted data augmentation strategies all contributed to a robust and reliable model that's deployable in real-time scenarios. In summary, this study does not merely introduce a novel architecture but offers compelling evidence that the intersection of model design and dataset integrity is fundamental to advancing the field of plant disease detection. The DenseNet201Plus model, when paired with a curated dataset like Mbozi, sets a new benchmark for accurate, efficient, and field-deployable crop disease diagnosis systems.

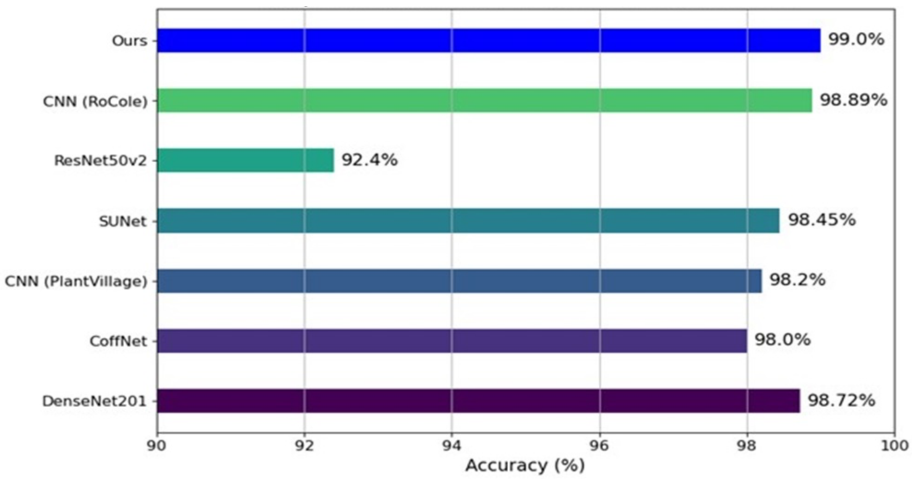

Figure 8. Comparison of accuracies with state-of-the-art models

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Table 4. Model Architecture and Dataset Quality Comparison for Classification Accuracy.

References	Model/Architecture	Dataset used	Accuracy%
[15]	Densenet201	Mbozi/Ethiopian	98.72
[1]	CoffNet	BRACOL	98
[8]	CNN	Plant Village	98.2
[24]	SUNet	JMuBEN/JMuBEN2	98.45
[25]	ResNet50v2	-	92.4
[26]	CNN	RoCole	98.89
Our Study	Densenet201Plus	Mbozi	99.0

5. CONCLUSION

This study uses DenseNet201Plus, an enhanced deep learning architecture that integrates with transfer learning, to enable early and accurate detection of CLR. By leveraging high-quality, locally collected Mbozi dataset images and optimized training strategies, the model achieved 99.0% accuracy, surpassing multiple state-of-the-art architectures. The results underscore the critical role of dataset quality and advanced model design in building reliable agriculture AI tools. From a practical standpoint point these results encourage deploying DenseNet201Plus on mobile edge devices can enable real-time, in-field disease monitoring for farmers, even in remote regions. This approach can significantly improve early detection and enable faster interventions to protect yields and reduce fungicide use. However, the study performance was evaluated primarily on a controlled dataset, meaning environmental variability such as lighting changes, occluded leaves, and mixed infections may affect scalability. Future research should address these challenges by expanding training datasets to include diverse environmental and geographical conditions, as well as developing multiclass classification capabilities to detect multiple coffee diseases simultaneously. By integrating robust architectures, quality data, and an accessible deployment platform, this approach offers a scalable pathway for precision agriculture, empowering farmers worldwide with AI-driven early warning systems.

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