



Refining CNN-Based Models for Multi-Class Corn Leaf Disease Classification

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Abstract

Corn leaf disease significantly impacts agricultural productivity and national food security, particularly in regions with high dependence on maize as a staple commodity. Manual disease identification remains challenging due to the need for expert agronomists, inconsistent environmental conditions, and visual similarities among disease patterns, often resulting in delayed decision-making and inaccurate control measures. Deep learning-based image classification has emerged as an effective solution for plant disease identification; however, existing models often face limitations regarding overfitting, poor generalization, and insufficient performance when applied to multi-class agricultural image datasets. Therefore, this research aims to develop an Improved EfficientNetB0 model for the multi-class classification of maize leaf diseases comprising Healthy, Leaf Blight, Leaf Rust, and Leaf Spot categories. A dataset of 4,000 images was used and processed through resizing, normalization, and augmentation techniques. Five CNN backbones; EfficientNetB0, MobileNetV2, ResNet50, DenseNet121, and InceptionV3—were initially evaluated, and EfficientNetB0 demonstrated the highest baseline performance. The model was subsequently enhanced through fine-tuning, regularization (dropout and batch normalization), and cosine learning rate scheduling. Experimental results show that the Improved EfficientNetB0 achieved superior performance with an accuracy of 0.9671, macro precision of 0.9665, macro recall of 0.9666, and macro F1-score of 0.9661, exceeding all baseline models. These findings demonstrate that the proposed framework effectively improves maize disease classification accuracy and contributes a robust solution for smart agriculture applications. Future work may integrate real-time deployment and mobile-based decision support for field-level monitoring.

Keywords: CNN; corn leaf disease; multi-class classification; deep learning; image classification

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1. Introduction

Corn (*Zea mays* L.) plays a central role in agricultural systems, contributing to food supply chains, livestock production, and industrial processing [1–5]. As the second most widely cultivated cereal crop after rice [6], corn serves as an essential resource for food consumption [7–9], livestock feed production [10], and bioethanol manufacturing [11]. The increasing global demand for corn has intensified efforts to improve agricultural productivity and support sustainable food supply systems [12–15]. In many developing countries, including Indonesia, corn is also considered a strategic crop that contributes to national food sovereignty programs and agricultural

development initiatives [16]. However, corn productivity is frequently threatened by biotic stress factors, particularly leaf diseases that significantly reduce crop yield and quality [17–19]. Among the most destructive foliar diseases are Leaf Blight, Leaf Rust, and Leaf Spot, which commonly infect corn plants during early growth stages and spread rapidly under favorable environmental conditions [20–24]. These diseases weaken photosynthesis, accelerate leaf senescence, and may cause major production losses if not detected early.

Therefore, early detection and accurate identification of corn leaf diseases are essential for improving crop protection strategies and maintaining agricultural

productivity. Conventional plant disease identification largely depends on manual observation performed by agricultural experts [25–27]. Although widely practiced, this approach has several limitations. Disease identification based on human observation is often subjective and depends heavily on the expertise and experience of the observer, which may lead to inconsistent diagnostic results [28–30]. In addition, prolonged visual examination can cause fatigue and reduce diagnostic accuracy, especially when large agricultural areas must be monitored. The problem becomes more complex because many plant diseases exhibit visually similar symptoms such as lesions, discoloration patterns, or leaf spots that are difficult to differentiate through human observation alone [31–33]. These limitations may delay disease identification and treatment decisions, allowing infections to spread further and reducing crop productivity. Consequently, the need for intelligent disease detection solutions continues to increase, offering fast, accurate, and scalable diagnostic support for farmers and agricultural practitioners [34–38].

Recent developments in computer vision, particularly deep learning, have enabled automated recognition of plant diseases using image-based analysis [39–41]. Convolutional Neural Networks (CNNs) have become the dominant approach for image-based plant disease classification because they can automatically learn hierarchical spatial features from raw image data without requiring manual feature engineering [42–46]. Compared with traditional machine learning approaches such as Support Vector Machines (SVM), Random Forest, or K-Nearest Neighbor (KNN), CNN architectures are capable of extracting complex visual patterns including texture variations, shape structures, and color distributions in plant leaf images, leading to improved classification performance. In addition, transfer learning has further enhanced CNN-based classification systems by enabling pretrained models to be adapted to specific agricultural datasets. Well-known architectures such as EfficientNet, MobileNet, DenseNet, ResNet, and Inception have demonstrated strong performance in plant disease classification tasks, particularly when training datasets are limited [47].

Building upon these developments, several studies have proposed architectural improvements to enhance maize leaf disease classification performance. ConvNeXt-based models enhanced with attention mechanisms and data augmentation techniques have achieved classification accuracy above 95% across multiple maize disease categories [48]. Other research introduced lightweight CNN architectures integrating long–short attention mechanisms and multi-scale feature fusion to improve efficiency and generalization, especially for deployment in resource-constrained environments [49]. More recent approaches have explored attention mechanisms combined with multi-level feature extraction to represent fine-grained spatial details alongside broader

contextual patterns in maize leaf images, resulting in improved performance metrics such as accuracy, precision, recall, and F1-score [50]. Additionally, several studies incorporated Explainable Artificial Intelligence (XAI) techniques such as LIME and SHAP to increase model transparency by highlighting disease-relevant regions in leaf images [51]. Mobile-based implementations using pretrained architectures such as VGG, ResNet, and AlexNet have also demonstrated the feasibility of real-time corn leaf disease detection systems integrated with mobile platforms [52].

Despite recent advancements, several limitations persist in corn leaf disease classification research. Many studies focus on improving a single CNN architecture without systematic comparisons across backbone models under consistent experimental settings. As a result, the relative effectiveness of different CNN architectures for multi-class classification remains unclear. Furthermore, optimization strategies such as progressive fine-tuning, dropout regularization, enhanced data augmentation, and adaptive learning rate scheduling are often not uniformly applied or thoroughly investigated. Although high accuracy has been reported, evaluation procedures are often limited and lack comprehensive analysis using metrics such as confusion matrices and class-wise performance assessment. To address these gaps, this study benchmarks five widely used CNN architectures (EfficientNetB0, MobileNetV2, ResNet50, DenseNet121, and InceptionV3) under consistent conditions to identify the most effective baseline model.

The selected model is refined through progressive fine-tuning, batch normalization, dropout, enhanced augmentation, and adaptive learning rate scheduling. Its performance is then assessed using multiple classification metrics. This framework provides systematic benchmarking and an improved EfficientNetB0 model with enhanced accuracy and robustness for multi-class corn leaf disease classification.

2. Methods

This research adopts a structured experimental framework to develop and assess a model for multi-class classification based on deep learning techniques. The workflow consists of four main stages: data acquisition, preprocessing, model development, and evaluation. This design enables consistent evaluation and supports reliable comparison across different models.

2.1 Research Framework

The research workflow diagram illustrates the process from dataset acquisition to final model evaluation, highlighting the comparison of baseline models and the subsequent refinement strategy to improve performance.

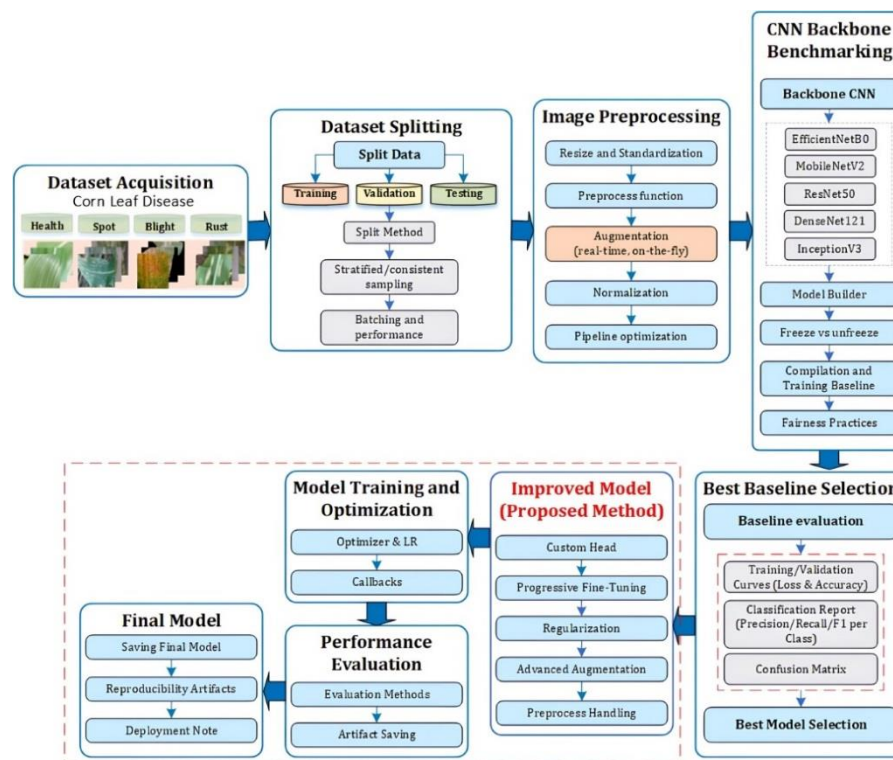


Figure 1. Research Framework

As shown in Figure 1, the research process covers all stages from data collection to final evaluation and deployment. The data are organized into training, validation, and testing groups with balanced class representation. In the preprocessing stage, images undergo resizing, normalization, and augmentation (e.g., rotation, zooming, and flipping) to improve generalization and reduce overfitting. Subsequently, five CNN architectures (EfficientNetB0, MobileNetV2, ResNet50, DenseNet121, and InceptionV3) are trained and evaluated under consistent settings to enable fair comparison.

Using multiple performance measures, including accuracy, precision, recall, F1-score, and confusion matrix analysis, EfficientNetB0 is selected as the best baseline model. It is then refined using augmentation, progressive fine-tuning, batch normalization, additional dense layers, dropout optimization, and learning-rate scheduling. The refined model is evaluated using training curves, classification reports, confusion matrices, and ROC curves. The final stage involves saving the best model and preparing it for potential deployment in intelligent agricultural disease-monitoring systems.

2.2 Dataset

A publicly available corn leaf disease dataset from Kaggle (ndisan) is employed in this study, comprising four classes: Healthy, Leaf Blight, Leaf Rust, and Leaf Spot. In total, the dataset includes 4000 RGB images collected under diverse environmental conditions, such as variations in illumination, leaf positioning, background noise, and partial occlusions. For

evaluation purposes, the data are divided into three subsets: 70% for training, 15% for validation, and 15% for testing, with class proportions maintained across each subset.

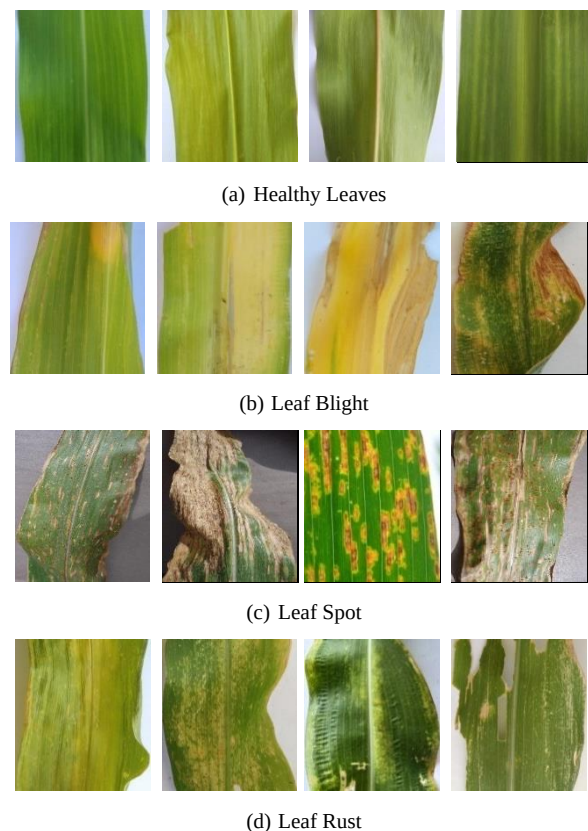


Figure 2. Corn Leaf Disease Dataset Sample (a) Healthy Leaves, (b) Leaf Blight, (c) Leaf Spot, and (d) Leaf Rust

Figure 2 presents representative samples of the corn leaf disease dataset used in this study, illustrating four categories: Healthy, Leaf Blight, Leaf Spot, and Leaf Rust. Each class exhibits distinct visual characteristics, such as uniform green texture in healthy leaves, elongated necrotic lesions in Leaf Blight, scattered circular spots in Leaf Spot, and rust-colored pustules in Leaf Rust. These variations highlight the complexity of multi-class classification, especially when certain symptoms share similar color patterns or textures, making accurate discrimination challenging for both manual observation and automated models.

2.3. Proposed Refinement

Figure 3 illustrates the proposed refinement strategy designed to improve the performance of the EfficientNetB0 baseline model. The framework highlights architectural modifications, optimization strategies, and fine-tuning mechanisms to enhance feature representation and classification accuracy for multi-class corn leaf disease detection. The process begins with an ImageNet-pretrained EfficientNetB0 backbone, which is initially frozen to preserve general

visual features. The resulting feature maps are then processed using a Global Average Pooling layer to reduce dimensionality while retaining essential spatial information.

Beyond architectural improvements, the refinement incorporates several training strategies: progressive fine-tuning by selectively unfreezing deeper layers of the backbone, ReduceLROnPlateau scheduling to dynamically adjust learning rate, the Adam optimizer for stable gradient updates, and Early Stopping to retain the best model while avoiding unnecessary training epochs. The hyperparameter configuration used in the EfficientNetB0 refinement is guided by empirical practices reported in previous deep learning studies. The Dense layer with 256 neurons is employed to enrich high-level feature representations while maintaining computational efficiency. Batch normalization is introduced to stabilize the training process and accelerate convergence. Two Dropout layers with rates of 0.4 and 0.3 are applied to reduce overfitting, which are commonly used regularization strategies in CNN-based image classification models [47], [53].

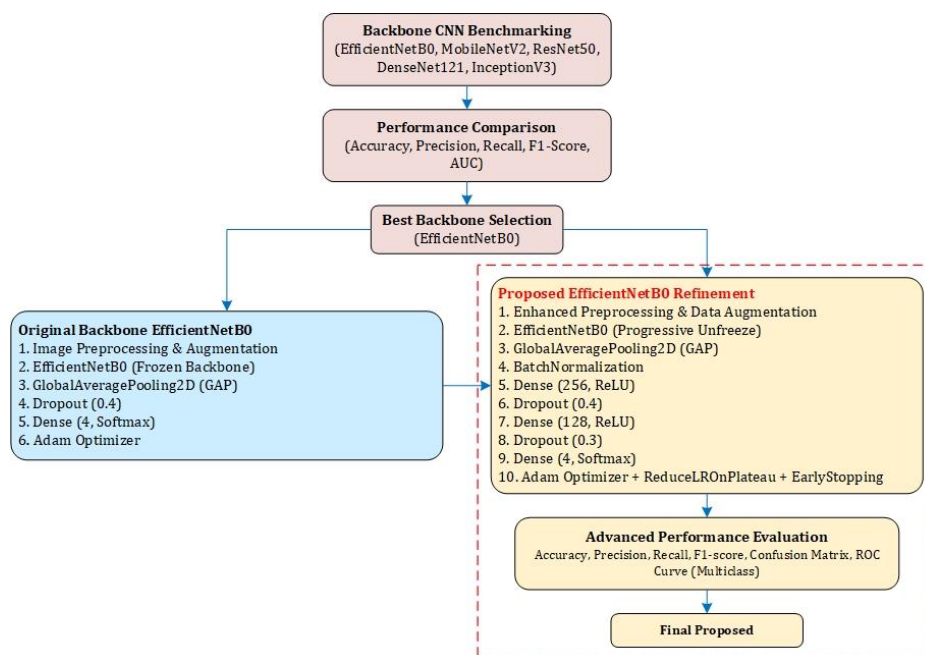


Figure 3. Proposed Refinement

In addition, the ReduceLROnPlateau scheduler is used to dynamically adjust the learning rate during training, while the Adam optimizer is widely adopted for adaptive gradient optimization in transfer learning models. Similar optimization strategies have been reported in CNN-based plant disease classification studies.

Through the combination of architectural enhancements, regularization mechanisms, and adaptive optimization, the proposed refinement method significantly improves generalization capability and classification performance compared to the baseline EfficientNetB0 model.

2.4 Evaluation

In this study, the performance of the classification model is evaluated using four widely adopted metrics: accuracy, precision, recall, and F-score [53]. Accuracy measures the proportion of correctly classified samples, providing an overall performance indicator. Precision evaluates the reliability of positive predictions, indicating how many predicted positives are truly correct. Recall measures the model's ability to detect actual positive cases, reflecting its sensitivity. The F-score, derived from precision and recall, provides a balanced evaluation for datasets with uneven class distribution.

3. Results and Discussions

To evaluate the proposed refinement strategy, experiments were conducted using five CNN backbones and an improved EfficientNetB0 model. The results are presented systematically to compare baseline and refined models across metrics such as loss, accuracy, confusion matrices, classification performance, and ROC curves. Visual outputs are discussed to reflect model behavior, with the analysis organized into four subsections highlighting key differences.

3.1 Training Loss and Accuracy Analysis

This subsection analyzes model training behavior using loss and accuracy curves (Figure 4a–4f) to assess learning stability, generalization, and overfitting. All models show decreasing loss and increasing accuracy over epochs, while differences in their learning patterns form the basis for selecting EfficientNetB0 as the best baseline model. EfficientNetB0 shows the most stable and consistent learning pattern among all backbones, leading to its selection as the baseline model for refinement.

Compared to other architectures, it exhibits more stable convergence and a smaller gap between training and validation accuracy, indicating better generalization.

Therefore, the refinement focuses on optimizing EfficientNetB0 to further improve classification performance. The training and validation loss curves decrease smoothly with minimal divergence, indicating low overfitting. The model achieves validation accuracy in the range of 92–94%, with a small gap between training and validation accuracy. This stability confirms EfficientNetB0 as the most reliable backbone and justifies its selection as the baseline for refinement (Figure 4.a).

MobileNetV2 shows fast convergence in early epochs, but its validation accuracy curve is more fluctuating than EfficientNetB0's. A slight gap between training and validation accuracy emerges midway through training, suggesting mild underfitting. While MobileNetV2 remains efficient in computation, its performance is inferior to EfficientNetB0, making it less suitable as the refinement baseline (Figure 4.b).

ResNet50 achieves steadily increasing training accuracy but exhibits higher validation loss that does not decline as smoothly as expected. This behavior suggests a tendency toward mild overfitting, likely due to its deeper architecture. Although powerful, ResNet50's stability is weaker than EfficientNetB0, reducing its suitability for further refinement (Figure 4.c).

DenseNet121 shows good early-stage convergence, but the curves start to fluctuate in the middle of training, likely influenced by its dense connectivity pattern and heavy parameterization. The validation

accuracy remains lower compared to other models, indicating underfitting or insufficient adaptation to the dataset's characteristics. Its inconsistent behavior makes it a weaker candidate relative to EfficientNetB0 (Figure 4.d).

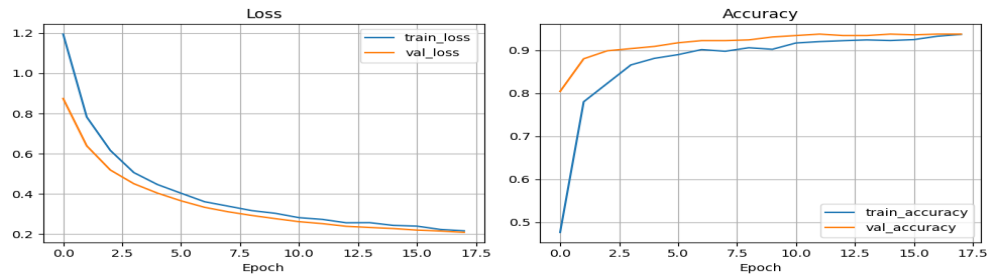
InceptionV3 records relatively high training accuracy but with significant oscillations in validation loss. These fluctuations are a strong indicator of overfitting, especially since InceptionV3 typically requires larger datasets for stable convergence. The gap between training and validation accuracy further strengthens this indication (Figure 4.e).

The refined model shows the best convergence profile, with training and validation loss curves closely aligned, indicating strong generalization. It achieves a validation accuracy of 96.7%, outperforming all backbone models. This improvement stems from the refinement strategy, including enhanced preprocessing and augmentation, progressive layer unfreezing, batch normalization, dual dropout, ReduceLROnPlateau scheduling, and EarlyStopping, which collectively stabilize training, reduce overfitting, and improve final accuracy (Figure 4f).

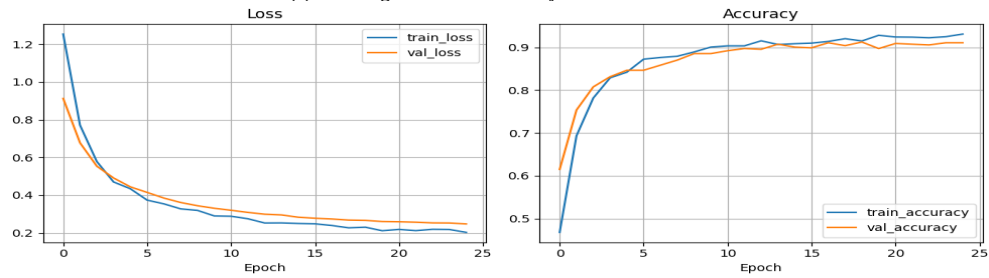
Analysis of all six figures shows that EfficientNetB0 provides the most balanced and stable backbone performance, while the proposed refinement achieves the highest accuracy with the most stable loss curve. These findings demonstrate that the refinement strategy effectively boosts baseline performance and improves generalization to unseen corn leaf disease images.

3.2 Discussions

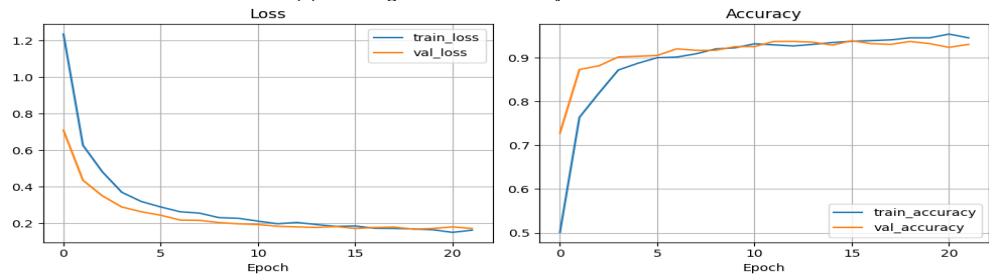
This subsection evaluates five CNN backbone models (VGG16, MobileNetV2, DenseNet121, InceptionV3, and EfficientNetB0) using confusion matrices, classification reports, and ROC curves to assess their multiclass classification performance and identify the most reliable baseline architecture. The analysis also includes the Proposed EfficientNetB0 Refinement as an enhanced version of the baseline model. The visualizations include Figures 4a–4e (Confusion Matrices), Figures 5a–5e (Classification Reports), and Figures 6a–6e (ROC Curves), while Figures 4f, 5f, and 6f present the refined model. The EfficientNetB0 confusion matrix shows strong diagonal values, indicating accurate classification for most classes. However, some misclassifications occur among visually similar categories, suggesting that while overall performance is stable, sensitivity to subtle feature differences remains limited (Figure 5a). The MobileNetV2 confusion matrix shows moderate classification performance, with correct predictions for several classes but noticeable misclassifications across visually similar categories. This indicates that although MobileNetV2 is computationally efficient, its lightweight architecture struggles to capture fine-grained discriminative features needed for accurate corn leaf disease classification (Figure 5b).



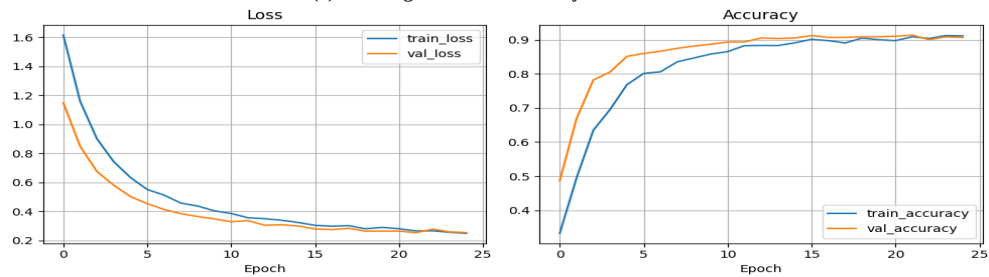
(a) Training Loss and Accuracy – EfficientNetB0



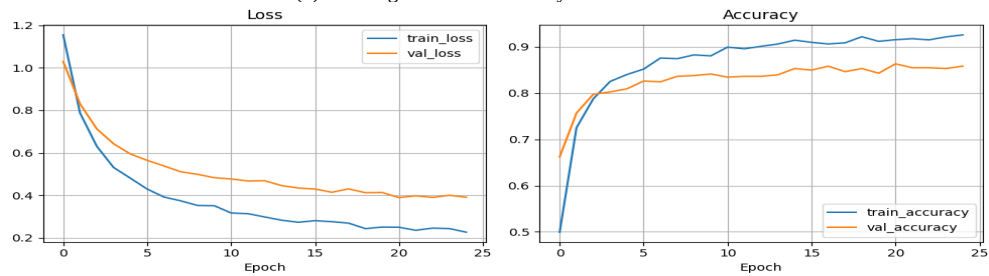
(b) Training Loss and Accuracy – MobileNetV2



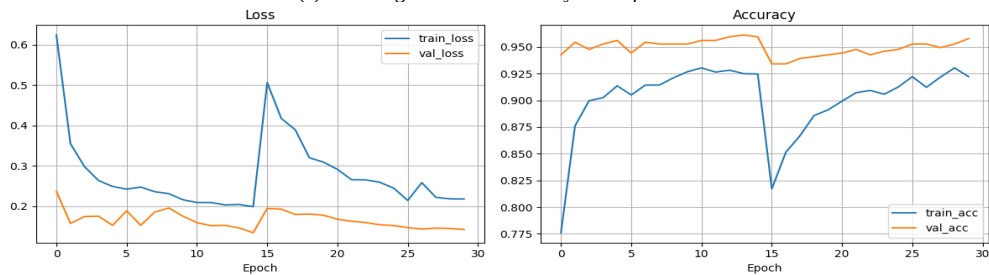
(c) Training Loss and Accuracy – ResNet50



(d) Training Loss and Accuracy – DenseNet121



(e) Training Loss and Accuracy – InceptionV3



(f) Training Loss and Accuracy – Proposed EfficientNetB0 Refinement

Figure 4. Comparison of Training Loss and Accuracy – (a) EfficientNetB0, (b) MobileNetV2, (c) ResNet50, (d) DenseNet121, (e) InceptionV3, (f) Proposed EfficientNetB0 Refinement

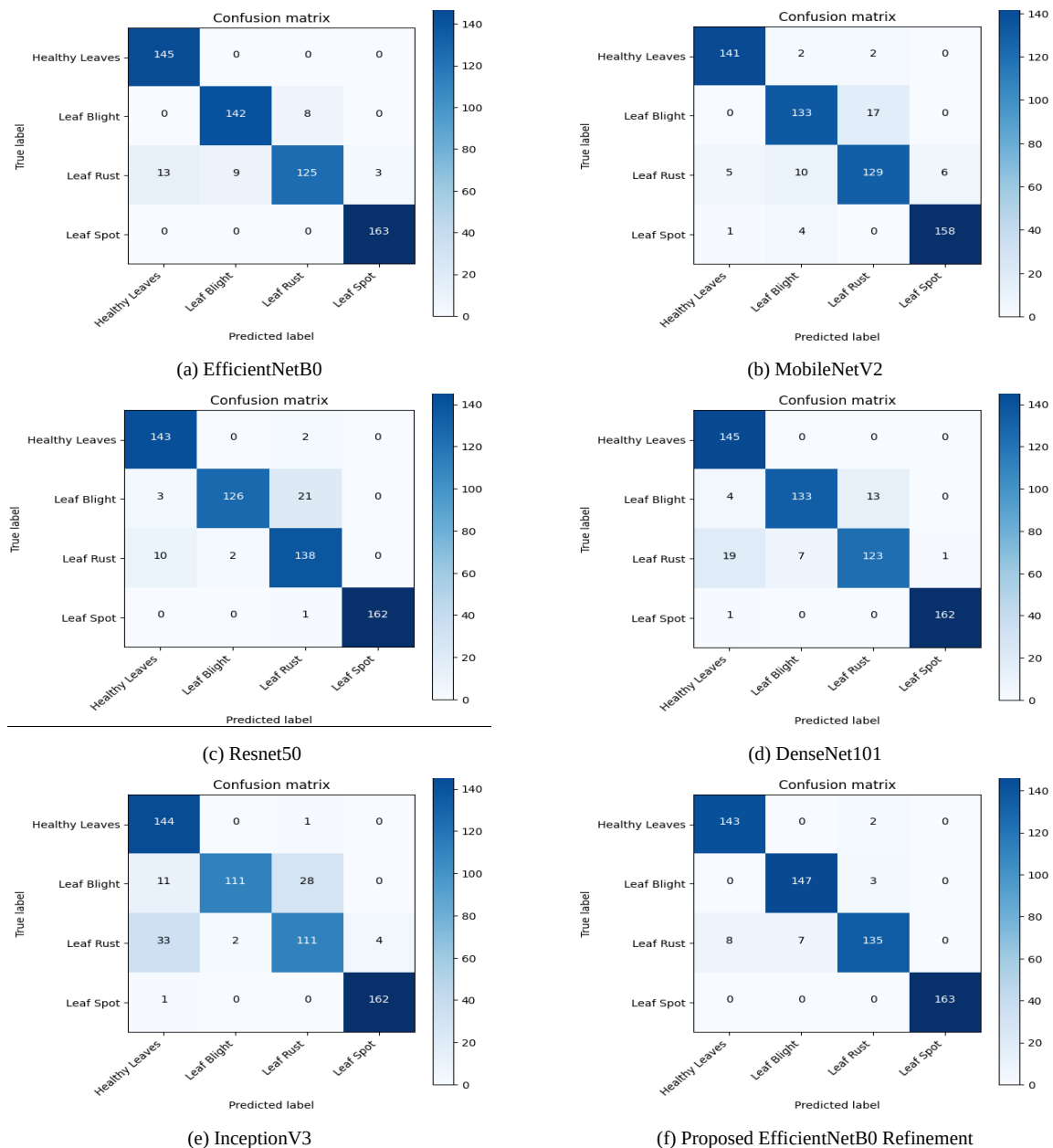


Figure 5. Comparison of Confusion Matrix – (a) EfficientNetB0, (b) MobileNetV2, (c) ResNet50, (d) DenseNet121, (e) InceptionV3, (f) Proposed EfficientNetB0 Refinement

The ResNet50 confusion matrix shows strong performance with many correct predictions along the diagonal. However, some misclassifications persist among classes with subtle texture similarities, indicating that although residual connections capture deeper features, the model still struggles to fully distinguish closely related disease categories (Figure 5c).

The DenseNet121 confusion matrix shows strong feature discrimination with consistent correct predictions along the diagonal. However, some misclassifications persist among visually similar classes, indicating that although DenseNet121 effectively reuses features, it still struggles to capture fine-grained differences (Figure 5d).

The confusion matrix of InceptionV3 indicates that the majority of samples are classified correctly, although some errors remain, particularly between diseases with similar visual characteristics. Despite capturing features at multiple receptive fields, the model still struggles with subtle symptom differences (Figure 5e).

The Proposed EfficientNetB0 Refinement confusion matrix shows the most accurate and consistent predictions, with a strong diagonal indicating minimal misclassification. The refinement enhances feature sensitivity, improving differentiation between subtly similar diseases. Only minor errors remain, demonstrating improved class separability and robustness in multi-class corn leaf disease classification (Figure 5f).

To extend the confusion matrix analysis, the following subsection presents the classification reports of all six models, offering clearer insight into their precision,

recall, and F1-score performance across the four disease classes.

Classification Report:				
	precision	recall	f1-score	support
Healthy Leaves	0.9177	1.0000	0.9571	145
Leaf Blight	0.9404	0.9467	0.9435	150
Leaf Rust	0.9398	0.8333	0.8834	150
Leaf Spot	0.9819	1.0000	0.9909	163
accuracy			0.9457	608
macro avg	0.9450	0.9450	0.9437	608
weighted avg	0.9460	0.9457	0.9446	608

(a) Classification Report EfficientNetB0

Classification Report:				
	precision	recall	f1-score	support
Healthy Leaves	0.9592	0.9724	0.9658	145
Leaf Blight	0.8926	0.8867	0.8896	150
Leaf Rust	0.8716	0.8600	0.8658	150
Leaf Spot	0.9634	0.9693	0.9664	163
accuracy			0.9227	608
macro avg	0.9217	0.9221	0.9219	608
weighted avg	0.9223	0.9227	0.9225	608

(b) Classification Report MobileNetV2

Classification Report:				
	precision	recall	f1-score	support
Healthy Leaves	0.9167	0.9862	0.9502	145
Leaf Blight	0.9844	0.8400	0.9065	150
Leaf Rust	0.8519	0.9200	0.8846	150
Leaf Spot	1.0000	0.9939	0.9969	163
accuracy			0.9359	608
macro avg	0.9382	0.9350	0.9345	608
weighted avg	0.9397	0.9359	0.9358	608

(c) Classification Report ResNet50

Classification Report:				
	precision	recall	f1-score	support
Healthy Leaves	0.8580	1.0000	0.9236	145
Leaf Blight	0.9500	0.8867	0.9172	150
Leaf Rust	0.9044	0.8200	0.8601	150
Leaf Spot	0.9939	0.9939	0.9939	163
accuracy			0.9260	608
macro avg	0.9266	0.9251	0.9237	608
weighted avg	0.9286	0.9260	0.9252	608

(d) Classification Report DenseNet121

Classification Report:				
	precision	recall	f1-score	support
Healthy Leaves	0.7619	0.9931	0.8623	145
Leaf Blight	0.9823	0.7400	0.8441	150
Leaf Rust	0.7929	0.7400	0.7655	150
Leaf Spot	0.9759	0.9939	0.9848	163
accuracy			0.8684	608
macro avg	0.8782	0.8667	0.8642	608
weighted avg	0.8813	0.8684	0.8668	608

(e) Classification Report InceptionV3

Classification Report:				
	precision	recall	f1-score	support
Healthy Leaves	0.9470	0.9862	0.9662	145
Leaf Blight	0.9545	0.9800	0.9671	150
Leaf Rust	0.9643	0.9000	0.9310	150
Leaf Spot	1.0000	1.0000	1.0000	163
accuracy			0.9671	608
macro avg	0.9665	0.9666	0.9661	608
weighted avg	0.9673	0.9671	0.9668	608

(f) Classification Report Proposed Refinement

Figure 6. Comparison of Classification Report (a) EfficientNetB0, (b) MobileNetV2, (c) ResNet50, (d) DenseNet121, (e) InceptionV3, (f) Proposed EfficientNetB0 Refinement

EfficientNetB0 demonstrates strong and balanced performance across all classes. Precision ranges from 0.9177 to 0.9819, while recall varies between 0.8333 and 1.0000. The model performs exceptionally well on Healthy Leaves and Leaf Spot, both reaching 100% recall, reflecting perfect sensitivity for these categories. The lowest recall occurs in Leaf Rust (0.8333), indicating occasional misclassification with visually similar diseases. The macro-average F1-score of 0.9437 and overall accuracy of 0.9457 confirm EfficientNetB0 as the most reliable baseline among the evaluated backbones (Figure 6.a). MobileNetV2 shows moderately strong performance, with precision ranging from 0.8716 to 0.9640 and recall from 0.8600 to 0.9724. The lowest recall occurs in Leaf Rust (0.8600), indicating difficulty in distinguishing its features. Although F1-scores are acceptable (0.8658–

0.9664), they remain below EfficientNetB0. The macro-average F1-score (0.9219) and accuracy (0.9227) reflect its limitations in handling fine-grained disease differences (Figure 6b). ResNet50 records solid precision values (from 0.8519 to 1.0000) and relatively stable recall, although Leaf Blight shows a noticeable decline (0.8400). F1-scores fall in the range of 0.9065 to 0.9969, indicating strong performance overall but with decreased sensitivity for blight lesions. The macro-average F1-score of 0.9350 and accuracy of 0.9359 position ResNet50 as a competitive but slightly less stable model compared to EfficientNetB0 (Figure 6.c). DenseNet121 displays good precision (0.8580–0.9939) and high recall for Healthy Leaves (1.0000) and Leaf Spot (0.9939). However, recall for Leaf Rust drops to 0.8200, which reduces its per-class F1-score (0.8601). The macro-

average F1-score (0.9237) and accuracy (0.9260) indicate that while DenseNet121 handles healthy samples very well, it struggles more with disease-class differentiation, particularly rust (Figure 6.d). InceptionV3 exhibits the weakest overall performance among the baselines. Precision varies from 0.7619 to 0.9823, while recall is notably lower in Leaf Blight (0.7400) and Leaf Rust (0.7400). This results in lower F1-scores (from 0.8441 to 0.9848), reflecting substantial confusion between disease categories. The macro-average F1-score (0.8667) and accuracy (0.8684) confirm that InceptionV3 is less effective in capturing discriminative features for corn leaf diseases (Figure 6.e). The refined EfficientNetB0 achieves the highest and most consistent performance across all models. Precision reaches 1.0000 for Leaf Spot and ranges from 0.9470 to 1.0000 across classes. Recall is nearly perfect (0.9000–1.0000), with some classes reaching 100%. F1-scores range from 0.9310 to 1.0000, resulting in a macro-average F1-score of 0.9666 and accuracy of 0.9671. These results confirm

the effectiveness of the refinement strategy (Figure 6f).

3.3 Comprehensive Performance Comparison

The classification results demonstrate a clear performance ranking among the evaluated backbone models. Although all architectures can classify the four corn leaf disease categories, their performance varies substantially. EfficientNetB0 is identified as the most robust baseline, and its optimized version consistently outperforms all other models, achieving the highest precision, recall, and F1-score across all classes. This superiority is clearly reflected in the Overall Performance Comparison (Table 1), where the proposed refinement achieves the highest macro F1-score and overall accuracy. These findings confirm that the refinement strategy significantly enhances the discriminative capability and generalization performance of the baseline model, establishing the proposed approach as the best-performing method in the complete evaluation.

Table 1. Overall Performance Comparison

Model	Best Class Precision	Lowest Class Precision	Best Recall	Lowest Recall	Best F1-score	Lowest F1-score	Macro F1-score	Accuracy
EfficientNetB0	0.9819	0.9177	1.0000	0.8333	0.9909	0.8834	0.9437	0.9457
MobileNetV2	0.9640	0.8716	0.9724	0.8600	0.9664	0.8658	0.9219	0.9227
ResNet50	1.0000	0.8519	0.9862	0.8400	0.9969	0.9065	0.9350	0.9359
DenseNet121	0.9939	0.8580	1.0000	0.8200	0.9939	0.8601	0.9237	0.9260
InceptionV3	0.9823	0.7619	0.9931	0.7400	0.9848	0.8441	0.8667	0.8684
Proposed EfficientNetB0 Refinement	1.0000	0.9470	1.0000	0.9000	1.0000	0.9310	0.9666	0.9671

Table 1 presents the overall performance comparison of the five CNN backbone models and the proposed EfficientNetB0 refinement for multi-class corn leaf disease classification. The comparison is conducted using key evaluation metrics, including accuracy, macro-averaged precision, recall, and F1-score, to ensure a fair and comprehensive assessment across all disease classes. Among the baseline models, EfficientNetB0 achieves the strongest overall performance, demonstrating balanced accuracy and consistently high macro-averaged metrics compared to MobileNetV2, ResNet50, DenseNet121, and InceptionV3.

In contrast, lighter architectures such as MobileNetV2 show reduced performance, particularly in recall and F1-score, indicating limitations in capturing fine-grained disease patterns. InceptionV3 exhibits the lowest overall accuracy, reflecting difficulties in distinguishing visually similar disease classes. The proposed refinement increases the accuracy from 94.57% to 96.71% compared to the original EfficientNetB0 model. This improvement indicates that the applied optimization strategies, including progressive fine-tuning, regularization mechanisms, and adaptive learning rate scheduling, effectively enhance the model's classification capability.

The proposed EfficientNetB0 refinement significantly outperforms all baseline models across every evaluation metric. It achieves the highest overall accuracy and macro F1-score, indicating improved class-wise balance and superior generalization. The increase in macro-averaged metrics highlights the model's enhanced capability to handle minority and visually challenging classes, which is critical for real-world agricultural applications. Overall, Table 1 clearly demonstrates that the proposed refinement strategy effectively strengthens the baseline EfficientNetB0 architecture, resulting in a more robust and reliable classification model. The results demonstrate that the proposed approach is effective and suitable for intelligent corn disease monitoring systems.

To further support these quantitative results, Figure 7 presents sample predictions generated by the proposed model on test images. The examples illustrate that the model can accurately classify different corn leaf disease categories, including Healthy, Leaf Blight, Leaf Rust, and Leaf Spot, under varying visual conditions. These qualitative results reinforce the model's robustness and demonstrate its ability to distinguish between visually similar disease patterns in practical scenarios.



Figure 7. Sample Predictions

3.4 Comparative State-of-the-Art Analysis

To further contextualize the effectiveness of the proposed method, this subsection compares the obtained results with previously published state-of-the-art studies on corn leaf disease classification. The objective of this analysis is to position the proposed EfficientNetB0 refinement within recent research developments and to highlight its relative advantages

and limitations in comparison with existing approaches. By examining differences in model architecture, learning strategies, dataset characteristics, and reported performance metrics, this comparative evaluation provides a clearer perspective on how the proposed method advances current research in automated corn disease recognition.

Table 2. Comparative State-of-the-Art Analysis

Author	Dataset (brief)	Method / Model	Accuracy
Li et al. (2023) [48]	Multi-class maize disease images (public datasets)	Improved ConvNeXt (transfer learning)	95.20%
Zhang et al. (2024) [49]	Multi-class maize (corn) leaf disease images; experimental dataset with 124 unseen test images	LSANNet (Lightweight convolutional neural network with long-short attention blocks)	94.35%
Zhu et al. (2024) [50]	Multi-class corn (maize) leaf disease image dataset collected under field conditions	Hybrid deep learning framework combining CNN feature extraction and optimized classification layers	95.00%
Alpsalaz et al. (2025) [51]	Multi-class corn leaf disease images collected from public datasets and field-acquired images under natural conditions	Custom deep CNN framework for corn leaf disease recognition with enhanced feature extraction strategy	94.97%
Askale et al. (2025) [52]	Multi-class corn leaf disease images collected from public datasets and field observations	VGG16-based CNN deployed for mobile corn leaf disease classification	95%
EfficientNetB0 Baseline	Corn Leaf Disease (4k images, 4 classes)	EfficientNetB0 (pretrained)	94.57%
Proposed Refinement	Corn Leaf Disease (4k images, 4 classes)	Refined EfficientNetB0 (BN, GAP, Dense256, Dropout0.4/0.3, Progressive fine-tune, ReduceLROnPlateau, Adam, EarlyStopping)	96.71%

Table 2 compares the proposed method with recent state-of-the-art approaches using similar maize disease datasets. The comparison shows that previous methods generally achieve accuracy between 94% and 95%, while the proposed EfficientNetB0 refinement reaches 96.71%. This improvement indicates that the integration of progressive fine-tuning, regularization, and adaptive learning strategies contributes to better generalization and class discrimination. Moreover, unlike prior studies that rely on single-model optimization, this study emphasizes systematic backbone benchmarking before refinement, providing a more robust and validated model selection process.

4. Conclusions

This study presents a comprehensive investigation of deep learning approaches for multi-class corn leaf disease classification, focusing on backbone benchmarking and model refinement. Five CNN backbones (MobileNetV2, ResNet50, DenseNet121, InceptionV3, and EfficientNetB0) were evaluated using a public dataset with four disease classes. The results show that EfficientNetB0 achieved the most balanced and stable performance, justifying its selection for further refinement. Building on the selected baseline, the EfficientNetB0 model was

enhanced through the integration of global average pooling, batch normalization, optimized dense layers, dual dropout, progressive fine-tuning, adaptive learning rate scheduling, and early stopping. These improvements strengthen generalization and classification robustness, achieving an accuracy of 96.71%, which exceeds the baseline performance (94.57%) and recent state-of-the-art results. A comparative analysis with existing Scopus-indexed studies highlights the effectiveness of the proposed approach. Previous methods reported accuracies between 94.35% and 95.20%, including ConvNeXt-based, attention-based, hybrid, and mobile-oriented CNN models. In contrast, the refined EfficientNetB0 achieves higher performance while maintaining efficiency and stability, indicating that well-designed refinement strategies can outperform more complex architectures without significantly increasing computational cost. Overall, the findings confirm that the proposed EfficientNetB0 refinement provides a reliable and effective solution for automated corn leaf disease classification. The framework shows strong potential for deployment in intelligent agricultural systems, particularly for early disease detection and decision support in precision farming. Future work will focus on real-time deployment, robustness under varying illumination, and integration with edge or mobile platforms to enhance practical applicability.

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