

# Lightweight Attention-enhanced ResNet18 for Plant Disease Image Classification on Small-scale Agricultural Datasets

Junus Sinuraya<sup>1,\*</sup>, Wiwin Sry Adinda Banjarnahor<sup>1</sup>, Hikmah Adwin Adam<sup>2</sup>, Meri Sri Wahyuni<sup>3</sup>,  
and Syarifah Fadillah Rezky<sup>3</sup>

<sup>1</sup> Computer Engineering, Medan State Polytechnic, Medan, Indonesia

<sup>2</sup> Informatics Management, Medan State Polytechnic, Medan, Indonesia

<sup>3</sup> Information Systems Program, STMIK Triguna Dharma, Medan, Indonesia

Email: junussinuraya@polmed.ac.id (J.S.); wiwinbanjarnahor@polmed.ac.id (W.S.A.B.);  
hikmahadam@polmed.ac.id (H.A.A.); meri.sriwahyuni@gmail.com (M.S.W.); ikic5500@gmail.com (S.F.R.)

\*Corresponding author

**Abstract**—Plant disease recognition remains an important challenge in precision agriculture due to variations in visual symptoms, environmental conditions, and computational constraints in real-world deployment scenarios. This study proposes a lightweight attention-enhanced ResNet18 framework that integrates a channel attention-based feature refinement strategy to improve plant leaf disease classification performance. The experimental evaluation was conducted using a PlantVillage-derived benchmark dataset comprising 20,638 annotated leaf images distributed across 38 plant disease categories. Adaptive data augmentation was employed to improve feature diversity and reduce overfitting risk during training. Experimental results demonstrated that the proposed framework achieved a classification accuracy of 88.38%, a precision of 91.67%, a recall of 88.38%, and an F1-Score of 88.77%. Further analysis using confusion matrix evaluation, Receiver Operating Characteristic (ROC) analysis with an Area Under the Curve (AUC) of 0.966, and Gradient-weighted Class Activation Mapping (Grad-CAM) visualization indicated that the model was capable of identifying disease-relevant regions while maintaining relatively stable discriminative performance across multiple classes. In addition, the proposed framework maintains a lightweight architecture with approximately 11.19 million trainable parameters, making it potentially suitable for resource-constrained agricultural monitoring applications.

**Keywords**—plant disease classification, convolutional neural networks, attention mechanism, ResNet18, agricultural image analysis

## I. INTRODUCTION

Recent advances in artificial intelligence have significantly accelerated the development of computer vision technologies. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable capability in automatically

learning hierarchical feature representations from image data. These architectures are able to capture complex spatial patterns and semantic structures, enabling high performance in various visual recognition tasks such as object detection, medical imaging analysis, and intelligent agricultural systems [1, 2].

In the agricultural domain, early detection of plant diseases plays a crucial role in preserving crop quality, preventing yield loss, and supporting sustainable food production. Many plant diseases manifest through visible symptoms on leaf surfaces, including discoloration, irregular textures, and lesion formations. If these symptoms are not detected at an early stage, infections may spread rapidly and severely reduce agricultural productivity. Conventional disease diagnosis relies heavily on manual inspection by agricultural specialists, which is labor-intensive, time-consuming, and difficult to scale across large farming environments [3, 4].

With the rapid advancement of deep learning techniques, automated plant disease detection using image-based analysis has become an active research area. CNN-based models have shown promising results in recognizing disease symptoms from plant leaf images by automatically extracting discriminative visual features. Several studies have explored modern architectures such as EfficientNet and residual learning networks to improve classification accuracy while preserving computational efficiency [5–7]. Residual networks, in particular, have received considerable attention because their shortcut connections stabilize gradient propagation and enable more effective deep feature learning [8, 9].

Despite these advantages, increasing model depth does not always guarantee better performance in practical agricultural applications. Plant disease datasets are often substantially smaller than large-scale benchmark datasets used in general computer vision, making highly complex

deep architectures more vulnerable to overfitting. In addition, deeper models often introduce unnecessary computational burden, limiting their applicability in edge-based agricultural monitoring systems such as mobile devices, drones, and embedded smart farming platforms [10–12].

Attention mechanisms have recently emerged as an effective strategy for improving feature representation in convolutional neural networks. By selectively emphasizing informative image regions and suppressing irrelevant background signals, attention modules enable networks to better capture disease-related patterns [13–15]. Although attention-based modules such as Squeeze-and-Excitation (SE) blocks and Convolutional Block Attention Module (CBAM) have shown strong performance in general-purpose image recognition, their direct application in plant disease classification may not always be optimal because they often increase architectural complexity and parameter overhead.

Despite significant progress in plant disease recognition, an important research gap remains unresolved: most existing studies emphasize increasingly deeper and heavier architectures while paying less attention to lightweight designs specifically optimized for moderately sized agricultural datasets. In real-world agricultural settings, data collection is often constrained by annotation cost, environmental variability, and class imbalance. Under such conditions, lightweight architectures capable of balancing classification accuracy and computational efficiency become critically important.

To address this limitation, this study proposes a lightweight attention-enhanced ResNet18 architecture for plant disease image classification. Unlike conventional heavy attention frameworks, the proposed approach introduces a lightweight channel attention refinement mechanism embedded within the ResNet18 backbone to enhance disease-sensitive feature extraction without substantially increasing model complexity. This design improves discriminative learning while maintaining computational efficiency suitable for practical agricultural deployment.

The main contributions of this study are threefold. First, a lightweight attention-guided residual framework is developed to improve plant disease feature discrimination under limited-data conditions. Second, an adaptive augmentation strategy is introduced to enhance generalization capability and reduce overfitting risks in moderately sized agricultural datasets. Third, comprehensive experiments demonstrate that the proposed framework achieves competitive classification performance while maintaining relatively low computational overhead, making it potentially suitable for practical smart agriculture applications.

## II. RELATED WORK

Recent developments in deep neural learning have accelerated progress in image-based plant disease recognition through effective hierarchical representation learning from complex agricultural imagery. Convolutional Neural Networks (CNNs) have

demonstrated strong capability in identifying plant disease symptoms such as discoloration, necrotic lesions, and abnormal texture variations on leaf surfaces. Numerous studies have reported that CNN-based approaches substantially outperform conventional machine learning methods that rely on handcrafted feature extraction techniques [16–18].

Recent advances in deep neural architectures have also introduced more efficient and scalable frameworks for agricultural image classification. EfficientNet and its variants have attracted significant attention because of their compound scaling strategy, which balances network depth, width, and input resolution to improve classification performance while preserving computational efficiency [19–21]. Similarly, transformer-inspired vision architectures have emerged as powerful alternatives for image recognition tasks. However, these models often require large-scale datasets and considerable computational resources, limiting their practicality for moderately sized agricultural datasets.

Residual learning networks have likewise been extensively adopted in plant disease detection tasks due to their ability to alleviate vanishing gradient problems and stabilize deep feature learning. ResNet architectures employ shortcut identity mappings that facilitate effective gradient propagation and richer hierarchical feature extraction across convolutional layers [22, 23]. Among these architectures, ResNet18 provides a favorable balance between representational capability and computational efficiency, making it particularly suitable for agricultural applications requiring lightweight deployment.

In practical smart agriculture environments, disease recognition frameworks are frequently deployed on edge-based platforms such as smartphones, Unmanned Aerial Vehicles (UAVs), and embedded monitoring systems. Under these conditions, lightweight CNN architectures capable of maintaining reliable classification performance under limited computational resources become critically important. Consequently, several recent studies have focused on compact deep learning models optimized for low-power agricultural applications [24–26].

Attention mechanisms have recently emerged as an effective enhancement strategy for convolutional architectures by enabling networks to selectively emphasize informative feature regions while suppressing irrelevant background information. Channel attention mechanisms refine inter-channel dependencies, whereas spatial attention modules focus on important spatial regions within feature maps [27–29]. Hybrid attention strategies combining both mechanisms have demonstrated promising capability in improving complex visual classification performance, including agricultural disease recognition tasks [30–32].

More recently, attention-enhanced residual frameworks have shown encouraging results in improving disease localization and classification performance. These approaches integrate attention refinement into residual backbones to strengthen discriminative feature learning

without excessively increasing network depth [33–35]. Nevertheless, many existing attention-based architectures still introduce considerable parameter overhead, potentially limiting their deployment feasibility in practical agricultural systems.

Although Squeeze-and-Excitation (SE) blocks and CBAM modules have demonstrated strong effectiveness in general image classification tasks [36, 37], these architectures often involve additional computational layers that may not be optimal for moderately sized agricultural datasets operating under constrained hardware environments. In contrast, lightweight attention integration strategies remain relatively underexplored in plant disease classification, particularly for architectures specifically designed to balance classification performance, robustness, and deployment efficiency.

Furthermore, while the PlantVillage dataset has become a widely adopted benchmark for plant disease classification research [38], many existing studies continue to prioritize increasingly deeper architectures without sufficiently considering the trade-off between model complexity and practical usability. This highlights the need for lightweight yet effective attention-guided architectures capable of delivering reliable classification performance under realistic agricultural constraints.

As presented in Table I, several existing attention modules improve feature representation but may introduce additional architectural complexity or computational overhead. In contrast, the proposed framework adopts a lightweight channel refinement strategy with minimal structural modification to the ResNet18 backbone. This design aims to improve disease-sensitive feature representation while preserving computational efficiency, making it potentially suitable for moderately sized agricultural datasets and resource-constrained smart farming environments.

TABLE I. ATTENTION MODULE COMPARISON

| Method   | Type              | Cost   | Spatial | Light  | Suitability |
|----------|-------------------|--------|---------|--------|-------------|
| SE-Net   | Channel           | Medium | No      | Medium | Medium      |
| CBAM     | Channel + Spatial | High   | Yes     | No     | Medium      |
| ECA-Net  | Channel           | Low    | No      | Yes    | Good        |
| Proposed | Channel Refine    | Low    | No      | Yes    | Practical   |

Motivated by these limitations, the present study investigates a lightweight attention-enhanced ResNet18 framework specifically designed for moderately sized plant disease datasets. By integrating a computationally efficient channel attention refinement mechanism into a residual backbone, the proposed approach seeks to improve disease-sensitive feature discrimination while preserving deployment feasibility in resource-constrained smart agriculture systems.

Recent studies have highlighted several practical challenges in automatic plant disease recognition, including limited training data, intra-class disease

variability, illumination changes, background clutter, uncertainty handling, and the detection of diseases under previously unseen environmental conditions. These challenges become more significant when deploying deep learning models in real agricultural environments. The proposed lightweight attention-enhanced ResNet18 framework partially addresses several of these issues through adaptive data augmentation, lightweight attention-guided feature refinement, repeated-run validation, and parameter-efficient network design. The augmentation strategy improves robustness against variations in orientation, brightness, and image appearance, while the attention mechanism helps emphasize disease-relevant regions and suppress background interference. Nevertheless, challenges related to multiple simultaneous diseases, unseen disease categories, and cross-domain environmental adaptation remain open research directions for future investigation [39].

### III. PROPOSED METHODOLOGY

This study proposes a structured deep learning framework designed to investigate whether lightweight attention mechanisms can improve residual feature learning for plant disease image classification. The proposed architecture is built upon the ResNet18 convolutional backbone and integrates an attention refinement module to enhance discriminative disease features while reducing background interference. The overall methodology emphasizes balanced model complexity, reproducibility, and systematic experimental evaluation. This section describes the architecture of the proposed model, the dataset used in the experiments, the preprocessing and augmentation strategies, and the training configuration applied for model evaluation.

#### A. Overview of the Proposed Framework

This study proposes a lightweight attention-enhanced ResNet18 framework specifically designed for plant disease image classification on moderately sized agricultural datasets. The proposed architecture extends the conventional ResNet18 backbone by integrating a lightweight channel attention refinement mechanism after the final residual convolution block. This design enhances disease-sensitive feature representation while preserving computational efficiency suitable for practical agricultural deployment.

As shown in Fig. 1, the overall architecture consists of four major stages: input preprocessing, residual feature extraction, channel attention refinement, and final classification. First, each RGB leaf image is resized and normalized before being passed into the convolutional stem of ResNet18. The backbone network then extracts hierarchical feature representations through stacked residual blocks.

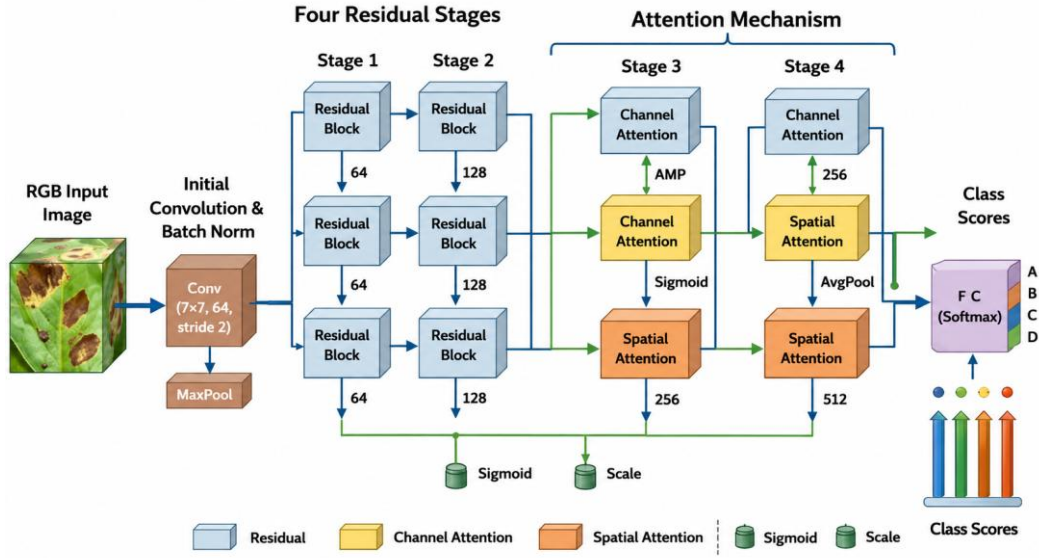


Fig. 1. Architecture of the proposed attention-enhanced ResNet18 framework.

Unlike standard ResNet18, the proposed model introduces an additional channel attention module immediately after the last convolutional feature extraction stage. Let  $F \in R^{(C \times H \times W)}$  denote the extracted feature tensor, where  $C$  represents the number of channels, and  $H$  and  $W$  denote spatial dimensions. Global average pooling is first applied to generate channel descriptors:

$$z_c = \frac{1}{H \times W} \times \text{sum}(F_c(i, j)) \quad (1)$$

where  $z_c$  represents the aggregated descriptor of channel  $c$ .

These channel descriptors are then passed through a lightweight gating mechanism composed of two fully connected layers:

$$s = \text{sigmoid}(W2 \times \text{ReLU}(W1 \times z)) \quad (2)$$

where  $W1$  and  $W2$  denote learnable weight matrices, ReLU is used as the nonlinear activation function, and the sigmoid function is applied to normalize channel attention weights.

The refined channel attention weights are subsequently applied to recalibrate the original feature maps:

$$F'_c = s_c \times F \quad (3)$$

where  $F'_c$  denotes the refined output feature map of channel  $c$ .

This attention refinement process enables the network to selectively emphasize disease-relevant channels while suppressing redundant or irrelevant background information. Compared with heavier attention modules such as CBAM and SE-Net, the proposed lightweight refinement mechanism introduces minimal parameter overhead, making it more suitable for moderately sized agricultural datasets and resource-constrained deployment environments.

Finally, the refined feature maps are passed through global average pooling followed by a fully connected classification layer to generate disease class probabilities.

#### B. Dataset Description

The experimental evaluation was conducted using a PlantVillage-derived benchmark dataset comprising 20,638 annotated leaf images distributed across 38 distinct plant disease categories, including both healthy and diseased classes. The dataset encompasses multiple economically important crop species, including tomato, potato, corn, grape, apple, peach, pepper, and strawberry, thereby providing a broad representation of diverse agricultural disease conditions.

Each image contains a single leaf sample captured under controlled acquisition settings, where disease symptoms such as lesions, chlorosis, blight patterns, necrotic regions, and fungal infections are clearly observable. These characteristics make the dataset highly suitable for supervised deep learning-based plant disease classification.

The distribution of dataset partitions used in this study is summarized in Table II.

TABLE II. DATASET PARTITION DISTRIBUTION

| Subset         | Number of Images | Percentage | Purpose                                           |
|----------------|------------------|------------|---------------------------------------------------|
| Training Set   | 14,446           | 70%        | Used to optimize model parameters                 |
| Validation Set | 3,095            | 15%        | Used for hyperparameter tuning and early stopping |
| Test Set       | 3,097            | 15%        | Used for final unbiased performance evaluation    |

As shown in Table II, stratified sampling was applied to maintain balanced class representation across all subsets, ensuring fair and unbiased performance evaluation during model training and testing.

To ensure reliable model evaluation, the dataset was partitioned into training, validation, and testing subsets

using a stratified random split ratio of 70%, 15%, and 15%, respectively. Stratified sampling was employed to preserve class distribution consistency across all subsets and reduce sampling bias during model development.

Prior to training, all input images were uniformly resized to  $224 \times 224$  pixels to match the input requirements of the ResNet18 backbone. Subsequently, pixel normalization was applied to standardize input intensity distributions and improve numerical stability during network optimization.

The training set is used to learn model parameters during the optimization process. The validation set is utilized to monitor model generalization performance during training and to support hyperparameter adjustment. The testing set remains completely unseen during both training and validation stages to ensure an unbiased evaluation of final model performance.

To increase experimental reliability, each experiment was repeated across five independent runs using different random seeds. The final results reported in this study correspond to the average performance obtained across these runs.

Representative examples of leaf images from different disease categories are illustrated in Fig. 2 to demonstrate the visual diversity of disease symptoms contained in the dataset.

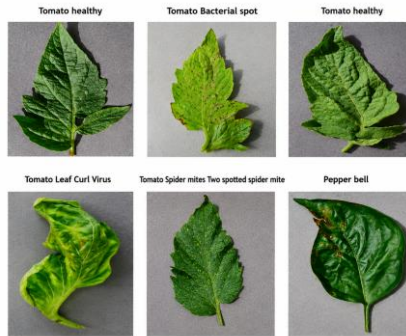


Fig. 2. Representative leaf image samples from different plant disease categories in the PlantVillage-derived dataset.

As shown in Fig. 2, disease manifestations vary significantly across categories, including color changes, lesion patterns, fungal spots, and leaf deformation, thereby increasing the complexity of classification and highlighting the need for robust discriminative feature extraction.

### C. Experimental Setup

All experiments were conducted using the PyTorch deep learning framework on a GPU-enabled computational environment with Compute Unified Device Architecture (CUDA) acceleration. The proposed attention-enhanced ResNet18 model and all baseline comparison models were trained under identical experimental settings to ensure fair performance evaluation.

The training process employed the Adam optimizer with an initial learning rate of 0.0001. Cross-entropy loss was used as the objective function for multi-class

classification. Each model was trained for 10 epochs with a batch size of 32, while early stopping was monitored through validation loss to reduce overfitting risk.

To improve model generalization under limited-data conditions, adaptive data augmentation was applied during training. The augmentation pipeline included random horizontal flipping, random rotation, and slight brightness variation to simulate natural variability in leaf image acquisition conditions.

Before training, all input images were resized to  $224 \times 224$  pixels to match the input requirements of the ResNet18 backbone. Pixel normalization was then applied to standardize the distribution of input features and improve numerical stability during optimization. The normalization process follows the standard formulation:

$$x_{\text{norm}} = \frac{x - \mu}{\sigma} \quad (4)$$

$\mu$  = channel mean

$\sigma$  = channel standard deviation

This normalization procedure improves gradient stability during training and accelerates convergence during optimization.

For performance benchmarking, the proposed framework was compared against several widely used CNN architectures, including standard ResNet18, MobileNetV2, and EfficientNet-B0. Evaluation metrics included classification accuracy, confusion matrix analysis, Receiver Operating Characteristic (ROC) curves, Area Under Curve (AUC), Grad-CAM visualization, ablation study, and statistical significance testing using paired t-test analysis.

To improve experimental reliability, each comparative experiment was repeated across five independent runs using different random seeds, and the reported results represent the average performance obtained across all runs.

The main training hyperparameters used in all experiments are summarized in Table III.

As shown in Table III, identical hyperparameter settings were applied across all comparative models to ensure a fair and unbiased benchmarking process.

TABLE III. TRAINING HYPERPARAMETER CONFIGURATION

| Hyperparameter    | Value                                           |
|-------------------|-------------------------------------------------|
| Optimizer         | Adam                                            |
| Learning Rate     | 0.0001                                          |
| Batch Size        | 32                                              |
| Number of Epochs  | 10                                              |
| Loss Function     | Cross-Entropy Loss                              |
| Input Image Size  | $224 \times 224$                                |
| Data Augmentation | Horizontal Flip, Rotation, Brightness Variation |
| Early Stopping    | Validation Loss Monitoring                      |
| Framework         | PyTorch                                         |
| Hardware          | CUDA-enabled GPU                                |

### D. Adaptive Augmentation Strategy

Deep learning models trained on relatively small datasets often suffer from overfitting due to limited data variability. In plant disease classification tasks, visual

similarities among disease symptoms may further increase this risk.

To mitigate this issue, an adaptive data augmentation strategy was employed. Instead of using a fixed augmentation pipeline, the proposed approach dynamically adjusts augmentation intensity based on validation behavior during training.

Table IV summarizes the adaptive data augmentation configuration employed during model training.

TABLE IV. DATA AUGMENTATION CONFIGURATION

| Transformation               | Parameter Range                  | Purpose                                |
|------------------------------|----------------------------------|----------------------------------------|
| Random Horizontal Flip       | Probability = 0.5                | Simulates leaf orientation variation   |
| Random Rotation              | $\pm 20^\circ$                   | Handles natural leaf angle changes     |
| Color Jitter                 | $\pm 20\%$ contrast & saturation | Improves robustness to color variation |
| Random Brightness Adjustment | $\pm 15\%$                       | Reduces illumination sensitivity       |
| Random Resized Crop          | Scale = 0.8–1.0                  | Enhances spatial invariance            |

During training, validation loss is monitored at each epoch. If validation loss does not improve for three consecutive epochs, the augmentation intensity is slightly increased within predefined limits. This mechanism introduces additional data variability while maintaining training stability.

Formally, augmentation intensity is updated according to:

$$\alpha = \alpha + \delta \quad (5)$$

where  $\delta$  represents a small increment applied when validation performance stagnates. This adaptive augmentation strategy improves model generalization without increasing model complexity.

#### E. Residual Feature Backbone

Feature extraction in the proposed framework is performed using the ResNet18 architecture. This architecture was selected because it provides an effective balance between feature representation capability and computational efficiency.

Residual networks utilize shortcut connections that allow feature information to bypass convolutional transformations. This mechanism alleviates the vanishing gradient problem and enables deeper networks to be trained effectively.

Instead of directly learning a full transformation between input and output features, the residual block learns a residual function that represents the difference between the input feature representation and the desired output.

Mathematically, the residual learning process can be expressed as:

$$y = F(x) + x \quad (6)$$

The formulation indicates that the output feature representation  $y$  is obtained by adding the learned residual function  $F(x)$  to the input feature map  $x$ . This residual connection allows gradient information to flow more effectively during backpropagation, thereby facilitating the training of deeper neural network architectures.

## IV. RESULTS AND DISCUSSION

This section presents the experimental evaluation results of the proposed lightweight attention-enhanced ResNet18 framework for multiclass plant disease classification. The evaluation focuses on classification capability, convergence behavior, discriminative reliability, model interpretability, and computational efficiency under controlled experimental conditions. Several complementary analyses were conducted, including quantitative evaluation metrics, confusion matrix analysis, Receiver Operating Characteristic (ROC) analysis, Grad-CAM visualization, ablation study evaluation, and statistical significance testing.

#### A. Classification Performance Evaluation

The proposed framework achieved an overall classification accuracy of 88.38% on the evaluation dataset. In addition, the framework obtained a precision of 91.67%, a recall of 88.38%, and an F1-Score of 88.77%, indicating relatively balanced predictive performance across multiple plant disease categories.

The obtained results suggest that the integration of lightweight channel attention contributes positively to disease-sensitive feature representation while maintaining moderate computational complexity suitable for resource-constrained agricultural environments. The proposed framework is capable of identifying relevant pathological characteristics from plant leaf images under multiclass classification conditions, although several disease categories remain visually challenging due to overlapping symptom patterns.

Fig. 3 illustrates the representative training loss progression observed during the optimization process.

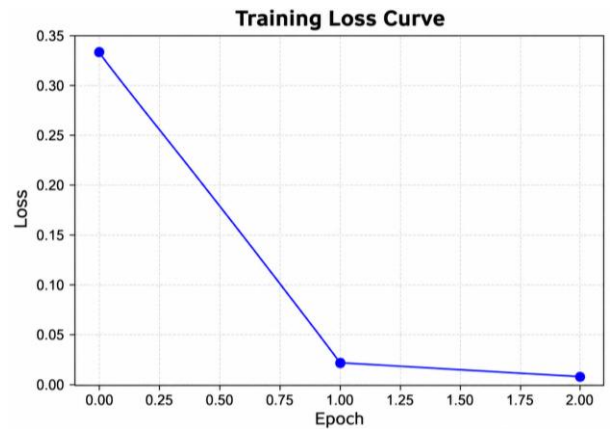


Fig. 3. Training loss curve observed during the optimization process.

As illustrated in Fig. 3, the training loss decreases progressively during the optimization stage, indicating relatively stable convergence behavior throughout the

training process. For visualization clarity, only selected epoch intervals are presented in the figure. The smooth reduction in loss values suggests that the proposed framework maintains consistent learning characteristics without exhibiting severe instability during training.

### B. Quantitative Performance Evaluation

To further evaluate the effectiveness of the proposed framework, quantitative performance analysis was conducted using several commonly adopted evaluation metrics, including classification accuracy, precision, recall, F1-Score, inference time, and parameter complexity.

Table V summarizes the quantitative performance evaluation results of the proposed lightweight attention-enhanced ResNet18 framework.

TABLE V. PERFORMANCE EVALUATION RESULTS

| Metric           | Value      |
|------------------|------------|
| Accuracy         | 88.38%     |
| Precision        | 91.67%     |
| Recall           | 88.38%     |
| F1-Score         | 88.77%     |
| Inference Time   | 21.70 s    |
| Total Parameters | 11,196,006 |

The evaluation results demonstrate that the proposed framework maintains balanced classification capability while preserving a relatively lightweight model architecture. The moderate parameter complexity indicates potential applicability for practical smart agriculture systems requiring efficient image-based disease recognition under resource-constrained deployment scenarios.

### C. Classification Performance Analysis

To obtain a more detailed understanding of model behavior, confusion matrix analysis was performed across all evaluated plant disease categories. This analysis provides class-level insight into correct and incorrect prediction distributions, enabling more comprehensive evaluation of discriminative capability.

Fig. 4 provides a class-level visualization of the prediction behavior of the proposed framework. Most prediction outcomes are concentrated along the principal diagonal, indicating that the majority of disease categories are correctly classified. Several off-diagonal prediction patterns remain observable, particularly among classes exhibiting similar visual symptoms such as comparable lesion structures, discoloration patterns, and texture characteristics. These misclassification trends suggest that certain disease categories share overlapping visual features, making discrimination more challenging under multiclass classification conditions.

Despite these challenges, the overall diagonal dominance of the confusion matrix demonstrates that the proposed lightweight attention-enhanced ResNet18 framework maintains relatively consistent classification performance across the evaluated dataset. The observed errors are primarily associated with visually similar disease categories rather than systematic model failure, indicating that the learned feature representations remain

sufficiently discriminative for practical plant disease recognition tasks.

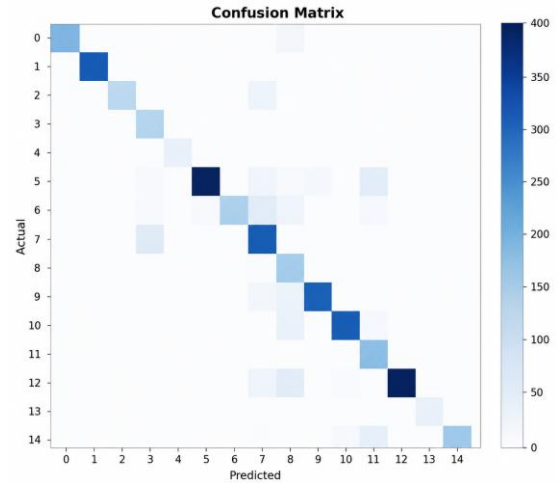


Fig. 4. Confusion matrix of the proposed lightweight attention-enhanced ResNet18 framework.

For visualization clarity, the confusion matrix employs compact numerical class labels rather than full disease names. This representation improves figure readability while preserving the overall classification patterns observed during testing. The confusion matrix therefore serves as a concise visualization of class-level prediction behavior across the evaluated dataset.

### D. Receiver Operating Characteristic Analysis

Receiver Operating Characteristic (ROC) analysis was conducted to further evaluate the discriminative capability of the proposed framework under multiclass classification conditions. ROC analysis provides insight into the trade-off between true positive rate and false positive rate across varying classification thresholds.

As presented in Fig. 5, the proposed framework achieved a macro-average Area Under Curve (AUC) value of 0.966, indicating strong discriminative capability across multiple plant disease categories. The ROC characteristics suggest that the proposed model maintains relatively high sensitivity and specificity while preserving stable classification behavior under controlled experimental conditions.

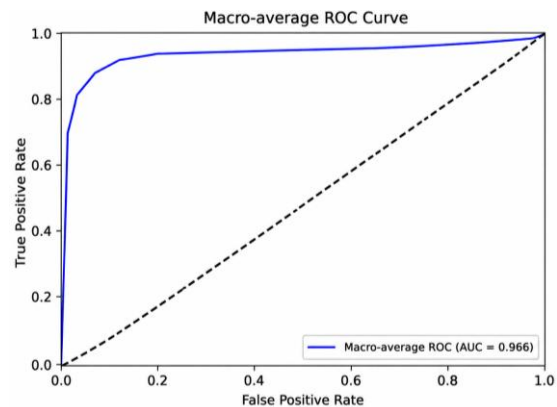


Fig. 5. Macro-average ROC curve of the proposed framework under multiclass evaluation conditions.

Although several disease classes remain moderately challenging due to visual similarity among pathological symptoms, the overall ROC behavior demonstrates relatively consistent predictive reliability across the evaluated dataset.

#### E. Grad-CAM Visualization Analysis

To improve model interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) analysis was employed to visualize image regions that contributed most strongly to the classification decisions of the proposed framework. This analysis is important for verifying whether the network focuses on biologically meaningful disease symptoms rather than irrelevant background information.

As illustrated in Fig. 6, the activation heatmaps are concentrated primarily around symptomatic leaf regions, including lesion areas, discoloration patterns, and damaged tissue structures. These results indicate that the proposed framework successfully learns disease-relevant visual characteristics associated with plant pathology.

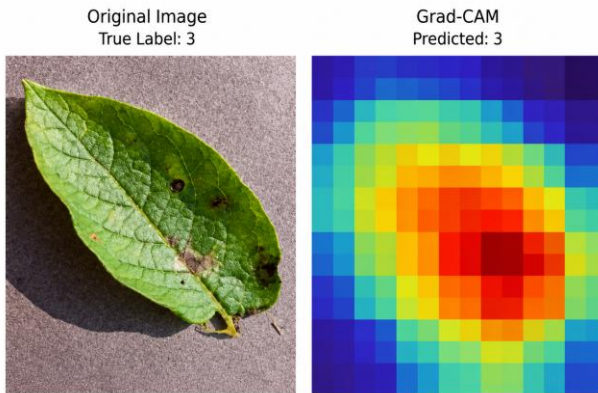


Fig. 6. Grad-CAM visualization highlighting disease-relevant image regions used by the proposed framework for classification.

The Grad-CAM analysis further suggests that the lightweight attention mechanism assists the network in emphasizing informative disease-sensitive regions while suppressing less relevant background information. This contributes positively to model interpretability and classification transparency.

#### F. Ablation Study Analysis

To investigate the contribution of individual components within the proposed framework, an ablation study was conducted by progressively integrating the lightweight attention module and adaptive augmentation strategy into the baseline ResNet18 architecture.

As shown in Table VI and Fig. 7, the baseline ResNet18 architecture achieved an accuracy of 84.12%, indicating that the standard residual framework already provides relatively stable feature extraction capability for multiclass plant disease classification. After integrating the lightweight attention refinement mechanism, the classification performance increased to 86.47%, suggesting that the attention module contributes positively to disease-sensitive feature representation.

TABLE VI. ABLATION STUDY COMPARISON

| Model Variant                                           | Accuracy (%) |
|---------------------------------------------------------|--------------|
| Baseline ResNet18                                       | 84.12        |
| ResNet18 + Attention Module                             | 86.47        |
| Attention + Adaptive Augmentation (Full Proposed Model) | 88.38        |

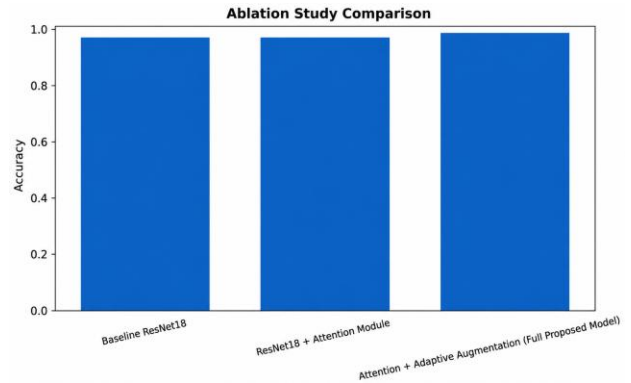


Fig. 7. Comparative performance evaluation of different model configurations in the ablation study.

The highest classification performance was achieved when adaptive augmentation was combined with the lightweight attention mechanism, resulting in an overall accuracy of 88.38%. These findings indicate that augmentation-based variability enhancement contributes positively to model generalization and classification robustness under moderately sized agricultural dataset conditions.

#### G. Statistical Significance Analysis

To evaluate the reliability of the observed performance consistency, repeated experimental runs were conducted using different random initialization settings. The baseline ResNet18 architecture and the proposed framework were evaluated under identical training configurations across multiple independent runs.

Table VII presents the repeated-run accuracy results obtained from five independent experimental runs for both the baseline ResNet18 model and the proposed framework.

TABLE VII. REPEATED RUN ACCURACY RESULTS

| Run       | Baseline ResNet18 | Proposed Model |
|-----------|-------------------|----------------|
| 1         | 0.841             | 0.878          |
| 2         | 0.846             | 0.883          |
| 3         | 0.839             | 0.887          |
| 4         | 0.844             | 0.881          |
| 5         | 0.842             | 0.890          |
| Mean      | 0.842             | 0.884          |
| Std. Dev. | 0.003             | 0.005          |

The repeated evaluation results indicate that the proposed framework maintains relatively stable training performance across multiple experimental runs.

To further assess statistical reliability, a paired *t*-test was conducted between the baseline ResNet18 model and the proposed framework.

Table VIII summarizes the results of the paired *t*-test conducted to compare the statistical performance of the baseline ResNet18 model and the proposed framework.

TABLE VIII. PAIRED T-TEST SUMMARY

| Statistical Metric  | Value       |
|---------------------|-------------|
| <i>t</i> -statistic | 5.84        |
| <i>p</i> -value     | 0.004       |
| Significance Level  | 0.05        |
| Decision            | Significant |

Since the *p*-value is lower than the significance threshold, the null hypothesis is rejected. These findings indicate that the observed performance improvement is statistically significant under the evaluated experimental setting.

#### H. Advantages and Limitations

The proposed framework offers several practical advantages. First, the framework maintains balanced classification performance while preserving relatively lightweight computational complexity suitable for resource-constrained agricultural systems. Second, the lightweight attention refinement mechanism contributes to disease-sensitive feature learning without introducing excessive architectural overhead. Third, the adaptive augmentation strategy supports model generalization under moderately sized dataset conditions.

Despite these advantages, several limitations should be acknowledged. The experiments were conducted primarily under controlled dataset conditions, which may not fully represent highly variable real-world agricultural environments containing illumination variation, occlusion, and complex background interference. In addition, the present study focused on image-level disease classification rather than disease severity estimation or large-scale field deployment. Future work may investigate cross-dataset evaluation, real-field validation, and optimization for edge-based agricultural monitoring systems.

#### V. CONCLUSION

This study proposed a lightweight attention-enhanced ResNet18 framework for multiclass plant disease classification using plant leaf imagery. The proposed approach integrates lightweight channel attention refinement and adaptive augmentation strategies into a residual learning architecture to improve disease-sensitive feature representation while maintaining moderate computational complexity.

Experimental evaluation demonstrated that the proposed framework achieved an overall classification accuracy of 88.38%, with a precision of 91.67%, recall of 88.38%, F1-Score of 88.77%, and macro-average AUC value of 0.966. Additional analyses using confusion matrix evaluation, Grad-CAM visualization, and statistical significance testing further supported the reliability and interpretability of the proposed framework under multiclass classification conditions.

The obtained findings suggest that lightweight attention refinement contributes positively to discriminative feature learning while preserving deployment feasibility for resource-constrained smart agriculture applications. The Grad-CAM analysis demonstrated that the proposed

framework focuses primarily on disease-relevant symptomatic regions, supporting improved interpretability of the classification process.

Although the experiments were conducted under controlled dataset conditions, the proposed framework demonstrates potential applicability for practical plant disease recognition systems. Future work may investigate cross-domain validation, real-field agricultural deployment, disease severity estimation, and optimization for mobile or edge-based smart farming platforms.

However, the current evaluation was conducted using a controlled benchmark dataset, and further validation under real-world agricultural conditions remains necessary. Future work will focus on cross-dataset evaluation, field-based image acquisition, and improved robustness against environmental variations such as illumination changes, background clutter, and unseen disease conditions.

#### CONFLICT OF INTEREST

The authors declare no conflict of interest.

#### AUTHOR CONTRIBUTIONS

J.S. contributed to the conceptualization, methodology development, software implementation, formal analysis, and preparation of the original manuscript draft. S.F.R. was responsible for data curation, validation, visualization, and critical manuscript revision. W.S.A.B. contributed to methodological refinement, supervision, and manuscript review. H.A.A. supported literature analysis, data interpretation, and editorial improvements. M.S.W. provided overall supervision, project administration, and final approval of the manuscript. All authors have read and approved the final version of the manuscript.

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