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PLANT AND DISEASE CLASSIFICATION WITH EXPLAINABLE AI IN WEB-BASED APPLICATION

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Abstract: The application of deep learning for plant and disease recognition has become increasingly popular; however, most studies address these tasks separately due to limitations in dataset availability for model training and testing. This study aims to overcome such constraints by developing a multi-output classification framework that simultaneously predicts both plant species and associated diseases. Three state-of-the-art architectures were employed: NASNetMobile, a CNN-based model; a hybrid CNN-LSTM; and a CNN integrated with an Attention mechanism. A combined dataset of over 15.678 images was compiled from multiple public sources, covering 10 plant species and 27 disease classes with diverse real-world conditions. The training process was done using two different approaches: with and without data augmentation. Model performance was evaluated using accuracy, precision, recall, and F1-score. The results show that NASNetMobile without data augmentation achieved the highest performance, with an F1-score of 99.79% for plant classification and 98.54% for disease classification, outperforming CNN-LSTM (98.86% and 95.2%) and CNN-Attention (98.65% and 93.3%). These findings demonstrate that lightweight yet robust architectures such as NASNetMobile can effectively bridge the gap between laboratory-trained models and field-ready agricultural applications, supporting the advancement of precision agriculture. To enhance interpretability, Local Interpretable Model-Agnostic Explanations (LIME) and Eigen-CAM were applied, providing intuitive visualizations that help users understand model predictions. The best-performing model was deployed in a web-based proof-of-concept application, developed using Streamlit. This work provides one of the first multi-output explainable frameworks for plant and disease classification deployable in a web-based system.

Keywords: multi-crop classification; NASNetMobile; CNN-LSTM; explainable ai; Streamlit application.

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1. INTRODUCTION

Artificial intelligence (AI) and deep learning have received growing attention in agriculture, particularly for tasks such as plant disease classification, crop yield prediction, and agronomic decision support [1], [2], [3]. Among various approaches, convolutional neural networks (CNNs) have consistently proven effective in detecting and diagnosing plant diseases from leaf images with high accuracy [4], [5], [6]. Recent advances have further integrated architectures such as EfficientNet, ResNet, and Vision Transformers to improve classification performance, especially when dealing with diverse datasets [7], [8], [9].

Despite these advancements, many existing studies still rely heavily on controlled datasets such as PlantVillage, which lack variability in background, illumination, and leaf damage [6], [10], [11]. Consequently, models trained under such conditions often fail to generalize to real-world environments, where images are captured under natural and more complex conditions [12], [13]. Moreover, while CNN-based methods achieve high performance, they struggle to capture sequential and spatial dependencies in disease progression, limiting their robustness in multi-class classification tasks [14], [15].

To address these limitations, researchers have begun to explore hybrid and attention-based architecture. CNN-LSTM models, for example, integrate spatial and sequential learning to capture patterns of disease spread across leaf structures [13], [16]. Similarly, attention mechanisms and multimodal transformers have been applied to improve model focus on disease-relevant regions, thereby enhancing both classification performance and interpretability [8], [12], [17]. However, such models often require high computational resources, making them less practical for lightweight applications deployable in agricultural fields [18], [19].

In this study, we propose a comprehensive framework for multi-class plant disease classification using three approaches: (i) NASNetMobile, a lightweight and efficient CNN architecture; (ii) CNN-LSTM, which combines spatial and sequential feature learning; and (iii) CNN with Attention Mechanism, which enhances model focus on critical leaf regions. In addition to classification performance, this study emphasizes interpretability by applying Explainable AI (XAI) methods such as LIME and Eigen-CAM to better understand how the models learn and make predictions.

2. Materials and Methods

2.1. Dataset

The dataset used in this study was compiled from several open-access repositories containing plant disease images, including PlantVillage, Kaggle Plant Pathology Challenge 2020, and other public collections [5], [10], [11]. A total of 15.678 images were collected, representing 10 plant species and 27 disease classes under diverse real-world conditions such as varying lighting, complex backgrounds, and partial leaf damage.

The dataset includes images of leaves from Bitter gourd, Bottle gourd, Cauliflower, Eggplant, Cucumber, Tomato, Bean, Cowpea, Radish, and Betel leaf. Each plant species contains multiple disease categories, including Downy mildew, Mosaic virus, Anthracnose, Leaf spot, Fusarium wilt, Verticillium wilt, and Bacterial blight, among others. Table 1 presents the detailed distribution of plant species, disease types, and the number of images per class. These data were curated and verified manually to ensure class balance and remove duplicates or low-quality images before model training.

2.2. Data Preprocessing

After collecting and merging all datasets from multiple open-access sources into a unified dataset, all images were resized to 224 × 224 pixels to ensure consistency across model inputs [4]. Data augmentation techniques such as random rotation, horizontal and vertical flipping, brightness adjustment, and contrast modification were applied to increase image diversity and reduce the risk of overfitting [11], [20]. The dataset was then split into 75% for training, 15% for validation, and 15% for testing. Finally, all pixel values were normalized into the [0,1] range to stabilize model training and accelerate convergence.

Table 1. Distribution of dataset used in this study

Plant	Disease	Number of Images
Bitter gourd	Downy Mildew	570
	Mosaic Virus	600
	Fusarium Wilt	502
Bottle gourd	Anthracnose,	601
	Downy Mildew	684

Cauliflower	Black Rot	560
	Downy Mildew	512
Eggplant	Verticillium Wilt	730
	Cercospora Leaf Spot	723
	Begomovirus	720
Cucumber	Anthracnose Lesions	535
	Downy Mildew	564
Tomato	Bacterial Spot	589
	Leaf Curl Virus	612
	Spotted Wilt	654
Bean	Blight	510
	Mosaic Virus	562
	Rust	568
Cowpea	Bacterial Wilt	581
	Mosaic Virus	579
	Septoria Leaf Spot	577
Radish	Black Leaf Spot	526
	Downy Mildew	601
	Mosaic Virus	548
	Flea Beetle	513
Betel Leaf	Leaf Rot	269
	Leaf Spot	688

2.3. MODEL ARCHITECTURES

The overall framework of the study is summarized in Fig. 1. It illustrates the sequential process beginning with dataset acquisition, image preprocessing (resizing, normalization, and augmentation), model training using three architectures (NASNetMobile, CNN-LSTM, and CNN-Attention), evaluation through accuracy and F1-score metrics, application of Explainable AI (Eigen-CAM and LIME), and final deployment into a Streamlit-based web interface.

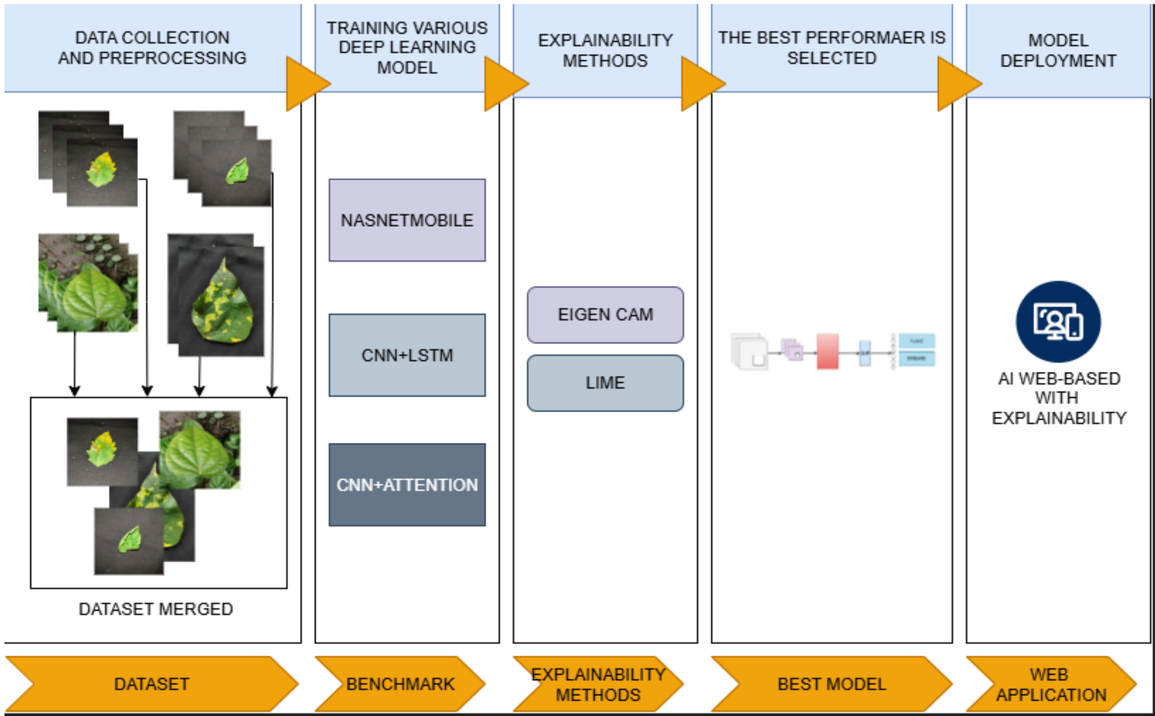


Fig. 1. General pipeline of the proposed study

2.3.1. NASNetMobile

NASNetMobile is a lightweight variant of the Neural Architecture Search Network (NASNet), which automatically searches for the optimal convolutional cell structures to balance accuracy and computational cost [6]. The network consists of normal cells and reduction cells, which are stacked to build the final architecture. In this study, NASNetMobile was fine-tuned with an input size of 224×224, a dropout rate of 0.5, ReLU activation, and the Adam optimizer with a learning rate of 0.001. The model's classification head was adapted to output predictions for both plant species and disease categories.

After the feature extraction stage, a Global Average Pooling (GAP) layer was applied to reduce the dimensionality of the feature maps while preserving spatial information. This pooling strategy minimizes the number of trainable parameters and helps prevent overfitting compared to fully connected layers. From the GAP layer, the network branches into two parallel dense layers corresponding to multi-output classification: the first head predicts plant species, while the second head predicts disease categories. Each output head uses a softmax activation function to generate probability distributions across their respective classes. Fig. 2 illustrates the architecture of the NASNetMobile model used in this study.

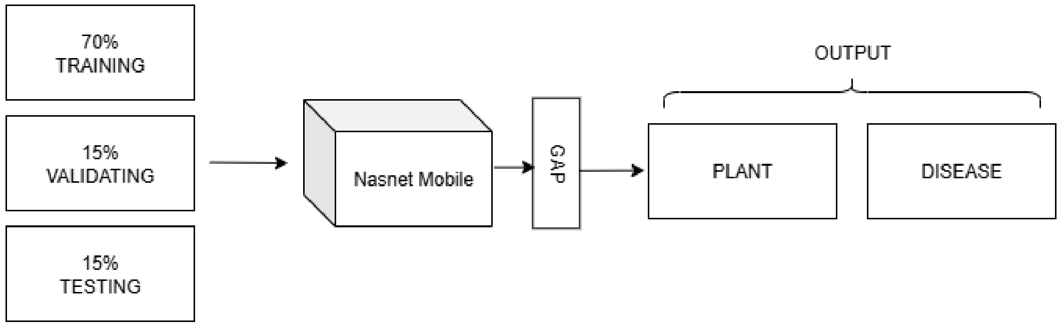


Fig. 2. Illustrates the architecture of the NASNetMobile model used in this study

The NASNetMobile architecture shown in Fig. 2 employs normal and reduction cells optimized through Neural Architecture Search (NAS). It uses convolutional layers with skip connections and batch normalization, followed by a global average pooling and a dense output layer. This model serves as the baseline for performance comparison due to its lightweight structure and high transfer-learning capability from ImageNet.

2.3.2. CNN-LSTM

The CNN-LSTM model combines convolutional layers for spatial feature extraction with LSTM layers to capture temporal or sequential dependencies across extracted feature maps [21]. CNN layers learn local features such as leaf texture and disease spots, while the LSTM component models the sequence of extracted features, enhancing the recognition of diseases that exhibit irregular distribution patterns across the leaf surface. The model used convolutional layers with kernel size 3×3, max-pooling layers, followed by LSTM layers with 128 units, and a fully connected classification layer with softmax activation. Fig. 3 presents the hybrid CNN-LSTM architecture used to capture both spatial and sequential features from plant disease images. The convolutional layers extract spatial features from image regions, while the LSTM layers learn temporal dependencies within flattened feature maps. This design aims to improve classification robustness in heterogeneous image conditions.

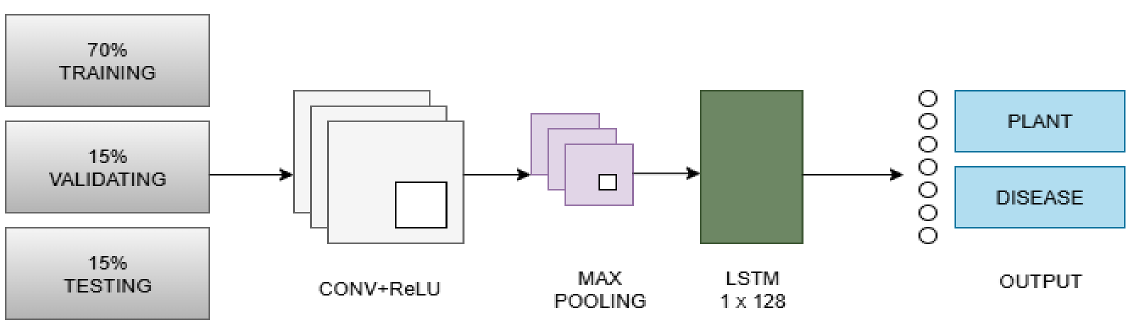


Fig. 3. CNN-LSTM architecture

2.3.3. CNN WITH ATTENTION MECHANISM

The third model incorporates an attention module into the CNN backbone to enhance the network's focus on disease-relevant regions [6], [8], [12]. The CNN extracts feature maps, which are then weighted by the attention mechanism to highlight critical areas of the leaf image while suppressing irrelevant background noise. This approach improves interpretability and ensures the classifier prioritizes regions with visible disease symptoms. The architecture includes convolutional layers, an attention module, global average pooling and a dense output layer. Fig. 4 depicts the CNN-Attention architecture.

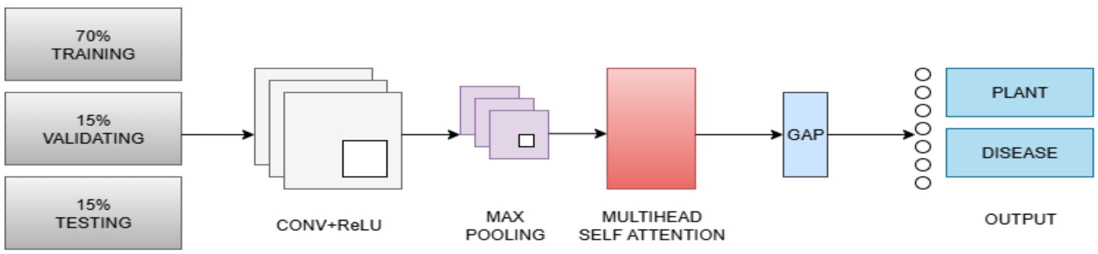


Fig.4. CNN-Attention architecture

The CNN-Attention model, as illustrated in Fig. 4, integrates a channel and spatial attention mechanism to dynamically emphasize relevant feature maps during training. The attention block enhances discriminative feature extraction, particularly for subtle disease symptoms that are visually similar across different leaf samples.

2.4. TRAINING AND EVALUATION

The models were trained using TensorFlow and Keras with GPU acceleration. The main training parameters included the ReLU activation function, Adam optimizer with a learning rate of 0.001, batch size of 32, dropout rate of 0.5, and a maximum of 10 epochs with an early stopping mechanism to prevent overfitting [22], [23].

Performances of all models were evaluated using four metrics: accuracy, precision, recall, and F1-score, calculated separately for plant classification and disease classification. The metrics are defined as follows:

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

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

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

$$F1 - Score = \frac{(2 \times Precision \times Recall)}{(Precision + Recall)}$$

where TP = true positives, TN = true negatives, FP = false positives, and FN = false negatives. These metrics provided a comprehensive assessment of the model's generalization ability across multiple tasks [4], [5].

2.5. PROTOTYPE APPLICATION

To ensure the practical applicability of the research findings in real agricultural contexts, the best-performing model, NASNetMobile, was deployed into a web-based prototype application developed using the Streamlit framework. The application was designed to enable real-time plant and disease identification through a simple and intuitive interface accessible to non-technical users such as farmers and agricultural practitioners.

The prototype allows users to upload a plant leaf image in JPG or JPEG format via the Upload button. Once the image is selected, clicking the Process button initiates the analysis. The system then simultaneously performs two classification tasks: 1) Identification of plant species, and 2) detection of the corresponding plant disease.

In addition to the classification outputs, the application provides Explainable AI (XAI) visualizations using the Eigen-CAM method, which highlights the most influential regions of the leaf image that contributed to the model's decision. This enables users to not only obtain diagnostic results but also to understand the reasoning behind the model's predictions in a transparent manner.

All computations were performed on a local server (localhost) using the pretrained NASNetMobile model. The application architecture consists of three main components:

1. Frontend (user interface): built with Streamlit, displaying image upload functionality, classification results, and XAI visualizations.
2. Backend (AI processing module): Python scripts responsible for loading the trained NASNetMobile model, performing inference, and generating both classification outputs and heatmaps.
3. Visualization module: integrates the Eigen-CAM algorithm to visualize the key regions of the leaf image influencing the model's decisions.

This prototype demonstrates that lightweight deep learning architectures such as NASNetMobile can be efficiently implemented in web-based systems without requiring extensive computational infrastructure. The approach provides a foundation for developing accessible, AIdriven plant disease diagnostic tools, which can be further expanded into cloud or mobile-based platforms to support precision agriculture in rural regions.

3. MAIN RESULTS

3.1. MODEL PERFORMANCE

The experimental results demonstrated that the NASNetMobile model achieved the best overall performance among the evaluated architectures. As shown in Table 2, NASNetMobile obtained an accuracy of 99.79% for plant classification and 98.57% for disease classification, surpassing both CNN-LSTM and CNN-Attention models. The CNN-LSTM achieved 98.86% and 94.99% accuracy for plant and disease classification, respectively, while CNN-Attention obtained 98.65% and 93.64%.

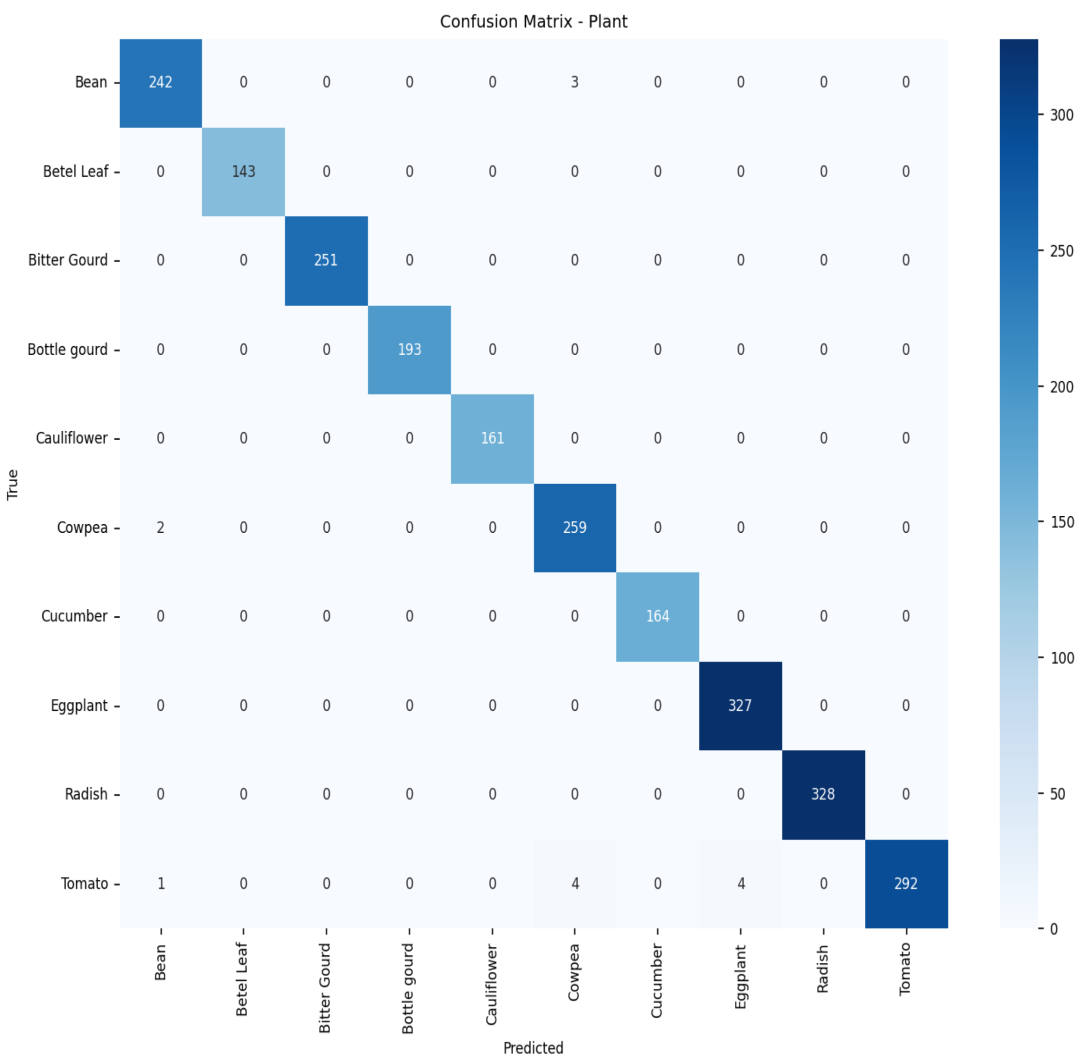
Table 2. Comparison of model performance for plant and disease classification

Model	Task	Accuracy	Precision	Recall	F1-Score
CNN-Attention	Plant	0.9865	0.9868	0.9865	0.9865
	Disease	0.9364	0.9356	0.9364	0.933
CNN-Attention +Augmented	Plant	0.9882	0.9884	0.9882	0.9882
	Disease	0.944	0.9512	0.944	0.9395
CNN-LSTM	Plant	0.9886	0.9887	0.9886	0.9886
	Disease	0.9499	0.9524	0.9499	0.9502
CNN-LSTM +Augmented	Plant	0.9789	0.9808	0.9789	0.9791
	Disease	0.9297	0.9316	0.9297	0.9262
NASNetMobile	**Plant**	**0.9979**	**0.9979**	**0.9979**	**0.9979**
	Disease	**0.9857**	**0.986**	**0.9857**	**0.9854**
NASNetMobile +Augmented	Plant	0.9941	0.9942	0.9941	0.9941
	Disease	0.9718	0.9742	0.9718	0.972

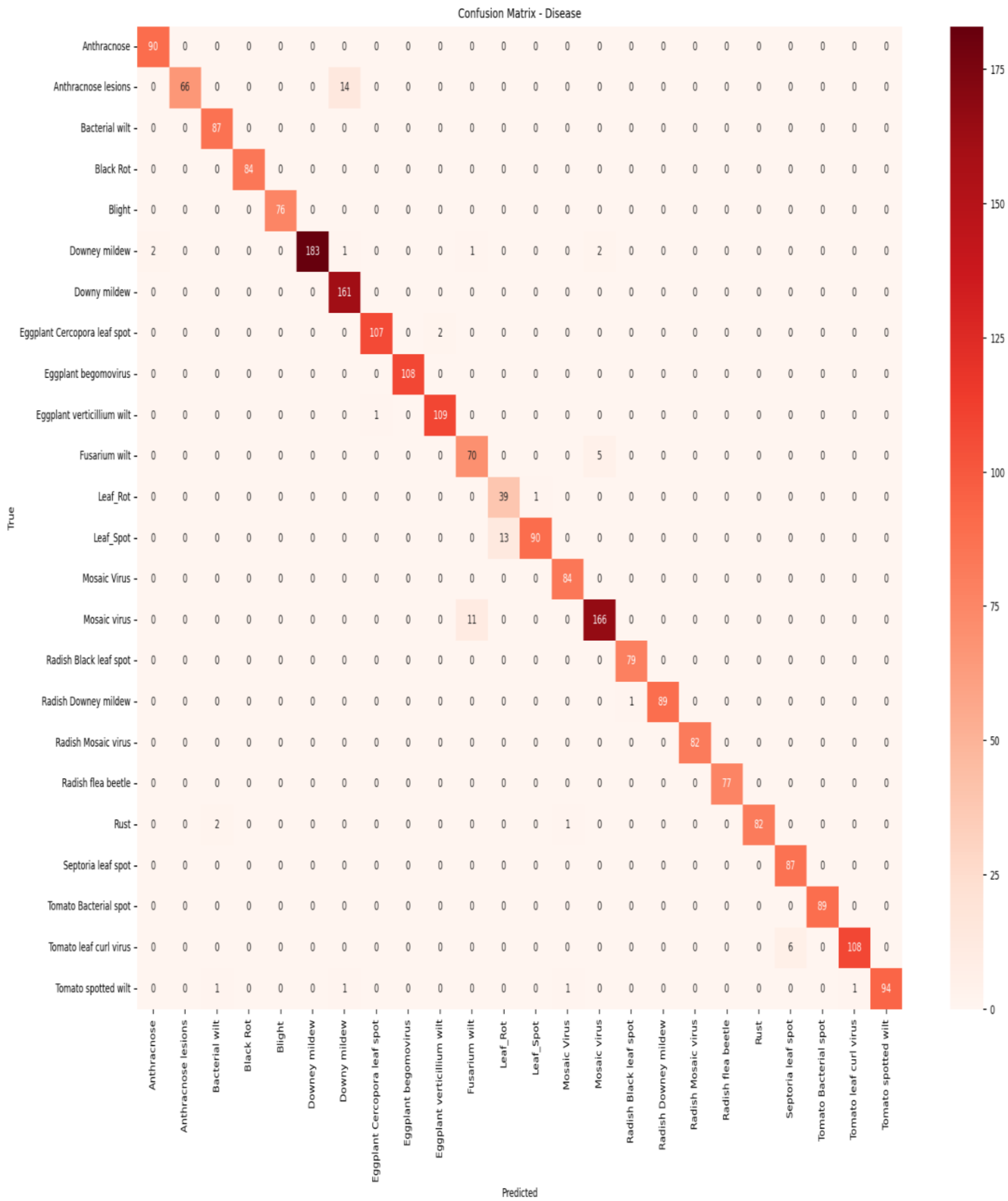
Data augmentation showed varied effects across architectures: it slightly improved CNN-Attention (disease accuracy increased to 94.40%) but reduced the performance of CNN-LSTM (92.97%) and NASNetMobile (97.18%). These results suggest that the pretrained NASNetMobile model exhibits superior robustness and generalization across the dataset, especially under diverse image conditions.

3.2. Confusion Matrix Analysis

Fig. 5 presents the confusion matrices for the best-performing NASNetMobile model in both plant and disease classification tasks. For plant classification, almost all species were correctly identified, with only minor misclassifications observed between visually similar plants such as Bean and Cowpea. For disease classification, the model demonstrated high accuracy across most categories, with slight confusion between visually overlapping diseases such as Anthracnose and Leaf Spot. Notably, certain diseases such as Downy mildew, Mosaic virus, and Radish flea beetle were classified with near-perfect accuracy, confirming the reliability of the model in identifying distinct disease symptoms.



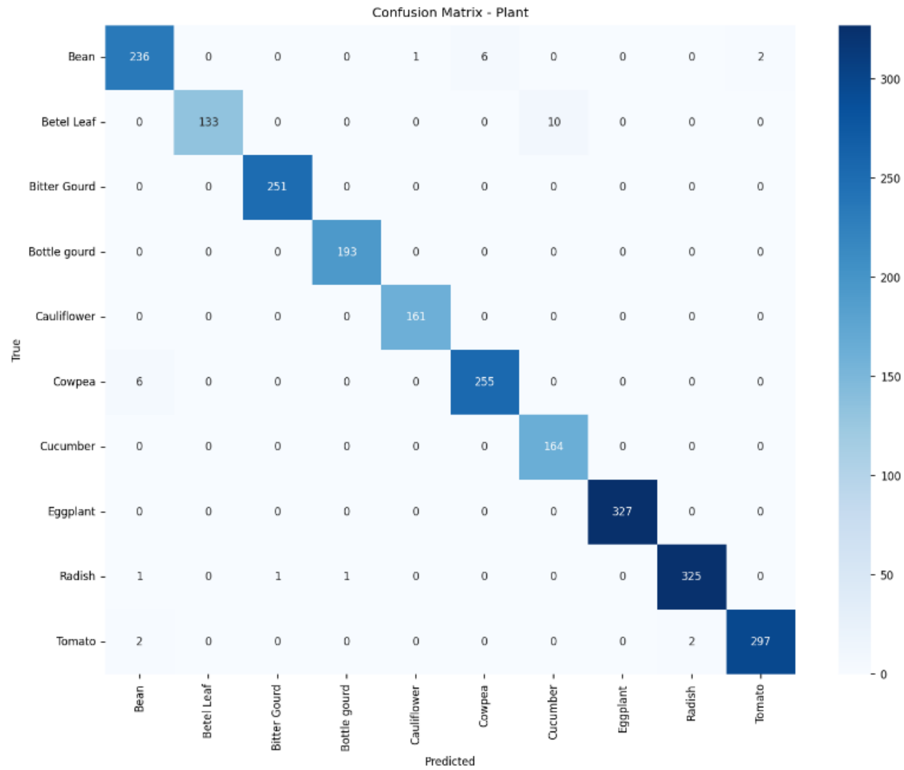
(a)



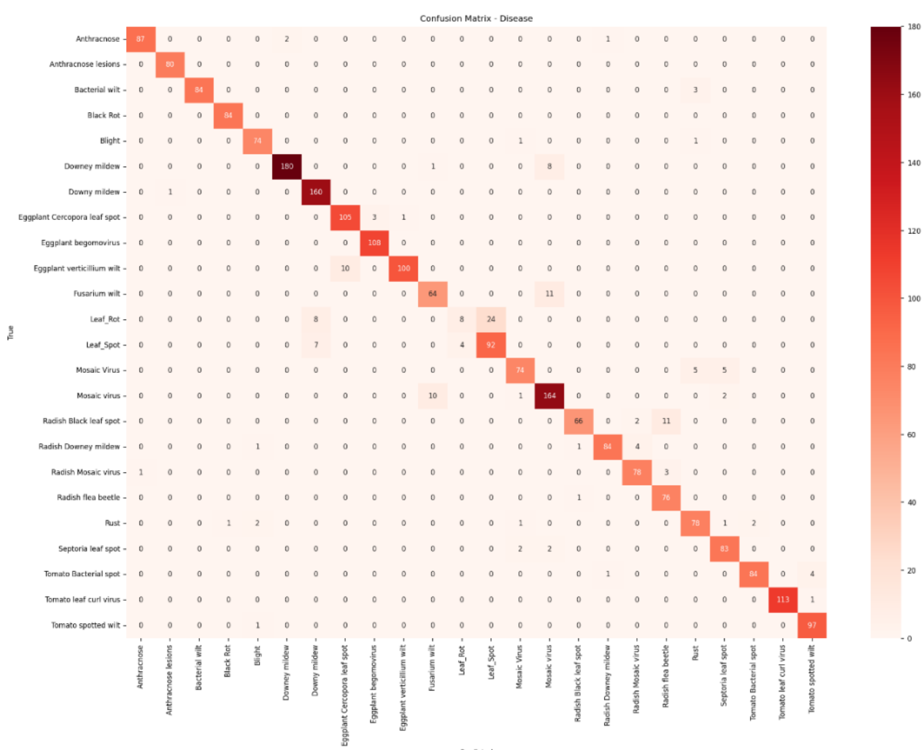
(b)

Fig. 5. Confusion matrices of NASNetMobile for plant (a) and disease (b) classifications

Fig. 6 illustrates the confusion matrices for the CNN-Attention model. While this architecture successfully identified most plant species, its disease classification accuracy was lower than that of NASNetMobile and CNN-LSTM. Misclassifications were observed for diseases with subtle color variations, suggesting that the attention mechanism, while helpful for spatial focus, may require further tuning to handle high inter-class similarity in plant disease images.



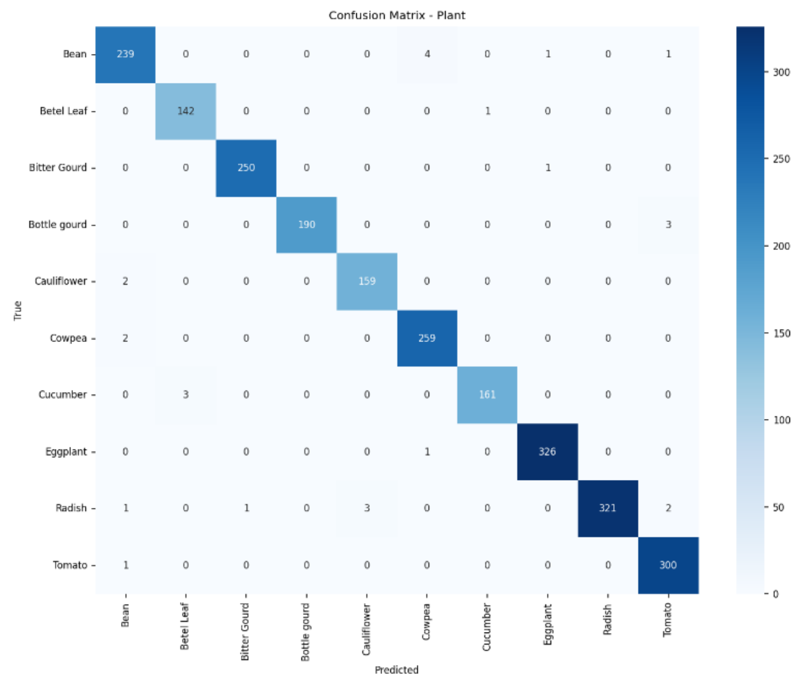
(a)



(b)

Fig. 6. Confusion matrices of CNN-Attention for plant (a) and disease (b) classifications

The confusion matrices of the CNN-LSTM model are displayed in Fig. 7. The model achieved strong performance but showed slightly higher confusion compared to NASNetMobile, particularly between visually similar leaf textures such as *Bean* and *Cowpea*. In disease prediction, the CNN-LSTM occasionally misclassified *Leaf Spot* as *Anthracnose*, likely due to overlapping lesion patterns across classes.



(a)

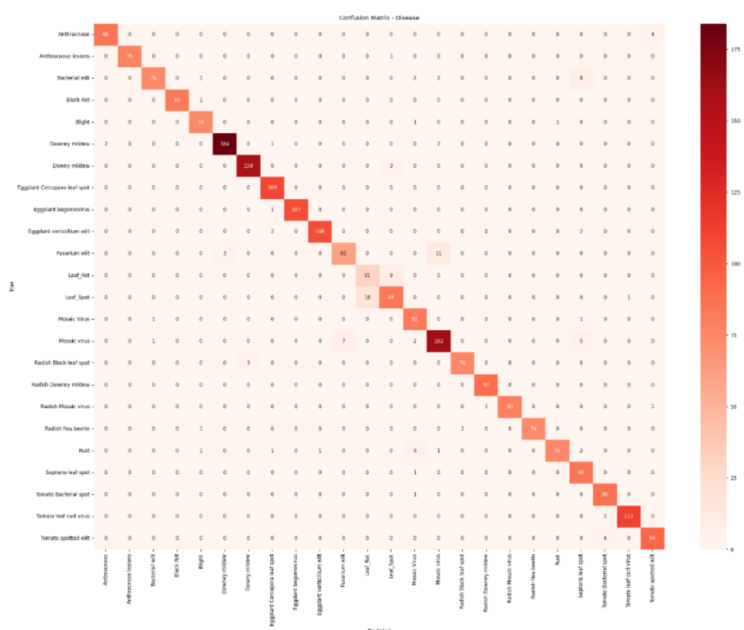


Fig. 7. Confusion matrices of CNN+LSTM for plant (a) and disease (b) classifications

3.3. TRAINING PERFORMANCE

Fig. 8 illustrates the training and validation curves for NASNetMobile. The accuracy of plant classification reached near-perfect values early in the training, while disease classification accuracy gradually improved and stabilized above 95%. Both training and validation losses decreased consistently and showed close alignment, indicating that the model achieved optimal convergence without signs of overfitting.

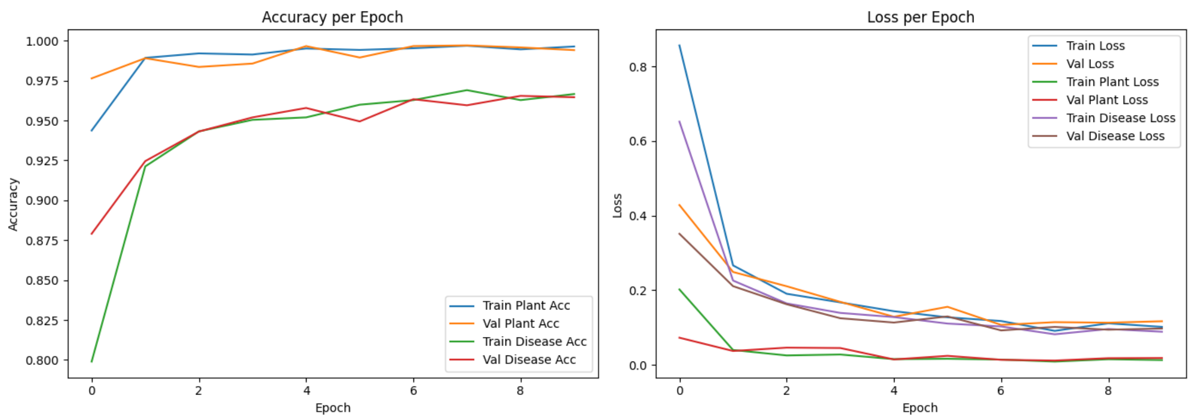


Fig. 8. Training and validation curves for NASNetMobile

The training and validation curves of the CNN-LSTM model are displayed on Fig. 9. The model reached relatively high accuracy during training; however, a slight gap between training and validation accuracy suggests moderate overfitting. This behavior may result from the model's higher parameter count and its sequential structure, which requires more data to capture long-range dependencies effectively. Nonetheless, the performance remained acceptable, confirming the model's ability to learn temporal and spatial features jointly.

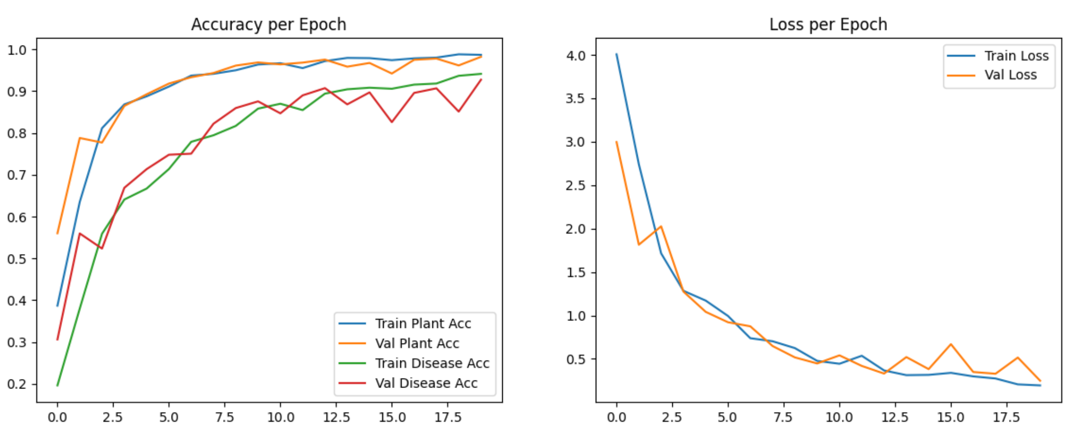


Fig. 9. Training and validation curves for CNN-LSTM

Fig. 10 shows the training and validation accuracy and loss curves for the CNN-Attention model. The results indicate that this model achieved rapid convergence during early epochs, but exhibited minor fluctuations in validation loss. This pattern reflects the dynamic weighting mechanism of the attention module, which improves focus on relevant image regions but may introduce slight instability during optimization. Despite this, the final validation accuracy remained high, confirming that the attention mechanism enhanced feature extraction for plant disease classification.

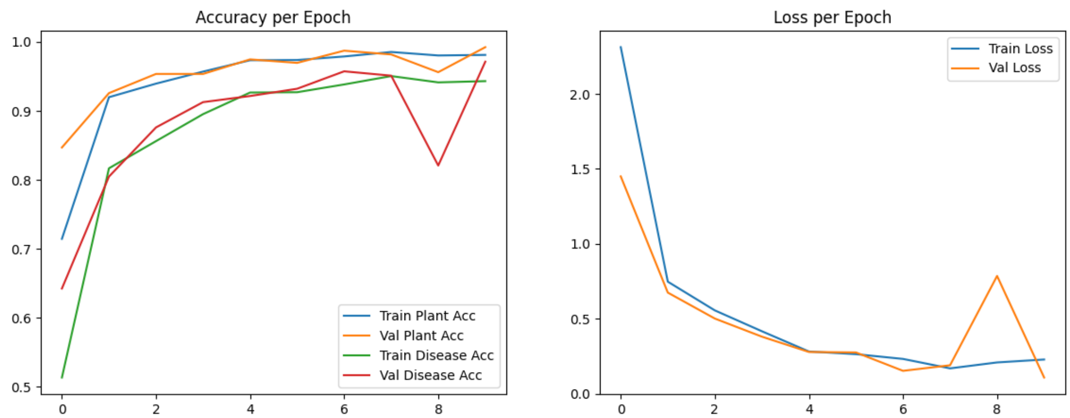


Fig. 10. Training and validation curves for CNN-Attention

3.4. Explainable AI (XAI) Visualization

Interpretability of the model's predictions was achieved using two Explainable AI techniques: Local Interpretable Model-Agnostic Explanations (LIME) and Eigen-CAM. As shown in Fig. 11, Eigen-CAM produced global heatmaps highlighting major leaf regions contributing to the classification decision, whereas LIME generated localized segment-based visualizations pinpointing the most influential regions. The complementary use of these two techniques provided both macro- and micro-level interpretability, enhancing user understanding and trust in model predictions.

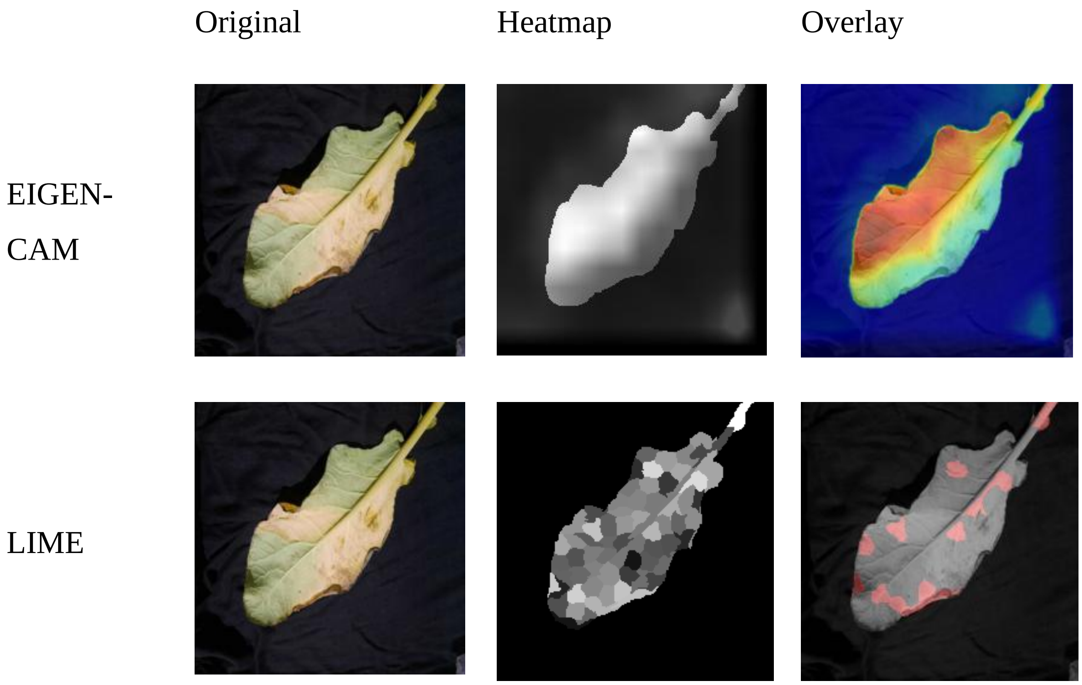


Fig. 11. Examples of XAI visualizations using LIME and Eigen-CAM

3.5. Prototype Application Deployment

To validate the real-world applicability of the model, the best-performing NASNetMobile was deployed as an interactive web-based prototype developed using Streamlit (Fig. 12). Users can upload a leaf image and instantly obtain:

1. Plant species classification.
2. Disease classification with confidence score.
3. Visualization of decision regions via Eigen-CAM.

This prototype demonstrates the feasibility of deploying an end-to-end explainable AI system for practical agricultural diagnostics, bridging the gap between laboratory-trained models and field-level decision support.

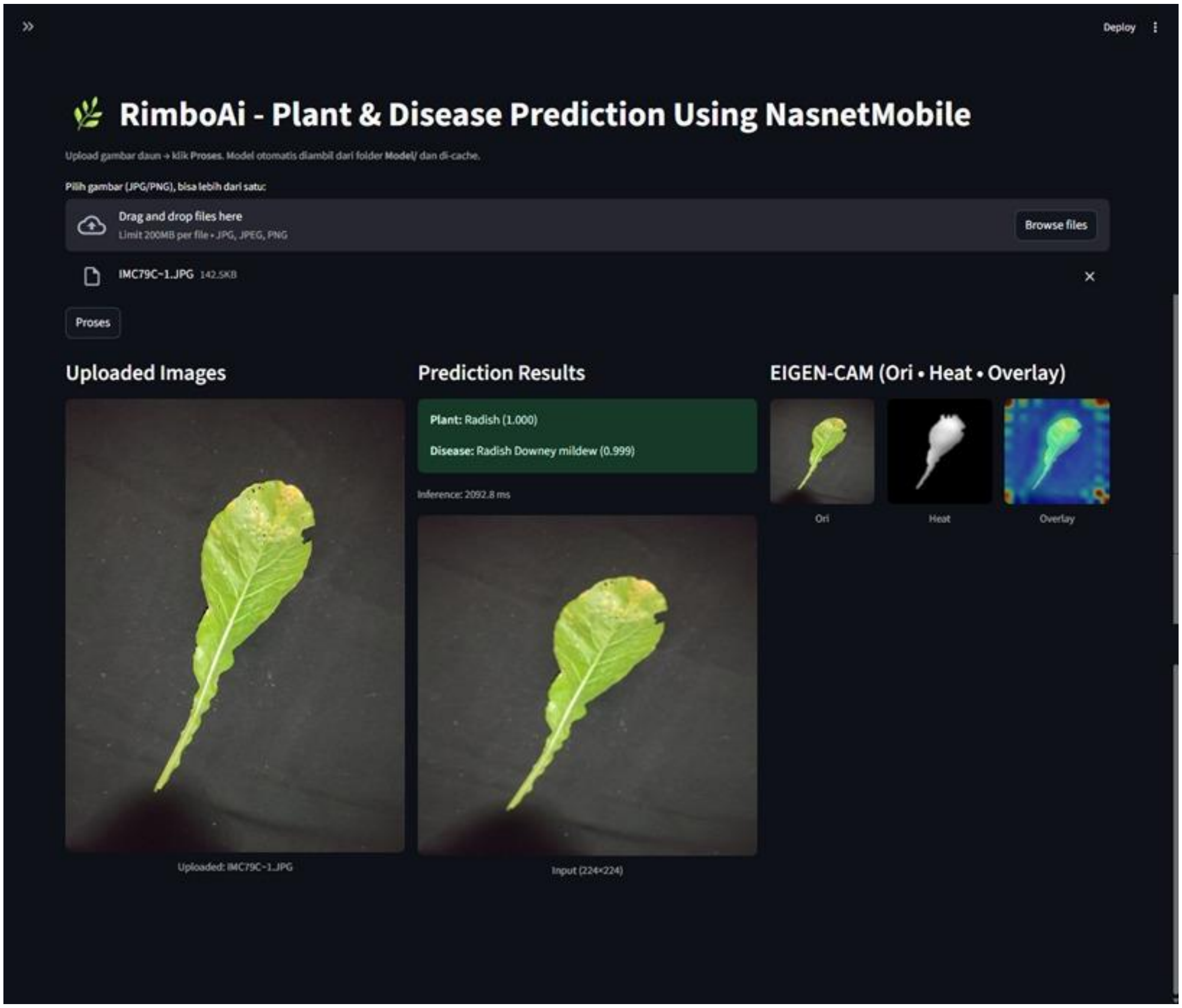


Fig. 12. AI-web application built using best model

4. DISCUSSION

The comparative analysis of three deep learning architectures NASNetMobile, CNN-LSTM, and CNN-Attention revealed that NASNetMobile consistently delivered superior classification performance for both plant species and disease detection. This result aligns with prior studies demonstrating that lightweight, search-optimized architectures can balance high accuracy and computational efficiency, making them particularly suitable for real-world agricultural [24], [25].

The exceptional performance of NASNetMobile can be attributed to its ability to automatically discover optimal convolutional cell structures through Neural Architecture Search (NAS). This process enhances the model's representational capacity while minimizing overfitting, which is an essential advantage for field conditions where image variability is high. In contrast, the CNN-LSTM and CNN-Attention models, despite their theoretical strengths in capturing temporal and spatial dependencies, required higher computational costs and exhibited lower generalization when faced with heterogeneous image backgrounds and lighting conditions.

The results also highlight the importance of dataset diversity and the challenges associated with plant disease classification in uncontrolled environments. Although data augmentation techniques increased sample variability, they did not always improve accuracy across all architectures. This suggests that pretrained models like NASNetMobile, which leverage large-scale ImageNet features, already possess strong generalization capabilities even without additional augmentation.

The explainability analysis using Eigen-CAM and LIME provided valuable insights into the internal reasoning of the models. Eigen-CAM offered a global understanding of discriminative regions, identifying broader leaf areas affected by disease, while LIME produced localized explanations that emphasized specific lesions or spots. This dual-layer interpretability is critical for building user trust and promoting the practical adoption of AI-based systems by farmers, agronomists, and agricultural extension workers. The use of explainable AI further supports transparency and accountability, which is a key aspects in deploying decision-support tools in sensitive domains like agriculture.

The successful deployment of NASNetMobile in a Streamlit-based web application demonstrates the potential of integrating high-performance AI models into accessible platforms. By enabling real-time classification and visualization through an intuitive interface, the prototype bridges the gap between research and practice. Similar approaches have been reported to accelerate technology transfer and improve precision agriculture outcomes by empowering non-expert users to make timely and evidence-based decisions [7], [26].

Nevertheless, some limitations remain. The current dataset, although diverse, still exhibits class imbalance and limited real-field variability, which could reduce robustness in unseen conditions. Additionally, the system focuses exclusively on image-based diagnosis without incorporating environmental or temporal data. These aspects can be addressed in future work by integrating multimodal data sources (e.g., weather conditions, soil data, or temporal disease progression) and exploring transformer-based architectures or federated learning frameworks for continual model improvement.

Overall, the findings of this study contribute to advancing the field of explainable deep learning for plant protection by combining high accuracy, model transparency, and deployment feasibility.

This integrated approach strengthens the bridge between artificial intelligence research and practical agricultural solutions, supporting the broader goal of sustainable and data-driven crop management.

5. Conclusion

This study evaluated and compared three deep learning architectures such as NASNetMobile, CNN-LSTM, and CNN-Attention for multi-class plant disease classification. The results showed that NASNetMobile achieved the best performance with 99.79% accuracy in plant classification and 98.57% in disease classification, outperforming CNN-LSTM (98.86% and 94.99%) and CNN-Attention (98.65% and 93.64%). NASNet Mobile demonstrated the advantage of being both lightweight and highly accurate, making it suitable for web-based deployment. CNN-LSTM also performed competitively, but required longer training time and exhibited minor risks of overfitting. Meanwhile, CNN-Attention produced the lowest performance, suggesting that attention mechanisms may require larger and more balanced datasets to reach optimal effectiveness.

These findings highlight NASNet as a strong candidate to bridge the gap between laboratory-trained models and real-world agricultural applications. The best-performing model was integrated into the AI web application, developed with Streamlit, enabling real-time disease detection accompanied by interpretability visualizations through Eigen-CAM. This integration has significant implications for precision agriculture, supporting farmers with more accurate and explainable decision-making tools.

Author Contributions

Dede Fauzi was responsible for conceptualization, methodology, dataset collection, and model development. Mahmud Isnan contributed to supervision, validation, web deployment, and manuscript review. Both authors discussed and approved the final version of the manuscript.

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Conflict of Interests

The authors declare that there is no conflict of interests.

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