A Lightweight Attention-Enhanced CNN-SVM Hybrid Approach for Maize Leaf Disease Classification

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Introduction

- **Maize (*Zea mays* L.)** -> one of the most widely cultivated cereal crops.

- Vital role in global food security, serving as:
  - A staple food for **humans**
  - A primary source of **animal feed**
  - A raw material for **industrial and biofuel production**

- Also contributes to **agricultural economies**, in developing countries.

- Maize production -> highly susceptible to **leaf diseases** - **curvularia leaf spot**, **small spot** and **rust**.

- These commonly occur under -> **high humidity** and **temperature**.

- If not detected early, they can cause **substantial yield losses**:
  - Reduced grain quantity
  - Degraded grain quality and market value

Fig. 1 Representative RGB image of a maize leaf exhibiting visible disease symptoms, characterized by yellow–brown pustules indicative of leaf rust infection.

Why This Work Matters?

<u>Motivation:</u>
- Current disease diagnosis methods rely on **manual visual inspection**:
    – Time-consuming and labor-intensive
    – Subjective and prone to human error
    – Not scalable for large agricultural fields

- **Deep learning–based approaches**, although effective, are often:
    – Computationally expensive
    – Difficult to deploy on low-resource devices commonly used by farmers

- There is a strong need for an **automated, accurate, and resource-efficient solution** for maize disease diagnosis.

<u>Key Contributions:</u>
- Proposed a lightweight **MobileNetV2–Convolutional Block Attention Module (CBAM)** architecture for efficient feature extraction from maize leaf images.
- Trained an independent **Support Vector Machine (SVM) classifier** on the deep features.
- Comprehensive experimental evaluation on **two benchmark leaf disease datasets**.
- Demonstrated superior performance over existing methods in terms of accuracy and effectiveness.
- Also, a **systematic ablation analysis** to access the contribution of each component.

Literature Analysis

Work	Approach	Accuracy (%)
Li et al. [1] - 2022	WG-MARNet	97.96
Pillai et al. [2] - 2023	Fusion model (CNN + VGG16 + Decision Tree)	96
Tariq et al. [3] - 2024	VGG16 + Explainable AI	94.67
Theerthagiri et al. [4] - 2024	Deep SqueezeNet	97
Liu et al. [5] - 2024	Multi-Scale Feature Fusion Network	97.45
Hu et al. [6] - 2024	LFMNet	94.12
Bachhal et al. [7] - 2024	Principal Feature Ranking-SVM Integration	96.67
Joyce et al. [8] - 2025	CNN, Transfer Learning	97

Proposed Methodology
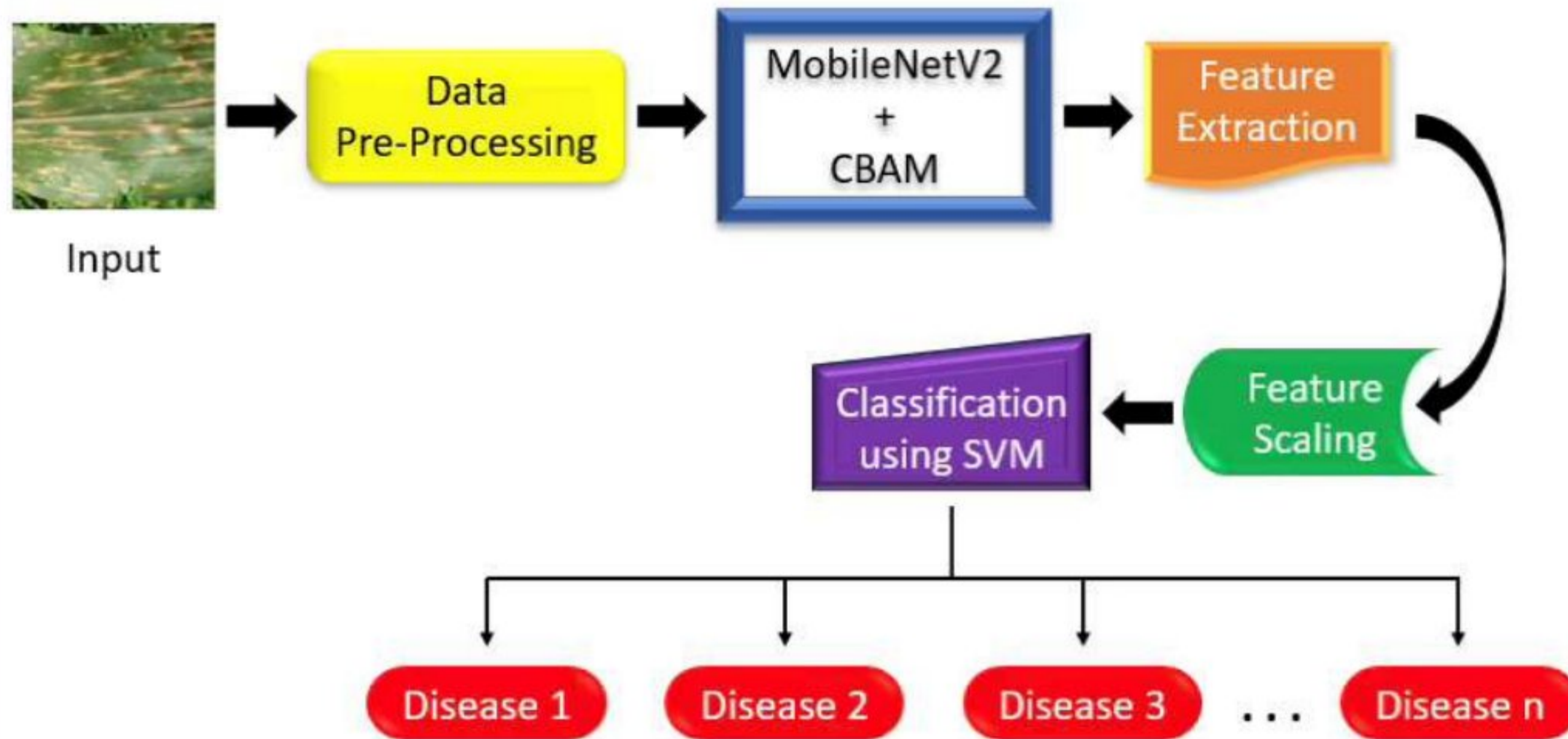
Fig. 2 Illustration of the proposed framework.

Phase 1: Feature Extraction (MobileNetV2–CBAM)
- **MobileNetV2 backbone** augmented with **CBAM** for attention-aware learning.
- CBAM incorporates:
  - **Channel attention** – identifies important feature dimensions
  - **Spatial attention** – focuses on disease-relevant regions in images
- The network learns enhanced disease representations from maize leaf images.
- **Trained end-to-end** using -> label smoothing, weight decay regularization, learning rate scheduling, early stopping to prevent overfitting.

Phase 2: Deep Feature Generation
- Classification layers are removed after training.
- The trained network acts as a **feature extractor**.
- Each input image (224 × 224 pixels) produces a **128-dimensional attention-enhanced feature vector**
- Extracted features are standardized using **StandardScaler**.

Phase 3: Classification Using SVM
- **Support Vector Machine (SVM)** used for final disease classification.
- **Radial-basis function (RBF) kernel** applied to model non-linear disease patterns.
- **Regularization parameter 'C'** empirically tuned:
  - Optimal performance achieved at **C = 30**
- **Class weights applied** to address dataset imbalance.

Result Analysis and Discussion

Data Acquisition and Pre-processing

I. **Kaggle Leaf Disease Dataset 1 [9]**

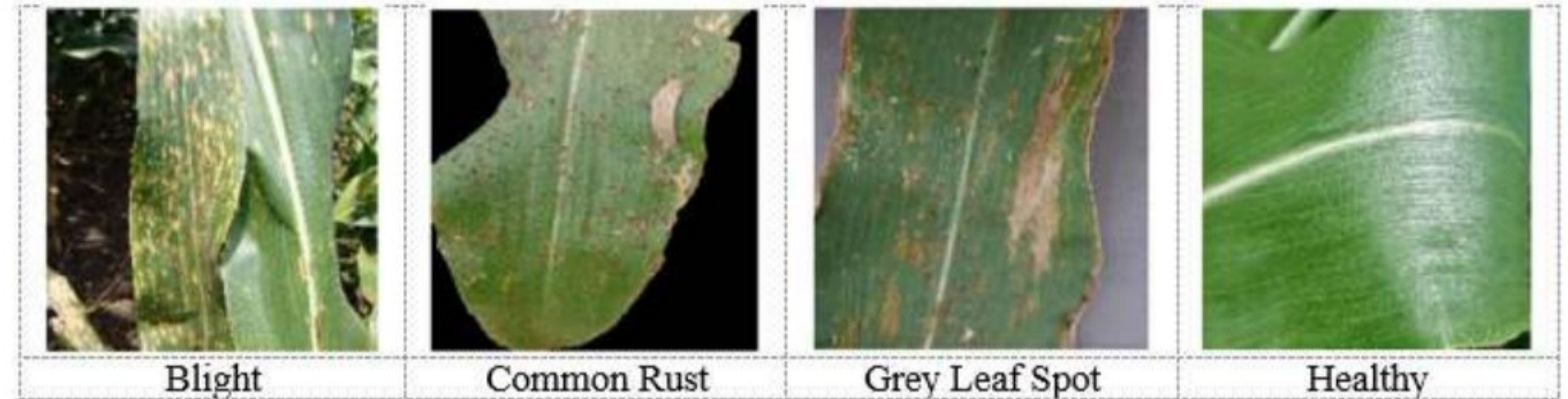**Total images: 4188**, categorized into **4 classes**:

- **Blight (Class 0): 1146 images**
- **Common Rust (Class 1): 1306 images**
- **Gray Leaf Spot (Class 2): 574 images**
- **Healthy (Class 3): 1162 images**

II. **Kaggle Leaf Disease Dataset 2 [10]**

Total images: 8852, categorized into **5 classes**:

- **Common Rust (Class 0): 1907 images**
- **Gray Leaf Spot (Class 1): 1642 images**
- **Healthy (Class 2): 1,859 images**
- **Northern Leaf Blight (Class 3): 1908 images**
- **Non-Maize Leaf (Class 4): 1536 images**

Blight   Common Rust   Grey Leaf Spot   Healthy

Fig. 3 Visual samples of maize leaf categories from the first dataset.

Common Rust   Grey Leaf Spot   Healthy   Northern Leaf Blight   Not Maize Leaf

Fig. 4 Visual samples of maize leaf categories from the second dataset.

✓ Dataset split -> **Train: 80%, Validation: 10%, Test: 10%**

✓ Images resized to **224 × 224 pixels**

✓ Pixel values scaled to **[0,1]**

✓ Data augmentation (training set only) -> **Random rotation (±30°), Horizontal and vertical flipping, Brightness adjustment (0.8 – 1.2), Zooming (up to 20%)**
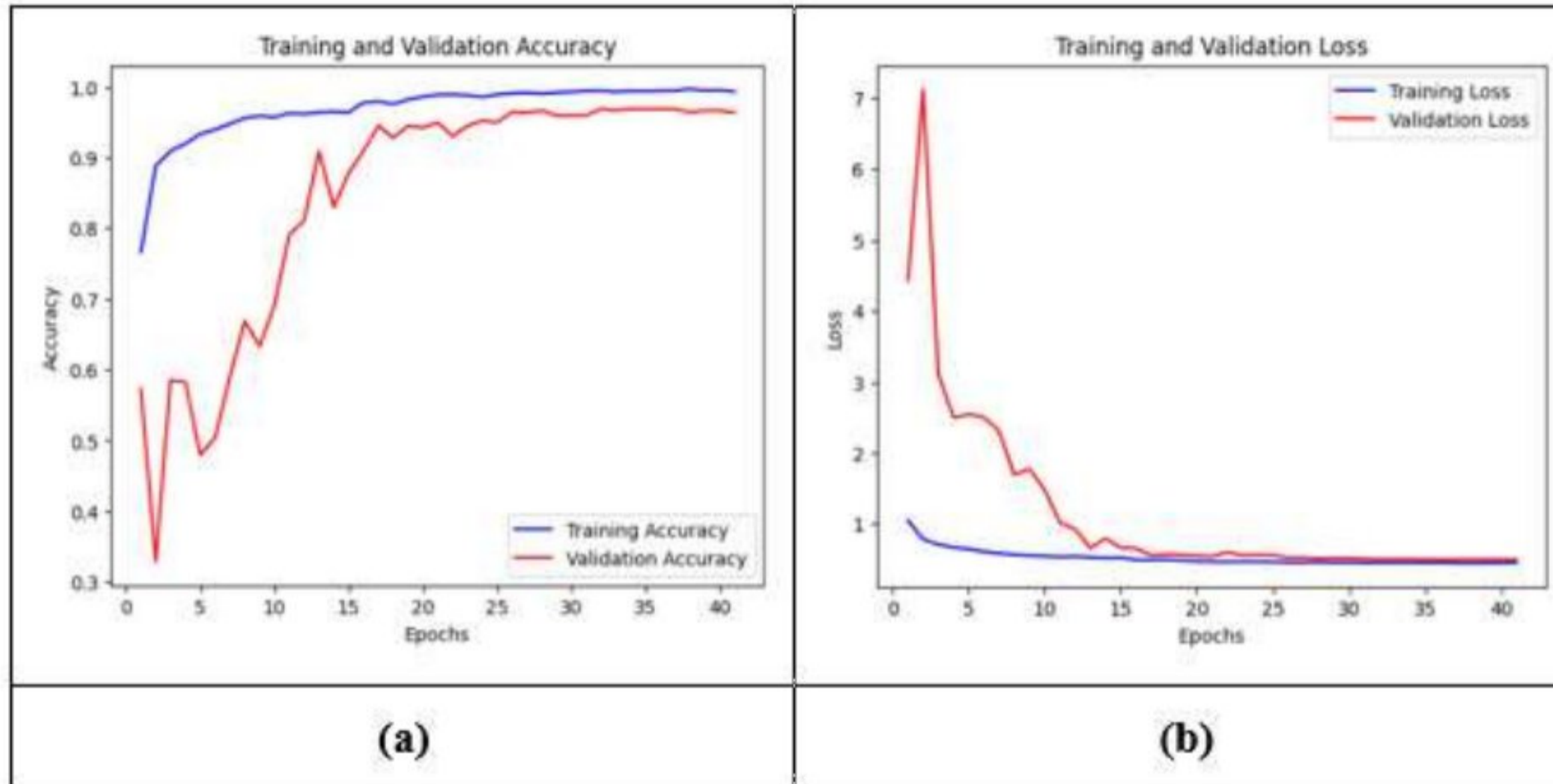
Result Analysis and Discussion (cont.)

I.   Kaggle Leaf Disease Dataset 1 [9]

Fig. 5 The MobileNetV2-CBAM model's performance during training and validation on the first dataset: (a) Accuracy Curves (b) Loss Curves.
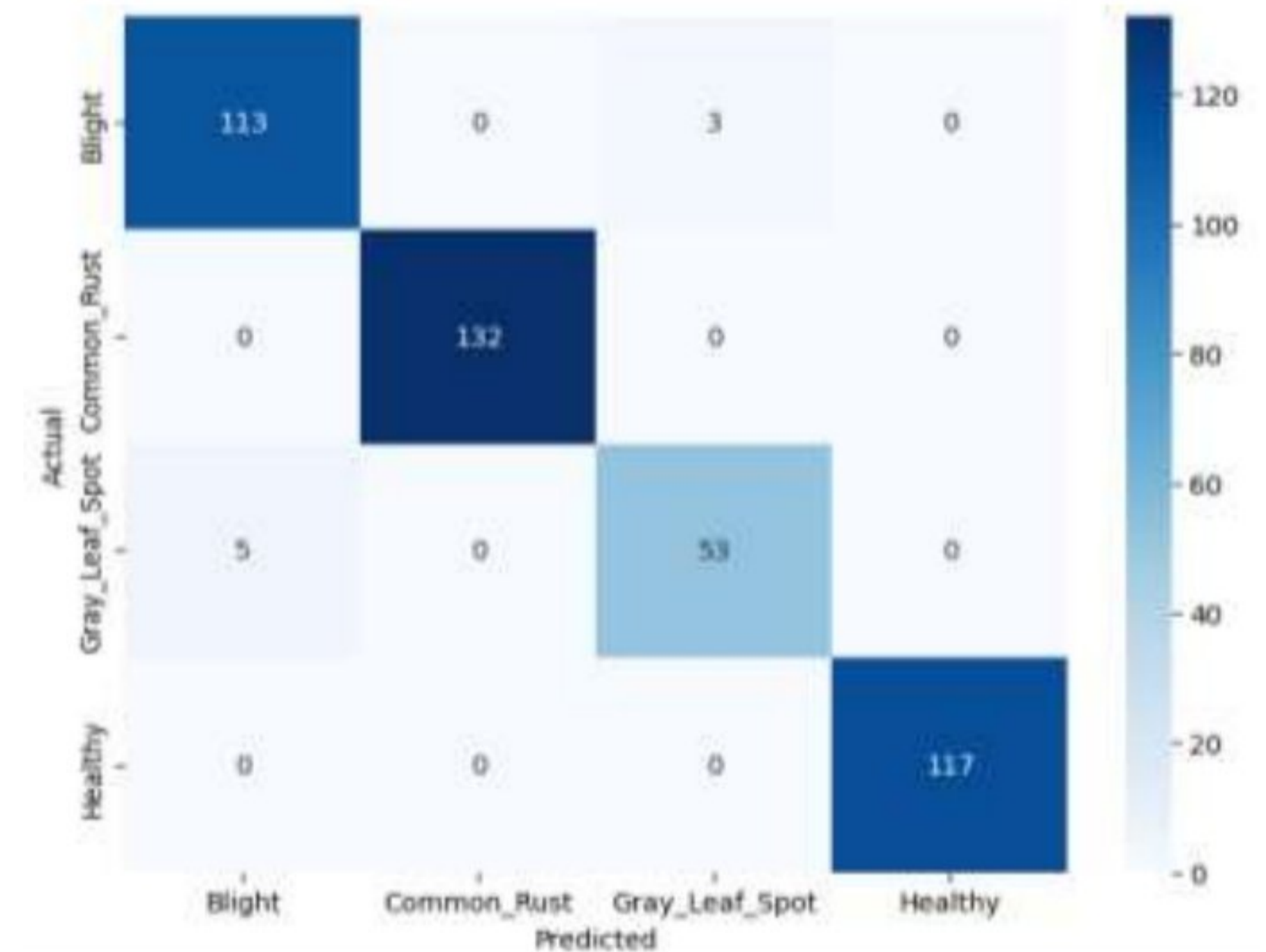

Fig. 6 Confusion matrix illustrating per-class performance of the proposed approach on the first dataset.

- Training completed in **41 epochs**
- Validation accuracy improved-> From **~57% (val loss ≈ 4.4)** To **>96% (val loss ≈ 0.5)**
- Learning rate adaptively reduced to **~2×10^{-6}**
- Training accuracy: **>99%**
- Validation accuracy: **96–97%**
- SVM Test Accuracy: **98.11%**
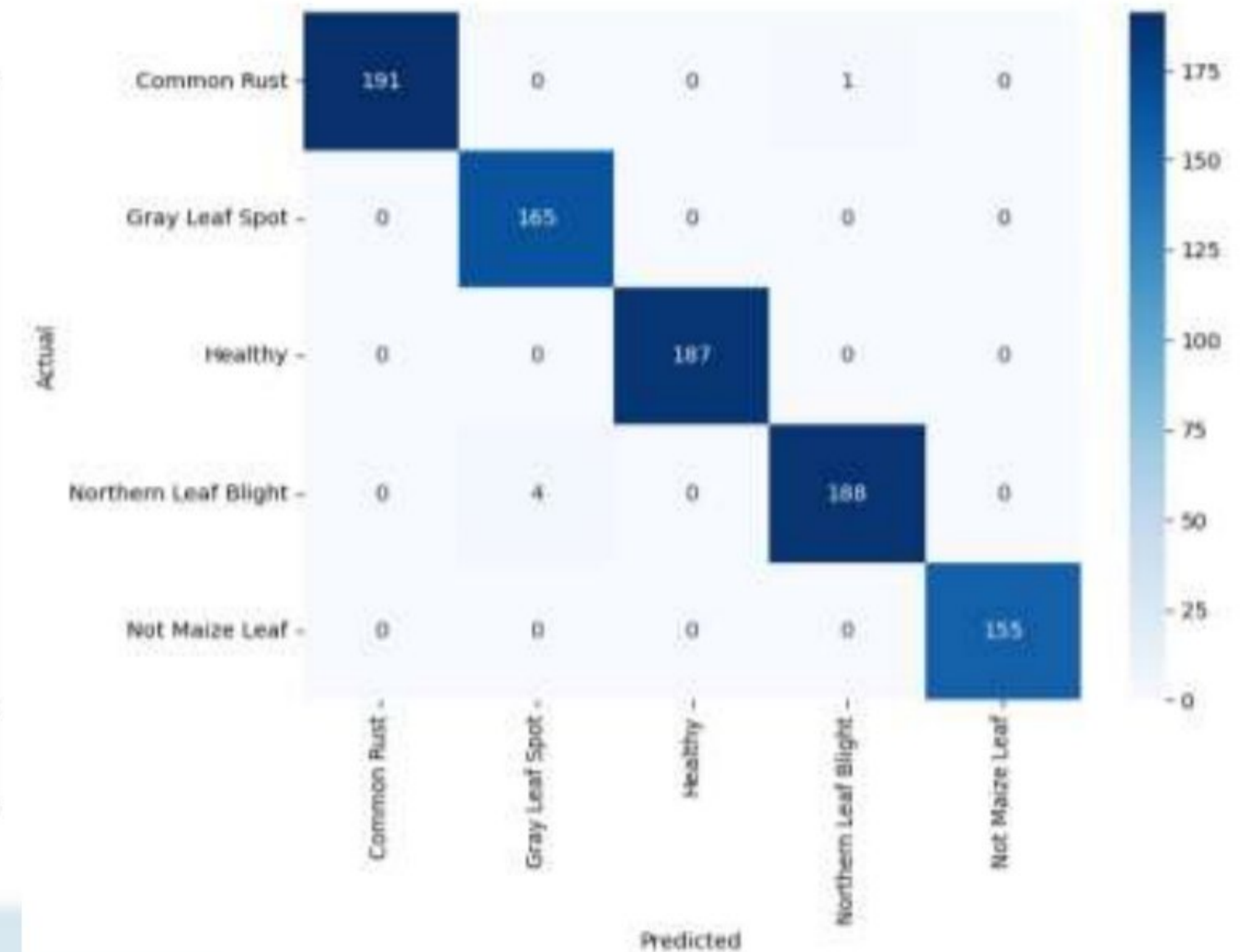- Precision, Recall, F1-score: **0.98 across all classes**

Result Analysis and Discussion (cont.)

II. Kaggle Leaf Disease Dataset 2 [10]
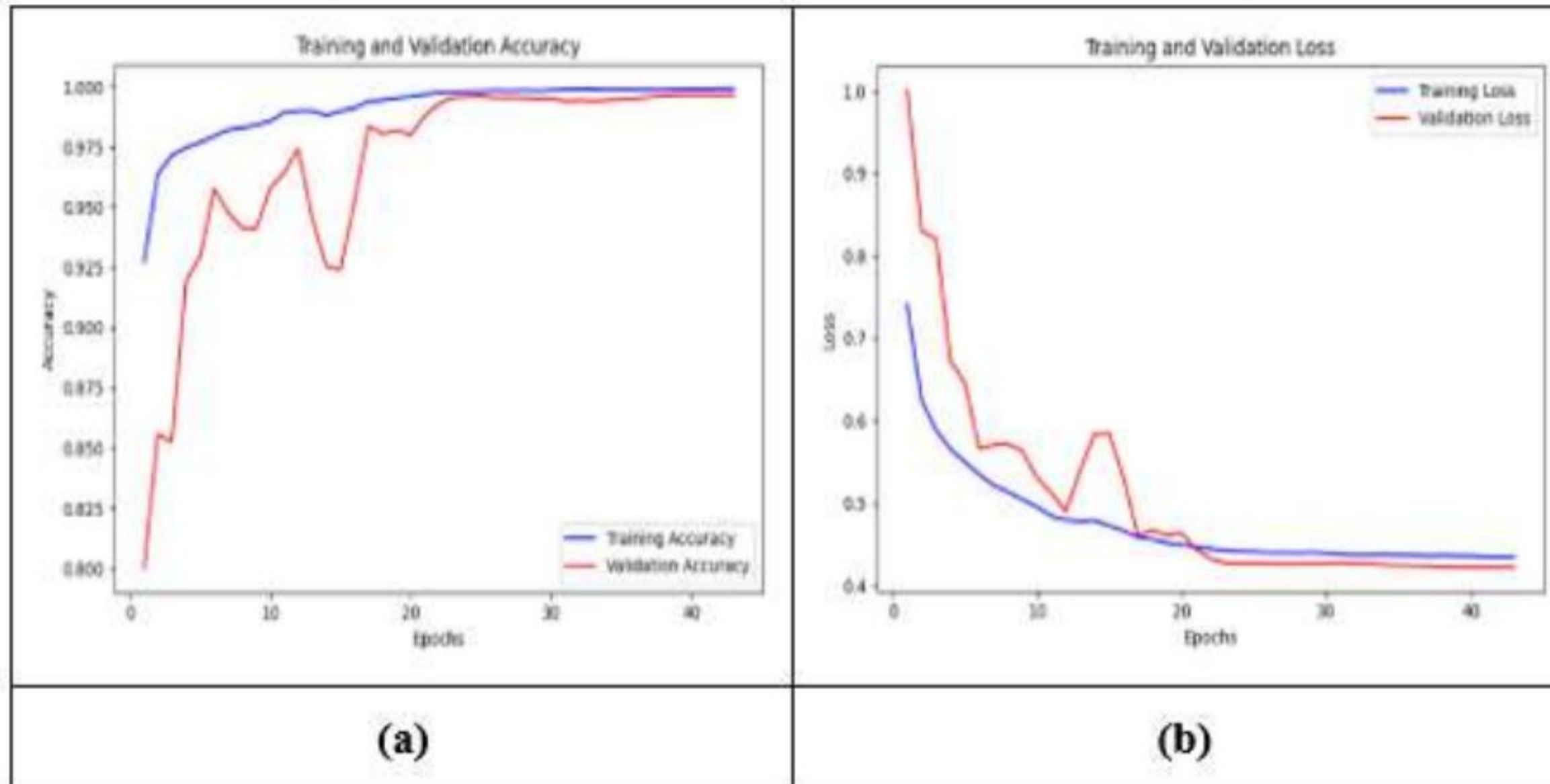
Fig. 7 The MobileNetV2-CBAM model's performance during training and validation on the second dataset: (a) Accuracy Curves (b) Loss Curves.

Fig. 8 Confusion matrix showing the performance of the proposed framework on the second dataset.

- Training completed in **45 epochs**
- Training accuracy -> Increased from **~78% to >99%**
- Validation accuracy -> Improved from **~77% to ~99.7%**
- Validation loss -> Decreased steadily to **~0.42**
- Learning rate adaptively reduced to **~2×10^{-6}**
- SVM classifier trained on deep features -> Achieved **99.44% test accuracy**
- Precision, Recall, F1-score: **> 0.99**

Result Analysis and Discussion (cont.)

Work	Approach	Accuracy (%)
Pillai et al. [7] - 2023	Fusion model (CNN + VGG16 + Decision Tree)	96
Tariq et al. [8] - 2024	VGG16 + Explainable AI	94.67
Theerthagiri et al. [9] - 2024	Deep SqueezeNet	97
Liu et al. [10] - 2024	Multi-Scale Feature Fusion Network	97.45
Proposed Framework - 2026	**MobileNetV2-CBAM + SVM**	**98.11**

Table 1. Performance comparison of recent methods versus the proposed framework on the first dataset.

Work	Approach	Accuracy (%)
Li et al. [11] - 2022	WG-MARNet	97.96
Hu et al. [12] - 2024	LFMNet	94.12
Bachhal et al. [13] - 2024	PRF-SVM Integration	96.67
Joyce et al. [14] - 2025	CNN, Transfer Learning	97
Proposed Framework - 2026	**MobileNetV2-CBAM + SVM**	**99.44**

Table 2. Performance comparison of recent approaches and the proposed framework on the second dataset.

Result Analysis and Discussion (cont.)

Ablation Analysis of the Proposed Framework

- Compared models -> **Baseline MobileNetV2, MobileNetV2 + CBAM (attention-enhanced)**, **Proposed Hybrid Model: MobileNetV2–CBAM + SVM**
- **Key Insights from Ablation Study:**
- ✓ Attention-weighted deep feature extraction significantly improves performance.
- ✓ Hybrid learning enhances decision boundary definition.
- ✓ Combining **DL-based attention mechanisms** with **classical ML (SVM)** yields:
  - Better generalization
  - Higher classification accuracy

Configuration	Dataset 1 (Accuracy in %)	Dataset 2 (Accuracy in %)
MobileNetV2	95.27	97.96
MobileNetV2-CBAM	97.16	98.99
MobileNetV2-CBAM + SVM	**98.11**	**99.44**

Table 3. Ablation study evaluating the effect of attention mechanism and hybrid DL-ML approach on the model performance.

Conclusion and Future Directions

- Proposed an **efficient hybrid framework** for maize leaf disease identification.
- Framework combines -> **MobileNetV2–CBAM** for attention-enhanced feature extraction, **SVM classifier** for robust disease classification.
- Achieved state-of-the-art performance:
- ✓ **98.11% accuracy** on Kaggle Leaf Disease Dataset 1
- ✓ **99.44% accuracy** on Kaggle Leaf Disease Dataset 2
- **Ablation analysis** confirms -> Effectiveness of **attention mechanisms (CBAM),** Benefit of **hybrid DL–ML learning.**
- The lightweight design makes the model suitable for **resource-constrained environments**.

- Future works can extend the framework to -> **other crops and plant diseases, diverse agricultural image scenarios**.
- Incorporate additional imaging modalities -> **hyperspectral imaging, thermal (thermography) imaging**.
- Optimize for edge and mobile deployment -> **model quantization, network pruning, lightweight inference pipelines**.

References

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[10] Kaggle Leaf Disease Dataset 2, https://www.kaggle.com/datasets/farmannaim/maizeleaf, last accessed 2025/07/19.