Green Intelligent Systems and Applications

Research Article
Volume 6(1), 2026, 108−119
https://doi.org/10.53623/gisa.v6i1.1158

Comparison of Tea Leaf Disease Classification Using SVM with MobileNetV2 and MobileNetV3-Small Feature Extractors

Muhammad Dzaky Raihan*, Novan Wijaya

Faculty of Computer Science and Engineering, Universitas Multi Data Palembang, South Sumatra, Indonesia

*Correspondence: muhammaddzakyraihan_2226250100@mhs.mdp.ac.id

SUBMITTED: 14 April 2026; REVISED: 13 May 2026; ACCEPTED: 17 May 2026

ABSTRACT: Tea is a strategic plantation commodity that serves as a major source of income for millions of rural families. However, its production is often threatened by devastating pests and diseases. Accurate and timely classification of diseases such as brown blight, gray blight, and tea algal leaf spot is crucial for maintaining crop quality. Traditional identification methods often involve observer subjectivity and require significant time. Although Convolutional Neural Networks (CNNs) have demonstrated effectiveness in automatic recognition, their application on mobile devices is often limited by high computational demands. Previous studies in the tea domain that use MobileNet as a feature extractor combined with an SVM classifier are still limited. Therefore, this study evaluates the implementation of this hybrid model for tea leaf disease classification. This study compares two models: MobileNetV2-SVM and MobileNetV3-Small-SVM, using the TeaLeafBD dataset. Empirical testing shows that both architectures achieve very comparable classification performance, with accuracy rates of 75.3% for MobileNetV2 and 75.1% for MobileNetV3-Small. Despite marginal differences in accuracy, the MobileNetV3-Small-SVM hybrid offers a lower computational footprint, reducing computational load by approximately fivefold and model size by more than half. These findings indicate that the MobileNetV3-Small-SVM architecture provides a favorable balance between recognition stability and resource efficiency. Consequently, this hybrid approach is a viable candidate for the development of on-site tea leaf disease diagnostic tools on resource-constrained mobile devices.

KEYWORDS: Tea leaf disease; feature extraction; support vector machine; computational efficiency

1. Introduction

Tea is a plantation commodity with high economic value that played a strategic role in both the global and national economies. The Food and Agriculture Organization reported that the value of global tea trade reached approximately USD 9.5 billion annually and served as a primary source of income for millions of families in rural areas. In Indonesia, tea is a key export commodity, with an export volume of approximately 44,000 tons in 2022 [1]. However, over the past decade, tea production in Indonesia has declined due to several factors, such as pest and disease attacks [2]. This situation confirms the important role of the tea industry in supporting the welfare of people in many producing countries, including Indonesia. Data from the Central Statistics Agency (BPS) [1] indicated that dry tea production from large plantations plummeted by almost 20% in two years, from 94,156 tons in 2020 to only 74,766 tons in 2022, in line with the shrinking area of large state plantations by 15.78% in 2021 and 8.43% in 2022. Yet, the Food and Agriculture Organization [3] emphasized the vital role of this sector in rural development and food security, with small-scale farmers contributing up to 60% of total global tea production. Given the significant economic dependence of millions of families on this sector, alongside the trend of declining land and national production, efforts to maintain productivity, including through disease control, are of paramount importance.

Tea leaf diseases were one of the factors that reduced the quality and quantity of tea production [2]. In line with this, Lien and Lai [4] stated that tea leaf diseases occurred in various forms, such as algal spot, brown blight, gray blight, Helopeltis infestation, red spot, red spider blight, and green mirid bug damage. These diseases, which were generally caused by insects and fungi, often occurred in warm and humid climates. Severe infestations could cause extensive leaf loss, thereby reducing yields. Accurate classification of tea leaf diseases played a vital role in effective prevention and control strategies, ultimately ensuring tea quality and yield [5]. Therefore, early disease identification was crucial to reduce losses, increase tea production and quality, and support the economic sustainability of the tea industry.

However, the process of directly identifying or classifying diseases using visual inspection and laboratory tests had several drawbacks, such as observer subjectivity and being time-consuming [6]. Therefore, an alternative approach to tea leaf disease identification was needed that minimized observer subjectivity while offering a more time-efficient diagnostic process. In the modern era, deep learning techniques have become a powerful tool in image recognition. Convolutional Neural Networks (CNNs), one of the deep learning approaches, have achieved impressive results in this field. The significance of CNNs in real-world applications has been demonstrated through various tasks such as object, face, bone, handwritten digit, and traffic sign recognition. The effectiveness of CNNs in image recognition has motivated researchers to expand their application into the agricultural sector, including plant species recognition, crop yield management, weed detection, soil and water management, fruit counting, pest and disease detection, plant nutritional status evaluation, and various other applications [7]. Therefore, CNNs are well suited for recognizing image patterns, including disease detection in plant leaves.

Recent studies have highlighted the effectiveness of CNNs in identifying tea leaf diseases, achieving high accuracy [4, 8–10]. However, the significant computational resources required by conventional CNNs hinder their direct deployment on low-power mobile devices in the field [10]. This limitation has necessitated lightweight architectures such as the MobileNet family, which reduces computational complexity through depthwise separable convolutions [11]. Its variants, particularly MobileNetV2 and MobileNetV3, have demonstrated strong performance in agricultural image recognition, either as end-to-end models [5, 13, 14] or as feature extractors combined with Support Vector Machine (SVM) classifiers [8, 15–18]. The use of MobileNet as a feature extractor with an SVM classifier has consistently improved both accuracy and efficiency in detecting diseases across various crops, such as tomatoes, rice, and coffee [15, 17, 18].

Despite the proven effectiveness of the hybrid MobileNet-SVM approach in various crops, a clear research gap remains in the tea leaf disease domain. Current research is still predominantly focused on using standard or lightweight end-to-end CNNs [19, 20]. The application of the CNN-SVM scheme, particularly utilizing MobileNet variants as feature extractors, remains relatively limited for tea leaves. Furthermore, explicit performance comparisons between different MobileNet variants specifically evaluating the architectural differences and complexity between MobileNetV2 and MobileNetV3-Small within this hybrid scheme, have rarely been reported using the same tea leaf dataset. Addressing this gap, this study aimed to explicitly compare the performance of MobileNetV2-SVM and MobileNetV3-Small-SVM in classifying tea leaf diseases using the TeaLeafBD dataset. The primary contribution of this research was to comprehensively evaluate the trade-off between classification accuracy and computational efficiency (such as parameter count, storage size, and processing load). The findings of this study provide a concrete academic reference for developing practical, image-based disease classification systems tailored for real-world deployment on resource-constrained mobile devices.

2. Materials and Methods

This study compares the performance of the model in classifying tea leaf diseases using SVM against MobileNetV2 and MobileNetV3-Small as feature extractors when viewed from the aspects of performance and computational efficiency on the teaLeafBD dataset. The following are the steps taken to build a tea leaf disease classification model using the extractor features of MobileNetV2 and MobileNetV3-Small.

Figure 1. Methods.

2.1 Dataset.

This study used the teaLeafBD dataset created by Alam et al. [21]. The dataset contains 5,278 JPG images of tea leaves, including both healthy and infected samples. It is publicly available and can be accessed through Kaggle and Mendeley Data at https://data.mendeley.com/datasets/744vznw5k2/4. The teaLeafBD dataset consists of seven classes: six disease categories (tea algal leaf spot, brown blight, gray blight, Helopeltis infestation, red spider, and green mirid bug) and one healthy leaf class. Each class is organized into a separate directory within the main *teaLeafBD* folder, which facilitates the training process for classification models.

Table 1. Dataset information.

Class & image	**Number of Image**	**Class**	**Number of Image**
Tea algal leaf spot 	418	Red spider 	515
Brown blight 	508	Green mirid bug 	1282
Gray blight 	1013	Healthy leaf 	935
Helopeltis 	607		
Total		**5278**	

According to Alam et al. [21], the dataset was collected in 2024 during the monsoon season from eight tea plantations in Bangladesh, located in the Sylhet and Sreemangal regions. Leaf samples were collected from these plantations and photographed under controlled conditions using a white background to enhance leaf clarity and reduce background noise.

2.2 Preprocessing.

In this study, the input image dimensions were set to 224 × 224 pixels. Howard et al. [15] demonstrated that the computational burden of this architecture increases quadratically with increasing input resolution. Therefore, a resolution of 224 × 224 was adopted to maintain computational efficiency while ensuring compatibility with feature extraction using pre-trained ImageNet weights, which were trained at the same resolution. Furthermore, this input size was selected to ensure comparability with previous studies, such as Esomonu et al. [15], which also used the same configuration. Pixel normalization was then applied using architecture-specific preprocessing functions for MobileNetV2 and MobileNetV3 to align the input intensity range with the ImageNet pre-trained weight distribution, replacing standard rescaling approaches.

2.3. Dataset Split and Data Augmentation

The dataset was divided using a hold-out strategy, with 80% used for training and 20% reserved for testing. Data augmentation was applied only to the training set to increase data variability without altering the intrinsic features of the disease classes. Following Esomonu et al. [15], augmentation techniques included random rotation, zoom, shear transformation, and horizontal flipping. This process aimed to improve the generalization ability of the model in classifying tea leaf diseases in the teaLeafBD dataset.

2.4. Feature extraction.

Feature extraction was performed using MobileNetV2 and MobileNetV3-Small as pretrained backbones with ImageNet weights. All backbone layers were frozen (trainable = false), allowing the networks to function solely as feature extractors without fine-tuning. Feature maps generated from the backbones were converted into one-dimensional feature vectors using a Global Average Pooling layer. These feature vectors were then organized into a feature matrix to be used as input for the Support Vector Machine (SVM) classifier, following the MobileNet–SVM framework adopted in Esomonu et al. [15].

2.5. Synthetic Minority Oversampling Technique (SMOTE).

To address class imbalance, the SMOTE was applied to the extracted feature vectors prior to SVM training. SMOTE was performed exclusively on the training data to ensure balanced class distribution during model learning. This approach has been shown to improve minority class detection performance in similar classification tasks.

2.6. Support vector machine.

After data balancing, the SVM classifier was trained. Prior to final model development, hyperparameter optimization was conducted using GridSearchCV, following the benchmark strategy of Izza and Lutfi [22]. A 10-fold cross-validation scheme was used to systematically evaluate parameter combinations based on validation performance.

The search space included C values ranging from 10 to 100, kernel types (linear, rbf, poly, and sigmoid), and gamma values ('scale' and 'auto'). The best-performing hyperparameter combination was then used to retrain the SVM using the full training dataset, producing the final models for both MobileNetV2-SVM and MobileNetV3-Small-SVM.

2.7. Model evaluation.

Model performance was evaluated using Accuracy, Precision, Recall, and F1-Score to assess classification effectiveness across tea leaf disease classes. According to Algani et al. [23], accuracy represents the proportion of correct predictions and is defined in Equation (1):

$$Accuracy = \frac{TN + TP}{FN + FP + TN + TP} \quad (1)$$

Precision is used to assess classifier performance in more detail. If the number of positive samples in plant leaf data is low, the precision value tends to be higher, whereas if the number of positive samples is high, the precision value tends to be lower [23]. Precision is expressed in equation (2).

$$Precision = \frac{TP}{FP + TP} \quad (2)$$

Recall is used to assess the level of coverage (completeness) of a classifier's ability to identify positive samples. The higher the recall value, the more positive samples the model successfully detected [23]. The recall formula is stated in equation (3).

$$Recall = \frac{TP}{FN + TP} \quad (3)$$

Recall dan precision dinilai menggunakan F1-score. F1-score dihitung berdasarkan nilai presisi dan recall [23]. Nilai F1 dituliskan dalam persamaan (4).

$$F1 - Score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \quad (4)$$

Here, TP denotes True Positive, TN denotes True Negative, FP denotes False Positive, and FN denotes False Negative [24]. In addition to classification performance, computational efficiency was evaluated using GFLOPs, model size, number of parameters, and inference time to provide a comprehensive comparison of model complexity and deployment feasibility. The overall experimental results are summarized in Table 1, which reports both classification performance and computational cost.

Table 1. Experimental Configuration.

Accuracy	**Precision**	**Recall**	**F1-Score**
0.753	0.76	0.75	0.74
GFLOP's	**Model Size**	**Number of Parameter**	**Inference Time**
0.6127 GFLOPs	36.57 MB	2,257,984	66,9 ms

3. Results and Discussion

To provide a comprehensive evaluation, the results of the MobileNetV2-SVM and MobileNetV3-Small-SVM architectures were analyzed comparatively. This section discusses their overall classification performance, computational efficiency, class-specific misclassifications, and visual feature space distributions.

3.1. Overall performance and efficiency comparison.

Based on empirical testing conducted on the teaLeafBD dataset, both architectures demonstrated highly competitive and similar classification performance. The evaluation metrics, including Accuracy, Precision, Recall, and F1-Score, are summarized in Table 1. The MobileNetV2-SVM model achieved an overall accuracy of 75.3%, while the MobileNetV3-Small-SVM model closely followed with 75.1%. Both models obtained identical precision (0.76), recall (0.75), and F1-score (0.74). This indicates that the spatial dimensionality reduction and parameter optimization introduced in the MobileNetV3-Small architecture did not significantly degrade the quality of the extracted feature representations. The model effectively retained discriminative features essential for SVM classification.

Table 1. Performance comparison of MobileNet-SVM models.

Model	Accuracy	Precision	Recall	F1-Score
MobileNetV2-SVM	0.753	0.76	0.75	0.74
MobileNetV3 small-SVM	0.751	0.76	0.75	0.74

However, the most notable difference between the two models lies in their computational requirements. Table 2 presents the comparison of computational efficiency metrics. While classification performances are nearly identical, Table 2 demonstrates that MobileNetV3-Small-SVM offers advantage in terms of resource efficiency. It successfully reduced the computational load by approximately five times (from 0.6127 to 0.1160 GFLOPs) and slashed the model size by more than half (from 36.57 MB to 14.74 MB). To provide a faster visual interpretation of this trade-off, Figure 2 illustrates the comparison between accuracy and model efficiency.

Table 2. Computational efficiency comparison.

Model	GFLOP's	Model Size	Number of Parameter	Inference Time
MobileNetV2-SVM	0.6127 GFLOPs	36.57 MB	2,257,984	66,9 ms
MobileNetV3 small-SVM	0.1160 GFLOPs	14.74 MB	939,120	33.67 ms

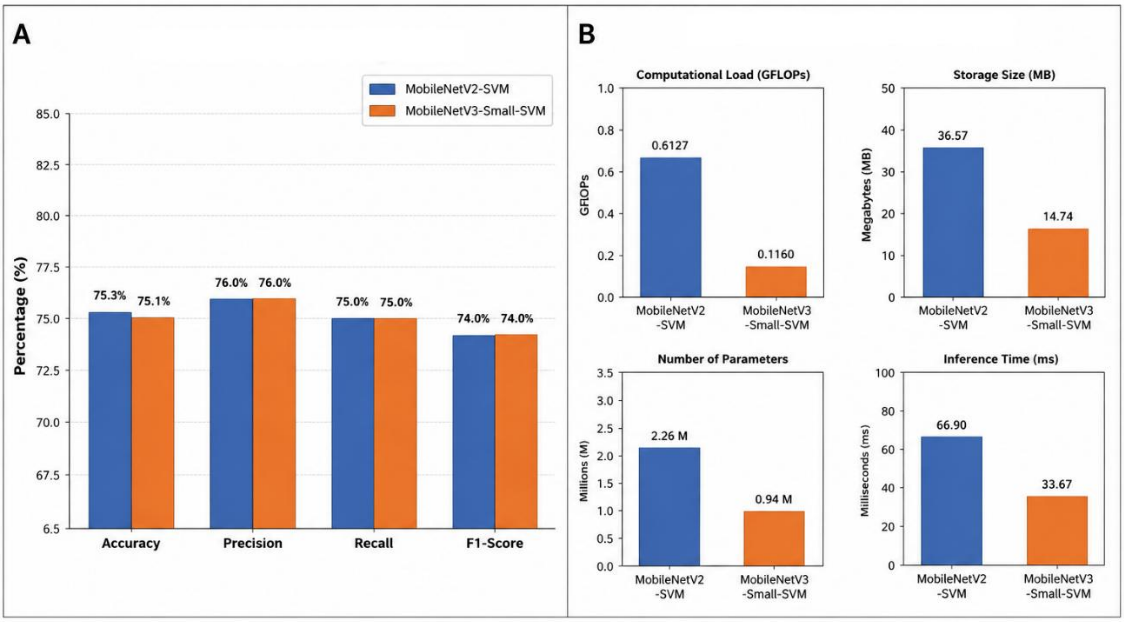

Figure 2. Comparison of performance metrics (A) and computational efficiency (B) between MobileNetV2-SVM and MobileNetV3-Small-SVM.

3.2. Misclassification and feature space analysis.

To better understand the models' performance across each tea leaf disease class, a side-by-side comparison of their confusion matrices is presented in Figure 3. The main diagonal of both matrices indicates the number of correct predictions. Both architectures demonstrated excellent image recognition performance for Class 6 (Green mirid bug) and Class 7 (Healthy leaf). MobileNetV3-Small showed a slight superiority in recognizing Class 3 (Gray Blight) and Class 7 (Healthy leaf) compared to V2, indicating that its backbone provided richer representations for these specific classes. Despite high recognition rates in certain classes, both matrices reveal a major shared challenge in classifying Class 2 (Brown Blight). Interestingly, there is a shift in the misclassification pattern between the two architectures. In the MobileNetV2 feature extraction, Class 2 is frequently confused with Class 1 (Tea algal leaf spot) and Class 3 (Gray Blight). However, in the MobileNetV3-Small feature extraction, Class 2 overlaps much more heavily with Class 3 (Gray Blight), with 35 misclassified samples. Furthermore, MobileNetV3-Small shows a slight decrease in performance for Class 4 (Helopeltis), where 25 samples were misclassified as healthy leaves.

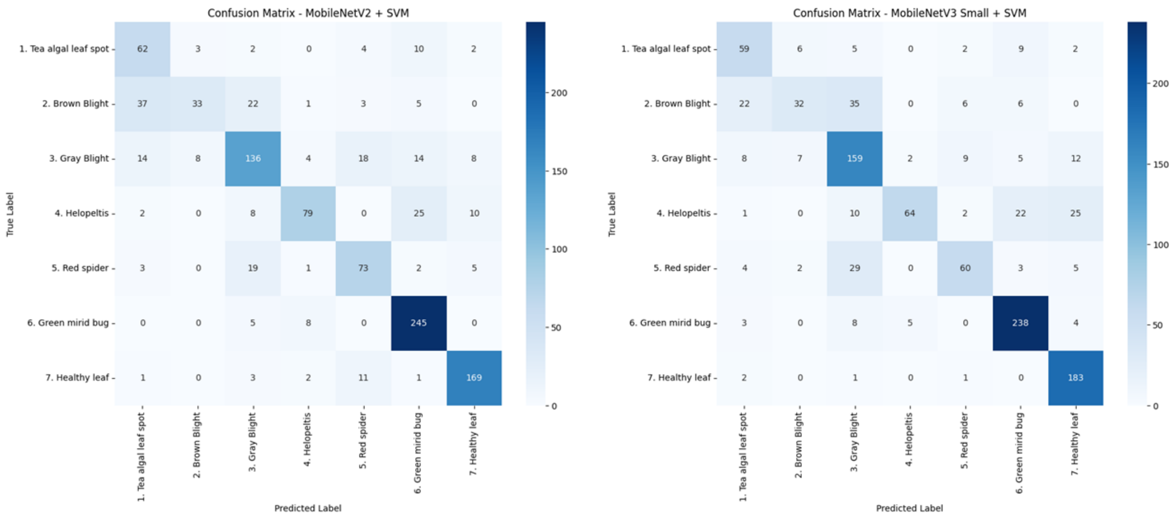

Figure 3. Confusion matrix comparison.

To visually support these misclassifications, Figure 4 presents an overlaid t-SNE dimensionality reduction of feature embeddings extracted from both MobileNetV2-SVM and MobileNetV3-Small-SVM architectures. The 2D feature space provides a clear qualitative interpretation of how each model organizes high-dimensional representations prior to classification. In both cases, Class 6 and Class 7 form compact, dense, and well-isolated clusters, indicating that their underlying visual patterns are highly distinctive and consistently captured by the feature extractors. This strong separability directly corresponds to their consistently high classification accuracy across both models. In contrast, a pronounced overlap is observed in the central embedding region involving Class 1, Class 2, Class 3, and Class 5. These classes are heavily interspersed, with no clear boundaries separating their distributions, suggesting that the learned feature space lacks sufficient discriminative power for these categories. The intermixing of these clusters visually explains the persistent misclassification among these classes and the overall performance ceiling of approximately 75% accuracy for both architectures. This limitation is primarily attributed to the high intra-class similarity and inter-class visual homogeneity, particularly in lesion texture, coloration, and shape variations, which reduce feature distinctiveness. Furthermore, despite differences in architectural depth and efficiency between MobileNetV2 and MobileNetV3-Small, both backbones exhibit similar clustering behavior, indicating that the bottleneck lies more in feature separability than model capacity.

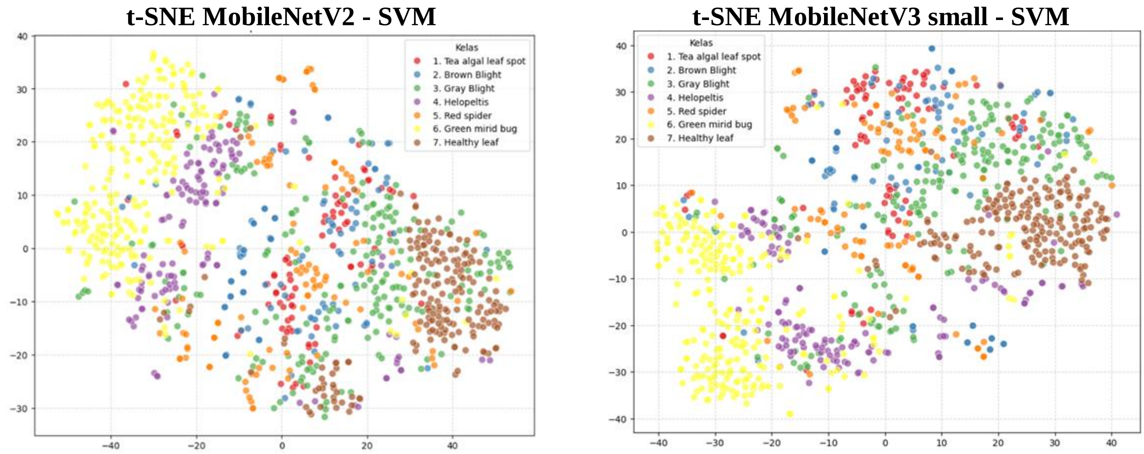

Figure 4. t-SNE visualization of feature embeddings from MobileNetV2-SVM (left) and MobileNetV3-Small-SVM (right).

3.3. Key findings.

To provide a consolidated interpretation of the experimental results, Table 3 summarizes the key characteristics, strengths, and limitations of both MobileNetV2-SVM and MobileNetV3-Small-SVM architectures, offering a clearer understanding of their comparative behavior in terms of accuracy, efficiency, and class-wise performance. MobileNetV2-SVM demonstrates a slightly higher classification accuracy of 75.3%, indicating marginally better feature discriminability in certain classes. It is particularly effective in identifying Class 1 (Healthy leaves) and Class 6 (Green mirid bug), with Class 6 achieving the highest correct predictions (245 samples). This suggests that the model is capable of capturing distinctive morphological patterns when visual differences are prominent. However, this performance advantage comes at the cost of higher computational complexity, requiring 0.6127 GFLOPs and a larger model size of 36.57 MB, making it less suitable for lightweight or real-time deployment scenarios. Its main limitation lies in the misclassification of Class 2 (Brown Blight), which is frequently confused with visually similar disease classes such as Tea Algal Leaf Spot and Gray Blight due to overlapping symptom textures and color distributions. In contrast, MobileNetV3-Small-SVM offers a significantly more efficient alternative, requiring only 0.1160 GFLOPs and 14.74 MB of storage while maintaining a comparable accuracy of 75.1%. Despite its compact architecture, it preserves strong recognition performance for most classes, particularly Class 6 (Green mirid bug), which still achieves high correct predictions (238 samples). Nevertheless, a slight performance degradation is observed in the recognition of Class 4 (Helopeltis), indicating reduced sensitivity to subtle feature variations. Its primary misclassification pattern remains similar to MobileNetV2, with Class 2 (Brown Blight) frequently overlapping with Class 3 (Gray Blight), accounting for 35 misclassified samples.

Table 3. Comparative Summary of MobileNetV2-SVM and MobileNetV3-Small-SVM.

Aspect	MobileNetV2-SVM	MobileNetV3-Small-SVM
Strengths	Achieves slightly higher accuracy (75.3%) and extracts highly distinctive features for healthy leaves and green mirid bugs.	Extremely efficient (0.1160 GFLOPs, 14.74 MB) while maintaining highly comparable accuracy (75.1%).
Weaknesses	High computational load (0.6127 GFLOPs) and large model size (36.57 MB).	Slight decrease in accuracy for recognizing Helopeltis (Class 4).
Best-performing class	Class 6: Green mirid bug (245 correct predictions).	Class 6: Green mirid bug (238 correct predictions).
Main misclassification issue	Class 2 (Brown Blight) is heavily confused with Tea Algal Leaf Spot and Gray Blight due to feature overlap.	Class 2 (Brown Blight) frequently overlaps with Class 3 (Gray Blight), resulting in 35 misclassified samples.

4. Conclusions

This study evaluated the performance of MobileNetV2-SVM and MobileNetV3-Small-SVM in classifying tea leaf diseases. The empirical results show that both models achieved highly comparable classification performance, with MobileNetV2-SVM reaching an accuracy of 75.3% and MobileNetV3-Small-SVM reaching 75.1%. Other metrics, such as precision (0.76), recall (0.75), and F1-score (0.74), were identical for both architectures, indicating that the lighter MobileNetV3-Small backbone successfully maintained the quality of extracted features. In terms of computational efficiency, MobileNetV3-Small-SVM demonstrated a significant advantage. It achieved a five-fold reduction in computational load (0.1160 GFLOPs vs. 0.6127 GFLOPs) and reduced the model size by more than half (14.74 MB vs. 36.57 MB) compared to MobileNetV2-SVM. These results suggest that MobileNetV3-Small-SVM is the more optimal model for deployment on resource-constrained mobile devices in tea plantations, as it offers a superior balance between performance stability and efficiency.Analysis of the confusion matrices and t-SNE visualizations revealed consistent patterns in both models. The architectures were highly effective in recognizing Class 6 (Green mirid bug) and Class 7 (Healthy leaf), which formed dense and well-isolated clusters in the feature space. However, a significant challenge remains in distinguishing Class 2 (Brown Blight), which frequently overlapped with Class 3 (Gray Blight) and Class 1 (Tea Algal Leaf Spot). The t-SNE plots confirmed substantial overlap in the central region of the feature space for these disease categories, explaining the accuracy plateau at approximately 75%. A primary limitation of this study is the reliance on static feature extraction using frozen pre-trained weights without fine-tuning. This approach may have prevented the models from fully adapting to domain-specific micro-textures of tea leaf lesions. Consequently, future research should implement end-to-end fine-tuning to allow convolutional filters to learn more discriminative features specifically for visually similar tea diseases, potentially overcoming the current performance bottleneck.

Acknowledgments

The author expresses sincere gratitude to Mr. Novan Wijaya, M.Kom., for his guidance and valuable feedback throughout this research. Appreciation is also extended to the board of examiners for their constructive evaluations and suggestions to improve the quality of this article.

Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this article.

References

[1] Statistik teh Indonesia 2022 (No. Publikasi 05100.2311). (accessed on 1 March 2026) Available online: https://www.bps.go.id/id/publication/2023/11/30/f48a9da03e67c8fe8ed74d10/statistik-teh-indonesia-2022.html.

[2] Mustikasari; Ramli, A.R.; Gibran, A.K. (2023). Analisis kinerja algoritma machine learning untuk deteksi penyakit daun teh dengan particle swarm optimization. *Journal of Embedded Systems, Security and Intelligent Systems*, *4*(2), 97–108. https://doi.org/10.59562/jessi.v4i2.708.

[3] International tea market: Market situation, prospects and emerging issues. (accessed on 1 March 2026) Available online: https://www.fao.org/3/cc0238en/cc0238en.pdf.

[4] Lien, B.-Y.; Lai, C.-C. (2025). A lightweight deep learning model for tea leaf disease identification. *Machine Learning and Knowledge Extraction*, *7*(4), 123. https://doi.org/10.3390/make7040123.

[5] Li, Y.; Lu, Y.; Liu, H.; Bai, J.; Yang, C.; Yuan, H.; Li, X.; Xiao, Q. (2024). Tea leaf disease and insect identification based on improved MobileNetV3. *Frontiers in Plant Science*, *15*, 1459292. https://doi.org/10.3389/fpls.2024.1459292.

[6] Lu, J.; Tan, L.; Jiang, H. (2021). Review on Convolutional Neural Network (CNN) applied to plant leaf disease classification. *Agriculture*, *11*(8), 707. https://doi.org/10.3390/agriculture11080707.

[7] Dhaka, V.S.; Meena, S.V.; Rani, G.; Sinwar, D.; Kavita; Ijaz, M.F.; Woźniak, M. (2021). A survey of deep convolutional neural networks applied for prediction of plant leaf diseases. *Sensors*, *21*(14), 4749. https://doi.org/10.3390/s21144749.

[8] Rehman, A.; Akram, M.; Waleed, A.; Hafeez, A.; Basit, A.; Zubair, M. (2025). A hybrid model for crop disease detection based on deep learning and support vector machine. *International Journal of Innovations in Science & Technology*, *7*(2), 845–857. https://doi.org/10.33411/ijist/202572843855.

[9] Heng, Q.; Yu, S.; Zhang, Y. (2024). A new AI-based approach for automatic identification of tea leaf disease using deep neural network based on hybrid pooling. *Heliyon*, *10*(4), e26465. https://doi.org/10.1016/j.heliyon.2024.e26465.

[10] Rahat, I.S.; Ghosh, H.; Dara, S.; Kant, S. (2025). Towards precision agriculture tea leaf disease detection using CNNs and image processing. *Scientific Reports*, *15*, Article 17571. https://doi.org/10.1038/s41598-025-02378-0.

[11] Sandler, M.; Howard, A.; Zhu, M.; Zhmoginov, A.; Chen, L.-C. (2018). MobileNetV2: Inverted residuals and linear bottlenecks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 4510–4520. https://doi.org/10.1109/CVPR.2018.00474.

[12] Howard, A.; Sandler, M.; Chu, G.; Chen, L.-C.; Chen, B.; Tan, M.; Wang, W.; Zhu, Y.; Pang, R.; Vasudevan, V.; Le, Q. V.; Adam, H. (2019). Searching for MobileNetV3. Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), 1314–1324. https://doi.org/10.1109/ICCV.2019.00140.

[13] Zaki, S.Z.M.; Zulkifley, M.A.; Stofa, M.M.; Kamari, N.A.M.; Mohamed, N.A. (2020). Classification of tomato leaf diseases using MobileNet V2. *IAES International Journal of Artificial Intelligence*, *9*, 290−296. https://doi.org/10.11591/ijai.v9.i2.pp290-296.

[14] Liu, R. (2023). Paddy disease classification based on the lightweight MobileNet-V2. *Highlights in Science, Engineering and Technology*, *57*, 126–133. https://doi.org/10.54097/hset.v57i.9990.

[15] Esomonu, N.F.; Eze, U.F.; John-Otumu, A.M.; Ayogu, I.I.; Nwokonkwo, O.C.; Oshoiribhor, E. O.; Okolie, S. A.; Nwokorie, E. C.; Mbamala, C. V.; Dokun, O. (2023). A hybrid model using

MobileNetV2 and SVM for enhanced classification and prediction of tomato leaf diseases. *SSRG International Journal of Electrical and Electronics Engineering*, *10*(8), 37–50. https://doi.org/10.14445/23488379/IJEEE-V10I8P104.

[16] Kurniawan, R.; Siaga, E.; Samsuryadi, S.; Susilo, A.T.; Sunardi, L. (2025). Hybrid DCNN-SVM architecture for optimizing sugarcane leaf disease classification. *IAENG International Journal of Computer Science*, *52*(4), 974–985.

[17] Dimara, D.; Rahmat, B.; Maulana, H. (2025). Identifikasi penyakit daun padi dengan metode transfer learning MobileNet–support vector machine. *JATI (Jurnal Mahasiswa Teknik Informatika)*, *9*(3), 5413–5420. https://doi.org/10.36040/jati.v9i3.14245.

[18] Hong, L.T.T.; Tu, D.Q.; Do, N.D.; Huy, N.S. (2024). Coffee leaf rust disease detection using MobileNetV2-based feature extractor, SVM classifier and visualization technique. *Journal of Military Science and Technology*, Special Issue No. 8, 33–43. https://doi.org/10.54939/1859-1043.j.mst.CSCE8.2024.33-43.

[19] Hairah, U.; Septiarini, A.; Puspitasari, N.; Tejawati, A.; Hamdani, H.; Priyatna, S.E. (2024). Classification of tea leaf disease using convolutional neural network approach. *International Journal of Electrical and Computer Engineering (IJECE)*, *14*(3), 3287–3294. https://doi.org/10.11591/ijece.v14i3.pp3287-3294.

[20] Rahman, H.; Ahmad, I.; Jon, P.H.; Salam, A.; Rabbi, M.F. (2024). Automated detection of selected tea leaf diseases in Bangladesh with convolutional neural network. *Scientific Reports*, *14*, Article 14097. https://doi.org/10.1038/s41598-024-62058-3.

[21] Alam, B.M.S.; Ahammed, F.; Kibria, G.; Noor, M. T.; Shikdar, O. F.; Mahzabin, K. I.; Niloy, N. T.; Ali, M.N.Y. (2025). teaLeafBD: A comprehensive image dataset to classify the diseased tea leaf to automate the leaf selection process in Bangladesh. *Data in Brief*, *61*, 111769. https://doi.org/10.1016/j.dib.2025.111769.

[22] Izza, M.; Lutfi, M. (2025). Detection of sugarcane leaf disease using pre-trained feature extraction and SVM method. *Journal of Applied Informatics and Computing*, *9*(5), 2296–2302. https://doi.org/10.30871/jaic.v9i5.10626.

[23] Algani, Y.M.A.; Caro, O.J.M.; Bravo, L.M.R.; Kaur, C.; Al Ansari, M.S.; Bala, B.K. (2023). Leaf disease identification and classification using optimized deep learning. *Measurement: Sensors*, *25*, 100643. https://doi.org/10.1016/j.measen.2022.100643.

[24] Fenu, G.; Malloci, F.M. (2023). Classification of pear leaf diseases based on ensemble convolutional neural networks. *AgriEngineering*, *5*(1), 141–152. https://doi.org/10.3390/agriengineering5010009.