Universiti Teknologi MARA

I-URIID 2025

INTERNATIONAL UNDERGRADUATE RESEARCH INNOVATION, INVENTION AND DESIGN

UNDERGRADUATES PIONEERING TOMORROW'S BREAKTHROUGH

E-BOOK OF EXTENDED ABSTRACTS

FLORAGUARD: A CNN-BASED FUNGAL DETECTION SYSTEM FOR SMART HORTICULTURE

Muhamad Syakir Alif Mohd Saren[1], and Saffa Raihan Zainal Abidin[2*]

[1]Universiti Teknologi MARA, (UiTM), Cawangan Terengganu Kampus Kuala Terengganu, 21080 Kuala Terengganu, Terengganu
[2]Universiti Teknologi MARA (UiTM) Cawangan Pahang, Kampus Raub, Felda Krau, 27600 Raub, Pahang

*saffaraihan@uitm.edu.my

ABSTRACT

Fungal diseases represent one of the most damaging threats to ornamental plant productivity and economic value, particularly in nursery and horticultural sectors. Traditional detection methods rely heavily on manual inspection, which is inefficient, inconsistent, and inaccessible to non-specialists. This project introduces FloraGuard, a novel lightweight detection system powered by Convolutional Neural Network (CNN) architecture using MobileNet-V2, designed to automate the identification of four common fungal diseases—powdery mildew, black spot, rust, and botrytis blight—from leaf images. A curated dataset of 568 labelled images was preprocessed through normalization, augmentation, and filtering to enhance model robustness. The final trained model demonstrated 95.73% accuracy, with high F1-scores across all classes, and was integrated into a user-friendly GUI accessible via web or mobile interface. FloraGuard has potential to reduce fungicide overuse, minimise losses, and democratise plant disease management for small-scale growers. Its relevance aligns with SDG Goals 2 and 12 and provides a scalable foundation for commercial and academic extensions.

Keywords: Fungal Detection, MobileNet-V2, Image Classification, Smart Agriculture, Sustainable Horticulture

INTRODUCTION

The global ornamental plant industry, valued at over USD 50 billion, is driven by increasing demand for high-quality flowering plants in landscaping, interior design, and therapeutic horticulture (González-Briones et al., 2025). However, fungal infections pose major challenges, leading to visible damage, premature senescence, and reduced marketability. Common diseases such as powdery mildew, rust, black spot, and botrytis blight are widespread. Recent studies report that up to 70% of flowering plants are susceptible to fungal pathogens, resulting in significant yearly yield losses and financial impacts (Qiu et al., 2024). Despite these risks, disease detection in nurseries and small-scale operations largely relies on manual visual assessments, printed leaf catalogues, or informal consultations—methods that are often slow, unreliable, and inaccessible to rural or amateur growers (Nwaneto & Yinka-Banjo, 2025).

To address this limitation, there is a clear need for scalable, automated detection systems accessible to non-experts. This study proposes a lightweight image classification tool that uses Convolutional Neural Networks (CNNs), specifically the MobileNet-V2 architecture, for fungal disease detection in flowering plants. The tool is designed for real-time use on mobile and low-cost devices, supporting early diagnosis and timely intervention in varied cultivation settings. This research also contributes to the United Nations Sustainable Development Goals, particularly Goal 2 (Zero Hunger) and Goal 12 (Responsible Consumption and Production), by reducing fungicide overuse and encouraging sustainable plant health practices (Assaf et al., 2025; Prabhu & Dilip, 2024).

OBJECTIVES

This study was conducted with the following objectives:

i. To design and train a CNN model using MobileNet-V2 to automatically classify disease types from leaf images.
ii. To develop an intuitive, user-friendly interface (GUI) that allows users to upload and analyze images for real-time fungal detection.
iii. To evaluate the model performance using key classification metrics and benchmark it against conventional detection methods.

METHODOLOGY

The FloraGuard fungal detection system was developed through a structured eight-phase methodology. Figure 1 shows the diagram for FloraGuard fungal detection methodology.

The first phase involved a comprehensive literature review and problem identification, focusing on gaps in current plant disease detection methods and justifying the use of lightweight CNN models for real-time diagnosis. In the second phase, a curated dataset of 568 labelled images depicting four common fungal infections—powdery mildew, black spot, rust, and botrytis blight—was acquired from RoboFlow, ensuring sufficient diversity and annotation quality. The third phase, data preprocessing, applied several enhancements including normalisation, image augmentation, blur filtering using Laplacian variance, bounding box cropping, and label harmonisation to prepare the dataset for training. The fourth phase centred on model development, where MobileNet-V2—a lightweight convolutional neural network—was adapted using transfer learning, with custom classification layers added to fine-tune the model for the specific fungal classes.

In the fifth phase, model training and validation were performed using a 70/15/15 split for training, validation, and testing datasets respectively, and optimised using the Adam optimiser and categorical cross-entropy loss function. The sixth phase focused on GUI development and integration, where a user-friendly interface was built using Streamlit and Flask to allow non-experts to upload images and receive real-time predictions, designed especially for mobile and low-resource environments. In the seventh phase, performance evaluation was conducted using metrics such as accuracy, precision, recall, and F1-score, and the system achieved 95.73% accuracy with an inference time of less than two seconds per image. Finally, the eighth phase involved system deployment and documentation, where the trained model was saved, the application was packaged for demonstration, and technical documentation was prepared for potential IP filing, user dissemination, and future scalability.

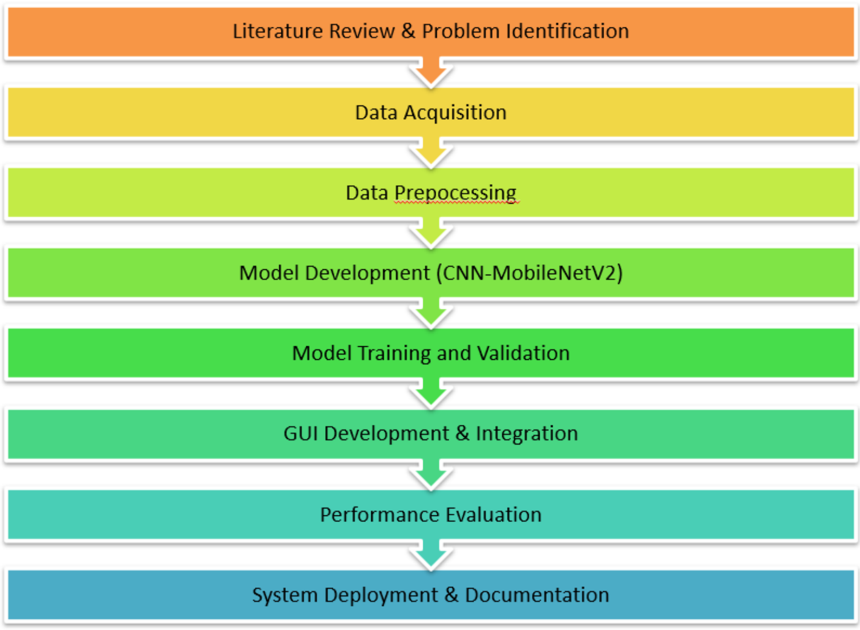

Figure 1: FloraGuard fungal detection methodology

RESULTS AND DISCUSSION

The results of the FloraGuard system demonstrate high model effectiveness and practical usability. The MobileNet-V2 CNN model achieved an overall accuracy of 95.73%, confirming its ability to correctly classify a wide range of fungal leaf diseases. The model's average recall score of 95.0% highlights its sensitivity in correctly identifying actual cases of disease, while an average precision of 96.2% indicates a low false-positive rate. The F1-score, which balances precision and recall, was recorded at 94.8%, validating the model's consistency across all four disease categories. As summarized in Table 1, the system also exhibited a low inference time of under 2 seconds, making it suitable for real-time deployment. Notably, powdery mildew and rust achieved the highest recall rates at 99%, reflecting exceptional model accuracy for these classes. Despite being underrepresented in the dataset, botrytis blight still attained an 87% recall, indicating robust generalization. When benchmarked against traditional machine learning classifiers such as Support Vector Machines (SVM) and Random Forests, FloraGuard's CNN model delivered up to a 20% improvement in F1-score, underscoring its superior adaptability to image-based classification tasks. Informal user testing further revealed that non-technical users found the graphical interface intuitive and efficient, appreciating its visual feedback, simplicity, and compatibility with low-spec devices. These findings confirm that FloraGuard is not only accurate in detection but also highly usable and ready for broader implementation. Table 1 shows exceptional classification performance.

Table 1: Exceptional classification performance

Metric	Value
Accuracy	95.73 %
Recall (Avg)	95.0 %
Precision (Avg)	96.20 %
F1-Score (Avg)	94.80 %
GUI Inference Time	< 2 seconds

CONCLUSION

In conclusion, the FloraGuard system presents a practical and innovative solution to the long-standing challenge of fungal disease detection in flowering plants, particularly within the ornamental horticulture sector. By leveraging the MobileNet-V2 CNN architecture and integrating it into a user-friendly graphical interface, the system successfully bridges the gap between advanced artificial intelligence and accessible agricultural technology. The model achieved high accuracy and robust performance across multiple metrics, proving its reliability for real-time classification. Furthermore, the system's low computational demand and ease of use make it highly applicable for small-scale growers, educators, and community gardening programs. Beyond technical performance, FloraGuard aligns with sustainability goals by promoting early disease intervention and reducing excessive fungicide use. With its strong foundation in research, demonstrated usability, and potential for commercialization, FloraGuard represents a scalable, socially relevant, and forward-looking innovation in the field of smart agriculture.

ACKNOWLEDGEMENT

The author would like to express sincere gratitude and appreciation to Universiti Teknologi MARA (UiTM) Terengganu Kampus and Universiti Teknologi MARA (UiTM) Pahang Kampus Raub for providing the essential facilities, infrastructure, and academic environment that made this research possible. Although this study was self-funded, the access to computing resources, laboratory support, and mentorship throughout the project played a pivotal role in its successful completion. Special thanks are also extended to the faculty and technical staff whose guidance and assistance greatly enriched the development of the FloraGuard system.

REFERENCES

Assaf et al. (2025). RTR_Lite_MobileNetV2: A lightweight model for real-time plant disease detection on Raspberry Pi. Elsevier - Computers and Electronics in Agriculture.

González-Briones, A., López Florez, S., Chamoso, P., Castillo-Ossa, L. F., & Corchado, E. S. (2025). Enhancing plant disease detection: Incorporating advanced CNN architectures for better accuracy and interpretability. *International Journal of Computational Intelligence Systems*, 18, 120.

Nwaneto, C. B., & Yinka-Banjo, C. (2025). Harnessing deep learning algorithms for early plant disease detection: a comparative study between MobileNet-V2 and MobileNet-V3. *Ife Journal of Science*, Jan 23, 2025.

Prabhu, D., & Dilip, G. (2024). Chilly leaves diseases identification using MobileNet V2 deep learning model. *Journal of Electrical Systems and Research*, 12(1), 35–42.

Qiu, H., Yang, J., Jiang, J., & Zhang, W. (2024). Mob-PSP: Modified MobileNet-V2 network for real-time detection of tomato diseases. *Journal of Real-Time Image Processing*, 21, 181.