Intelligent Methods in Engineering Sciences 4(2): 15-21, 2025

INTELLIGENT METHODS IN ENGINEERING SCIENCES

https://www.imiens.org

International Open Access

August, 2025

e-ISSN 2979-9236

Research Article

https://doi.org/10.58190/imiens.2025.123

Fusion-Aware Lightweight CNN with Channel-Wise Attention for Rose Leaf Disease Classification in Multispectral Color Domains

Yusuf YAMAN [a,*], ***Esra KAYA*** [b]

[a] *Selçuk University, Faculty of Technology, Department of Electrical and Electronics Engineering, Konya, Türkiye*
[b] *Selçuk University, Faculty of Technology, Department of Electrical and Electronics Engineering, Division of Circuits and Systems, Konya, Türkiye*

ARTICLE INFO

Article history:
Received 15 June 2025
Accepted 5 July 2025

Keywords:
CNN,
SE-ECA Bloks

ABSTRACT

The rose plant holds significant economic and cultural value, not only as an ornamental species but also due to its widespread use across various industrial domains such as cosmetics, medicine, and perfumery. In this context, the early and accurate detection of leaf diseases is crucial for ensuring the healthy cultivation of rose plants. This study presents a novel approach that integrates image processing and deep learning techniques for the detection of common leaf diseases in rose plants. The proposed method utilizes the RoseNet dataset, which consists of three classes: Black Spot, Downy Mildew, and Fresh Leaf. Input images were converted into RGB, HSV, and YCrCb color spaces and then fused at the channel level to enhance spectral diversity and improve the model's learning capacity. The developed convolutional neural network (CNN) architecture was enriched with channel attention mechanisms, namely Squeeze-and-Excitation (SE) and Efficient Channel Attention (ECA) blocks. Class imbalance issues were addressed through class weighting and label smoothing strategies. The model's performance was evaluated using multiple metrics such as accuracy, precision, recall, and F1-score. Achieving an accuracy of 95.65%, the proposed model outperformed widely used CNN architectures in the literature. Furthermore, with a low parameter count (1.03M) and a fast test time (376 ms), the model is well-suited for deployment on embedded systems. The findings demonstrate that attention mechanisms are effective in enhancing class discrimination, particularly in low-sample-size datasets. Thus, the proposed model offers a reliable, cost-effective, and AI-based solution for the diagnosis of plant leaf diseases.

1. Introduction

Early diagnosis and accurate identification of plant diseases are of paramount importance in enhancing agricultural product quality and minimizing yield losses. The agricultural sector is under increasing pressure to ensure food security, driven by factors such as the growing global population and climate change. Timely detection of diseases that threaten plant health has become an indispensable component of sustainable agricultural practices. Traditional diagnostic methods are typically based on visual inspection and expert opinion, which are often time-consuming, costly, and subjective—thereby limiting their applicability in large-scale agricultural areas.

In recent years, rapid advancements in artificial intelligence and image processing techniques have accelerated research into the automatic and reliable diagnosis of plant diseases. Deep learning models, in particular, offer high diagnostic accuracy owing to their capacity to extract meaningful features from complex image data. As a result, both time efficiency is improved and human error is significantly reduced.

One of the most prominent applications of these technological developments is the diagnosis of diseases affecting the rose plant (Rosa spp.). Beyond its ornamental value, the rose plant has extensive applications in the cosmetics, perfumery, and pharmaceutical industries, rendering it a strategic agricultural commodity with high economic value. Turkey is one of the world's leading producers of rose oil, with the Isparta province and its surrounding regions known for intensive rose cultivation. According to data from the Turkish Statistical Institute (TÜİK), over 10,000 tons of rose flowers are harvested annually, with a substantial portion exported. Therefore, ensuring the healthy development of rose plants and managing plant diseases effectively are of great importance for both economic sustainability and industrial product quality.

Mohanty et al. [1] classified leaf diseases using convolutional neural network (CNN) models based on the PlantVillage dataset, which comprises a total of 54,306 leaf images divided into 38 distinct classes. This study stands out as one of the pioneering works in the field,

* **Corresponding Author:** 228270001007@ogr.selcuk.edu.tr

highlighting the effectiveness of image-based diagnosis. Ferentinos [2] conducted a comparative analysis of different CNN architectures—namely AlexNet, GoogLeNet, and VGG—for the classification of various foliar diseases in agricultural plants. The study demonstrated that transfer learning methods can exhibit strong performance even when applied to limited datasets. Sankaran et al. [3] systematically evaluated sensor-based plant health monitoring techniques by comparing hyperspectral, thermal, and fluorescence imaging methods. Kamilaris and Prenafeta-Boldú [4] discussed the role of deep learning in agricultural production within a broad literature framework, emphasizing the importance of processing time and model complexity in addition to classification accuracy. Ali et al. [5] presented a comprehensive review encompassing proposed models, datasets, and evaluation metrics for plant disease detection. Similarly, Too et al. [6] investigated the comparative performance of various pretrained CNN models, including DenseNet, ResNet, and MobileNet. In a comparable approach, Fuentes et al. [7] employed a YOLO-based object detection system to identify both diseases and pests in tomato plants in real time. From a more classical perspective, Arivazhagan et al. [8] successfully classified banana plant diseases using feature extraction methods based on color and shape. These studies represent pre-deep-learning approaches and continue to serve as valuable benchmarks in the literature.

Although studies specifically targeting rose plants remain limited compared to the broader plant health monitoring literature, research in this area has gained substantial momentum, particularly following the development of rose-specific image databases such as RoseNet after 2023. In a 2023 study, a CNN-based model developed using the RoseNet dataset successfully classified common rose leaf diseases, including Black Spot, Powdery Mildew, and Downy Mildew [9]. This work is notable for demonstrating the effectiveness of enriching image color channels and addressing class imbalance in improving model performance.

Similarly, a 2024 study utilizing the RoseNet dataset proposed a preprocessing step incorporating color space transformations and spectral information integration, resulting in the development of a lightweight CNN model suitable for mobile applications [10]. Furthermore, Latifah et al. [11] applied hyperparameter optimization techniques—such as RMSprop and early stopping—on the Rose Leaf Disease dataset to achieve high classification accuracy, underscoring the model’s generalizability and practical viability. Mridha et al. [12] proposed a high-performance model for leaf disease detection using a transfer learning approach based on the Xception architecture. Their dataset included rose, mango, and tomato leaf images, demonstrating the model’s capability to generalize across species. Rajbongshi et al. [13] employed the MobileNet architecture to develop mobile-compatible AI solutions for classifying rose leaf diseases. Most recently, Hu et al. [14] enhanced the feature extraction capacity of deep learning models using Squeeze-and-Excitation (SE) blocks—channel-wise attention mechanisms—which significantly improved classification performance, especially in tasks involving subtle visual differences among rose leaf diseases.

These recent studies clearly highlight the need for models specifically tailored to rose leaf disease classification and reinforce the originality of the present research. Addressing this gap in the literature, the current study aims to develop a lightweight and optimized CNN architecture capable of delivering high classification accuracy and practical applicability using a balanced and challenging dataset. Ultimately, this research seeks to contribute to the proliferation of digital diagnostic systems in ornamental plant agriculture.

2. MATERIALS AND METHODS

2.1. Dataset

In this study, the RoseNet dataset a customized image dataset specifically developed for detecting common diseases in rose plant leave was utilized. The dataset comprises three classes: Black Spot, Downy Mildew, and Fresh Leaf. It contains a total of 917 images, with an imbalanced class distribution. Therefore, data augmentation techniques were not employed; instead, the class imbalance was addressed through the application of class weighting during model training.

All images were resized to 256×256 pixels, and the dataset was divided into training and testing subsets using a stratified sampling strategy with an 85%–15% split, respectively. In this method, each class was proportionally sampled and distributed into the training and testing subsets to ensure that the class representation remained consistent across both partitions. Given that class imbalance may adversely affect model performance, stratified sampling was deliberately chosen to improve data representativeness and preserve the distributional integrity of each class during model evaluation.

2.2. Preprocessing Pipeline

Color, texture, and brightness variations observed on plant leaves are key indicators for disease detection. In this study, in order to extract more comprehensive information from different color components, the images were transformed into RGB, HSV, and YCrCb color spaces. As illustrated in Figure 1, a sample image from the Downy Mildew class is shown after preprocessing for each color space. These transformed images were then concatenated along the channel axis to form a 9-channel tensor. This fusion approach was observed to enhance the model's ability to learn diverse spectral features more effectively across different color dimensions. The resulting composite structure can be mathematically expressed as follows:

$$G_f = [G_{RGB} \mid G_{HSV} \mid G_{YCrCb}] \in R^{256x256x9} \quad (10)$$

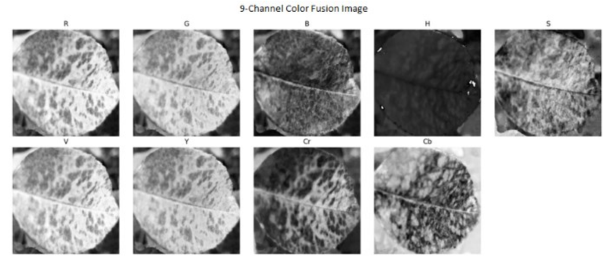

Figure 1. Image After Preprocessing in Multiple Color Spaces

Subsequently, all tensors were channel-wise normalized to have a mean of 0 and a standard deviation of 1. This preprocessing step ensured numerical stability and enabled faster convergence during training. Class labels were converted into numerical format to facilitate compatibility with the model input. To enhance the model's generalization ability and to prevent over-confident predictions, the label smoothing technique was applied. In this approach, instead of assigning a probability of 1 to the target class, it is slightly reduced to 1−ε (e.g., 0.9), while the remaining probability is distributed among the non-target classes (e.g., 0.05 each), allowing the model to learn in a more flexible and robust manner. In addition, due to the presence of class imbalance in the dataset, a class-weighted loss function was employed to support the learning of minority classes. In this strategy, the loss contribution of each class was weighted inversely proportional to the number of its instances, aiming to ensure fair and balanced learning across all categories.

2.3. Design of the Proposed Deep Learning Framework

In this study, a custom-designed Convolutional Neural Network (CNN) architecture is proposed, developed from scratch to support color channel fusion and enhanced through integrated attention mechanisms. The model is designed to operate on 9-channel input tensors with a resolution of 256×256 pixels. In the initial stage of the architecture, two consecutive convolutional layers are employed for primary feature extraction. Each convolutional layer is followed by batch normalization and a Rectified Linear Unit (ReLU) activation function. At the end of these blocks, spatial dropout layers are incorporated to mitigate overfitting by randomly deactivating portions of the activation maps. These layers form modular structures in which feature extraction and attention mechanisms work in synergy. An overview of the proposed architecture is illustrated in Figure 2.

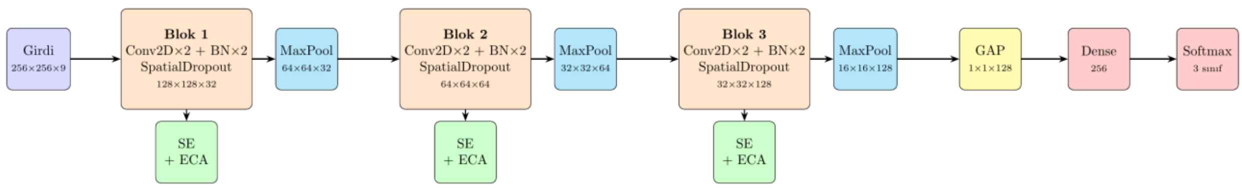

Figure 2. Block Diagram

After each convolutional block, Squeeze-and-Excitation (SE) blocks were integrated to emphasize the informational contribution of each channel in the input tensor. Additionally, Efficient Channel Attention (ECA) blocks were employed to model inter-channel dependencies based on local neighborhood interactions. The SE block consists of three fundamental steps: First, a global average pooling (GAP) operation is applied to the input tensor to extract a summary vector (z_c) for each channel. Then, this vector is passed through a series of fully connected layers, where it is processed using ReLU and sigmoid activation functions to obtain channel-wise attention scores (s_c).

In the final step, each channel (X_c) is rescaled by its corresponding attention score, performing an element-wise multiplication between the attention vector and the original tensor. This operation enables an adaptive feature recalibration, highlighting channels based on their information density.

$$z_c = \frac{1}{H.W} \sum_{i=1}^{H} \sum_{J=1}^{W} X_{i,j,c} \quad (1)$$

$$s_c = \sigma\,(W_2 \,.\, \delta(W_1 \,.\, z_c)) \quad (2)$$

$$X'_C = s_c \,.\, X_c \quad (3)$$

ECA blocks offer a more streamlined alternative to SE blocks by modeling channel attention through a non-parametric approach. This structure applies 1D convolution over the channel-wise summary vector to learn contextual relationships among channels. Due to its low parameter requirements, the ECA mechanism is particularly well-suited for use in mobile and embedded systems. The resulting attention coefficients are directly applied to the input tensor, effectively guiding the model to focus on the most informative channels. A visual representation of both the SE and ECA blocks is provided in Figure 3.

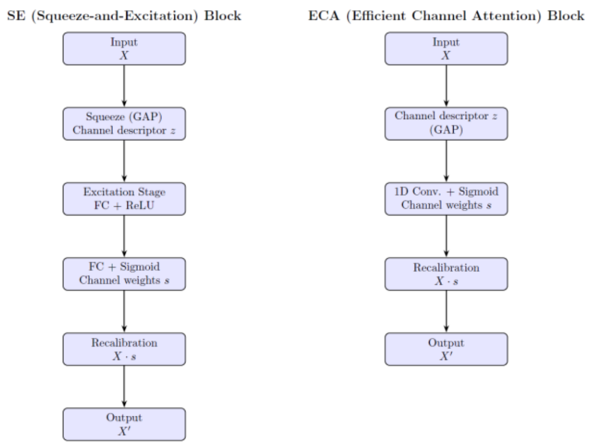

Figure 3. Structural Representation of SE and ECA Blocks

Thanks to these mechanisms, the model has become more sensitive to color and structural patterns that represent prominent disease symptoms in leaf images. Mathematically, the contribution of these attention mechanisms can be explained by their direct impact on the learning process through vector-wise rescaling of the feature maps.

The attention coefficients applied in SE blocks enhance the gradient sensitivity of the corresponding channels during backpropagation, thereby reinforcing inter-class discriminative capability. This is particularly effective in improving the learning of disease classes with lower representation in the dataset.

In ECA blocks, the 1D convolution operation captures local channel dependencies in a parameter-efficient manner. The resulting attention weights are applied to each channel output in a less complex but still effective way. As a result, the model's overall classification accuracy increases, and more importantly, its generalization performance on test data improves significantly. Following these blocks, a max pooling layer is employed to reduce the spatial dimensionality of the feature maps. A global average pooling (GAP) layer then removes the spatial information entirely, resulting in a fixed-length feature vector. This vector is processed by a fully connected dense layer with 256 neurons, followed by a dropout operation to mitigate overfitting. Finally, a softmax output layer is used for three-class classification.

The model was trained with the following configuration:

Optimizer: Adam (learning rate = 1e−4)

Loss function: Categorical cross-entropy with label smoothing

Batch size: 16

Epochs: 200 (with early stopping set to 20 epochs)

Callbacks: ModelCheckpoint, ReduceLROnPlateau

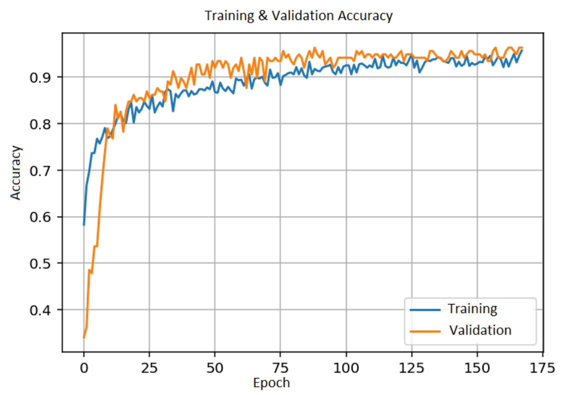

Figure 4. Training and Validation Accuracy Curve

As illustrated in Figure 4, the training process progressed rapidly and steadily, with the validation accuracy reaching approximately 90% within the first 10 epochs. No significant divergence was observed between the training and validation curves. In particular:

The early stopping strategy effectively prevented overfitting.

Thanks to label smoothing, the validation curve occasionally surpassed the training curve, indicating improved generalization.

Class weighting contributed to a better representation of underrepresented classes.

3. RESULTS AND DISCUSSION

In this study, a novel convolutional neural network (CNN) architecture was proposed, incorporating color space fusion and enhanced by Squeeze-and-Excitation (SE) and Efficient Channel Attention (ECA) blocks. The model's classification performance was evaluated on the RoseNet dataset, focusing on three classes: Black Spot, Downy Mildew, and Fresh Leaf. The performance of the model was analyzed not only in terms of accuracy, but also using multiple evaluation metrics such as precision, recall, F1-score, as well as training and inference time. In this respect, the proposed model distinguishes itself from conventional CNN-based approaches in the literature through its methodological depth and comparative comprehensiveness.

On the test dataset, the model achieved an overall accuracy of 95.65%, with a precision of 95.68%, recall of 95.65%, and F1-score of 95.64%. These results demonstrate a high degree of consistency and robustness across all major classification metrics.

As shown in Figure 5, the model achieved 100% classification accuracy for the Downy Mildew class, correctly predicting all samples belonging to this category. In the case of the Black Spot class, a small number of misclassifications were observed, most of which were confused with the Fresh Leaf class. This suggests the presence of borderline cases where the visual symptoms of disease resemble those of healthy leaves.

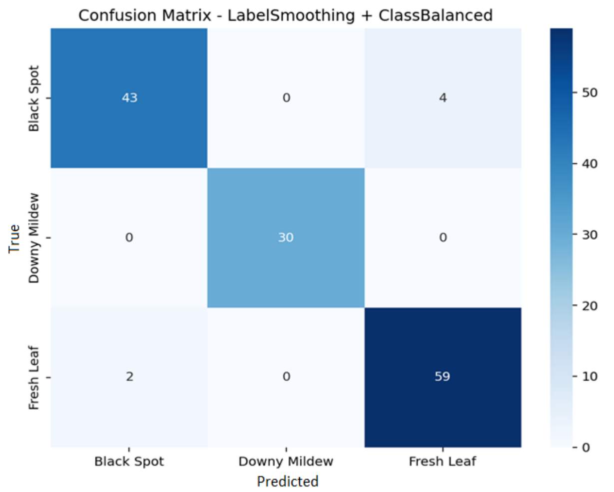

Figure 5. Test Confusion Matrix

The success of the proposed model can be attributed to three key factors:

1-) Color Space Fusion (RGB + HSV + YCrCb): The enrichment of visual spectral diversity through a 9-channel input enabled more effective discrimination of disease patterns based on texture and color.

2-) Attention Blocks (SE + ECA): Channel-wise attention mechanisms emphasized the relative importance of each feature map, enhancing the model's ability to distinguish between classes.

3-) Validation-Oriented Training: Techniques such as Z-score normalization, label smoothing, and class weighting mitigated inter-class imbalances and significantly improved the model's generalization capability.

Moreover, the proposed model was evaluated not only in terms of classification accuracy, but also with respect to model complexity, processing time, and metric diversity. This comprehensive assessment demonstrates a scientifically rigorous and holistic approach that differentiates the proposed method from similar studies in the literature. A comparative summary of key related works is presented in Table 1 below.

Table 3.1. Literature Comparison

Ref No	Author(s)	Year	Dateset Characteristics	Method	Performance Metrics
1	Mohanty et al.	2016	PlantVillage dataset (e.g., tomato, potato) with 38 classes and 54,306 images	CNN	Accuracy: 99,35%
2	Ferentinos	2018	Various plants – 25 classes, 87,848 images	AlexNet, GoogLeNet, VGG	Accuracy: 99,53%
3	Sankaran et al.	2010	Diverse plant species (hyperspectral images)	Hyperspectral, thermal, and fluorescence analysis	
4	Kamilaris & Prenafeta-Boldú	2018	Various plants – Review, class information varies	CNN, RNN	
5	Ali et al.	2021	Different plant species – Review study	Deep Learning methods	
6	Too et al.	2019	PlantVillage (Multiple plant species) – 38 classes, 54,306 images	DenseNet, ResNet, MobileNet	Accuracy: 99,44%
7	Fuentes et al.	2017	Tomato – 9 classes, 13,424 images	YOLO	Precision: 89,2%, Recall: 83,9%
8	Arivazhagan et al.	2013	Banana – 4 classes, 500 images	Color + shape features	Accuracy: 91,79%
9	Rahman et al.	2020	Various plants – 5 classes, 3,000 images	GAN + CNN	Accuracy: 96,4%, F1-score: 94,8%
10	Basak, Shuvo	2025	RoseNet (Rose) – 3 classes, 917 images	Lightweight CNN +Color transformation	Accuracy: 96,1%
11	Latifah Nabilah et al.	2023	Kaggle (Rose Leaf Disease) – ~14,910 images, 3 classes	CNN + RMSprop, Early Stopping	Accuracy: 99.96%
12	Mridha et al.	2024	Rose, Mango, Tomato – Mixed leaf data, multi-class	Xception-based transfer learning architecture	Accuracy: 98% Precision: 99% Recall: 98% F1-score: 98%
13	Rajbongshi et al.	2020	RoseNet (Rose) – 3 classes, 917 images	MobileNet	Accuracy: 96,11%
	Yapılan Çalışma	2025	RoseNet (Rose) – 3 classes, 917 images	CNN + SE-ECA Blocks	Accuracy: 95.65%, F1-score: 95,64% Precision: 95,68%, Recall: 95,65%

Upon examining the studies presented in Table 1, it is evident that a wide range of approaches have achieved remarkably high accuracy rates in the field of image-based plant disease classification. Most of these studies rely on large-scale datasets (e.g., PlantVillage) and powerful deep learning architectures (such as AlexNet, VGG, DenseNet, Xception), while leveraging techniques such as data augmentation, transfer learning, color space transformation, and optimization algorithms to enhance model performance.

The performance of the present study becomes more meaningful when compared specifically with similar research conducted on the RoseNet dataset. For instance, models developed by Rajbongshi et al. (2020) and Basak & Shuvo (2025) using the same dataset reported accuracy rates of 96.11% and 96.1%, respectively. In contrast, our study achieved 95.65% accuracy and an F1-score of 95.64%, through a custom-designed CNN architecture enhanced with Squeeze-and-Excitation (SE) and Efficient Channel Attention (ECA) blocks. These results indicate a performance level that is highly comparable and consistent with the aforementioned studies.

While some studies employing larger and more diverse datasets such as Latifah Nabilah et al. (2023) have reported accuracy rates exceeding 99%, such high performance is often attributed to the dataset's volume and variability, as well as the representational power of transfer learning-based deep architectures. Therefore, in small-scale and limited data environments, the performance of models built from scratch gains importance in terms of architectural efficiency and interpretability when assessed comparatively.

Indeed, models achieving high accuracy through GAN-based data generation (Rahman et al., 2020) or transfer learning with pretrained architectures like Xception (Mridha et al., 2024) also highlight the necessity for models to be not only accurate but also resource-efficient and customizable for real-world deployment. In this context, the proposed model demonstrates a competitive level of performance compared to other recent works based on the RoseNet dataset, while offering a more practical and application-oriented solution through its low parameter count and short inference time.

4. CONSLUSION

This study proposes a novel convolutional neural network (CNN) architecture for the detection of common fungal diseases in rose leaves. The model is enhanced with channel-wise color space fusion (RGB, HSV, YCrCb) and attention mechanisms, specifically Squeeze-and-Excitation (SE) and Efficient Channel Attention (ECA) blocks. The architecture was evaluated on the RoseNet dataset for a three-class disease classification task, achieving an accuracy of 95.65%, along with high performance in precision, recall, and F1-score metrics. The SE and ECA blocks, which emphasize salient features at the channel level, significantly improved the model's discriminative capability by enhancing class separability.

With a total parameter count of only 1.03 million and an inference time of 376 ms per image, the proposed model demonstrates strong potential for deployment on embedded or mobile systems. Moreover, the use of Z-score normalization, class-weighted loss, and label smoothing helped mitigate overfitting tendencies during training and contributed to a well-balanced classification performance. The architecture developed in this study offers a competitive performance with reduced computational demand and faster inference, underscoring the importance of locally optimized deep learning models for constrained environments.

Furthermore, testing the generalizability of the model on datasets involving different plant species and disease types, as well as evaluating its deployment on low-power microcontroller platforms (e.g., Raspberry Pi, Jetson Nano), could support the broader adoption of this approach as a real-time, cost-effective decision support system for both academic research and practical field applications.

Declaration of Ethical Standards

This study does not involve any human participants or animal testing. Therefore, ethical approval was not required. All data used in this research were obtained from publicly available sources or generated in the laboratory under standard conditions.

Credit Authorship Contribution Statement

Yusuf Yaman: Conceptualization, Methodology, Software, Formal analysis, Writing – Original Draft. Asst. Prof. Dr. Esra Kaya: Supervision, Validation, Writing – Review & Editing.

Declaration of Competing Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Funding / Acknowledgements

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. The authors would like to thank Selçuk University Faculty of Technology for their technical support during this study.

Data Availability

The dataset used in this study is publicly available and can be accessed freely from the original source. All data were used in compliance with the source's terms and conditions

References

[1] Mohanty, S. P., Hughes, D. P., & Salathé, M., "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, p. 1419, 2016. DOI: 10.3389/fpls.2016.01419

[2] Ferentinos, K. P., "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018. DOI: 10.1016/j.compag.2018.01.009

[3] Sankaran, S., Mishra, A., Ehsani, R., & Davis, C., "A review of advanced techniques for detecting plant diseases," Computers and Electronics in Agriculture, vol. 72, no. 1, pp. 1–13, 2010. DOI: 10.1016/j.compag.2010.02.007

[4] Kamilaris, A., & Prenafeta-Boldú, F. X., "Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, 2018. DOI: 10.1016/j.compag.2018.02.016

[5] Ali, I., Zhu, C., & Zhou, M., "Plant disease identification using deep learning: A review," Plants, vol. 10, no. 10, p. 2123, 2021. DOI: 10.3390/plants10102123

[6] Too, E. C., Yujian, L., Njuki, S., & Yingchun, L., "A comparative study of fine-tuning deep learning models for plant disease identification," Computers and Electronics in Agriculture, vol. 161, pp. 272–279, 2019. DOI: 10.1016/j.compag.2018.03.032

[7] Fuentes, A., Yoon, S., Kim, S., & Park, D. S., "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," Sensors, vol. 17, no. 9, p. 2022, 2017. DOI: 10.3390/s17092022

[8] Arivazhagan, S., Shebiah, R. N., et al., "Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features," CIGR Journal, vol. 15, no. 1, pp. 211–217, 2013.

[9] M. Ali-Alvy, G. K. Khan, M. J. Alam, S. Islam, M. Rahman, and M. S. Rahman, "Rose Plant Disease Detection using Deep Learning," in Proc. 2023 7th Int. Conf. on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2023, pp. 1244–1249. DOI: 10.1109/ICOEI56765.2023.10126031

[10] Basak, Shuvo, Unveiling the Enigma: Advancing Rose Leaf Disease Detection with Transformed Images and Convolutional Neural Networks, 2025. DOI: 10.5281/zenodo.8111573

[11] Nabilah, L., Nisar, N., Amnah, A., & Arfida, S., "Enhancing Rose Leaf Disease Detection Accuracy Using Optimized CNN Parameters," Bulletin of Computer Science and Electrical Engineering, vol. 4, no. 2, pp. 83–88, 2024. DOI: 10.25008/bcsee.v4i2.1184

[12] Mridha, M. F., Alfarhood, S., Rahman, M. M., Alam, T., & Uddin, M. N., "Transforming leaf disease diagnosis through deep transfer learning: An Xception-based approach," Plant Direct, vol. 9, no. 6, p. e1505857, 2025. DOI: 10.1002/pld3.1505857

[13] Rajbongshi, A., Sarker, T., Ahamad, M., & Rahman, M., "Rose Diseases Recognition using MobileNet," in Proc. ISMSIT, pp. 1–7, 2020. DOI: 10.1109/ISMSIT50672.2020.9254420

[14] Hu, J., Shen, L., & Sun, G., "Squeeze-and-Excitation Networks," in Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), pp. 7132–7141, 2018. DOI: 10.1109/CVPR.2018.00745