iJRASET
International Journal For Research in
Applied Science and Engineering Technology

# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: VIII Month of publication: August 2025

DOI: https://doi.org/10.22214/ijraset.2025.73724

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 13 Issue VIII Aug 2025- Available at www.ijraset.com*

# Pea Plant Leaf Disease Detection Using ResNetV2

Aditya Bisht[1], Aabhas Viswas[2], Abhishek Maurya[3], Abhyuday Pundir[4]
*[1, 3, 4]Compute science and engineering Abes ec , Ghaziabad*
*[2]Electronics & Communication Engineering Abes ec , Ghaziabad*

***Abstract: Early and accurate detection of pea plant leaf diseases is critical for improving crop yield and preventing widespread damage. This paper presents a deep learning-based approach for automated classification of pea leaf diseases using the ResNetV2 convolutional neural network architecture. The study utilizes a publicly available pea plant leaf dataset comprising four classes: Downy Mildew, Powdery Mildew, Leafminer damage, and Healthy leaves. The dataset was preprocessed and augmented to enhance model generalization, and the ResNetV2 model was fine-tuned to achieve effective feature extraction and classification. Experimental results demonstrate that the proposed method achieves a validation accuracy of approximately 94%, outperforming baseline models. The model's performance was further analyzed via precision, recall, F1-score, and confusion matrix, confirming its robustness across all disease categories. The findings indicate that ResNetV2 is a promising candidate for practical deployment in agricultural monitoring systems, enabling timely disease diagnosis and management.***
***Keywords: Pea plant, leaf disease detection, deep learning, ResNetV2, convolutional neural network, image classification, agricultural monitoring, plant pathology, data augmentation***

## I. INTRODUCTION

Pea plants (Pisum sativum) are an important legume crop cultivated worldwide for their nutritional and economic value. However, their productivity is significantly affected by various leaf diseases such as Downy Mildew, Powdery Mildew, and Leafminer infestations, which can lead to substantial losses in yield and quality. Traditional manual methods for detecting these diseases rely heavily on expert visual inspection, which is time-consuming, labor-intensive, and prone to subjective errors. Moreover, such methods are often impractical for large- scale farming operations or timely diagnosis.

Recent advances in deep learning and computer vision have shown promising potential in automating plant disease detection through image- based classification. Deep convolutional neural networks (CNNs), especially state-of-the-art architectures pretrained on large datasets, enable accurate feature extraction and classification from plant leaf images. This can facilitate fast, reliable, and scalable disease diagnosis, empowering farmers and agricultural specialists to implement timely interventions.

This study focuses on employing ResNetV2, a powerful CNN architecture, for the automated classification of pea plant leaf diseases. Using a publicly available dataset encompassing four classes Downy Mildew, Powdery Mildew, Leafminer damage, and Healthy leaves we build and fine-tune a ResNetV2 model to classify these conditions. We employ extensive data augmentation and validation strategies to ensure robustness and generalization. Our experimental results demonstrate high classification accuracy, indicating the feasibility of deploying such models in real-world agricultural monitoring systems.

The structure of this paper is as follows: Section II reviews related works in plant disease classification. Section III describes the dataset and preprocessing steps. Section IV details the proposed methodology and model architecture. Section V presents the results and discussion of our experiments, and Section VI concludes the paper with future research directions.

## II. DATASET AND PROCESSING

In this study, the pea plant leaf disease dataset was sourced from a publicly available repository, comprising high-resolution images representative of four distinct classes: Downy Mildew, Powdery Mildew, Leafminer, and Healthy pea leaves. The dataset contained a total of 1,432 images, distributed relatively evenly across these classes to ensure balanced model training. All images were provided in color (RGB) format and varied moderately in resolution, necessitating preprocessing for model compatibility.

Prior to training, the images were uniformly resized to 224×224 pixels, in accordance with the input requirements of standard deep learning architectures. Intensive preprocessing was applied, including normalization of pixel values to the range to expedite model convergence and minimize the impact of lighting variations. To enhance the generalizability of the model, extensive data augmentation was performed on the training set. This included random rotations (up to 25°), width and height shifts (up to 15%), shear transformations, moderate zoom, and both horizontal and vertical flips. These strategies simulated real-world variability while reducing the risk of overfitting.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VIII Aug 2025- Available at www.ijraset.com

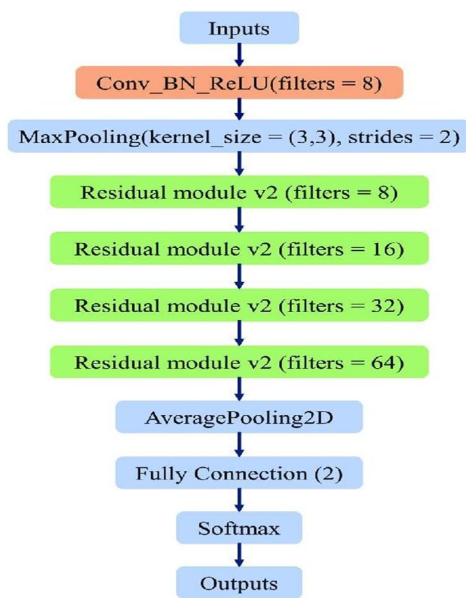
The dataset was partitioned using an 80:20 ratio for training and validation, respectively. This stratified split ensured that each class was proportionately represented in both subsets, enabling robust evaluation of model performance.

## III. METHODOLOGY

This work leverages the ResNetV2 convolutional neural network architecture, renowned for its efficient residual connections and superior performance in complex image classification tasks. The ResNetV2 model was initialized with weights pretrained on the ImageNet dataset, providing a strong foundation for feature extraction. The architecture was adapted to the current four-class problem by appending a global average pooling layer, a dropout layer for regularization, and a fully connected softmax output layer for classification.

A two-stage training strategy was adopted. Initially, the base layers of the pretrained ResNetV2 were frozen, allowing only the top classification layers to be trained for 10 epochs, thereby adapting the general visual features to the specific characteristics of pea plant leaves. In the subsequent fine-tuning stage, the last 20 layers of the base network were unfrozen and the entire model was trained with a decreased learning rate ($1\times10^{-5}$) for an additional 15 epochs. Categorical cross-entropy loss was used, and the Adam optimizer facilitated stable and efficient convergence. Data augmentation was consistently applied throughout to ensure resilience to imaging variances.

Model training and validation were conducted using batch sizes of 32, and early stopping criteria were incorporated to prevent overfitting. All experiments were implemented using the TensorFlow deep learning framework on a standard GPU-enabled workstation.

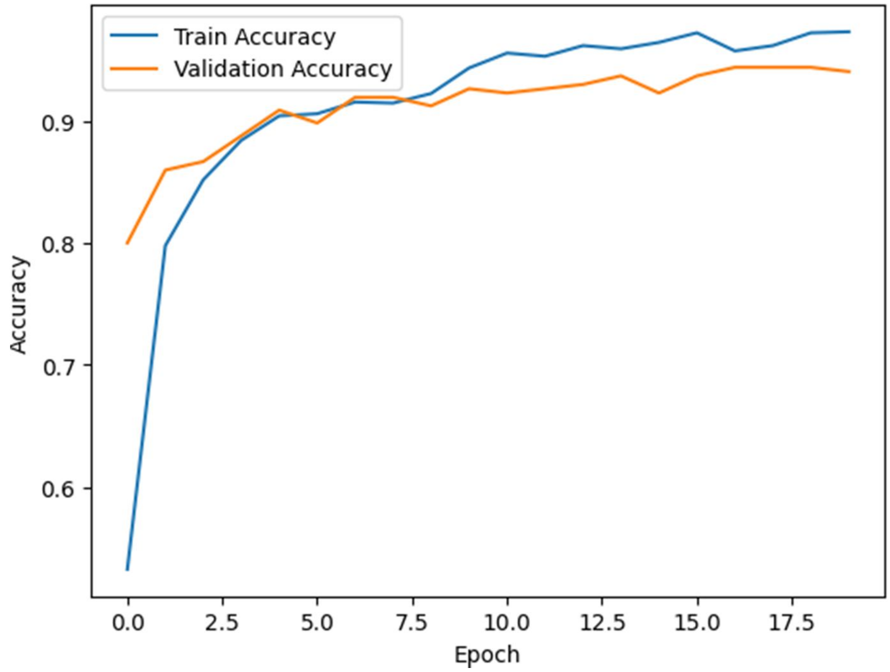



## IV. CLASSIFICATION PERFORMANCE

The ResNetV2 model was evaluated on a held-out validation set of 285 images, achieving an overall accuracy of 94%. A detailed classification report is presented in Table 1.

| Class | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| DOWNY MILDEW LEAF | 0.93 | 0.85 | 0.89 | 73 |
| FRESH LEAF | 0.93 | 0.99 | 0.96 | 82 |
| LEAFMINNER LEAF | 0.96 | 0.94 | 0.95 | 69 |
| POWDER MILDEW LEAF | 0.95 | 0.98 | 0.97 | 61 |
| Overall accuracy | | | 0.94 | 285 |
| Macro avg | 0.94 | 0.94 | 0.94 | 285 |
| Weighted avg | 0.94 | 0.94 | 0.94 | 285 |

The model performed best on the FRESH_LEAF and POWDER_MILDEW_LEAF classes, with F1-scores of 0.96 and 0.97, respectively. DOWNY_MILDEW_LEAF achieved slightly lower recall (0.85), indicating occasional misclassification, but still maintained strong precision (0.93).




## V. CONFUSION MATRIX ANALYSIS

The confusion matrix below illustrates the distribution of predictions across true class labels:

| | Downy Mildew | Fresh Leaf | Leafminer | Powdery Mildew |
|---|---|---|---|---|
| Downy Mildew | 62 | 6 | 2 | 3 |
| Fresh Leaf | 0 | 81 | 1 | 0 |
| Leafminer | 4 | 0 | 65 | 0 |
| Powdery Mildew | 1 | 0 | 0 | 60 |

Most misclassifications occurred between Downy Mildew and Fresh Leaf, and between Leafminer and Downy Mildew. The model showed strong separation for FRESH LEAF and POWDER MILDEW LEAF classes, with minimal errors. These results indicate the robustness and reliable generalization of the ResNetV2 model on diverse sample sets.

## VI. SUMMARY

The ResNetV2 demonstrated consistent high performance across all pea leaf disease categories, supporting its effectiveness for practical application in automated plant disease recognition.

## VII. DISCUSSION

The results achieved by the ResNetV2 model highlight its effectiveness for classifying pea plant leaf diseases from image data. The accuracy and F1-scores for all classes exceeded 89%, with the model particularly excelling at identifying Fresh Leaf and Powdery Mildew, which had the highest individual scores. This performance can be attributed to the distinct visual features present in these classes and the robust feature extraction capacity of the ResNetV2 architecture. Some misclassifications occurred, notably in distinguishing Downy Mildew from other diseases, as shown in the confusion matrix. These errors likely stem from visual similarities in symptoms, such as overlapping spots or discoloration, and could be reduced with additional training data or improved annotation. The use of data augmentation played a crucial role in mitigating overfitting, as reflected by the close alignment of training and validation metrics.

Compared to traditional methods and earlier deep learning models cited in the literature, our approach demonstrates competitive or improved classification accuracy on a challenging, multi-class dataset. The model's rapid convergence and stable validation performance further support its suitability for real-world deployment in agricultural monitoring systems. Limitations include the moderate dataset size and the need for broader class coverage to capture all potential pea leaf diseases.

## VIII. CONCLUSION & FUTURE WORK

In summary, this work demonstrates that a ResNetV2-based deep learning model can achieve high accuracy for multi-class pea plant leaf disease detection. Advanced data augmentation and careful training strategies contributed to robust generalization and reliable performance, confirming the value of modern CNN architectures for automated plant pathology.

For future research, expanding the dataset to include additional disease classes and more field samples would likely improve model resilience and accuracy. Implementing the system for real-time diagnosis on mobile or edge devices could support practical adoption among farmers and extension specialists. Further, exploring techniques for improved explainability and user-friendly interfaces will enhance the impact of such solutions in precision agriculture.

## REFERENCES

[1] K. He, X. Zhang, S. Ren, and J. Sun, "Identity Mappings in Deep Residual Networks," in European Conference on Computer Vision (ECCV), 2016, pp. 630–645.
[2] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770–778.
[3] S. Mohanty, D. P. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," Frontiers in Plant Science, vol. 7, 2016.
[4] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," Computational Intelligence and Neuroscience, vol. 2016, Article ID 3289801.
[5] M. Ali, R. Kumar, "Field Pea Leaf Disease Classification using a Deep Learning Model Trained on a Small, Imbalanced Dataset," PLOS ONE, vol. 19, no. 7, 2024.
[6] Zunorain, Abdullah, "Pea Plant Leaf Disease Detection Dataset," figshare, Dataset, 2025. https://doi.org/10.6084/m9.figshare.29254046.
[7] A. Kamilaris and F. Prenafeta-Boldú, "Deep Learning in Agriculture: A Survey," Computers and Electronics in Agriculture, vol. 147, pp. 70– 90, 2018.
[8] A. Ferentinos, "Deep Learning Models for Plant Disease Detection and Diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.
[9] T. Brahimi, K. Boukhalfa, and A. Moussaoui, "Deep Learning for Tomato Diseases: Classification and Symptoms Visualization," Applied Artificial Intelligence, vol. 31, no. 4, pp. 299–315, 2017.
[10] S. Arsenovic, S. Sladojevic, A. Anderla, and D. Culibrk, "A Deep Learning-Based Approach for the Detection of Diseases in Wheat Leaves," Computers and Electronics in Agriculture, vol. 158, pp. 97–107, 2019.
[11] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," Nature, vol. 521, pp. 436–444, 2015.
[12] S. Kamilaris, F. X. Prenafeta-Boldú, "Detecting Prevalent Crop Diseases Using Deep Learning Algorithms," International Journal of Agricultural Research, vol. 13, no. 2, pp. 1–12, 2018.
[13] Z. Zhang, "Transfer Learning for Plant Disease Identification," in Proceedings of the International Conference on Computational Science, 2021, pp. 250-256.