ITM Web of Conferences **79**, 01047 (2025)
*KEIS-2025*
https://doi.org/10.1051/itmconf/20257901047

# Intelligent Plant Disease Detection and Classification using HV-GNN with Ontology-Driven Knowledge Embedding

*P.* Nagarathna[1], *Abdul* Lateef Haroon P.S[2*], *G.* Srinivasalu[3], and *Ashok* Kumar Pamidi Venkata[4]

[1]Department of Computer Science, Nitte Meenakshi Institute of Technology, Nitte (Deemed to be University), Bengaluru, India
[2]Department of Electronics and Communication Engineering, Ballari Institute of Technology and Management, Ballari, India
[3]Department of Electronics and Communication Engineering, Cambridge Institute of Technology, Bengaluru, India
[4]Megan Soft INC, Livonia, United States

**Abstract.** In recent years, intelligent plant disease detection has become an essential task in agriculture for ensuring crop health and improving yield. Detection and classification of plant diseases remain a challenging problem due to the vast numbers of plants species worldwide and the numerous diseases that negatively affect crop production. However, existing Deep Learning (DL) methods are used for plant disease detection and classification suffer from overfitting, limited robustness, and lack of interpretability. To overcome these issues, this paper proposes a Hybrid Vision Graph Neural Network with Ontology-Driven Knowledge Graph Embedding (HV-GNN-OKGE) method for effective plant disease detection and classification. The HV-GNN method captures both local and global structural features through isotropic and pyramid layers. While the ontology-driven embedding integrates semantic relationships among plant species, symptoms, and diseases to enrich classification with domain knowledge. The performance of the proposed HV-GNN-OKGE method is evaluated using two publicly available datasets: Plant Leaf Dataset (4,590 images, 22 classes) and PlantVillage (2,052 images, 2 classes) are used for training and evaluation, with preprocessing techniques including augmentation, resizing, and normalization to enhance image quality. Experimental results demonstrate that the proposed HV-GNN-OKGE achieves an accuracy of 99.95%, significantly outperforming existing deep learning models in plant disease detection and classification.

## 1 Introduction

Plant diseases, which threaten the world's food supply, highlight the importance of effective detection and management to sustain agricultural productivity, ensure food security, and promote economic growth [1]. In the initial stages of the agricultural industry, experts manually examined crop diseases; however, this method is prone to human error [2]. Neutralize disease and saving plants is possible with early detection, sooner they are discovered, the greater prevention of losses and protection of crops [3]. Undetected diseases lead to substantial reductions in crop yield and quality and pose severe economic losses while threatening food security on a large scale. In traditional methods of disease diagnosis, manual inspection by an expert is subjective and time consuming [4]. Pests, rapid ecological degradation, population expansion, and rice diseases threaten the global food security and climate change. Annual rice production reduced by this disease [5]. The detection of numerous plant diseases relies predominantly on visual assessments. Framers and experts visually inspect plants to detect diseases [6]. For crop diseases, visual inspection of leaf crown structure and color pattern remains central to conventional field scouting. Detecting PDs takes time and effort and requiring the naked eye, experience, and knowledge to identify disease indicators in plant leaves [7]. Leaf diseases are the most damaging to rice production throughout the growing and harvesting seasons. A correct diagnosis reduces or avoids the destructive impact of the illness [8]. The global economy cost approximately $220 billion annually due to plant disease limiting crop yield, according to the Food and Agriculture Organization of the United Nations (FAO) [9]. Current research indicates that innovative Deep Learning (DL) techniques outperform methods using hand-engineered features once sufficient data are available, as major causes for the most noticeable features are removed from the image using CNN techniques. A DL-based method for plant disease classification and detection using the RNN method extracts the most prominent features from crop images, aiming to improve accuracy and reduce manual inspection [10].

Key contribution of the paper:

1. Proposes a HV-GNN-OKGE method that integrates GNN, HV-GNN, isotropic and pyramid layers with ontology-based knowledge graph embedding to extract both local and global relational features for plant disease detection and classification.
2. Method ontology-based knowledge graph embedding (OKGE) to capture domain-specific

* Corresponding author: abdul.lh@bitm.edu.in

semantic relationships, improve feature representation, and enhance classification accuracy.
3. It strengthens the multi-scale and contextual representation of plant leaf features while reducing feature redundancy, achieving robust performance compared to conventional CNN and hybrid models.
4. A classification layer that utilized the enriched feature map to accurately detect plant disease categories across diverse datasets is used.
5. This demonstrates superior performance on the PlantVillage and PlantDoc datasets, achieving 99.99% and 99.97% accuracy, respectively, outperforming the existing advanced methods.

The rest of a remaining sections are as follows: Section 2, literature survey; Section 3, methodologies; Section 4, Results and Discussion; Section 5, Discussion; and Section 6, Conclusion and Future work.

## 2 Literature Survey

Some DL methods for plant disease classification and detection are discussed in this section.

Meenakshi Srivastava et al. [11] developed a plant leaf disease detector and a classifier method used Deep Learning. The methodology used five Deep Convolutional Neural Network (DCNN), namely Vgg16, MobileNetV2, Xception, InceptionV3, and DenseNet121, to detect and classify plant diseases. The performance was evaluated using two datasets, Mendeley (plant leaf dataset) and PlantVillage, and the experimental results showed a higher classification accuracy. However, the proposed method currently lacks pest detection functionality, which limits its diagnostic scope and reduces its adaptability to heterogeneous agricultural environments.

Masoud Rezaei et al. [12] developed a few-shot learning (FSL) method using five images per class in the Machine Learning (ML) process to alleviate the data scarcity problem and detect plant diseases. The developed method, integrated with a feature attention (FA) module, formed the overall PMF+FA method and was based on a PMF pipeline of pre-training, meta-learning, and fine-tuning. Implemented using Vision Transformers (ViT) and ResNet50, the FA method reduced the impact while emphasizing discriminative image parts. For the FSL, two public plant disease datasets were repurposed and the results demonstrated that the PMF + FA pipeline outperformed the baseline PMF. However, the complexity of vision transformer models restricted their practical application to low-power devices.

Ao Zhang et al. [13] developed a Swin-Axial Transformer method based on a Swin Transformer (ST), where the TokenEmbedder module reduced the number of tokens and multi-scale deep convolution efficiently extracted image features, significantly lowering computational costs. Combining the Axial Compression module and Detail Enhancement module, the model efficiently extracted global semantic features and effectively supplemented the local detail information. The experimental results demonstrated that the method achieved precision and provided an efficient and reliable solution for large-scale crop disease detection. However, the model requires improved robustness, as its detection capabilities are affected by complex backgrounds, lighting changes, and partial occlusions, limiting the Swin-Axial Transformer's adaptability and generalization across various complex environments and large-scale, real-time monitoring tasks.

Ila Kaushik et al. [14] developed a Depth-wise Separable-based adaptive Deep Neural Network (DSDNN) for detecting plant diseases. Initially, a Gaussian filter was applied for normalization and pre-processing. Subsequently, using an enthalpy-based graph-clustering method, plant segmentation was performed, followed by feature extraction techniques. The developed method achieved higher accuracy using a PlantVillage dataset of healthy and unhealthy leaves was used for model training. However, DSDNNs are effective and efficient but have some issues: their pointwise convolution layer limits feature interaction, they overfit small datasets, and focusing on channels causes the loss of important spatial details needed for tasks such as image segmentation.

Wasswa Shafik et al. [15] introduced Early Fusion (AE) and Lead Voting Ensemble (LVE), two-plant disease detection (PDDNet) methods, fine-tuned nine pre-trained CNN by deep feature extraction after integration for efficient plant disease classification and identification. The performance of various CNN model combinations was determine using a Logistic Regression (LR) classifier. For the evaluation, the PlantVillage dataset was used, and the experimental results showed that DDNet-AE and PDDNet-LVE achieved high accuracy. However, plant disease detection struggles with collecting real-time data, detecting diseases on multiple leaves, and handling complex backgrounds. There is also a need for lighter models and better leaf localization using vision transformers.

Problem Statement: Accurate plant disease detection is challenging due to the limitations of traditional CNN-based methods in capturing both local and global relational dependencies across leaf features. Single-scale feature extraction often fails to represent multi-scale and semantic relationships, whereas conventional methods may suffer from redundancy and poor generalization across diverse datasets, resulting in reduced classification accuracy and reliability.

Objective: To address these challenges, this paper proposes HV-GNN-OKGE, a hybrid variational graph neural network that integrates GNN, HV-GNN, and isotropic and pyramid layers with ontology-based knowledge graph embedding. This method effectively captures local and global features, preserves semantic relationships, and reduces the feature redundancy. Enriched features are fed into a classification layer to improve disease detection accuracy, robustness, and computational efficiency across the PlantVillage and PlantDoc datasets.

## 3 Proposed Method

As shown in Figure 1, this section presents the background of DL methods and the proposed methodology.

This paper proposes the HV-GNN-OKGE method, a hybrid variational graph neural network designed for ontology-based knowledge graph embedding and plant disease classification. The architecture integrates isotropic and pyramid graph layers to extract both local and global relational dependencies from the plant disease ontology graphs. The isotropic layer captures uniform feature propagation across graph nodes, whereas the pyramid layer hierarchically aggregates multi-scale semantic representations, thereby enhancing robustness and scalability. To further improve representation learning, ontology-based knowledge graph embedding (OKGE) is incorporated, ensuring domain-specific relational knowledge is preserved during training. The fused feature representations are then passed through a classification layer for accurate leaf disease detection. Experimental evaluation of the PlantVillage and PlantDoc datasets demonstrates that HV-GNN-OKGE achieves superior performance compared to existing methods, providing reliable, high-accuracy plant disease classification.

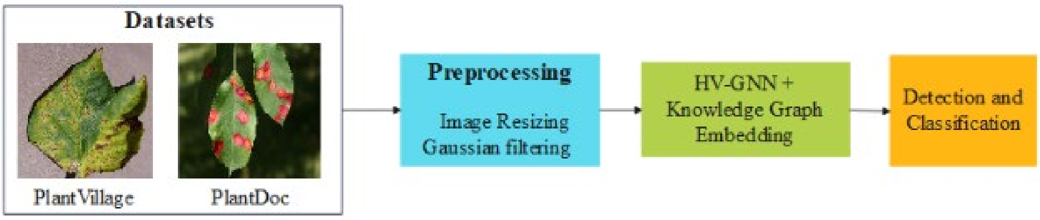


**Fig. 1.** Illustrates the overall proposed work, showing the complete workflow and the key stages involved in the methodology for multimodal biometric authentication.

### 3.1 Dataset Descriptions

The effectiveness of the proposed method to validate, this paper used two datasets, PlantDoc and PlantVillage.

#### *3.1.1 PlantDoc dataset*

Designed for plant disease detection, the PlantDoc dataset is based on real-world scenarios. Comprising 13 major crops and 27 disease types, it includes 2,598 high-resolution and clearly annotated images [17]. The dataset was collected from natural environments, occluded leaves, complex backgrounds, and lighting variations, making it highly representative of practical scenarios. Widely used to evaluate DL models in plant disease detection and classification tasks, the PlantDoc dataset benefits from its unique environmental conditions and diverse disease types. Sample images from the PlantDoc dataset are illustrated in Figure 2.


**Fig. 2.** illustrates representative images from the PlantDoc dataset.

#### *3.1.2 PlantVillage dataset*

The PlantVillage dataset is specifically designed for plant disease classification and detection, and is a publicly available resource [16]. The dataset included 38 disease types and 14 crop types, with 54,306 high-quality, clearly annotated leaf images. Collected under controlled laboratory conditions has a uniform background with minimum noise, making it suitable for transfer learning (TL) and supervised learning. Dataset generalization to real-life scenarios is limited to its idealized environment. It serves as a key benchmark dataset in plant disease research and is widely used to evaluate the model performance in plant disease classification. Sample images from the PlantVillage dataset are shown in Figure 3.


**Fig. 3.** illustrates sample images from the PlantVillage dataset.

### 3.2 Preprocessing

Plant leaf images were first acquired from the PlantDoc and PlantVillage datasets and then preprocessed for further processing. Preprocessing, which is considered a vital step, is performed to eliminate noise, artifacts, and other unwanted elements. The proposed preprocessing step includes two key phases: Gaussian filtering and image resizing. Image resizing is vital because of the variation in pixel values, as the dimensions of the training and testing images may differ. To match the dimensions of the training images, the imresize () function adjust the image dimensions. Next, a Gaussian filter applied to the input plant leaf image to remove noise and improve its quality. In the Gaussian filter, noise elimination and image smoothing are achieved through the Gaussian smoothen operator function as a 2D convolutional operator. Equation (1) provides its mathematical from, employing Gaussian hump-shaped kernels instead of the mean filter.

$$H(U,V) = \frac{1}{2\pi\rho^2}\left(e^{-\left(\frac{u^2+v^2}{2\rho^2}\right)}\right) \quad (1)$$

Where $V$ denotes the distance in the vertical direction, $U$ is the horizontal axis, and ρ is a Gaussian distribution.

## 3.3 Detection and Classification using Hybrid Vision Graph Neural Network with Ontology-Driven Knowledge Graph Embedding

### *3.3.1 Graph Neural Network with Hybrid Vision*

A multilayer HV-GNN architecture is used to predict plant leaf disease using isotropic and pyramid methods. By compiling multiple GNN layers, the network architecture allows each layer to have a different architecture. All nodes, learn local features near them and a broad relationship using the same message-passing mechanism. This enabled the capture of typical disease signs, including textural alterations and smaller lesions, as shown in Equation (2).

$$Message\ (x,y) = f\big(Feature\ (y), Edge\ Weight(x,y)\big) \quad (2)$$

The associated weight (x, y) corresponds to Edge Weight, Feature (y) denotes the feature vector of the neighboring node (y), while f denotes the learnable function transforming a neighbor feature according to the edge weight.

$$m_x^{(l)} = AGGREGATE\big(\{f_y^{l-1}\ |y \in N(x)\}\big) \quad (3)$$

The Transition Layer, shown in Equation (3), is placed between the pyramid and isotropic layers. In the layer $l$, the message received by node $x$ is represents $m_x^{(l)}$. neighboring nodes y from the previous layer (l−1) are combined by AGGREGATE. The set of neighbor node $x$ is denotes as N (x) and node y feature vector from layer $(l-1)$ is given as $f_y^{(l-1)}$.

By applying Node Coarsening, the pyramid layers combine several nodes from the earlier into one, preserves key information while limiting graph resolution and integrates the cluster node characteristics for preparation of pyramid layer processing. In the next pyramid layers, Lower pyramid layers capture features from limited neighborhood around each node, allowing detailed inspection of regions that highlight subtle disease symptoms.

$$m_x^{(l)} = AGGREGATE\big(\{f_y^{l-1}\ |y \in N_k(x)\}\big).W_k^{(l)}R \quad (4)$$

$N_k(x)$ in Equation (4) denotes the neighbor of node $x$ in layer $l$, within receptive field size $k$, increasing through the pyramid. In layer $l$, the learnable vector $W_k^{(l)}$corresponds to receptive field of size $k$. By optimizing information according to scale, due to wider receptive fields higher pyramid layers in the network is absorb more information relevant to context. Since the message-carrying functions of the layers are customized for Capturing large-scale disease patterns and leaf health necessitates the use of varying receptive fields and scale-aware techniques. In the case of coffee plant disease prediction, a pyramid layer in the isotropic final levels uses global and local data refines node representations.

### *3.3.2 Knowledge Graph Embedding*

The process of knowledge graph embedding involves transforming the elements of a KG into a semantically continuous lower-dimensional space. Gaining significant attention is the mapping of entire graphs or their nodes into vector spaces. This method offers scalability and simplifies complex problem resolution, including link-based clustering, entity resolution, and KG completion. Embedding learning involves encoding entities as distributed points and relationships as vectors, utilizing a scoring function, and employing an optimization procedure. The embedding models in this paper were selected with careful consideration of performance, scalability, and interpretability. DistMult, ComplEx, and TransE were incorporated due to their effectiveness in handling large KGs. These models are computationally efficient, suitable for large-scale KG embedding tasks, and easily scaled to handle larger graphs. Relations are modeled as translations in the embedding space by TransE, which provides a clear and intuitive insight into entity links, though some methods are less interpretable. Interpretable embeddings were also achieved by DistMult and ComplEx, which represent entity relation interactions using bilinear and trilinear Hermitian dot products.

# 4 Result and Discussion

The experiments were performed using a Window10 OS with 8 GB RAM and an Intel Core i5 processor. Implementation on both datasets was performed using Python version 3.8 tool, NVIDIA GTX 1070 GPU, OpenCV 3.2.4, PyTorch, and Google Colab Pro.

## 4.1 Evaluation Metrics

The performance was evaluated of each method for plant disease classification and detection; the definitions of these matrices are provided in Table 1.

**Table 1.** Demonstrates evaluation metrics.

| Metric | Formula |
|---|---|
| Accuracy | $\frac{\boldsymbol{TP\ +TN}}{\boldsymbol{TP+TN+FP+FN}}$ |
| Precision | $\frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}}$ |
| Recall | $\frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}}$ |
| F1 Score | $\boldsymbol{2\times\frac{precision\ \times Recall}{precision\ +Recall}}$ |

## 4.2 Performance Analysis

The performance of proposed HV-GNN-OKGE method on two benchmark datasets is evaluated and compared with traditional CNN-based models, namely, VGG16, MobileNetV2, and DenseNet121. In terms of accuracy, the proposed HV-GNN-OKGE method achieves 99.99% accuracy on the PlantVillage dataset and 99.97% on the PlantDoc dataset, significantly outperforming existing models. Similarly, the proposed HV-GNN-OKGE method demonstrated higher recall, precision, and F1-score than VGG16, MobileNetV2, and DenseNet121. Overall, the results demonstrated that the HV-GNN-OKGE method is highly suitable for plant leaf illness identification and classification. Table 2 shows the performance analysis of CSMG.

**Table 2.** Demonstrate the performance analysis of CSMG.

| Datasets | Models | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|---|
| PlantVillage | VGG16 | 86 | 84 | 87 | 82 |
| | MobileNetV2 | 95 | 96 | 93 | 97 |
| | DenseNet121 | 87 | 89 | 96 | 81 |
| | Proposed Method (HV-GNN-OKGE) | 99.99 | 99.80 | 99.50 | 99.77 |
| PlantDoc | VGG16 | 85 | 78 | 87 | 88 |
| | MobileNetV2 | 87. | 81 | 83 | 82 |
| | DenseNet121 | 70 | 72 | 79 | 90 |
| | Proposed Method (HV-GNN-OKGE) | 99.97 | 9.20 | 98.99 | 98.90 |

## 4.3 Computational Complexity

The proposed HV-GNN-OKGE method is evaluated for training and inference time and compared with traditional models, such as VGG16, MobileNetV2, and DenseNet121. The training time of 89 s is lower than that of VGG16 (153 s), MobileNetV2 (124 s), and DenseNet121 (163 s). Similarly, the inference time of the HV-GNN-OKGE method is 11 s, compared to VGG16 49 sec, MobileNetV2 57 sec, and DenseNet121 43 sec. The results of the HV-GNN-OKGE method reduce the training and inference times, making it highly efficient. The proposed HV-GNN-OKGE method is computationally lightweight and is suitable for plant leaf illness identification and classification, Table 3 shows the complexity of DL models.

**Table 3.** Complexity of deep learning models (in seconds).

| Models | Training Time (s) | Inference Time (s) |
|---|---|---|
| VGG16 | 153 | 49 |
| MobileNetV2 | 124 | 57 |
| DenseNet121 | 163 | 43 |
| Proposed (HV-GNN-OKGE) | 89 | 11 |

## 4.4 Statistical Analysis

Compared to the traditional DenseNet121, PDDNet-LVE, ProtoNet+FA+ini, and DSDNN methods, the proposed HV-GNN-OKGE method demonstrates superior accuracy and adaptability across both the PlantVillage and PlantDoc datasets. The improvement in the classification accuracy was statistically significant ($p < 0.05$), as validated by a paired t-test conducted over 10 independent runs. These results confirm the robustness, reliability, and effectiveness of the proposed HV-GNN-OKGE method for scalable and precise plant disease identification.

## 4.5 Ablation Study

The ablation study in this section demonstrates that each component of the proposed HV-GNN-OKGE method enhances performance using the PlantVillage and PlantDoc datasets. Starting with the base GNN, the accuracy is comparatively lower; however, introducing the HV-GNN architecture improved the hierarchical representation and increased accuracy. When isotropic and pyramid layers are included, the method becomes more effective at extracting multiscale features, leading to a better F1-score, precision, and recall. Finally, integrating OKGE optimization strengthens knowledge graph embedding and reduces redundancy, enabling the proposed HV-GNN-OKGE method to achieve a superior performance. Each added component contributes significantly, thereby enhancing the method to achieve a high classification accuracy and reliability, Table 4 shows the ablation study.

**Table 4.** shows the ablation study.

| Dataset | Models | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|---|
| PlantVillage | GNN (Base) | 94.85 | 93.20 | 92.80 | 93.00 |
| | HV-GNN | 96.75 | 95.60 | 95.20 | 95.35 |
| | HV-GNN + Isotropic + Pyramid Layer | 98.60 | 98.00 | 97.70 | 97.85 |
| | Proposed (HV-GNN-OKGE) | 99.99 | 99.80 | 99.50 | 99.77 |
| PlantDoc | GNN (Base) | 91.95 | 90.50 | 90.10 | 90.30 |
| | HV-GNN | 94.20 | 93.00 | 92.70 | 92.85 |
| | HV-GNN + Isotropic + Pyramid Layer | 97.05 | 96.10 | 95.70 | 95.85 |
| | Proposed (HV-GNN-OKGE) | 99.97 | 99.20 | 98.99 | 98.90 |

### 4.6 Comparative Analysis

The proposed HV-GNN-OKGE method is evaluated on the PlantVillage and PlantDoc datasets and compared with the existing approaches. On the PlantVillage dataset, DenseNet121 [11] achieved 98.9% accuracy, whereas PDDNet-LVE [15] achieved 96.74% accuracy. In contrast, the proposed HV-GNN-OKGE achieved 99.99%, significantly outperforming previous methods. Similarly, on the PlantDoc dataset, ProtoNet+FA+ini [12] obtained 86.79% accuracy, and DSDNN [14] achieved 97.5%. However, the proposed HV-GNN-OKGE has 99.97% accuracy, surpassing all baseline models. These results confirm the effectiveness and superiority of HV-GNN-OKGE for robust plant disease classification, Table 5 shows the comparative analysis.

**Table 5.** Comparative analysis of PlantVillage and PlantDoc.

| Datasets | Models | Accuracy (%) |
|---|---|---|
| PlantVillage | DenseNet121 [11] | 98.9 |
| | PDDNet-LVE [15] | 96.74 |
| | Proposed (HV-GNN-OKGE) | 99.99 |
| PlantDoc | ProtoNet+FA+ini [12] | 86.79 |
| | DSDNN [14] | 97.5 |
| | Proposed (HV-GNN-OKGE) | 99.97 |

## 5 Discussion

The experimental evaluation demonstrates that the proposed HV-GNN-OKGE method significantly outperforms existing methods on the PlantVillage and PlantDoc datasets. The integration of GNN, HV-GNN, and isotropic pyramid layers ensures the effective extraction of global features and local, strengthening spatial and contextual representation for disease classification. Ontology-based knowledge graph embedding further enhances semantic feature learning and improves the generalization across diverse datasets. The ablation study confirms that each component contributes positively to performance, with isotropic and pyramid layers improving feature richness, and HV-GNN-OKGE achieving optimal accuracy. Additionally, the method exhibits superior computational efficiency with reduced training and inference times compared with baseline models, making it highly suitable for plant disease detection applications.

## 6 Conclusion

This paper proposes the HV-GNN-OKGE method, a plant disease detection and classification combining GNN, HV-GNN, isotropic and pyramid layers, and OKGE to capture both spatial and semantic features. The HV-GNN-OKGE method effectively improved the feature representation and classification accuracy and robustness. Experimental results on the PlantVillage and PlantDoc datasets demonstrate that HV-GNN-OKGE outperforms existing methods, achieving 99.99% accuracy for PlantVillage and 99.97% for PlantDoc. The ablation study validated the contribution of each component, whereas computational analysis showed reduced training and inference times, confirming its efficiency. Overall, the HV-GNN-OKGE provides a reliable, scalable, and high-performance solution for plant disease identification. Future work will focus on integrating additional crop datasets, improving real-time deployment, reducing complexity, and enhancing adaptability to diverse agricultural environments.

## Reference

1. S. Aboelenin, F.A. Elbasheer, M.M. Eltoukhy, W.M. El-Hady, K.M. Hosny, A hybrid framework for plant leaf disease detection and classification using convolutional neural networks and vision transformer. Complex Intell. Syst. **11**, 142 (2025). https://doi.org/10.1007/s40747-024-01764-x
2. A. Bilal, J.A. Khan, A. Alzahrani, K. Almohammadi, M. Alamri, X. Liu, Fuzzy deep learning architecture for cucumber plant disease detection and classification. J. Big Data **12**, 117 (2025). https://doi.org/10.1186/s40537-025-01156-z
3. I. Bouacida, B. Farou, L. Djakhdjakha, H. Seridi, M. Kurulay, Innovative deep learning approach for cross-crop plant disease detection: A generalized method for identifying unhealthy leaves. Inf. Process. Agric. **12**, 54-67 (2025). https://doi.org/10.1016/j.inpa.2024.03.002
4. N. Nigar, H.M. Faisal, M. Umer, O. Oki, J.M. Lukose, Improving plant disease classification with deep-learning-based prediction model using explainable artificial intelligence. IEEE Access **12**, 100005-100014 (2024). https://doi.org/10.1109/ACCESS.2024.3428553
5. K. Mahadevan, A. Punitha, J. Suresh, Automatic recognition of rice plant leaf diseases detection using deep neural network with improved threshold neural network. e-Prime Adv. Electr. Eng. Electron. Energy **8**, 100534 (2024). https://doi.org/10.1016/j.prime.2024.100534
6. S. Bhagat, M. Kokare, V. Haswani, P. Hambarde, T. Taori, P.H. Ghante, D.K. Patil, Advancing real-time plant disease detection: A lightweight deep learning approach and novel dataset for pigeon pea crop. Smart Agric. Technol. **7**, 100408 (2024). https://doi.org/10.1016/j.atech.2024.100408
7. J.G. Kotwal, R. Kashyap, P.M. Shafi, Artificial driving based EfficientNet for automatic plant leaf disease classification. Multimed. Tools Appl. **83**, 38209-38240 (2024). https://doi.org/10.1007/s11042-023-16882-w
8. K. Mahadevan, A. Punitha, J. Suresh, A novel rice plant leaf diseases detection using deep spectral generative adversarial neural network. Int. J. Cogn. Comput. Eng. **5**, 237-249 (2024). https://doi.org/10.1016/j.ijcce.2024.05.004

9. W. Macdonald, Y.A. Sari, M. Pahlevani, Grow-light smart monitoring system leveraging lightweight deep learning for plant disease classification. Artif. Intell. Agric. **12**, 44-56 (2024). https://doi.org/10.1016/j.aiia.2024.03.003
10. M. Pajany, S. Venkatraman, U. Sakthi, M. Sujatha, M.K. Ishak, Optimal fuzzy deep neural networks based plant disease detection and classification on UAV-based remote sensed data. IEEE Access. **12**, 162131-162144 (2024). https://doi.org/10.1109/ACCESS.2024.3488751
11. M. Srivastava, J. Meena, Plant leaf disease detection and classification using modified transfer learning models. Multimed. Tools Appl. **83**, 38411-38441 (2024). https://doi.org/10.1007/s11042-023-16929-y
12. M. Rezaei, D. Diepeveen, H. Laga, M.G. Jones, F. Sohel, Plant disease recognition in a low data scenario using few-shot learning. Comput. Electron. Agric. **219**, 108812 (2024). https://doi.org/10.1016/j.compag.2024.108812
13. A. Zhang, W. Liu, Plant disease detection using an innovative Swin-Axial transformer. IEEE Access. **13**, 111938-111952 (2025). https://doi.org/10.1109/ACCESS.2025.3578486
14. I. Kaushik, N. Prakash, A. Jain, Plant disease detection using a depth-wise separable-based adaptive deep neural network. Multimed. Tools Appl. **84**, 887-915 (2025). https://doi.org/10.1007/s11042-024-19047-5
15. W. Shafik, A. Tufail, C. De Silva Liyanage, R.A.A.H.M. Apong, Using transfer learning-based plant disease classification and detection for sustainable agriculture. BMC Plant Biol. **24**, 136 (2024). https://doi.org/10.1186/s12870-024-04825-y
16. PlantVillage dataset link: https://www.kaggle.com/datasets/emmarex/plantdisease (Accessed on 25.08.2025)
17. PlantDoc dataset link: https://www.kaggle.com/datasets/abdulhasibuddin/plant-doc-dataset (Accessed on 25.08.2025)