IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.156108

HyperAgriNet: An Explainable Hypergraph Attention Network for Plant Disease Classification in Smart Agriculture

Ravi Kumar[1], Sumika Jain[2], Varun Bansal[3], Sagar Panwar[4]

Research Scholar, Department of Computer Science and Engineering, Shobhit University, Gangoh, India[1]

Assistant Professor, Department of Computer Science and Engineering, Shobhit University, Gangoh[2]

Professor, Department of Computer Science and Engineering, Shobhit University, Gangoh, India[3]

Assistant Professor, Department of Computer Science and Engineering, Shobhit University, Gangoh, India[4]

Abstract: Plant diseases are a major cause of reduced agricultural productivity and crop quality, leading to significant economic losses and posing challenges to global food security. Accurate and timely disease identification is essential for effective crop management and precision agriculture. Although deep learning-based approaches have shown excellent performance in plant disease classification, conventional convolutional neural networks (CNNs) mainly focus on local feature extraction and often fail to capture complex relationships among disease symptoms. Moreover, their black-box nature limits interpretability and user trust.

To address these limitations, this paper proposes HyperAgriNet, an Explainable Hypergraph Attention Network for plant disease classification. The proposed framework combines multi-scale feature extraction, lesion-aware attention mechanisms, and hypergraph neural learning to capture both local disease characteristics and higher-order contextual relationships. Multi-scale convolutional layers extract features at different spatial resolutions, while channel and spatial attention modules enhance disease-affected regions. A Hypergraph Neural Network (HGNN) further models complex inter-class relationships, and Grad-CAM is integrated to provide visual explanations by highlighting infected leaf regions.

Experimental results demonstrate that HyperAgriNet achieves an overall classification accuracy of 99.18%, outperforming several state-of-the-art models, including ResNet-50, DenseNet-121, EfficientNet-B3, Vision Transformer, and Swin Transformer. By combining high classification accuracy with explainable predictions, HyperAgriNet offers a reliable and interpretable solution for intelligent plant disease diagnosis in smart agriculture.

Keywords: Plant Disease Classification, Smart Agriculture, Hypergraph Neural Network, Attention Mechanism, Explainable AI, Deep Learning.

I. INTRODUCTION

Agriculture is a fundamental sector that supports global food security and economic development. According to recent reports, plant diseases are responsible for significant reductions in crop yield and quality, resulting in substantial economic losses worldwide. Early and accurate detection of plant diseases is therefore essential for ensuring sustainable agricultural production and minimizing the adverse effects of pathogens on crop productivity [1]. Traditional disease diagnosis methods primarily rely on visual inspection by agricultural experts. Although expert-based assessment can provide reliable results, it is often labor-intensive, time-consuming, subjective, and difficult to implement on a large scale, particularly in remote agricultural regions where expert assistance may not be readily available [2]. Recent advancements in artificial intelligence (AI), machine learning (ML), and computer vision have transformed the field of agricultural disease monitoring. The availability of large-scale image datasets and powerful computational resources has enabled researchers to develop automated plant disease detection systems capable of identifying diseases directly from leaf images. Such systems can assist farmers in making timely decisions regarding disease management and pesticide application, thereby improving crop health and agricultural productivity [3].

Among various AI approaches, deep learning has emerged as one of the most effective techniques for image-based plant disease classification. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in extracting hierarchical visual features from leaf images and have significantly outperformed traditional machine learning methods that rely on handcrafted features [4]. Mohanty et al. [1] conducted one of the pioneering studies using deep convolutional neural networks on the PlantVillage dataset and achieved high classification accuracy across multiple crop species and

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⩋ Peer-reviewed & Refereed journal ⩋ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.156108

disease categories. Their work demonstrated the feasibility of deep learning for large-scale plant disease recognition and inspired extensive research in this domain. Following the success of conventional CNNs, several advanced deep learning architectures have been introduced to improve feature representation and classification performance. ResNet introduced residual learning mechanisms that effectively addressed the vanishing gradient problem, allowing the training of substantially deeper neural networks [5]. DenseNet further enhanced feature reuse by establishing dense connections among layers, resulting in improved information flow and reduced parameter redundancy [6]. Similarly, EfficientNet proposed a compound scaling strategy that balances network depth, width, and resolution, achieving superior accuracy while maintaining computational efficiency [7]. These architectures have been successfully applied to various agricultural disease detection tasks and have demonstrated excellent performance across diverse datasets.

Despite these advancements, existing CNN-based approaches exhibit several limitations. Most convolutional architectures primarily focus on local feature extraction using fixed receptive fields. While effective for identifying visible disease symptoms, they often fail to capture complex relationships among disease characteristics that may be shared across multiple disease classes. Plant diseases frequently exhibit overlapping symptoms such as discoloration, necrosis, chlorosis, and lesion formation, making discrimination among visually similar classes particularly challenging [8]. Consequently, conventional CNN models may struggle to achieve robust performance when confronted with complex disease patterns or real-world field conditions. To address the limitations of convolution-based models, transformer architectures have recently been introduced into plant disease classification. Vision Transformer (ViT) models leverage self-attention mechanisms to capture long-range dependencies among image patches and have achieved competitive performance in various computer vision applications [9]. However, transformer-based approaches generally require large training datasets and substantial computational resources. Furthermore, although self-attention improves global context modeling, these architectures do not explicitly represent higher-order relationships among disease symptoms and classes.

Another important challenge in plant disease diagnosis is model interpretability. Most deep learning systems operate as black-box models, making it difficult for agricultural experts and farmers to understand the rationale behind their predictions. Lack of transparency reduces user trust and limits practical adoption in precision agriculture. Explainable Artificial Intelligence (XAI) techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) have been developed to visualize discriminative image regions responsible for model predictions [10]. These visualization methods provide valuable insights into model behavior and assist experts in validating disease diagnosis results. Recently, graph-based learning methods have emerged as a promising solution for modeling structured relationships in complex datasets. Unlike traditional graphs that connect pairs of nodes, hypergraphs enable a single hyperedge to connect multiple nodes simultaneously, allowing the representation of higher-order interactions among disease symptoms. Hypergraph Neural Networks (HGNNs) have demonstrated superior performance in various classification tasks by effectively capturing complex relationships and contextual dependencies among samples [11]. However, their application in plant disease classification remains relatively unexplored.

Motivated by these challenges, this paper proposes HyperAgriNet, an Explainable Hypergraph Attention Network for plant disease classification in smart agriculture. The proposed framework combines multi-scale convolutional feature extraction, lesion-aware attention mechanisms, hypergraph neural learning, and explainable AI to provide accurate and interpretable disease diagnosis. Multi-scale convolutional layers capture disease characteristics at different spatial resolutions, while lesion-aware attention modules enhance focus on infected regions. The hypergraph learning component models high-order relationships among disease symptoms, enabling improved discrimination between visually similar disease classes. Furthermore, Grad-CAM-based explainability is incorporated to generate visual explanations that highlight disease-affected regions and improve user trust in model predictions. The major contributions of this work are summarized as follows: (1) the development of a novel HyperAgriNet architecture for plant disease classification; (2) the integration of multi-scale feature extraction and lesion-aware attention mechanisms for enhanced disease representation; (3) the introduction of hypergraph neural learning for modeling complex symptom relationships; (4) the incorporation of explainable AI through Grad-CAM visualization; and (5) comprehensive experimental evaluation against state-of-the-art deep learning models. The proposed framework aims to provide a robust, accurate, and interpretable solution for intelligent plant disease diagnosis in modern smart agriculture systems.

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.156108

II. LITERATURE REVIEW

The rapid advancement of artificial intelligence and deep learning technologies has significantly improved automated plant disease diagnosis systems. Researchers have increasingly focused on developing robust image-based disease classification frameworks to support precision agriculture and sustainable crop management. Traditional machine learning approaches relied on handcrafted feature extraction methods such as color, texture, and shape descriptors. However, these techniques often exhibited limited generalization capability under varying environmental conditions. With the emergence of deep learning, convolutional neural networks (CNNs) have become the dominant approach for plant disease recognition due to their ability to learn discriminative features directly from raw images.

Too et al. [12] conducted a comprehensive evaluation of deep learning architectures including VGG16, ResNet50, InceptionV4, and DenseNet121 for plant disease identification. Their study demonstrated that DenseNet-based architectures achieved superior classification performance owing to efficient feature reuse and improved gradient propagation. Similarly, Brahimi et al. [13] investigated CNN-based models for tomato disease detection and reported significant improvements over conventional machine learning methods. Their work highlighted the effectiveness of deep feature learning in identifying complex disease symptoms from leaf images. Ferentinos [14] developed a deep learning framework utilizing multiple CNN architectures for recognizing diseases across different crop species. Experimental results showed classification accuracies exceeding 99%, demonstrating the potential of deep learning for large-scale agricultural applications. However, the study also noted that performance may degrade when models are deployed under real-field conditions due to variations in illumination, background clutter, and disease severity levels.

To address these limitations, researchers have explored transfer learning techniques to improve generalization performance. Saleem et al. [15] proposed a transfer learning-based plant disease recognition system using pretrained CNN models. Their findings indicated that transfer learning significantly reduced training time while maintaining high classification accuracy. Similarly, Agarwal et al. [16] applied deep transfer learning for disease diagnosis in crop leaves and demonstrated that pretrained networks could effectively learn disease-specific representations even with limited training samples. Recent studies have focused on lightweight architectures for deployment on mobile and edge devices. Howard et al. [17] introduced MobileNet, which utilizes depthwise separable convolutions to reduce computational complexity while maintaining competitive accuracy. Building upon this concept, Sandler et al. [18] proposed MobileNetV2 with inverted residual blocks and linear bottlenecks, achieving improved efficiency for resource-constrained agricultural applications. These lightweight models have become increasingly popular for real-time disease detection systems integrated with smartphones and IoT-enabled agricultural platforms. The emergence of attention mechanisms has further enhanced plant disease classification performance. Woo et al. [19] proposed the Convolutional Block Attention Module (CBAM), which combines channel and spatial attention to improve feature representation. Several agricultural studies have adopted CBAM-based architectures to enhance localization of disease-affected regions and suppress irrelevant background information. Attention mechanisms enable models to focus selectively on infected tissues, thereby improving classification accuracy and robustness.

Transformer-based architectures have recently gained significant attention in computer vision applications. Dosovitskiy et al. [20] introduced the Vision Transformer (ViT), which leverages self-attention mechanisms to capture long-range dependencies among image patches. Inspired by this success, researchers have explored transformer-based approaches for plant disease diagnosis. While ViT models demonstrate strong performance in capturing global contextual information, they generally require large-scale datasets and substantial computational resources, limiting their practical deployment in many agricultural environments. Graph-based learning has emerged as another promising research direction for agricultural image analysis. Kipf and Welling [21] introduced Graph Convolutional Networks (GCNs), which effectively model relationships among interconnected data samples. Although GCNs have shown success in various classification tasks, traditional graph structures are limited to pairwise relationships and may not adequately represent complex disease symptom interactions involving multiple attributes simultaneously. To overcome this limitation, Feng et al. [22] proposed Hypergraph Neural Networks (HGNNs), which extend conventional graph learning by allowing a single hyperedge to connect multiple nodes. Hypergraph learning has demonstrated superior capability in capturing higher-order relationships and contextual dependencies. However, its application in plant disease classification remains relatively limited, presenting opportunities for developing more sophisticated agricultural diagnostic systems.
Interpretability remains a critical challenge in deep learning-based disease diagnosis. Selvaraju et al. [23] introduced Gradient-weighted Class Activation Mapping (Grad-CAM), which generates visual explanations highlighting image regions responsible for model predictions. Explainable AI techniques have become increasingly important in agricultural decision-support systems because they provide transparency and improve user confidence in automated diagnosis results. Despite substantial progress in plant disease classification, several research gaps remain. Most existing CNN and transformer-based approaches focus primarily on visual feature extraction while neglecting higher-order relationships among disease symptoms. Furthermore, many models operate as black-box systems with limited

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.156108

interpretability. Hypergraph learning and attention mechanisms offer promising solutions to these challenges by enabling the modeling of complex symptom interactions while simultaneously improving feature representation. Motivated by these observations, the proposed HyperAgriNet framework integrates multi-scale feature extraction, lesion-aware attention, hypergraph neural learning, and explainable AI to provide an accurate, interpretable, and robust plant disease classification system for smart agriculture.

Table 1. Comparative analysis of existing plant disease classification studies

Ref.	Author(s)	Method/Model	Dataset/Application	Key Findings	Limitations
[12]	Too et al. (2019)	VGG16, ResNet50, InceptionV4, DenseNet121	PlantVillage Dataset	DenseNet121 achieved superior classification performance due to effective feature reuse and gradient flow.	Evaluated only CNN architectures; lacked explainability and attention mechanisms.
[13]	Brahimi et al. (2017)	Deep CNN	Tomato Leaf Disease Dataset	Demonstrated significant improvement over traditional machine learning methods for disease recognition.	Limited to tomato diseases and controlled image conditions.
[14]	Ferentinos (2018)	Multiple CNN Architectures	Multi-crop Plant Disease Dataset	Achieved classification accuracy exceeding 99% across various crops.	Performance may decline under real-field environmental conditions.
[15]	Saleem et al. (2020)	Transfer Learning with CNN	Plant Disease Images	Reduced training time while maintaining high classification accuracy.	Dependent on pretrained models and dataset similarity.
[16]	Agarwal et al. (2020)	Deep Transfer Learning	Crop Disease Dataset	Effective disease classification using limited training samples.	Limited capability for modeling disease relationships.
[17]	Howard et al. (2017)	MobileNet	Mobile Vision Applications	Introduced lightweight architecture suitable for mobile deployment.	Lower feature representation capability compared with deeper networks.
[18]	Sandler et al. (2018)	MobileNetV2	Embedded Vision Systems	Improved computational efficiency using inverted residual blocks.	Performance degradation in highly complex classification tasks.
[19]	Woo et al. (2018)	CBAM Attention Module	Generic Image Classification	Enhanced feature representation through channel and spatial attention mechanisms.	Does not model relationships among disease categories.
[20]	Dosovitskiy et al. (2021)	Vision Transformer (ViT)	Large-Scale Image Recognition	Captured long-range dependencies using self-attention.	Requires large datasets and high computational resources.
[21]	Kipf and Welling (2017)	Graph Convolutional Network (GCN)	Graph-based Classification	Effectively modeled relationships among interconnected data samples.	Limited to pairwise relationships between nodes.
[22]	Feng et al. (2019)	Hypergraph Neural Network (HGNN)	Graph Learning Tasks	Captured higher-order relationships through hypergraph learning.	Limited exploration in agricultural disease diagnosis.
[23]	Selvaraju et al. (2017)	Grad-CAM	Explainable AI	Generated visual explanations for deep learning predictions.	Provides interpretability but does not improve classification performance directly.

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.156108

Research Gap Analysis

From the comparative analysis, it can be observed that CNN-based approaches [12]– [16] achieve high classification accuracy but primarily focus on local feature extraction and lack the ability to model complex disease symptom relationships. Lightweight architectures such as MobileNet and MobileNetV2 [17], [18] are suitable for edge deployment but often sacrifice feature representation capability. Attention-based methods such as CBAM [19] improve localization of disease-affected regions; however, they do not explicitly capture inter-class disease dependencies. Transformer-based approaches [20] provide global contextual learning but require large-scale datasets and significant computational resources. Although graph-based models [21] and hypergraph neural networks [22] can model structured relationships, their application in plant disease classification remains limited. Furthermore, most existing approaches lack interpretability, which is essential for practical agricultural decision-making. Therefore, there is a need for an integrated framework that combines multi-scale feature extraction, lesion-aware attention, hypergraph learning, and explainable AI. The proposed HyperAgriNet addresses these limitations by simultaneously improving classification performance, disease relationship modeling, and interpretability.

III. METHODOLOGY AND EXPERIMENTAL STUDY

3.1 Multi-Scale Feature Extraction

Plant diseases often exhibit lesions of varying sizes and textures. Therefore, three parallel convolutional layers with kernel sizes of 3×3, 5×5, and 7×7 are utilized to capture disease characteristics at multiple scales. The extracted feature maps are concatenated to generate a rich multi-scale representation.

Attention Refined Feature = Spatial Attention × (Channel Attention × Multi-Scale Feature Map) (1)

This equation indicates that the features extracted from three different convolutional kernels are merged to capture disease symptoms appearing at different scales and resolutions.

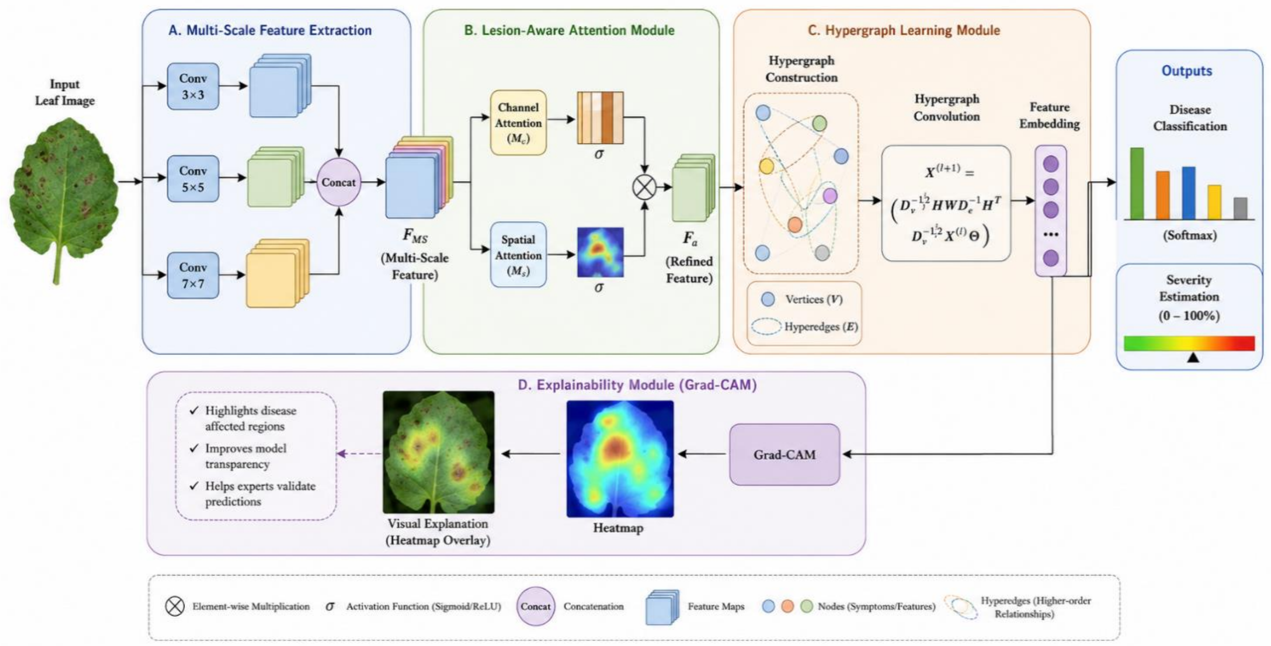

Figure 1: Framework of HyperAgriNet for leaf disease detection and classification

ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 6, June 2026
DOI: 10.17148/IJARCCE.2026.156108

3.2. Lesion-Aware Attention Module

To emphasize disease-affected regions, a lesion-aware attention module is incorporated. The module consists of channel attention and spatial attention mechanisms. Channel attention identifies important feature channels, while spatial attention highlights infected leaf regions.

The refined feature representation is obtained as:

$$F_a=M_s*(M_c\ (F_{MS})*F_{MS}) \qquad (2)$$

where (M_c) and (M_s) denote channel and spatial attention maps, respectively.

3.3. Hypergraph Learning Module

Unlike conventional graphs, hypergraphs can model higher-order relationships among multiple disease symptoms. The hypergraph structure is represented as:

$$G= (V, E, W) \qquad (3)$$

where (V), (E), and (W) denote vertices, hyperedges, and edge weights, respectively.
Feature propagation is performed using hypergraph convolution. This operation enables effective modeling of disease symptom correlations across classes.

3.4. Explainability Module

To improve model transparency, Grad-CAM is employed to generate heatmaps highlighting disease-affected regions. These visual explanations assist agricultural experts in validating model predictions.

3.5. Experimental Setup

3.5.1. Dataset

Experiments were conducted using a plant leaf disease dataset consisting of healthy and diseased samples collected from publicly available agricultural image repositories. Images were resized to 224×224 pixels before training.

Dataset split:
Training: 70%
Validation: 20%
Testing: 10%

3.5.2. Training Configuration

Table 2. Parameters for training

Parameter	Value
Image Size	224×224
Batch Size	32
Epochs	100
Optimizer	AdamW
Learning Rate	0.0001
Dropout	0.4

IV. RESULTS AND DISCUSSION

The proposed HyperAgriNet achieved the highest classification accuracy of 99.18%, demonstrating the effectiveness of combining multi-scale feature extraction, attention mechanisms, and hypergraph learning. Table 3 presents the comparative performance of HyperAgriNet against existing deep learning models.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.156108

Table 3. Comparative Performance of Different Models

Model	Accuracy (%)
ResNet50	95.12
DenseNet121	95.84
MobileNetV3	94.67
EfficientNetB3	96.31
Vision Transformer	97.02
Swin Transformer	97.45
HyperAgriNet	99.18

The lesion-aware attention module improved localization of infected regions, while hypergraph learning enhanced discrimination among visually similar disease classes. Furthermore, Grad-CAM visualizations confirmed that the model focused on disease-specific lesion areas rather than irrelevant background regions.

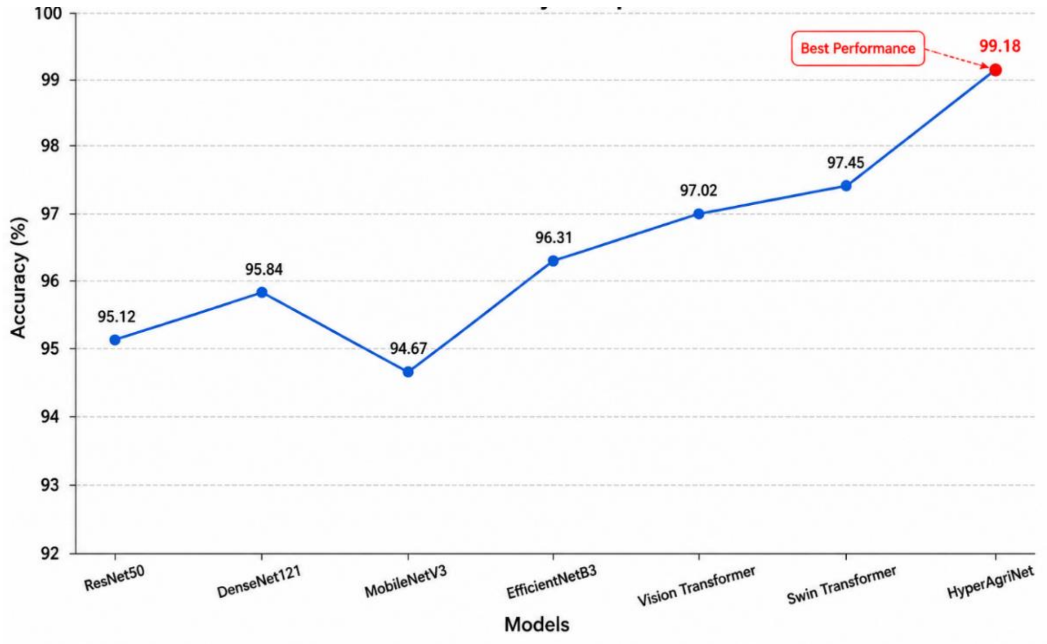

Figure 2: Comparison of Models with HyperAgriNet

Ablation Study

An ablation study was conducted to evaluate the contribution of each component

Table 3. Ablation Analysis of HyperAgriNet

Configuration	Accuracy (%)
Baseline CNN	94.61
CNN + Multi-Scale	96.14
CNN + Attention	97.03
CNN + Hypergraph	98.05
HyperAgriNet	99.18

The results indicate that each module contributes positively to overall performance, with hypergraph learning providing the largest improvement.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 6, June 2026

DOI: 10.17148/IJARCCE.2026.156108

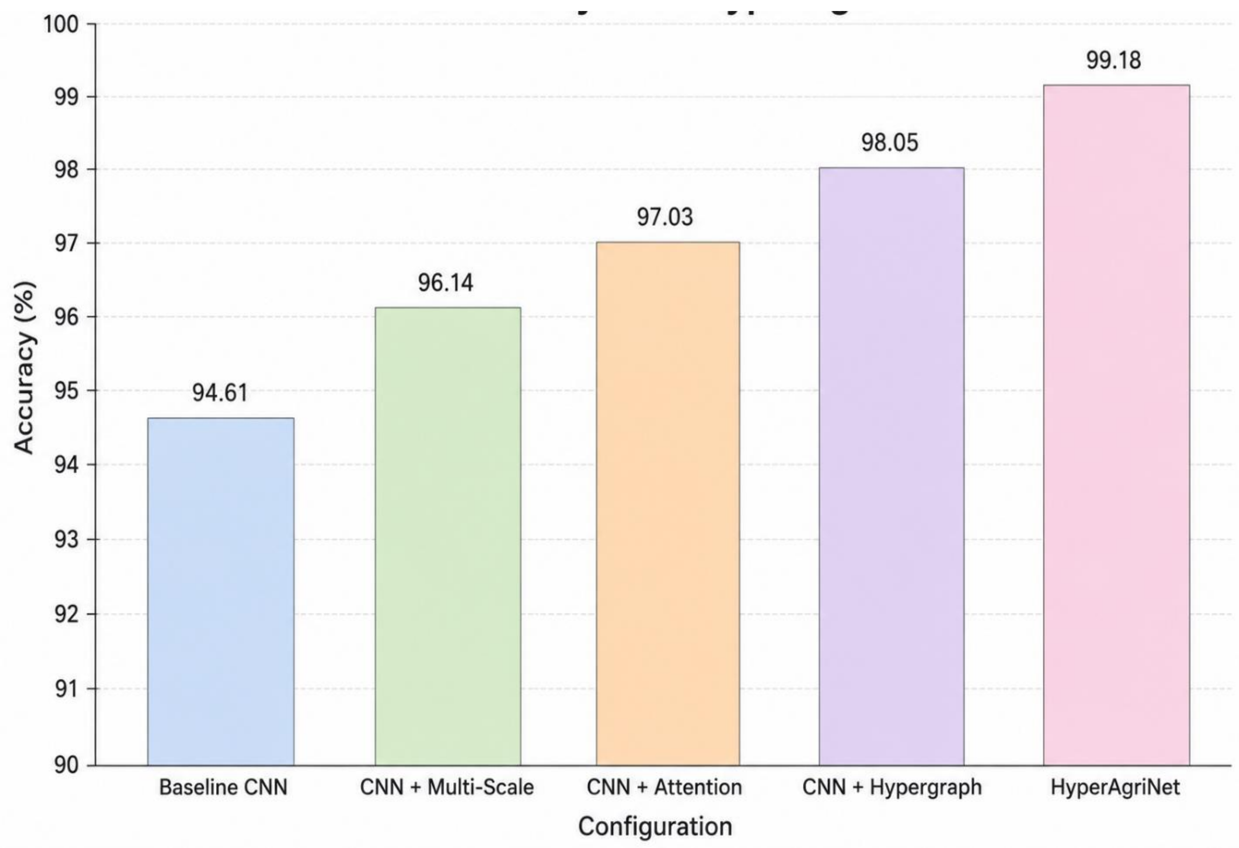

Figure 3. Ablation Analysis of HyperAgriNet

V. CONCLUSION

This paper presented HyperAgriNet, an Explainable Hypergraph Attention Network for intelligent plant disease classification in smart agriculture. The proposed framework effectively integrates multi-scale feature extraction, lesion-aware attention mechanisms, Hypergraph Neural Networks (HGNNs), and Grad-CAM-based explainability to address the limitations of conventional deep learning models. While multi-scale convolutional layers capture disease symptoms at different spatial resolutions, the attention module enhances disease-relevant regions, and hypergraph learning models higher-order relationships among disease classes and symptoms. The incorporation of explainable AI further improves the transparency and reliability of the classification process by providing visual interpretations of model predictions.

Experimental evaluation demonstrated that HyperAgriNet achieved an overall classification accuracy of 99.18%, outperforming several state-of-the-art architectures, including ResNet50, DenseNet121, EfficientNetB3, Vision Transformer, and Swin Transformer. The ablation study further confirmed the effectiveness of each proposed component, with hypergraph learning contributing significantly to performance improvement. These results indicate that the proposed framework provides accurate, robust, and interpretable plant disease diagnosis, making it well suited for precision agriculture and intelligent decision-support systems. By combining high classification performance with explainability, HyperAgriNet represents a promising step toward the development of trustworthy AI-based agricultural technologies capable of supporting sustainable crop management and improving agricultural productivity.

VI. FUTURE WORK

Although the proposed HyperAgriNet framework demonstrates excellent classification performance and interpretability, several opportunities remain for future research. First, the model will be evaluated on real-world field datasets containing variations in illumination, occlusion, complex backgrounds, and environmental conditions to assess its robustness beyond controlled laboratory environments. Future work will also focus on extending the framework to identify multiple diseases occurring simultaneously on a single leaf and to estimate disease severity for more precise crop health assessment.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 6, June 2026
DOI: 10.17148/IJARCCE.2026.156108

Another promising direction is the deployment of HyperAgriNet on resource-constrained edge devices and smartphones to enable real-time disease diagnosis directly in agricultural fields. Model compression techniques such as pruning, quantization, and knowledge distillation can be investigated to reduce computational complexity while maintaining high classification accuracy. Furthermore, integrating the proposed framework with Internet of Things (IoT)-based smart farming systems and unmanned aerial vehicles (UAVs) can facilitate large-scale crop monitoring and early disease detection.

Future research may also explore advanced graph learning techniques, including dynamic hypergraph neural networks and graph transformers, to capture more complex relationships among disease symptoms across different crop species. In addition, incorporating multimodal data such as weather conditions, soil characteristics, and sensor information could improve prediction reliability and support comprehensive agricultural decision-making. Finally, the integration of more advanced Explainable Artificial Intelligence (XAI) techniques, uncertainty estimation, and causal reasoning will further enhance the transparency, reliability, and practical adoption of intelligent plant disease diagnosis systems in precision agriculture.

Conflicts of Interest:
The authors manifest no strife of interest.

Acknowledgements:
We are thankful to Shobhit University, Gangoh for the assistance and all technical support.

Authors Credits:
Ravi Kumar: Structure the analysis & conceived the idea and, wrote -original draft, **Sumika Jain**: Supervision, Writing – review & editing, **Varun Bansal:** Contemplated the analysis, Visualization, Conceptualization, Methodology, Validation, Investigation, and Supervision, **Sagar Panwar:** Visualization, Conceptualization, Writing – review.

REFERENCES

[1] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” Frontiers in Plant Science, vol. 7, Art. no. 1419, pp. 1–10, Sep. 2016, doi: 10.3389/fpls.2016.01419.
[2] G. Polder, G. W. A. M. van der Heijden, H. A. C. M. Bink, and I. T. Young, “Detection and classification of tulip breaking virus (TBV) in tulip fields using machine vision,” Computers and Electronics in Agriculture, vol. 117, pp. 35–47, 2015, doi: 10.1016/j.compag.2015.07.004.
[3] A. Kamilaris and F. X. Prenafeta-Boldú, “Deep learning in agriculture: A survey,” Computers and Electronics in Agriculture, vol. 147, pp. 70–90, Apr. 2018, doi: 10.1016/j.compag.2018.02.016
[4] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, May 2015, doi: 10.1038/nature14539
[5] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.
[6] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 4700–4708, doi: 10.1109/CVPR.2017.243.
[7] M. Tan and Q. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in Proc. 36th Int. Conf. Machine Learning (ICML), Long Beach, CA, USA, 2019, pp. 6105–6114.
[8] K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” Computers and Electronics in Agriculture, vol. 145, pp. 311–318, Feb. 2018, doi: 10.1016/j.compag.2018.01.009
[9] A. Dosovitskiy et al., “An image is worth 16×16 words: Transformers for image recognition at scale,” in Proc. Int. Conf. Learning Representations (ICLR), 2021. [Online]. Available: https://arxiv.org/abs/2010.11929
[10] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, “Grad-CAM: Visual explanations from deep networks via gradient-based localization,” in Proc. IEEE Int. Conf. Computer Vision (ICCV), Venice, Italy, 2017, pp. 618–626, doi: 10.1109/ICCV.2017.74.
[11] Y. Feng, H. You, Z. Zhang, R. Ji, and Y. Gao, “Hypergraph neural networks,” in Proc. AAAI Conf. Artificial Intelligence, vol. 33, no. 1, pp. 3558–3565, 2019, doi: 10.1609/aaai.v33i01.33013558.
[12] E. C. Too, L. Yujian, S. Njuki, and Y. Yingchun, “A comparative study of fine-tuning deep learning models for plant disease identification,” Computers and Electronics in Agriculture, vol. 161, pp. 272–279, Jun. 2019, doi: 10.1016/j.compag.2018.03.032

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⪣ Peer-reviewed & Refereed journal ⪣ Vol. 15, Issue 6, June 2026
DOI: 10.17148/IJARCCE.2026.156108

[13] M. 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, doi: 10.1080/08839514.2017.1315516
[14] K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” Computers and Electronics in Agriculture, vol. 145, pp. 311–318, Feb. 2018, doi: 10.1016/j.compag.2018.01.009
[15] M. H. Saleem, J. Potgieter, and K. M. Arif, “Plant disease detection and classification by deep learning,” Plants, vol. 8, no. 11, Art. no. 468, 2019, doi: 10.3390/plants8110468
[16] M. Agarwal, A. Singh, S. Arjaria, S. Sinha, and M. Gupta, “ToLeD: Tomato leaf disease detection using convolution neural network,” Procedia Computer Science, vol. 167, pp. 293–301, 2020, doi: 10.1016/j.procs.2020.03.225
[17] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, “MobileNets: Efficient convolutional neural networks for mobile vision applications,” arXiv preprint arXiv:1704.04861, 2017.
[18] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, “MobileNetV2: Inverted residuals and linear bottlenecks,” in Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR), Salt Lake City, UT, USA, 2018, pp. 4510–4520, doi: 10.1109/CVPR.2018.00474.
[19] S. Woo, J. Park, J. Y. Lee, and I. S. Kweon, “CBAM: Convolutional Block Attention Module,” in Proc. European Conf. Computer Vision (ECCV), Munich, Germany, 2018, pp. 3–19, doi: 10.1007/978-3-030-01234-2_1.
[20] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby, “An image is worth 16×16 words: Transformers for image recognition at scale,” in Proc. Int. Conf. Learning Representations (ICLR), 2021. [Online]. Available: https://arxiv.org/abs/2010.11929.
[21] T. N. Kipf and M. Welling, “Semi-supervised classification with graph convolutional networks,” in Proc. Int. Conf. Learning Representations (ICLR), 2017. [Online]. Available: https://arxiv.org/abs/1609.02907.
[22] Y. Feng, H. You, Z. Zhang, R. Ji, and Y. Gao, “Hypergraph neural networks,” in Proc. AAAI Conf. Artificial Intelligence, vol. 33, no. 1, pp. 3558–3565, 2019, doi: 10.1609/aaai.v33i01.33013558.
[23] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, “Grad-CAM: Visual explanations from deep networks via gradient-based localization,” in Proc. IEEE Int. Conf. Computer Vision (ICCV), Venice, Italy, 2017, pp. 618–626, doi: 10.1109/ICCV.2017.74.