RESEARCH ARTICLE Indian Journal of Agricultural Research, Volume 60 Issue 6: 912-918 (June 2026)

Dual-encoder Variational Autoencoder for Detection and Classification of Plant Leaf Diseases

Astha Sharma[1], Ashwni Kumar[1]

10.18805/IJARe.A-6451

ABSTRACT

Background: Plant disease detection remains a major challenge in agriculture, with direct implications for improving crop productivity and ensuring food security. Seasonal variation significantly influences plant characteristics, making the classification of plant leaves by season-specifically summer and winter-important for optimizing disease detection and management strategies.

Methods: In this study, a plant leaf disease detection dataset was developed and categorized based on seasonal conditions. The dataset includes 47 classes representing summer crops and 16 classes for winter crops. To classify plant leaf diseases effectively, we propose a novel dual-encoder Variational Autoencoder (VAE) model that integrates ResNet and VGGNet as parallel encoders. These encoders extract complementary feature maps from the seasonal datasets, which are then concatenated to improve classification accuracy.

Result: Experimental evaluation demonstrates the robustness and accuracy of the proposed approach. The dual-encoder VAE achieved a classification accuracy of 98.86% on the summer dataset and 97.53% on the winter dataset, highlighting the model's ability to generalize effectively across seasonal variations in plant leaf disease detection.

Key words: Computer vision, Leaf disease detection, Summer, Variational autoencoder, Winter.

INTRODUCTION

Agriculture is the backbone of global food security, providing essential resources for survival. It supports livelihoods, drives rural development and fuels economic growth. Sustainable agriculture (Mehta *et al*., 2025) ensures environmental balance, conserves biodiversity and mitigates climate change. Advancements in agricultural technology enhance productivity, reduce waste and promote long-term ecological and societal well-being. Plant health plays a vital role in ensuring global food security, agricultural sustainability and economic stability. Among the various threats to plant health, leaf diseases are particularly harmful as they directly affect photosynthesis, plant growth and ultimately crop yield. These diseases are caused by a wide range of pathogens, including fungi, bacteria, viruses and pests and can spread rapidly under favorable environmental conditions. Early and accurate detection of leaf diseases is essential for effective crop management and disease control. Traditional methods of disease diagnosis often rely on manual inspection by trained agronomists or pathologists. However, this approach is time-consuming, labor-intensive and prone to human error, especially when large-scale farming operations are involved or when symptoms are subtle or similar across different diseases. With the rise of precision agriculture and smart farming technologies, automated leaf disease detection systems have emerged as a promising solution. These systems leverage image processing, machine learning and deep learning techniques to identify disease patterns from leaf images with high accuracy. In particular, Convolutional Neural Networks (CNNs) have shown remarkable performance in feature extraction and classification tasks related to plant pathology. Leaf disease datasets are often limited in size and diversity, making it difficult to train generalized models. Additionally, environmental factors such as lighting, background noise and seasonal variations can affect the accuracy of detection systems. To address these issues, researchers are exploring novel architectures, transfer learning and data augmentation techniques to improve model robustness and scalability.

This study aims to contribute to this growing field by proposing an advanced deep learning framework for automated leaf disease detection. By combining biologically informed dataset design and robust feature extraction techniques, the goal is to enhance the accuracy, reliability and practical applicability of disease detection systems in real-world agricultural settings. Leaf disease detection is very important to control the spread of diseases to protect the plant food from the gigantic effect on

[1]Department of Electronics and Communication Engineering, Indira Gandhi Delhi Technical University for Women, Delhi-110 006, India.

Corresponding Author: Astha Sharma, Department of Electronics and Communication Engineering, Indira Gandhi Delhi Technical University for Women, Delhi-110 006, India.
Email: asthasharma092@gmail.com
ORCIDs: 0000-0001-6610-7538, 0009-0000-8322-2343

How to cite this article: Sharma, A. and Kumar, A. (2026). Dual-encoder Variational Autoencoder for Detection and Classification of Plant Leaf Diseases. *Indian Journal of Agricultural Research.* **60(6):** 912-918. doi: 10.18805/IJARe.A-6451.

Submitted: 11-08-2025 **Accepted:** 13-01-2026 **Online:** 09-02-2026

developing food crops (Wassan *et al*., 2025 and Kanade *et al*., 2025). Therefore, early detection, management and prevention of disease in plants are precisely essential. In recent years, Convolutional Neural Networks (CNN)-based architectures are widely used in the field of plant leaf disease detection (Stewart *et al*., 2019; Xie *et al*., 2020; Saleem *et al*., 2022; Afzaal *et al*., 2021; Wu and Xu, 2019; Tetila *et al*., 2019; Yu and Son, 2020; Liu *et al*., 2021; Jiang *et al*., 2019), indicating the growing popularity of deep learning-based methods. Compared to standard machine learning classification strategies that manually select features, deep neural networks provide an end-to-end pipeline to automatically extract robust features, significantly expanding the availability of leaf disease identification.

Depending on the season, plant diseases might vary greatly. Summer is typically characterized by high temperatures, elevated humidity and frequent rainfall in many agricultural regions. These conditions create an ideal environment for several bacterial and fungal pathogens to thrive. The pathogens not only show high virulence during summer but also present distinctive visual symptoms, such as water-soaked lesions, concentric ring patterns and mold growth, which must be detected accurately for timely intervention. Winter, on the other hand, presents a different set of challenges. Lower temperatures and reduced humidity favor the development of specific cold-tolerant pathogens and virus vectors. For instance, some pathogens-like bacteria and fungi-are more active in the warm, humid summer months, whereas others might flourish in the less humid, drier winters. Determining these seasonal fluctuations aids in the creation of more efficient control plans suited to seasons. The way diseases appear on plant leaves may vary with the season. It is crucial to categorize diseases according to the season because some may present with distinct symptoms in the winter than in the summer. This differentiation can enhance the precision of diagnosis and the effectiveness of treatment. It is essential to categorize plant leaf diseases based on the summer and winter seasons to improve overall agricultural practices, manage diseases effectively and make accurate diagnostics. In the end, healthier crops and increased agricultural productivity are supported by this classification, which guarantees a more accurate response to seasonal pathogen behaviour. Also, agriculture-related data are scarce, particularly when it comes to identifying leaf diseases. The quantity and variety of labelled samples are relatively minimal since labelling training data necessitates specific domain expertise and collecting vast amounts of disease data is a waste of time and energy. Thus, the primary obstacle to further increasing the accuracy of leaf disease identification is the lack of training samples. Researchers typically use conventional data augmentation techniques to address this problem (Zhu *et al*., 2017). Generative model-based data expansion techniques have emerged as a research hotspot in recent years and have been used in a variety of sectors (Ke *et al*., 2019; Tran *et al*., 2021; Konidaris *et al*., 2019; Liu *et al*., 2020; Kapadnis, n.d.). It is capable of overcoming numerous challenges that arise in various complex probability computations including maximum likelihood estimate and related techniques.

Motivated by these challenges, this study proposes a novel dual-encoder Variational Autoencoder (VAE) framework that addresses both seasonal variability and data scarcity in plant leaf disease detection. By combining ResNet and VGGNet Metagar *et al*. (2024) as parallel feature extractors, the model captures diverse feature representations and improves classification performance. A custom-built seasonal dataset, categorized into 47 summer and 16 winter disease classes, further enables the model to learn season-specific patterns effectively.

The key contributions of this work are threefold: (1) we introduce a unique seasonally partitioned plant leaf disease dataset; (2) we propose a dual-encoder VAE model for enhanced feature learning and classification; and (3) we demonstrate that incorporating seasonal categorization significantly boosts the accuracy and robustness of plant disease detection models.

The proposed system can be deployed in precision agriculture systems, particularly mobile-based or edge computing platforms, enabling real-time, accurate and season-aware crop disease diagnosis. This has the potential to improve yield, reduce pesticide misuse and contribute to more sustainable farming practices. The proposed model's results have several practical uses in farming and food-production systems. It can be incorporated into smartphones or drone-based monitoring systems for immediate field assessment, allowing farmers to take prompt corrective measures to minimize crop losses. Agricultural extension services and plant clinics could leverage this technology to aid in disease monitoring and early-warning systems. Additionally, predictions that consider seasonal changes enable optimized pesticide application, efficient crop management and sustainable farming practices in line with climate-smart agriculture initiatives. These applications highlight the proposed system's potential to enhance global food security and aid decision-making for various stakeholders within the agricultural sector.

The structure of the rest of paper is as follows: Section 2 describes the Materials and Methods which includes the details for the dataset collection and its customization with the details of the proposed methodology. Section 3 provides detailed analysis of the results obtained with the discussions. Finally, we conclude the paper in Section 5 by highlighting the advantages of the proposed work with its future scope.

MATERIALS AND METHODS

The research was conducted at the Department of ECE, Indira Gandhi Delhi Technical University for Women (IGDTUW) Lab, Delhi, during the data curation and experimentation phase, where all activities related to preprocessing, model development and performance evaluation took place. The dataset was obtained from Kaggle, a well-known public data platform, which guarantees the accessibility and reproducibility of the experiments. The entire research effort spanned from 2023 to 2025, encompassing dataset refinement, architectural design, model training and comprehensive validation. References (https://www.kaggle.com/datasets/nirmalsankalana/plant-diseases- training-dataset; https://www.kaggle.com/datasets/tahmidmir/pumpkin-leaf-diseases-dataset-from-bangladesh; https://www.kaggle.com/datasets/manojgadde/yellow-vein-mosaic-disease; He *et al*., 2016; Simonyan, 2014) cite the sources for the summer and winter data subsets. This section outlines the datase used and the methodology adopted for the detection and classification of plant leaf diseases using a Variational Autoencoder (VAE)-based framework. The proposed approach incorporates a seasonal perspective by dividing the dataset into two primary categories-summer and winter-to enhance the accuracy and adaptability of the model under varying environmental conditions. Prior to training, the dataset underwent a comprehensive data preparation and cleaning process. Initially, all images were screened for quality, relevance and resolution. Only high-quality images, with clear visibility of the leaf and disease symptoms, captured under proper lighting and with minimal background noise, were selected for inclusion. This step ensures that the model is trained on consistent and informative visual data, minimizing the potential for misclassification due to poor input quality. Additionally, all images were accurately labeled according to their respective disease class to ensure correct ground truth during model training and evaluation.

A thorough understanding of the various plant species and their associated diseases was acquired during the data curation phase to avoid labeling inconsistencies. This domain knowledge played a key role in ensuring that each image corresponds to the correct disease class. The research has been carried out dataset was sourced from Kaggle, a widely-used public data platform, ensuring accessibility and reproducibility of the experiments. References (https://www.kaggle.com/datasets/nirmal sankalana/plant-diseases-training-datase;https://www.kaggle.com/datasets/tahmidmir/pumpkin-leaf-diseases-dataset-from-bangladesh.;https://www.kaggle .com/datasets/manojgadde/yellow-vein-mosaic-disease.; He *et al*., 2016; Simonyan, 2014) provide the sources for the summer and winter data subsets.

The summer dataset consists of 50,523 images categorized into 47 distinct disease classes, while the winter dataset comprises 15,082 images grouped into 16 classes. These categories include a variety of crops and disease types that commonly occur in their respective seasons. The comprehensive breakdown of the class distribution for both summer and winter datasets is presented in Table 1.

This seasonally divided dataset provides the foundation for the proposed dual-encoder VAE model, which aims to accurately detect and classify plant diseases by capturing subtle visual differences across seasonal variations.

Variational autoencoder

The variational autoencoder (VAE) is a type of generative model based on deep learning that combines principles from probabilistic graphical models and neural networks. Unlike traditional autoencoders that learn a deterministic mapping for data reconstruction, VAEs introduce a probabilistic latent space and aim to learn the underlying distribution of the input data, allowing them to generate new, synthetic samples similar to the original data.

Fig 1 shows the basic architecture of a variational autoencoder which consists of an encoder and a decoder. The encoder functions as the variational posterior $q\varphi\ (z \mid x)$ while the decoder functions as a generative model thereby, representing the likelihood $p\theta\ (x|z)$. Given the posterior and the likelihood, we can define a joint inference distribution as:

$$q\varphi\ (z, x) = p\theta\ (x)\ q\varphi\ (z \mid x) \qquad ...(1)$$

For a multivariate gaussian distribution function with diagonal covariance matrix $p_z(z) = \mathcal{N}(z;\ 0,1)$. The model parameter θ parameterizes the weights and biases in the decoder, whereas the variational parameter φ parameterizes them in the encoder. Encoders in VAEs produce μ and log (σ^2) and create $\in$ from $\mathcal{N}(0,1)$, from which z is sampled using a reparameterization method, in contrast to autoencoders, which producez (a probability distribution reflecting the latent embeddings). Further, the variable z is then fed as input to the decoder which is used for the reconstruction defined as:

$$z = g(\in, \varphi, \xi) = \mu + \sigma \odot \in \qquad ...(2)$$

Where,
$\odot$ = An element-wise multiplication.
z= The probability distribution.
x= The input.
Assuming $z \sim \mathcal{N}(\mu, \sigma^2)$, then z can be reparametrized by:

$$z = \mu + \sigma\in,\ \in \sim p(\in) = \mathcal{N}(0,1) \qquad ...(3)$$

Dual encoder-vae

The Dual Encoder Variational Autoencoder (Dual Encoder-VAE) is an enhanced generative model that builds upon the traditional Variational Autoencoder (VAE) by integrating two parallel encoders instead of one. This architecture is designed to fuse feature representations from different encoder networks, there by capturing more diverse and complementary information from the input data.

Table 1: Proposed dataset details.

Categories	#Images	#Classes
Summer	50523	47
Winter	15082	16

This approach is particularly valuable for complex tasks such as leaf disease detection, where symptoms may vary subtly across seasons or disease types.

This section provides the details for the proposed ensemble variational autoencoder for detection and classification of plant leaf diseases as depicted in Fig 2. The architecture of the proposed VAE is built using two encoder that exploits ensemble learning, a reparameterization network, a classification head and a decoder. Deep learning techniques significantly enhance plant disease detection accuracy. For example, encoder-based architectures such as ResNet and VGGNet are widely used to extract discriminative features from leaf images (Kashyap *et al*., 2025). Also, the CNN models employed are used without classification layers.

The ResNet50 encoder follows the same architecture as discussed in He *et al*. (2016). Furthermore, the VGG16-based encoder is designed as discussed in (Simonyan, 2014). For reparameterization, a linear layer is used to convert the encoders' outputs to the latent space's dimension. Further, using a conventional normal Gaussian distribution with a mean and variance, we conduct random sampling. The mean and variance, which have the same dimension as the latent space, are implemented using two linear layers. Equation (2) was applied to sample z and the standard deviation is calculated from the variance.

Additionally, the classification head transforms z linearly after receiving it as an input. Fig 2 shows the output for the categorization head. Ultimately, the decoder executes the encoder's opposite function. It takes z as input, upsamples it using ConvTranspose2d and outputs the result.

RESULTS AND DISCUSSION

Chis section describes the results obtained for the proposed model on the summer and winter datasets. The experiments are first carried out on Summer Dataset which contains 50523 images split into 47 classes. Afterwards, for the experimental validation for the proposed model experiments are further extended to winter dataset that contains 15082 images split into 16 classes. Fig 3 presents a sample images from summer and winter dataset.

In the proposed model, an essential initial step involves the pre-processing of plant leaf images obtained from the dataset. Raw images often contain various forms of visual noise, distortions, or irrelevant background information that can significantly impact the accuracy and robustness of the system. These inconsistencies may arise due to environmental conditions, such as lighting variations, camera focus issues, shadows, or background clutter during image capture. If not addressed properly, such noise can adversely affect the performance of the downstream deep learning (Pakruddin *et al*., 2025) components, particularly in tasks involving fine grained classification such as leaf disease detection. To mitigate this, a dedicated image pre-processing pipeline is employed to clean and enhance the raw input data. The pre-processing stage focuses on noise reduction, contrast enhancement, normalization and, where necessary, image resizing or cropping. By filtering out irrelevant visual artifacts and standardizing the input, the model is better equipped to focus on disease-specific features present on the leaf surface. This improves not only the image quality but also ensures that the subsequent learning stages operate on consistent and meaningful data representations. Once the images are efficiently pre-processed, they are passed into the proposed Variational Autoencoder (VAE) framework. The VAE relies heavily on the quality of input data for effective latent feature extraction and reconstruction. By

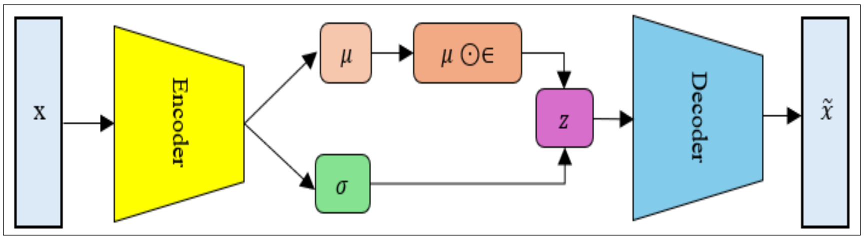

Fig 1: Architecture of basic variational autoencoder.

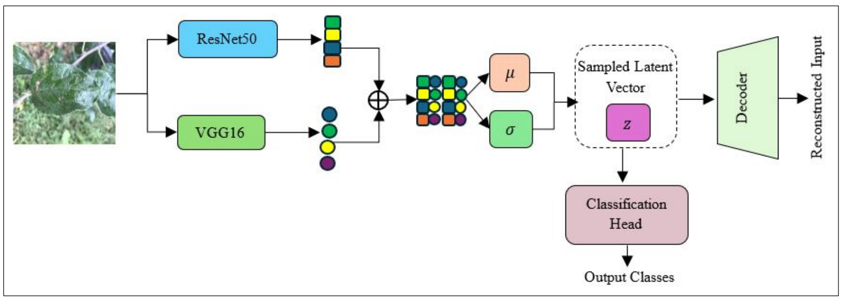

Fig 2: Proposed methodology: Dual encoder VAE.

ensuring that the input images are clean and uniform, the encoder networks (*e.g.*, ResNet and VGGNet in the dual-encoder architecture) can more accurately capture relevant patterns associated with various plant diseases (Alhussaen *et al*., 2025) across different seasonal conditions. Furthermore, the detailed hyperparameter configuration used in the training and optimization of the proposed model is provided in Table 2. These settings play a critical role in the model's overall learning behavior, convergence and generalization capabilities.

To measure the efficiency and efficacy of the proposed model, Accuracy, Precision, Recall and F-1 scores is evaluated. The mathematical formulation of metrics that are employed in the study for correctly examining the proposed model is specified below:

$$\text{Accuracy}\ (\alpha) = \frac{TP + TN}{\mathcal{N}} \quad ...(4)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad ...(5)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad ...(6)$$

$$F\text{-}1 = \frac{2^{*}\text{Precision}^{*}\text{Recall}}{(\text{Precision} + \text{Recall})} \quad ...(7)$$

Where, true positive, true negative, false positive and false negative are represented by TP, TN, FP, FN.

Fig 4 denotes the training and accuracy curve for the proposed model on the summer and winter datasets. From the curves it is evident that the proposed model accuracy increases as the number of epochs increases while the loss decreases with increase in number of epochs. Also, Table 3 provides the quantitative results obtained for the proposed model on the summer and winter dataset. Also, Fig 5 denotes the confusion matrix obtained for the winter dataset.

1. This section analyzes the performance trends noticed in the results. The proposed model achieved remarkable accuracy (>97%) on both datasets, demonstrating its strong capability to identify and categorize various plant leaf diseases across different environmental conditions.
2. The balanced values of precision and recall indicate that the model successfully minimizes both false positives and false negatives.
3. The elevated F1-scores highlight the effectiveness of the dual-encoder architecture in capturing detailed disease characteristics from leaf images.

Table 2: Hyperparameters values for the proposed model.

Parameters	Values
Learning rate	0.0001
Epochs	50
Batch size	16
Optimizer	Adam
Dropout	0.5
Regularization	0.001
Activation function	ReLU

Table 3: Results obtained for the proposed model on summer and winter datasets.

Category	Acc	P	R	F-1
Summer	98.86%	98.21%	97.8%	97.19%
Winter	97.53%	97.5%	96.8%	97.03%

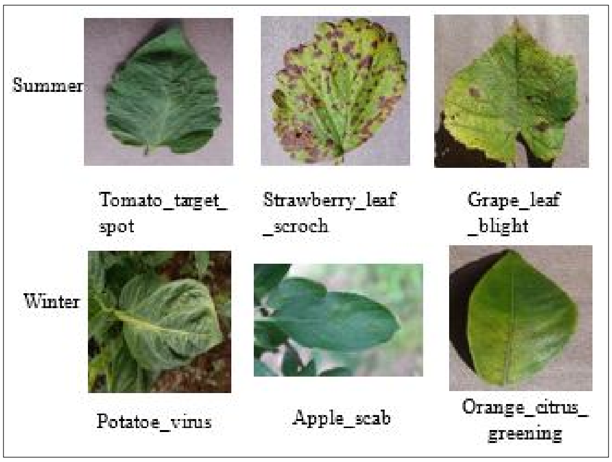

Fig 3: Sample of images from the proposed dataset.

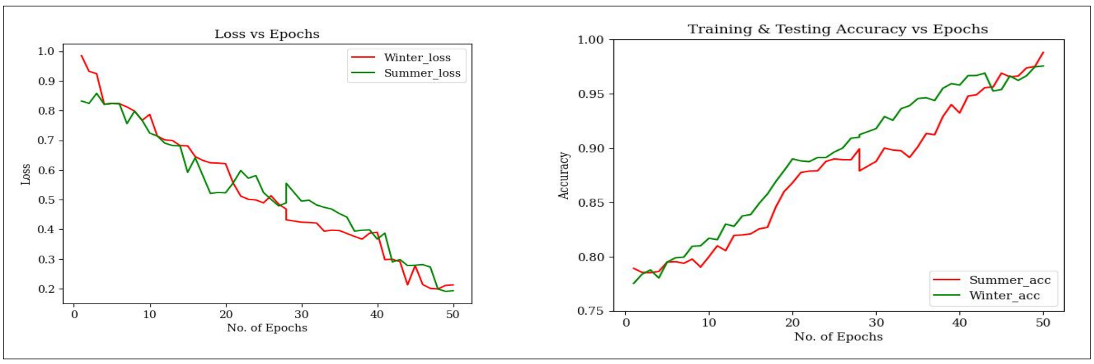

Fig 4: Loss and accuracy curve for the proposed model on summer and winter datasets.

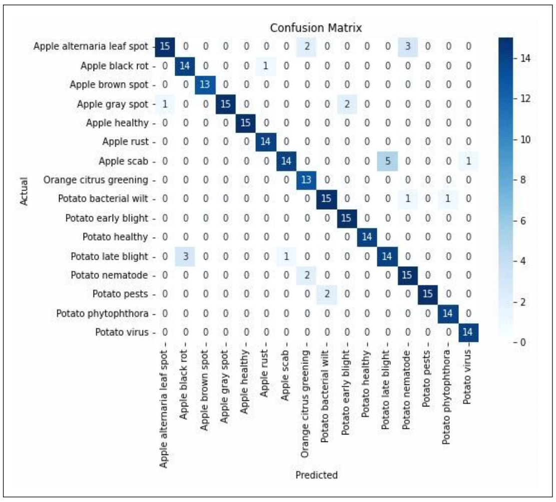

Fig 5: Confusion matrix obtained for the proposed model on winter dataset.

4. The confusion matrix presented in (Fig 5) further validates the reliability of the predictions, showing a small number of misclassifications.
5. The superior performance indicates that the combination of pre-processing and advanced feature encoding enhances classification accuracy compared to conventional deep learning methods for detecting plant diseases.

CONCLUSION

This paper presents a novel two encoder-based VAE for efficient detection and classification of plant leaf diseases. The proposed model exploits ResNet and VGGNet driven encoders and one decoder. Prior to reparameterization, the feature maps from the two encoders are concatenated to sample the latent vector. After that, the latent vector is sent to the decoder to rebuild the input image and to the classification head for classification. To validate the effectiveness of the proposed dual encoder VAE this paper also proposes a plant leaf disease dataset for summer and winter seasons. The proposed dual-encoder VAE model provides an accuracy of 98.86% on summer dataset whereas on winter dataset the accuracy is obtained is 97.53% respectively. This makes it evident that the proposed model improves disease detection performance by better handling fine-grained seasonal variations in leaf appearance. Furthermore, in future, this work could have a big influence on sustainable agriculture by assisting farmers worldwide with disease management, early diagnosis and crop loss prevention thanks to developments in multi-modal data, transfer learning, real-time applications and model explainability.

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my supervisor for their invaluable guidance, continuous support and constructive feedback throughout the course of this research. Their expertise and encouragement played a pivotal role in the successful completion of this work. I am also thankful to the Department of Electronics and Communication Engineering, [IGDTUW], for providing the necessary facilities and academic environment to conduct this research.

Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Informed consent

No experiments have been conducted on animals/humans.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. This study did not receive any specific grant, funding, or sponsorship from public, commercial, or non-profit organizations. The design of the study, data collection, analysis, interpretation of results and preparation of the manuscript were conducted independently by the authors without any external influence.

REFERENCES

Afzaal, H., Farooque, A.A., Schumann, A.W., Hussain, N., McKenzie-Gopsill, A., Esau, T., Abbas, F. and Acharya, B. (2021). Detection of a potato disease (early blight) using artificial intelligence. *Remote Sensing.* **13(3):** 411. https://doi.org/10.3390/rs13030411.

Alhussaen, K. (2025). Root rot disease on tomato seedlings caused by *Pythium ultimum* and the effect of nutrient elements N, P and K on disease incidence. *Indian Journal of Agricultural Research*. **59(8):** 1224-1231. doi: 10.18805/IJARe.AF-919.

https://www.kaggle.com/datasets/manojgadde/yellow-vein-mosaic-disease.

He, K., Zhang, X., Ren, S. and Sun, J. (2016). Deep Residual Learning for Image Recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). (pp. 770-778). https://doi.org/10.1109/CVPR.2016.90.

Jiang, P., Chen, Y., Liu, B., He, D. and Liang, C. (2019). Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks. *IEEE Access.* **7:** 59069-59080. https://doi.org/10.1109/ACCESS.2019.2914929.

Kanade, A.K., Potdar, M.P., Balol, G., Rathod, N., Pooja, S., Huligol, S.N., Channakeshava, R. and Vijaykumar, K.N. (2025). Artificial intelligence based precise disease detection in soybean using real-time object detectors. *Legume Research*. **48(11):** 1878-1883. doi: 10.18805/LR-5431.

https://www.kaggle.com/datasets/sujaykapadnis/watermelon-disease-recognition-dataset.

Kashyap, N. and Kashyap, A.K. (2025). Deep learning VGG19 model for precise plant disease detection. *Agricultural Science Digest*. 1-8. doi: 10.18805/ag.D-6220.

Ke, X., Zou, J. and Niu, Y. (2019). End-to-end automatic image annotation based on deep CNN and multi-label data augmentation. *IEEE Transactions on Multimedia.* **21(9):** 2093-2106. https://doi.org/10.1109/TMM.2019.2898320.

Konidaris, F., Tagaris, T., Sdraka, M. and Stafylopatis, A. (2019). Generative Adversarial Networks as an Advanced Data Augmentation Technique for MRI Data. In: Proceedings of the 14th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2019), Prague, Czech Republic. **5:** 48-59.

Liu, B., Tan, C., Li, S., He, J. and Wang, H. (2020). A data augmentation method based on generative adversarial networks for grape leaf disease identification. *IEEE Access.* **8:** 102188-102198. https://doi.org/10.1109/ACCESS.2020.2998575.

Liu, X., Min, W., Mei, S., Wang, L. and Jiang, S. (2021). Plant disease recognition: A large-scale benchmark dataset and a visual region and loss reweighting approach. *IEEE Transactions on Image Processing.* **30:** 2003-2015. https://doi.org/10.1109/TIP.2021.3053992.

Mehta, R.A., Kumar, P., Prem, G., Aggarwal, S. and Kumar, R. (2025). Leveraging artificial intelligence for disease diagnosis in agricultural crops: A review. *Indian Journal of Agricultural Research*. **59(5):** 681-690. doi: 10.18805/IJARe.A-6363.

Metagar, S.M. and Walika, G.A. (2024). Machine learning models for plant disease prediction and detection: A review. *Agricultural Science Digest*. **44(4):** 591-602. doi: 10.18805/ag.D-5893.

https://www.kaggle.com/datasets/tahmidmir/pumpkin-leaf-diseases-dataset-from-bangladesh.

Pakruddin, B. and Hemavathy, R. (2025). Performance evaluation of deep learning models for multiclass disease detection in pomegranate fruits. *Indian Journal of Agricultural Research*. **59(10):** 1535-1542. doi: 10.18805/IJARe.A-6396.

Saleem, M.H., Potgieter, J. and Arif, K.M. (2022). Plant disease detection and classification by deep learning. *Plants.* **11(3):** 468. https://doi.org/10.3390/plants11030468.

https://www.kaggle.com/datasets/nirmalsankalana/plant-diseases-training-dataset.

Simonyan, K. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint* arXiv:1409.1556. https://arxiv.org/abs/1409.1556.

Stewart, E.L., Wiesner-Hanks, T., Kaczmar, N., DeChant, C., Wu, H., Lipson, H., Nelson, R.J. and Gore, M.A. (2019). Quantitative phenotyping of northern leaf blight in UAV images using deep learning. *Remote Sensing.* **11(18):** 2209. https://doi.org/10.3390/rs11182209.

Tetila, E.C., Machado, B.B., Menezes, G.K., Oliveira, A.D.S., Alvarez, M., Amorim, W.P., De Souza Belete, N.A., Goncalves Da Silva, G. and Pistori, H. (2019). Automatic recognition of soybean leaf diseases using UAV images and deep convolutional neural networks. *IEEE Geoscience and Remote Sensing Letters.* **17(5):** 903-907. https://doi.org/10.1109/LGRS.2019.2933089.

Tran, N.T., Tran, V.H., Nguyen, N.B., Nguyen, T.K. and Cheung, N.M. (2021). On data augmentation for GAN training. *IEEE Transactions on Image Processing.* **30:** 1882-1897. https://doi.org/10.1109/TIP.2021.3053766.

Wassan, S., Cho, O.H. and AlQahtan, S.A. (2025). Automated detection of groundnut plant leaf diseases using convolutional neural networks. *Legume Research*. **48(3):** 79-86. doi: 10.18805/LRF-814.

Wu, Y. and Xu, L. (2019). Crop organ segmentation and disease identification based on weakly supervised deep neural network. *Agronomy.* **9(12):** 737. https://doi.org/10.3390/agronomy9120737.

Xie, X., Ma, Y., Liu, B., He, J., Li, S. and Wang, H. (2020). A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks. *Frontiers in Plant Science*. **11:** 751. https://doi.org/10.3389/fpls.2020.00751.

Yu, H.J. and Son, C.H. (2020). Leaf Spot Attention Network for Apple Leaf Disease Identification. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). Seattle, WA, USA. (pp. 52-53). https://doi.org/10.1109/CVPRW50498.2020.00011.

Zhu, J., Park, T., Isola, P. and Efros, A.A. (2017). Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV). Venice, Italy. (pp. 2223-2232). https://doi.org/10.1109/ICCV.2017.244.