A-6553
[1-9]

RESEARCH ARTICLE Indian Journal of Agricultural Research

A Comparative Study of Convolutional Neural Network based Transfer Learning Models for Plant Disease Detection

Chika K. Gangadharan[1], P.M. Jasmine[2], Roshni Alex[1], M.K. Sabu[3]

10.18805/IJARe.A-6553

ABSTRACT

Background: Plant diseases significantly threaten global food security, reducing potential harvests and sometimes causing total crop failure. Traditional detection methods, which rely on manual inspection and laboratory testing, are time-consuming, costly and prone to human error.

Methods: To address these challenges, this study applies transfer learning techniques using deep convolutional neural networks for accurate and efficient plant disease detection. A comparative analysis of nine pretrained models, VGG16, VGG19, ResNet50, ResNet101V2, MobileNetV2, InceptionV3, DenseNet121, InceptionResNetV2 and Xception was conducted on the PlantVillage dataset, focusing on apple, potato and peach leaf images.

Result: Results show that DenseNet121 and ResNet101V2 achieved the highest accuracy, particularly for potato leaves with 98.5%, while MobileNetV2 also performed well with up to 99% accuracy for apple and peach leaves. The study demonstrates that transfer learning effectively enhances plant disease classification, enabling faster, more reliable and resource efficient detection for precision agriculture.

Key words: Convolutional neural network, Deep learning, Plant disease detection, Transfer learning models.

INTRODUCTION

Across the world, infectious plant diseases can significantly reduce crop yields and in severe cases, cause total crop failure, highlighting a significant risk to food security. Conventional monitoring mainly relies on experts for manual inspections and laboratory testing (Ozair *et al.*, 2024). These methods require more resources and take considerable time (Bhargava *et al.*, 2024; Jafar *et al.*, 2024; Lu *et al.*, 2017) and are prone to human errors. As a result, real-time surveillance on a large scale becomes challenging and costly. The delay in decision-making due to a lack of knowledge in specific areas creates problems for farmers. Plant disease always threatens food security, thereby reducing the yield so early detection is essential for effective disease management (Peyal *et al.*, 2021).

Traditional machine learning (ML) techniques for classifying plant diseases rely on manually created features, which often struggle to scale and adapt to larger, more diverse datasets (Mehta *et al.*, 2025), thus limiting their practical application (Peyal *et al.*, 2021). Deep learning addresses this limitation Abd Algani *et al.* (2023) by automatically learning detailed visual features from images, by identifying significant variations in colour, texture and shape without manual intervention and by achieving high accuracy on a wide range of leaf image datasets (Shoaib *et al.*, 2023). Convolutional neural networks (CNN) are particularly powerful (Hossen *et al.*, 2025; Sathishkumar *et al.*, 2022) as they extract important patterns and perform various leaf-disease tasks (Reddy and Kumari, 2026) while modern architectures such as ResNets, DenseNets and Inception-based models can capture complex structures (Tugrul *et al.*, 2022). Transfer learning models play an important role in detecting plant diseases at an early stage (Ashmafee *et al.*, 2023; Gogoi *et al.*, 2023). These models are first pre-trained on large image datasets and then fine-tuned on specific target datasets for accurate disease identification (Peyal *et al.*, 2021). Standard CNN architectures such as VGG, Inception, ResNet, DenseNet and EfficientNet consistently achieve very high accuracy, on curated datasets like plant village (Department of Computer Science, Sukkur IBA University, Pakistan *et al.*, 2020; Krishna *et al.*, 2025; Mohameth *et al.*, 2020; Mohanty *et al.*, 2016a). For instance, EfficientNet-B3 hybrids can achieve maximum accuracy proving the effectiveness of deep residual-inception features (Chug *et al.*, 2023). Hybrid CNN-ML pipelines

[1]Department of Electronics, MES College Marampally, Aluva-683 105, Kerala, India.
[2]MES Kallady College, Mannarkkadu-678 583, Kerala, India.
[3]Cochin University of Science and Technology, Kalamassery-682 022, Kerala, India.

Corresponding Author: Chika K. Gangadharan, Department of Electronics, MES College Marampally, Aluva-683 105, Kerala, India. Email: chika4895@gmail.com

ORCIDs: 0009-0006-1430-6889, 0000-0002-1829-0486, 0000-0002-1373-6960, 0000-0002-4958-5033

How to cite this article: Gangadharan, C.K., Jasmine, P.M., Alex, R. and Sabu, M.K. (2026). A Comparative Study of Convolutional Neural Network based Transfer Learning Models for Plant Disease Detection. *Indian Journal of Agricultural Research.* 1-9. doi: 10.18805/IJARe.A-6553.

Submitted: 11-04-2026 **Accepted:** 08-07-2026 **Online:** 11-08-2026

combine deep feature extraction with classical classifiers (Sujatha *et al*., 2025) often outperform on smaller datasets like plant village and kaggle rice leaf (Upadhyay and Kumar, 2022), while field datasets such as plant Doc or Embrapa show reduced performance due to varying lighting, complex backgrounds and inconsistent imaging conditions (Chug *et al*., 2023).

Custom CNNs designed for specific crops gives lower accuracy than transfer-learned models but still competitive (Haridasan *et al*., 2023). Even simple CNN models can reach good accuracy under controlled conditions, demonstrating that dataset quality and balance often matter more than model complexity (Sujatha *et al*., 2025). Transfer learning remains the dominant approach in this field (Jain and Periyasamy, 2022) (Mohanty *et al*., 2016b). Modified models maintain high performance even when mixing with curated and field images, showing the robustness of pretrained models (Kaur *et al*., 2023). Performance tends to decline slightly as the number of classes increases, but deep CNNs work well on curated datasets (Peyal *et al*., 2021; Sakkarvarthi *et al*., 2022; Tugrul *et al*., 2022). For larger, imbalanced datasets the transfer learning models are not so recommended (Arnal, 2019). All these methods reduce the need for computational resources and data, accelerates convergence within just a few epochs and enhance accuracy. It has been effectively implemented in various crops such as rice, corn, tomato, potato and so on, providing reliable classification of leaf diseases even with limited labelling and leading to numerous practical applications highlighted in recent studies.

In this paper, a comparative analysis is performed on nine transfer learning models, including VGG16 (Jain and Periyasamy, 2022), VGG19 (Panchal *et al*., 2023), ResNet50, ResNet101V2, MobileNetV2, InceptionV3, DenseNet121 (Srivastava and Meena, 2023), InceptionResNetV2 (Billa *et al*., 2024) and Xception, which are capable of detecting the affected plant leaves faster and more accurately (Sakkarvarthi *et al*., 2022). These models are trained and tested on the PlantVillage dataset (Ahmad *et al*., 2023) using the transfer learning method to detect and identify plant diseases automatically.

The upcoming section presents a concise description of the methodology used in this paper.

MATERIALS AND METHODS

The experiment was conducted at MES College Marampally, Aluva, Kerala during the period 2024-25. The dataset used for this study is the Plant Village dataset taken from Kaggle data repository. This paper presents a comprehensive approach to the diagnosis and detection of plant diseases using transfer learning techniques. The overall workflow of the analysis is illustrated in Fig 1. The subsequent subsections provide a detailed, step-by-step explanation of the methodology employed. Based on the survey findings, we selected nine transfer learning models for this comparative study, using the plant village dataset.

Dataset

The Plant Village dataset serves an important role in the field of agricultural computer vision, containing 54,309 images of both healthy and diseased leaves from 14 distinct crops, such as apple, potato, tomato, maize, grape, peach, strawberry, pepper, soybean and so on. Each image is labelled by crop type and disease condition. For every crop, there are images of different diseases as well as healthy samples, making the dataset useful for training and testing deep learning models. For this study, we utilize three subsets of plant village dataset (Ashmafee *et al*., 2023), namely apple, potato and peach. The apple dataset comprises 3,181 images split into three disease categories and one healthy group. The potato dataset comprises 3,251 images, grouped into two disease categories and one healthy category. The peach dataset includes 2,657 images organized into one disease category and one healthy group.

Data scaling/resizing

Data scaling is an essential pre-processing step when working with CNNs. This process standardizes all images in the dataset by adjusting their sizes to match the input requirements of the model (Kumari *et al*., 2025). Resizing the images before training also helps reduce

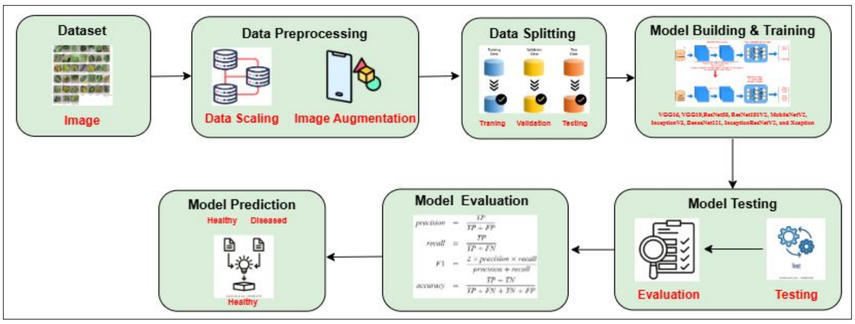

Fig 1: Workflow illustrating the research methodology.

memory usage, making the training process more efficient (Shree *et al*., 2025).

Data augmentation

Image augmentation is a technique used to artificially expand the dataset, enhancing the performance and generalization of the neural network. This method applies various transformations to training images, such as zooming, rotating, shifting, or flipping. In this study, the augmented image generator was implemented using the ImageDataGenerator API in the Keras deep learning framework. Four types of augmentations were applied: rotation, zooming, shearing and horizontal flipping. Data augmentation is applied using rotations of up to 40°, zoom levels of 20%, shear transformations of 20% and horizontal flipping to increase variability in the training dataset.

Data split

After preprocessing the images, the dataset is divided into three subsets: the training set is used for learning patterns and adjusting weights, the validation set helps tune hyperparameters and prevent overfitting and the test set provides a final unbiased evaluation on unseen data. For this study 80% of the images are used for training, 10% for validation and 10% for testing.

Model building and training

For building the model and training the datasets, this study employs transfer learning techniques.

Transfer learning is a technique in deep learning where pre-trained models are used to solve new tasks with limited labelled data. The first step towards using this pretrained model for transfer learning is to remove the final classification layer of the pretrained model and add a new classifier layer at the end and train it on the target dataset. During training, all layers of the pretrained model are frozen and only the newly added classifier layer is trained. As a result, very few parameters are getting trained and therefore, training happens fast. Since most of the pretrained weights are frozen, only the final layer weights are optimized to the new dataset.

Transfer learning architecture

Fig 2 illustrates the general architecture of transfer learning for plant disease detection. It is divided into two main parts:

Pre-trained model

The top section shows a convolutional neural network (CNN) originally trained on the ImageNet dataset. The network consists of convolutional layers for feature extraction and a fully connected dense layer for classification. This pre-trained model has learned general image features, such as edges, shapes and textures, from a large dataset.

Transfer learning for plant disease detection

The lower section shows how the pre-trained CNN is adapted to detect plant diseases. The convolutional layers from the pre-trained model are retained with their learned parameters indicated by Transfer Trained Parameters to leverage the previously learned features. The original fully connected layer is replaced with a new dense layer, which is specifically trained on the plant disease dataset. This new layer classifies images into plant disease class or the plant healthy class.

Transfer learning models

The models used for this study include VGG16, VGG19, ResNet50, ResNet101V2, MobileNetV2, InceptionV3, DenseNet121, InceptionResNetV2 and Xception, all of which are pretrained on ImageNet and subsequently fine-tuned for recognizing plant diseases.

VGG16 and VGG19 are deep CNNs with 16 and 19 layers, using small 3×3 convolutions, max-pooling and fully connected layers, with VGG19 offering more depth for better feature learning (Sakkarvarthi *et al*., 2022). ResNet50 introduces residual skip connections, allowing stable training of very deep networks with 50 layers. ResNet101V2, similar to ResNet50 but deeper, enhances representational power while maintaining training stability. InceptionV3 Sakkarvarthi *et al*. (2022) improves efficiency and accuracy using parallel convolutions, auxiliary classifiers and

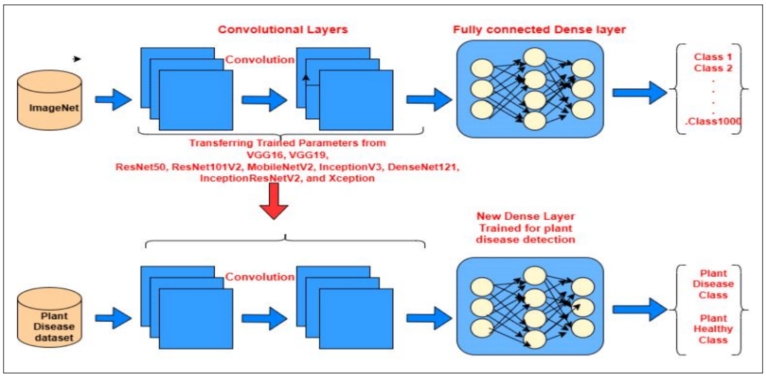

Fig 2: The general architecture of transfer learning.

reduction blocks. InceptionResNetV2 combines Inception modules with residual connections for powerful feature extraction (Jain and Periyasamy, 2022). Xception extends Inception by replacing standard convolutions with depthwise separable ones for greater efficiency (Jain and Periyasamy, 2022). MobileNetV2 is designed for lightweight use, employing inverted residual blocks with linear bottlenecks, making it suitable for mobile and edge devices. DenseNet121 connects each layer to all later layers for better gradient flow and feature reuse, achieving high accuracy with fewer parameters (Jain and Periyasamy, 2022).

The three datasets apple, peach and potato were trained using nine transfer learning models, which has to be tested to evaluate their performance.

Model testing

After training the models using transfer learning, the next step involves model testing to evaluate their performance and generalization capability. During testing, the trained models are applied to unseen images from the apple, potato and peach datasets to determine how accurately they can classify leaves as healthy or diseased. This phase assesses the models' effectiveness in recognizing various plant diseases based on the features learned during training.

Model evaluation

After testing the model with the new classifier, its performance is evaluated using four key metrics accuracy, precision, recall and F1-score, to assess how effectively it detects plant diseases (Sakkarvarthi *et al*., 2022).

Accuracy

Accuracy represents the proportion of correctly classified images out of the total number of samples. In other words, it is the ratio of correct predictions to the total predictions made, as expressed in Equation (1):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad ...(1)$$

Here,
TP= True positives.
TN= True negatives.
FP= False positives.
FN= False negatives.

Precision

Precision is the ratio of correctly classified positive samples (True positives) to the total number of samples predicted as positive. It indicates how many of the identified instances are actually relevant. Precision is computed by dividing the number of true positives by the total predicted positives, as shown in Equation (2):

$$\text{Precision} = \frac{TP}{TP + FP} \quad ...(2)$$

Recall

Recall, also known as sensitivity, measures the ability of the model to correctly identify actual positive instances. It represents the proportion of relevant samples that were correctly detected by the model out of all true positive cases. Recall is calculated as shown in Equation (3):

$$\text{Recall} = \frac{TP}{TP + FN} \quad ...(3)$$

F1-score

The F1-score is a key evaluation metric in machine learning that provides a single measure of a model's predictive performance by combining precision and recall, which often have a trade-off between them. The F1-score is computed as shown in Equation (4):

$$\text{F1-score} = \frac{\text{Precision*Recall}}{\text{Precision+Recall}} \quad ...(4)$$

Model prediction

Now, the model is fully trained and ready for prediction. When provided with an input image, it can accurately classify whether the leaf belongs to a healthy category or shows signs of disease. The model analyzes the visual features of the leaf such as color, texture and shape learned during training to make its decision. By leveraging transfer learning, it effectively distinguishes between healthy and diseased samples, enabling quick and reliable detection.

In summary, this section has outlined the methodologies used in the study, while the next section presents the Experimental Results based on the analysis.

RESULTS AND DISCUSSION

This section presents the experimental results and analysis of the nine selected models conducted using google colab. The performance of these architectures was evaluated through experiments on three plant disease datasets with the graphical results illustrated in Fig 3-5.

Performance analysis

The performance evaluation of nine models, which were tested on three different datasets is given below.

Apple dataset

In the apple dataset, models such as ResNet50, ResNet101V2, VGG16, DenseNet121 and Xception performed exceptionally well in detecting apple scab, achieving precision and F1-scores close to 1.0 and an overall accuracy of about 99%. For apple black rot, nearly all models produced excellent results, with accuracy ranging between 98% and 99%, although Inception ResNetV2 recorded a slightly lower recall of 0.94. In the case of cedar apple rust, most models reached near-perfect accuracy, while InceptionV3 showed a small decline with an F1-score of 0.92. For healthy leaf samples, the models also performed strongly, though InceptionV3 again showed a slightly lower precision of 0.94. The detailed performance metrics are summarized in Table 1.

Potato dataset

From Table 2, it is evident that in the potato dataset, ResNet101V2, MobileNetV2, DenseNet121 and Xception perform strongly in detecting early blight, while VGG16 and VGG19 show moderate results and ResNet50 performs the weakest with an accuracy of 58%. For late blight, DenseNet121 achieves the best performance with an F1-score of approximately 0.97, followed closely by ResNet101V2, MobileNetV2 and Xception, which also deliver strong results with slightly lower scores. The VGG models show weaker performance, reaching an F1-score of about 0.81, while ResNet50 records the lowest F1-score of 0.64 among all models. In the case of healthy leaves, DenseNet121 again performs best, achieving the highest metric values, followed by MobileNetV2 and Xception, which also produce strong results. The VGG models show only average performance and ResNet50 once again ranks lowest.

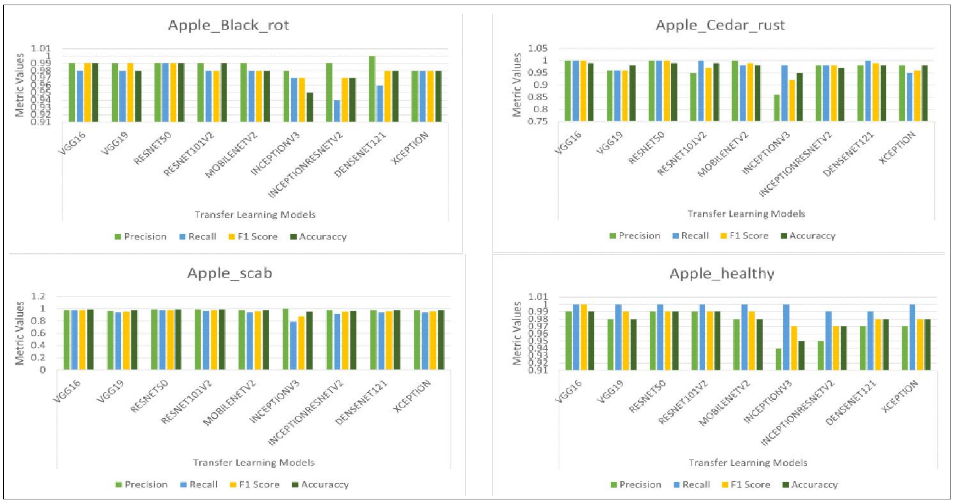

Fig 3: Performance evaluation of transfer learning models on apple dataset.

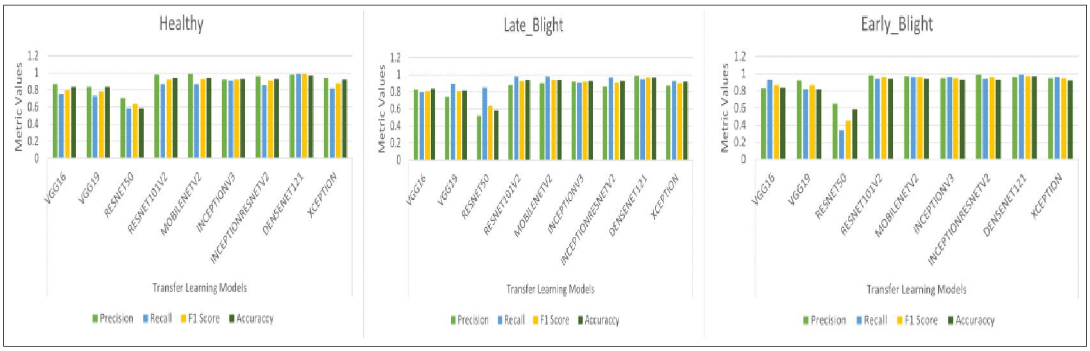

Fig 4: Performance evaluation of transfer learning models on potato dataset.

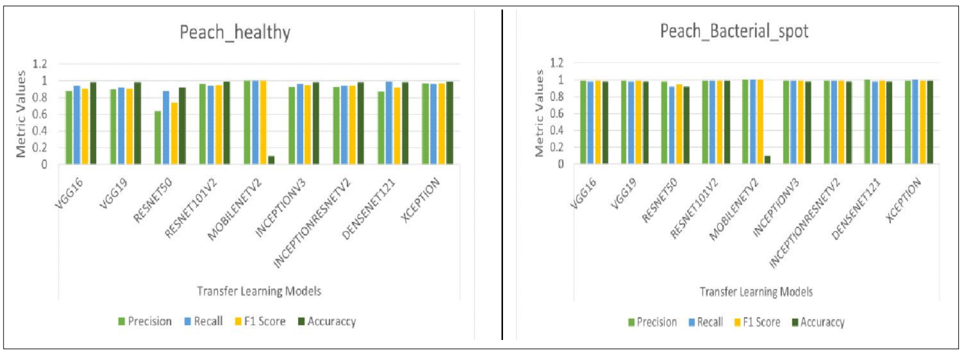

Fig 5: Performance evaluation of transfer learning models on peach dataset.

Table 1: Performance evaluation of transfer learning models on apple dataset.

	Metrics	Transfer learning models								
		VGG16	VGG19	ResNet50	RsNet101V2	MobileNetV2	InceptionV3	InceptionRes NetV2	DenseNet121	Xception
Apple_scab	Precision	0.98	0.97	0.99	0.99	0.98	1.00	0.98	0.98	0.98
	Recall	0.98	0.94	0.98	0.97	0.94	0.79	0.92	0.94	0.94
	F1 Score	0.98	0.95	0.98	0.98	0.96	0.88	0.95	0.96	0.96
	Accuracy	0.99	0.98	0.99	0.99	0.98	0.95	0.97	0.98	0.98
Black_rot	Precision	0.99	0.99	0.99	0.99	0.99	0.98	0.99	1.00	0.98
	Recall	0.98	0.98	0.99	0.98	0.98	0.97	0.94	0.96	0.98
	F1 Score	0.99	0.99	0.99	0.98	0.98	0.97	0.97	0.98	0.98
	Accuracy	0.99	0.98	0.99	0.99	0.98	0.95	0.97	0.98	0.98
Cedar_apple_rust	Precision	1.00	0.96	1.00	0.95	1.00	0.86	0.98	0.98	0.98
	Recall	1.00	0.96	1.00	1.00	0.98	0.98	0.98	1.00	0.95
	F1 Score	1.00	0.96	1.00	0.97	0.99	0.92	0.98	0.99	0.96
	Accuracy	0.99	0.98	0.99	0.99	0.98	0.95	0.97	0.98	0.98
Healthy	Precision	0.99	0.98	0.99	0.99	0.98	0.94	0.95	0.97	0.97
	Recall	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.00
	F1 Score	1.00	0.99	0.99	0.99	0.99	0.97	0.97	0.98	0.98
	Accuracy	0.99	0.98	0.99	0.99	0.98	0.95	0.97	0.98	0.98

Table 2: Performance evaluation of transfer learning models on potato dataset.

Dataset (Potato)	Metrics	Transfer learning models								
		VGG16	VGG19	ResNet50	ResNet101V2	MobileNetV2	InceptionV3	InceptionRes NetV2	DenseNet121	Xception
Early_blight	Precision	0.83	0.92	0.65	0.98	0.97	0.95	0.99	0.96	0.95
	Recall	0.93	0.82	0.34	0.94	0.96	0.96	0.94	0.99	0.96
	F1 score	0.87	0.87	0.45	0.96	0.96	0.95	0.96	0.97	0.95
	Accuracy	0.84	0.82	0.58	0.94	0.94	0.93	0.93	0.97	0.92
Late_Blight	Precision	0.83	0.74	0.52	0.88	0.90	0.92	0.86	0.99	0.87
	Recall	0.80	0.89	0.85	0.98	0.98	0.91	0.97	0.95	0.93
	F1 score	0.81	0.81	0.64	0.93	0.94	0.92	0.91	0.97	0.90
	Accuracy	0.84	0.82	0.58	0.94	0.94	0.93	0.93	0.97	0.92
Healthy	Precision	0.87	0.84	0.71	0.98	0.99	0.92	0.96	0.98	0.94
	Recall	0.75	0.73	0.58	0.87	0.87	0.91	0.86	0.99	0.82
	F1 score	0.80	0.78	0.64	0.92	0.93	0.92	0.91	0.99	0.88
	Accuracy	0.84	0.84	0.58	0.94	0.94	0.93	0.93	0.97	0.92

Table 3: Performance evaluation of transfer learning models on peach dataset.

Dataset (Peach)	Metrics	Transfer learning models								
		VGG16	VGG19	ResNet50	ResNet 101V2	MobileNet V2	Inception V3	InceptionRes NetV2	DenseNet 121	Xception
Peach_bacterial_spot	Precision	0.99	0.99	0.98	0.99	1.00	0.99	0.99	1.00	0.99
	Recall	0.98	0.98	0.92	0.99	1.00	0.99	0.99	0.98	1.00
	F1 Score	0.99	0.99	0.95	0.99	1.00	0.99	0.99	0.99	0.99
	Accuracy	0.98	0.98	0.92	0.99	1.00	0.98	0.98	0.98	0.99
Peach_healthy	Precision	0.88	0.90	0.64	0.96	1.00	0.93	0.93	0.87	0.97
	Recall	0.94	0.92	0.88	0.94	1.00	0.96	0.94	0.99	0.96
	F1 Score	0.91	0.91	0.74	0.95	1.00	0.95	0.94	0.92	0.97
	Accuracy	0.98	0.98	0.92	0.99	1.00	0.98	0.98	0.98	0.99

Peach dataset

In the peach dataset, bacterial spots are detected almost perfectly by all models, with MobileNetV2 reaching a perfect score of 1.00 for all metrics. For healthy leaves, MobileNetV2 also performs perfectly, while ResNet101V2, InceptionV3, InceptionResNetV2, Xception and DenseNet121 give strong results. The VGG models are slightly weaker compared to other models. A detailed summary of these performance metrics is presented in Table 3.

Significance of findings

This section highlights the importance and implications of the research results and explains how the findings contribute to plant disease detection.

DenseNet121 and ResNet101V2 are the best performers overall, especially on the potato dataset. MobileNetV2 is small, fast and accurate, making it both efficient and reliable. The VGG models need more computing power but usually give slightly lower results compared to newer models. ResNet50 is inconsistent, performing poorly on several tasks and needing extra tuning to improve. In the apple and peach datasets, most models perform well, but MobileNetV2 and DenseNet121 are the best choices when both speed and accuracy matter. For the potato dataset, DenseNet121 and ResNet101V2 are the top options, with MobileNetV2 and Xception also performing well. ResNet50 is not a good model for prediction in the case of potato and peach datasets, which need more improvements.

The results show that transfer learning models like DenseNet121, ResNet101V2 and MobileNetV2 can accurately detect plant diseases across different crops. Their strong performance highlights the potential of deep learning for early and automated disease detection, helping farmers make quicker and better decisions to protect crops and improve yield.

CONCLUSION

This paper presents a comparative analysis of plant disease detection in apple, potato and peach leaves using nine transfer learning architectures. The earlier sections describe the theoretical framework and methodology used for the study, which aims to identify the most suitable pretrained model for accurate and efficient plant disease detection. The models evaluated include VGG16, VGG19, ResNet50, ResNet101V2, MobileNetV2, InceptionV3, DenseNet121, InceptionResNetV2 and Xception. Among these, DenseNet121 and ResNet101V2 achieved the highest overall performance, particularly for potato leaves, while MobileNetV2 also produced strong results. The VGG models performed moderately well, whereas ResNet50 showed the least consistent outcomes. For the apple dataset, most models accurately identified apple scab, black rot, cedar apple rust and healthy leaves with nearly perfect accuracy of 99%. In the potato dataset, DenseNet121 and ResNet101V2 reached an average accuracy of 98.5%, while ResNet50 performed the weakest. For the peach dataset, MobileNetV2 achieved 99% accuracy in detecting bacterial spots and healthy leaves, with the VGG models showing slightly lower accuracy. Overall, models like DenseNet121, ResNet101V2, MobileNetV2 and Xception are reliable for detecting plant leaf diseases. These models can help farmers identify diseases early, reduce crop losses and improve farming practices while ResNet 50 is not a good choice for plant disease detection.

Conflict of interest

I would like to declare on behalf of all authors that there are no conflicts of interest regarding the publication of this paper.

REFERENCES

Abd Algani, Y.M., Marquez, C.O.J., Robladillo, B.L.M., Kaur, C., Al Ansari, M.S. and Kiran, B.B. (2023). Leaf disease identification and classification using optimized deep learning. *Measurement: Sensors*. **25:** 100643. https://doi.org/10.1016/j.measen.2022.100643.

Ahmad, A., Saraswat, D. and El Gamal, A. (2023). A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. *Smart Agricultural Technology*. **3:** 100083. https://doi.org/10.1016/j.atech.2022.100083.

Arnal, B.J.G. (2019). Plant disease identification from individual lesions and spots using deep learning. *Biosystems Engineering*. **180:** 96-107. https://doi.org/10.1016/j.biosystemseng.2019.02.002.

Ashmafee, M.H., Ahmed, T., Ahmed, S., Hasan, M.B., Jahan, M.N. and Rahman, A.B.M.A. (2023). An efficient transfer learning-based approach for apple leaf disease classification (arXiv:2304.06520). *arXiv*. https://doi.org/10.48550/arXiv.2304.06520.

Bhargava, A., Shukla, A., Goswami, O.P., Alsharif, M. H., Uthansakul, P. and Uthansakul, M. (2024). Plant leaf disease detection, classification and diagnosis using computer vision and artificial intelligence: A review. *IEEE Access*. **12:** 37443-37469. https://doi.org/10.1109/ACCESS.2024.3373001.

Billa, G.O., Malik, V.S.R., Bharath, E. and Sharma, S. (2024). Grapevine fruits disease detection using different deep learning models. *Multimedia Tools and Applications*. **84(9):** 5523-5548. https://doi.org/10.1007/s11042-024-19036-8.

Chug, A., Bhatia, A., Singh, A.P. and Singh, D. (2023). A novel framework for image-based plant disease detection using hybrid deep learning approach. *Soft Computing*. **27(18):** 13613-13638. https://doi.org/10.1007/s00500-022-07177-7.

Department of Computer Science, Sukkur IBA University, Pakistan., Chohan*, M., Khan, A., Department of Computer Science, Sukkur IBA University, Pakistan., Chohan, R., Department of Computer Science, Shah Abdul Latif University, Khairpur, Pakistan., Katpar, S. H., Department of Computer Science, Sukkur IBA University, Pakistan, Mahar, M.S. and Department of Computer Science, Sukkur IBA University, Pakistan. (2020). Plant disease detection using deep learning. *International Journal of Recent Technology and Engineering (IJRTE)*. **9(1):** 909-914. https://doi.org/10.35940/ijrte.A2139.059120.

Gogoi, M., Kumar, V., Begum, S., Sharma, N. and Kant, S. (2023a). Classification and detection of rice diseases using a 3-stage CNN Architecture with transfer learning approach. *Agriculture*. **13(8):** 1505. https://doi.org/10.3390/agriculture13081505.

Gogoi, M., Kumar, V., Begum, S., Sharma, N. and Kant, S. (2023b). Classification and detection of rice diseases using a 3-stage CNN architecture with transfer learning approach. *Agriculture*. **13(8):** 1505. https://doi.org/10.3390/agriculture13081505.

Haridasan, A., Thomas, J. and Raj, E.D. (2023). Deep learning system for paddy plant disease detection and classification. *Environmental Monitoring and Assessment*. **195(1):** 120. https://doi.org/10.1007/s10661-022-10656-x.

Hossen, M.I., Awrangjeb, M., Pan, S. and Mamun, A.A. (2025). Transfer learning in agriculture: A review. *Artificial Intelligence Review*. **58(4):** 97. https://doi.org/10.1007/s10462-024-11081-x.

Jafar, A., Bibi, N., Naqvi, R.A., Sadeghi-Niaraki, A. and Jeong, D. (2024). Revolutionizing agriculture with artificial intelligence: Plant disease detection methods, applications and their limitations. *Frontiers in Plant Science*. **15:** 1356260. https://doi.org/10.3389/fpls.2024.1356260.

Jain, B. and Periyasamy, S. (2022). Grapes disease detection using transfer learning. *arXiv preprint arXiv.* pp 2208.07647.

Kaur, P., Harnal, S., Gautam, V., Singh, M.P. and Singh, S. P. (2023). A novel transfer deep learning method for detection and classification of plant leaf disease. *Journal of Ambient Intelligence and Humanized Computing*. **14(9):** 12407-12424. https://doi.org/10.1007/s12652-022-04331-9.

Krishna, M.S., Machado, P., Otuka, R.I., Yahaya, S.W., Dos Santos, F.N. and Ihianle, I.K. (2025). Plant leaf disease detection using deep learning: A multi-dataset approach. *J.* **8(1):** 4. https://doi.org/10.3390/j8010004.

Kumari, B.M.K., Sayyad, S., Manjunatha, D. and Sayyad, F. (2025). Prediction of tomato leaf diseases using computational convolution neural network method. *Indian Journal of Agricultural Research*. **59(Special Issue):** 51-57. doi: 10.18805/IJARe.A-6348.

Lu, J., Hu, J., Zhao, G., Mei, F. and Zhang, C. (2017). An in-field automatic wheat disease diagnosis system. *Computers and Electronics in Agriculture*. **142:** 369-379. https://doi.org/10.1016/j.compag.2017.09.012.

Mehta, A.R., Kumar, P., Prem, G., Aggarwal, S. and Kumar, R. (2025). AI-powered Innovations in agriculture: A systematic review on plant disease detection and classification. *Indian Journal of Agricultural Research*. **59(9):** 1321-1330. doi: 10.18805/IJARe.A-6371.

Mohameth, F., Bingcai, C. and Sada, K.A. (2020). Plant disease detection with deep learning and feature extraction using plant village. *Journal of Computer and Communications*. **8(6):** 10-22. https://doi.org/10.4236/jcc.2020.86002.

Mohanty, S.P., Hughes, D.P. and Salathé, M. (2016a). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*. **7:** 1419. https://doi.org/10.3389/fpls.2016.01419.

Mohanty, S.P., Hughes, D.P. and Salathé, M. (2016b). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*. **7:** 1419. https://doi.org/10.3389/fpls.2016.01419.

Ozair, A.W., Umer, Z., Syed, Z.A.S. and Rijwan, K. (2024). Apple Leaf Disease Detection Using Transfer Learning. 2024 International Conference on Integrated Circuits and Communication Systems (ICICACS). https://doi.org/10.1109/icicacs60521.2024.10498746

Panchal, A.V., Patel, S.C., Bagyalakshmi, K., Kumar, P., Khan, I.R. and Soni, M. (2023). Image-based plant diseases detection using deep learning. *Materials Today: Proceedings*. **80:** 3500-3506. https://doi.org/10.1016/j.matpr.2021.07.281.

Peyal, H.I., Shahriar, S.M., Sultana, A., Jahan, I. and Mondol, M.H. (2021). Detection of Tomato Leaf Diseases Using Transfer Learning Architectures: A Comparative Analysis. 2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI), 1-6. https://doi.org/10.1109/ACMI53878.2021.9528199.

Reddy, K.S. and Kumari, K.P. (2026). Fruit Disease detection using ai: A review of classical and deep learning approaches. *Indian Journal of Agricultural Research*. **60(2):** 159-165. doi: 10.18805/IJARe.A-6436.

Sakkarvarthi, G., Sathianesan, G.W., Murugan, V.S., Reddy, A.J., Jayagopal, P. and Elsisi, M. (2022). Detection and classification of tomato crop disease using convolutional neural network. *Electronics*. **11(21):** 3618. https://doi.org/10.3390/electronics11213618.

Sathishkumar, M., Geetha, D.K. and Periyasamy, A. (2022). A survey on tapioca yield prediction and diseases identification using neural networks. *Neuroquantology*. **20(22).** doi: 10.48047/nq.2022.20.22.NQ10180.

Shoaib, M., Shah, B., El-Sappagh, S., Ali, A., Ullah, A., Alenezi, F., Gechev, T., Hussain, T. and Ali, F. (2023). An advanced deep learning models-based plant disease detection: A review of recent research. *Frontiers in Plant Science*. **14:** 1158933. https://doi.org/10.3389/fpls.2023.1158933.

Shree, N.S.V., Subramanian, R. and Basavaraj, G.N. (2025). Transfer learning-based areca nut (*Areca catechu*) disease detection using CNN and SVM approaches with ResNet-50 for improved deep learning performance. *Indian Journal of Agricultural Research*. **59(9):** 1385-1394. doi: 10.18805/IJARe.A-6404.

Srivastava, M. and Meena, J. (2023). Plant leaf disease detection and classification using modified transfer learning models. *Multimedia Tools and Applications*. **83(13):** 38411-38441. https://doi.org/10.1007/s11042-023-16929-y.

Sujatha, R., Krishnan, S., Chatterjee, J.M. and Gandomi, A.H. (2025). Advancing plant leaf disease detection integrating machine learning and deep learning. *Scientific Reports*. **15(1):** 11552. https://doi.org/10.1038/s41598-024-72197-2.

Tugrul, B., Elfatimi, E. and Eryigit, R. (2022). Convolutional neural networks in detection of plant leaf diseases: A review. *Agriculture*. **12(8):** 1192. https://doi.org/10.3390/agriculture12081192.

Upadhyay, S.K. and Kumar, A. (2022). A novel approach for rice plant diseases classification with deep convolutional neural network. *International Journal of Information Technology*. **14(1):** 185-199. https://doi.org/10.1007/s41870-021-00817-5.