



Deep Learning VGG19 Model for Precise Plant Disease Detection

Nikita Kashyap¹, Arun Kumar Kashyap²

10.18805/ag.D-6220

ABSTRACT

Background: Agriculture is very important for human existence since time immemorial. Approximately sixty percent of the world's population is dependent on agriculture and its allied activities. Due to plant diseases every year farmers bear heavy economic loss which can be reduced by having an early detection system for plant disease. Conventional plant disease detection techniques are laborious and based on chemical and analytical testing. In this work, we suggest a deep learning method to precisely detect plant diseases by applying the VGG19 convolutional neural network.

Methods: Modifications specifically designed for the classification of plant diseases were applied to the VGG19 model. By first freezing the bottom layers of the pre-trained VGG19 model-which had been trained on the ImageNet dataset-and then fine-tuning the upper layers to better fit the PlantVillage dataset, transfer learning was used. Resizing, standardization and data augmentation are a few of the image preprocessing approaches that were used to increase the variety of the dataset and boost model performance. The efficacy of the model was assessed through the use of metrics like F1-score, recall, accuracy and precision.

Result: The constructed model performed well in the classification of plant diseases, with over 95% accuracy on the test set. The success of the model in generalizing across different plant disease categories was largely attributed to the application of transfer learning and data augmentation. The findings show that deep learning techniques-in particular, the use of VGG19-can significantly enhance agricultural practices and decision-making processes by helping to quickly and accurately identify plant illnesses. VGG9-based image processing offers an accurate and automated solution for plant disease identification, achieving 98% accuracy in classifying healthy and diseased leaves. By integrating mobile applications, drones and smart farming cameras, farmers can detect diseases early and take timely action, improving crop health and yield. Future advancements in dataset expansion and real-time processing will further enhance its effectiveness in precision agriculture.

Key words: Convolution neural network, Deep learning, Plant disease, Transfer learning, Vgg19.

INTRODUCTION

Plants play a crucial role in the economy and in mitigating climate change. Since the UN General Assembly in 2019 recognized climate change as a global issue, numerous countries, including India, have embarked on initiatives to plant more trees and vegetation to help stabilize the climate. Research has demonstrated that the depletion of the ozone layer, exacerbated by industrial plant extinction, has significantly contributed to global warming. Future climate change is projected to occur at rates 10-100 times faster than the deglacial warming period (Martinelli *et al.*, 2015). Furthermore, the agricultural sector significantly benefits from plants and maintaining a balance in global food production presents a substantial challenge (Bossoet *et al.*, 2016). Plants are also vital in the healthcare industry. Given their importance to human survival, preserving plant health is a global priority. Just as diseases can impact human health, they can also affect plant health. Plant pests and diseases cause annual losses in food, fiber and ornamental crop production worth hundreds of billions of dollars (Singh *et al.*, 2022). While some plant diseases are caused by fungi or fungal-like organisms, others are due to bacteria and viruses, which severely affect food and feed crops. These diseases can spread from plant to plant, making early diagnosis and appropriate treatment crucial. However, detecting plant diseases at an early stage is notably challenging (Burne *et al.*, 2019).

¹Department of Electronics and Communication Engineering, School of Studies of Engineering and Technology, Guru Ghasidas Vishwavidyalaya, Bilaspur-495 001, Chattisgarh, India.

²Department of Biotechnology, Govt. E Raghavendra Rao PG. Science College, Bilaspur-495 001, Chattisgarh, India.

Corresponding Author: Nikita Kashyap, Department of Electronics and Communication Engineering, School of Studies of Engineering and Technology, Guru Ghasidas Vishwavidyalaya, Bilaspur-495 001, Chattisgarh, India.

Email: nikita2010k@gmail.com

ORCID: 00090007907053601, 000000031351832X2.

How to cite this article: 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.

Submitted: 10-10-2024 **Accepted:** 03-04-2025 **Online:** 14-05-2025

Plant disease is a major challenge for farmers and agriculturalists, as it can result in significant crop losses, reduced yields and economic losses (Monigari, 2021). Early detection and accurate diagnosis of plant diseases are crucial for effective management of plant diseases and to prevent their spread (Sankaran *et al.*, 2010). Traditionally, plant disease detection and diagnosis have been done through visual observation by experts, which can be time-consuming and subjective (Patel and Jaliya, 2020).

With growing technologies new advanced biology-based technologies came to existence. Apart from recent biological techniques (Shivappa *et al.*, 2024). In recent years, with the development of advanced technologies, such as machine learning and computer vision, there has been a growing interest in using artificial intelligence techniques for plant disease detection and diagnosis (Ayaz *et al.*, 2019). These techniques can help automate the process of detecting and diagnosing plant diseases, reduce the reliance on human experts and provide more accurate and timely diagnoses in the field itself (Sharma *et al.*, 2024). Artificial intelligence techniques used for plant disease detection and diagnosis typically involve the use of computer vision algorithms to analyze images of plant leaves, stems, or fruits (Anjna *et al.*, 2020). The algorithms can identify patterns and features in the images that are associated with specific diseases and use this information to classify and diagnose the disease. These techniques have shown promising results in detecting and diagnosing a wide range of plant diseases, including fungal, bacterial and viral diseases.

The common symptoms of plant disease which are the basis of plant disease detection include leaf rust (Common leaf rust in corn), stem rust (wheat stem rust), powdery mildew, sclerotinia (white mold), anthracnose (birds-eye spot on berries), phytophthora (damping off seedlings), leaf spot (septoria brown spot) and chlorosis (yellowing of leaves) (Jafar *et al.*, 2024). Most of these symptoms appear in the visual part of crop plants which can be easily detected by examining the aerial part of the crop plants. For traditional disease detection methods large number of human resources are required. In the modern age of technology and automation, traditional methods for identifying plant diseases lack efficiency (Kashyap and Kashyap, 2024). An automated system that can autonomously detect diseases would be significantly more effective (Shoaib *et al.*, 2023).

Convolutional neural networks (CNNs), one of the most recent developments in deep learning, have demonstrated considerable potential in automating the identification of plant diseases through image categorization (Alatawi *et al.*, 2022). CNNs have gained popularity because of their capacity to extract intricate properties from images, which makes them ideal for applications such as the identification of plant diseases (Yang *et al.*, 2024). For example, Mohanty *et al.*, (2016) achieved good accuracy rates even with insufficient training data, paving the way for the implementation of CNNs in this field. Their research demonstrated how deep learning may be used to automate disease detection, greatly lowering the need for specialized expertise and speeding up the diagnostic procedure. Subsequently, Ferentinos (2018) investigated the application of transfer learning in deep learning models for the diagnosis of plant diseases, showing that models that have already been trained-for example, using the ImageNet dataset-could significantly improve classification performance with little need for retraining. With this method, researchers can

enhance model skills in niche applications such as agriculture by utilizing large-scale information.

VGG19, a CNN architecture noted for its simplicity and depth, has been widely applied in several research for plant disease detection. One noteworthy study used photos of healthy and diseased plant pairs to build a disease detection model, using VGG19 and other pre-trained models (Jung *et al.*, 2023). The model successfully classified crops and disease kinds with a high accuracy of 97.09%, demonstrating the efficacy of VGG19 in differentiating between healthy and afflicted plants.

In one study, VGG19 was shown to be effective in differentiating between photos of healthy and diseased plants. After training on a dataset containing a range of plant species, the model achieved an accuracy rate of 95.6%. Using picture preprocessing and augmentation approaches, the researchers trained the model with the help of the PlantVillage dataset. According to their findings, VGG19 is a potent tool for early disease detection and classification in agricultural contexts because of its capacity to capture complex information in plant images (Nishant *et al.*, 2022). A different study that used VGG19 to identify potato illnesses had a 98.7% accuracy rate, which supported similar findings. The resilience of VGG19 for plant disease identification is further supported by the model's performance evaluation, which regularly produces better results when compared to other designs (Ghosh *et al.*, 2023).

Apart from its independent functions, VGG19 has been used to improve model performance when combined with transfer learning methods. One study employed a transfer learning strategy with VGG19 to classify tomato leaf diseases and it achieved an amazing 99.72% accuracy rate. This study highlighted that even with a small amount of training data, models can improve classification performance by utilizing pre-trained weights from big datasets thanks to transfer learning (Nguyen *et al.*, 2022). Even with smaller datasets, researchers can attain excellent classification accuracy by utilizing pre-existing information from larger datasets. Another paper examined several deep learning techniques for identifying plant diseases and emphasized the efficiency of transfer learning using architectures such as VGG19. The study found that by using learned features from large datasets, transfer learning not only shortens training times but also enhances model performance. This is especially helpful in agricultural situations, where it might be difficult to gather big labeled datasets (Liu and Wang, 2021). The architecture of VGG19 and transfer learning methods have worked well together to handle the challenges of plant disease identification.

MATERIALS AND METHODS

The present work was conducted in the Department of Electronics and Communication Engineering, Guru Ghasidas Vishwavidyalaya Bilaspur (C.G.) from January 2024 to July 2024. The procedure begins with the collection

of the dataset, image preprocessing, feature extraction and classification using the Pre-trained Convolutional Neural Network: VGG19. The block diagram of the system is shown in Fig 1.

Database discussion

We have gathered plant images from an open-source database named PlantVillage. The PlantVillage dataset comprises 54,303 photos and 38 classes representing 14 distinct plant species, of which 12 are healthy and 26

Table 1: Dataset Description.

Plant species	Disease condition	Number of images
Apple	Apple scab	630
	Black rot	621
	Cedar apple rust	275
	Healthy	1645
Grape	Black rot	1180
	Esca (Black_Measles)	1383
	Leaf blight	1076
	Healthy	423
Potato	Early blight	1000
	Late blight	1000
	Healthy	152
Tomato	Bacterial spot	2127
	Early blight	1000
	Healthy	1591
Total		14103

are diseased (Hughes and Salathe, 2015). The dataset contains colored pictures of various sizes from multiple categories, each representing a different type of plant disease or healthy leaf condition. The specific categories used in our work include plant species such as apple, grape, potato and tomato. Table 1 provides a description of these specific categories. Sample photos of various leaves from the dataset are shown in Fig 2.

The dataset of 14103 images is split into three sections: one for training, the second for validation and the third for testing. A random ratio is used to split the dataset. 15% (2113 Images) is set aside for the testing dataset, 15% (2113 Images) for the validation dataset and the remaining 70% (9877 Images) is for the training dataset. The dataset splitting is represented in Table 2.

Image preprocessing

Image preprocessing is a crucial step in preparing plant Leaf images from the plantvillage dataset for effective use in detection models. The three main stages of image preprocessing for this dataset typically include: Image Resizing, Segmentation and filtering. All leaf images were resized to 224×224 pixels to ensure uniformity and computational efficiency during model training. This standardization facilitates consistent processing and helps the model learn features efficiently across all images in the dataset.

Image segmentation and preprocessing are essential steps in our effort to improve plant disease detection

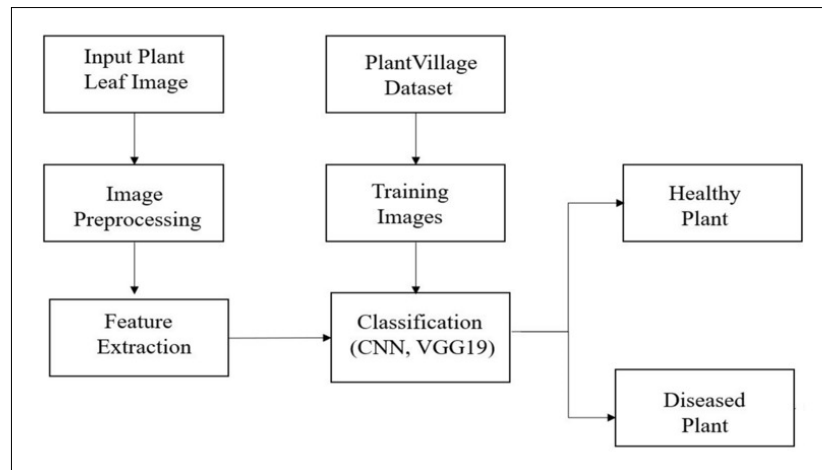


Fig 1: Flow diagram of the proposed method.

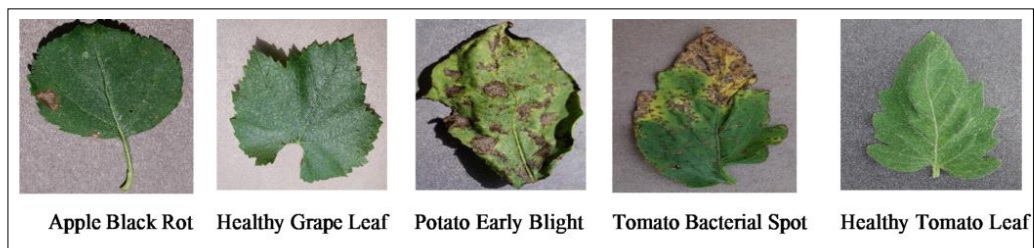


Fig 2: Sample of images from plant village dataset.

accuracy. For segmentation, a well-liked deep learning-based architecture called U-Net is employed. By separating afflicted from healthy areas, it effectively extracts fine-grained information from the input photos, allowing for the accurate localization of plant disease symptoms. The skip connections in U-Net's encoder-decoder architecture allow for efficient feature extraction while maintaining spatial information preservation. Gaussian filtering is used as a preprocessing step in addition to segmentation. By smoothing the images by convolution with a Gaussian kernel and keeping important details while removing extraneous ones, Gaussian filters aid in the reduction of noise in the images. By enhancing the quality of the input photos, this filtering makes sure that the model concentrates on pertinent characteristics for precise disease classification.

Model Architecture: VGG19

The deep learning model that is well-known for its performance in image classification applications is the VGG19 Model. There are 19 layers in the model: 3 fully

linked layers and 16 convolutional layers. It uses layers of small convolution filters (3×3) stacked on top of one another, then max-pooling layers to gradually lower the feature maps' spatial dimensions. VGG19 is used for the task of classifying plant diseases after adjustments are made to the network to make it more suitable for the particular purpose, as described in the Fig 3. An extensive description of how architecture is tailored is provided below.

Pre-trained model on ImageNet

Pre-trained on the massive ImageNet dataset, which has over a million images in 1000 categories, is the VGG19 model. The model can learn generalized features like edges, forms and textures thanks to this pre-training, which is helpful for a variety of image classification applications.

Layer freezing

To preserve the feature extraction skills acquired from the ImageNet dataset, the convolutional layers of the previously trained VGG19 are frozen during the first training phase. These layers concentrate on acquiring low-level properties,

Table 2: Overall dataset splitting.

Plant species	Database images	Training images	Validation images	Testing images
Apple scab	630	442	94	94
Apple black rot	621	435	93	93
Cedar apple rust	275	193	41	41
Healthy apple leaf	1645	1151	247	247
Grape black rot	1180	826	177	177
Grape esca	1383	969	207	207
Grape leaf blight	1076	754	161	161
Healthy grape leaf	423	297	63	63
Potato early blight	1000	700	150	150
Potato late blight	1000	700	150	150
Healthy potato leaf	152	108	22	22
Tomato bacterial spot	2127	1489	319	319
Tomato early blight	1000	700	150	150
Healthy tomato leaf	1591	1113	239	239
Total	14103	9877	2113	2113

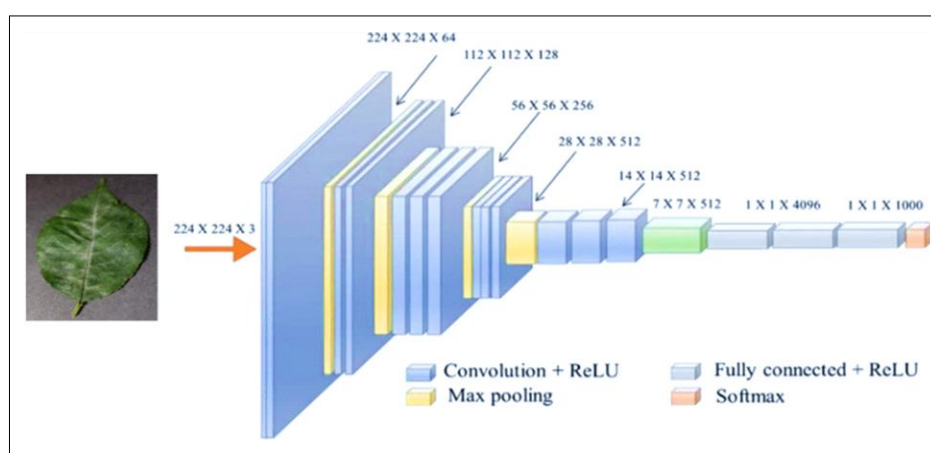


Fig 3: Representation of the VGG-19 architecture used in this research.

which are frequently applicable to other domains, such as photos of plants.

Fine-tuning the final layers

To specialize in the categorization of plant diseases, the fully connected and final convolutional layers are altered. In order to fine-tune the model to adapt its feature extraction to plant-specific features, such as leaf textures, forms and color changes associated with different diseases, it is necessary to unfreeze the final layers and train them on the PlantVillage dataset.

Fully connected layers

A modified structure takes the place of the original completely connected layers in VGG19, which were intended for 1000-class classification in ImageNet. After last convolutional layer, a flatten layer is used to convert the 2D feature maps into a 1D feature vector. Dense Layers are then added to enable the model to acquire intricate representations of the traits associated with plant diseases, along with one or more hidden layers. To mitigate overfitting, the dropout layer which involves randomly removing a certain percentage of neurons during training is inserted in between dense layers. Finally, the Output Layer consists of a fully linked softmax layer with as many nodes as there are classes in the plant disease classification job. The network generates a probability distribution across the disease categories thanks to the softmax activation function.

Activation functions

Except for the output layer, the ReLU activation function is applied after each convolutional and dense layer to add non-linearity. This helps the model discover complex patterns in the data.

Optimizer and loss function

Adam optimizer is used during training because it adjusts the learning rate during training to hasten the model's convergence. The difference between the expected and actual class labels is measured using the categorical cross-entropy loss function, which is minimized during training.

Transfer learning

Transfer learning is used in VGG19 to leverage the pretrained information. Only the fully connected layers of VGG19 are trained on the PlantVillage dataset at first, with the early convolutional layers being frozen. The final few convolutional block layers become unfrozen during training, enabling the network to be fine-tuned on characteristics unique to plant diseases.

Freezing Pre-trained layers

The VGG19 model's initial layers, which capture fundamental characteristics like edges, corners and textures, are frozen. These characteristics are helpful for the process of detecting plant diseases since they are

transferable and general across multiple domains. The model preserves the previously learned weights and avoids needless modification during training on the PlantVillage dataset by freezing these layers.

Fine-tuning higher layers

The higher layers of the model, which capture more task-specific information, are refined after the bottom layers are frozen. The last convolutional and fully connected layers are unfrozen during fine-tuning, which enables the model to pick up domain-specific information on plant illnesses. The reasoning for this is that features at a higher level, like distinct texture patterns or color distributions of diseased leaves, could diverge greatly from the features in the ImageNet dataset and require retraining.

Evaluation metrics

Evaluation of the VGG19 model is conducted on the test set to measure classification performance, utilizing metrics such as accuracy, precision, recall and F1-score by following formulae (Kashyap *et al.*, 2019):

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

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

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

$$\text{F1 Score} = 2 \times \frac{P \times R}{P + R} \quad \dots(4)$$

Where

TP = True positive.

FP = False positive.

TN = True negative.

FN = False negative.

P and R= Precision and recall respectively.

RESULTS AND DISCUSSION

Plant disease detection is crucial these days, as this research demonstrates. The detection model, utilizing pre-trained Convolutional Neural Networks VGG19, has exhibited noteworthy outcomes in its implementation on the Plantvillage datasets. The amalgamation of VGG19 architectures played a pivotal role in empowering the model to extract varied and informative features from plant images, thereby enhancing its capacity to discern distinct leaf conditions. Table 3 shows performance evaluation results for the Model- VGG19.

About 98% correctness is provided by classes like Healthy Apple Leaf, Healthy Potato Leaf and Tomato Bacterial Spot, Healthy Tomato Leaf. Less precision is provided by the Apple Black rot and Grape Esca (Black Measles). Our model's training and validation accuracy graph using the testing dataset is shown in the Fig 4.

The early and accurate identification of plant diseases is crucial for improving crop yield and reducing agricultural losses. Traditional disease detection methods rely on manual inspection, which can be time-consuming, subjective and error-prone (Hemanthakumar *et al.*, 2024). With advancements in deep learning, convolutional neural networks like VGG9 have emerged as powerful tools for automated plant disease identification using image processing techniques. The application of VGG9-based image analysis has demonstrated high accuracy in detecting various plant diseases, making it a promising solution for precision agriculture. In research applications, VGG9 has achieved an accuracy of 98% in classifying plant diseases from leaf images. The model effectively distinguishes between healthy and diseased leaves and further categorizes different disease types, such as powdery mildew, rust, bacterial blight and leaf spot. The deep learning architecture of VGG9, with multiple convolutional layers, enables it to extract detailed texture, color and shape features from leaf images, making it more

reliable than traditional image processing methods. Farmers can utilize VGG9-based mobile applications, drones, or smart farming cameras to capture real-time images of their crops. The model processes these images and provides instant diagnostic results, helping farmers take timely actions such as targeted pesticide application or disease management strategies.

One of the key benefits of using VGG9 for plant disease identification is its ability to work with diverse plant species and disease variations. However, certain challenges need to be addressed for optimal deployment. Variations in lighting conditions, overlapping leaves and image background complexity can affect the model's performance. Additionally, the model requires large and diverse datasets covering different crop varieties, environmental conditions and growth stages to ensure better generalization. Edge computing and cloud-based solutions can help integrate real-time disease detection into farm management systems, allowing farmers in remote areas to access AI-driven insights without needing high-end computing

Table 3: Performance evaluation results.

Category	Accuracy	Precision	Recall	F1 Score
Apple scab	95%	0.94	0.96	0.95
Apple black rot	94%	0.93	0.95	0.94
Cedar apple rust	96%	0.95	0.97	0.96
Healthy apple leaf	98%	0.97	0.97	0.97
Grape black rot	96%	0.95	0.97	0.96
Grape esca	94%	0.93	0.95	0.94
Grape leaf blight	95%	0.94	0.96	0.95
Healthy grape leaf	96%	0.95	0.97	0.96
Potato early blight	96%	0.95	0.97	0.96
Potato late blight	97%	0.96	0.98	0.97
Healthy potato leaf	98%	0.97	0.99	0.98
Tomato bacterial spot	98%	0.96	0.98	0.96
Tomato early blight	97%	0.95	0.96	0.95
Healthy tomato leaf	98%	0.97	0.99	0.98

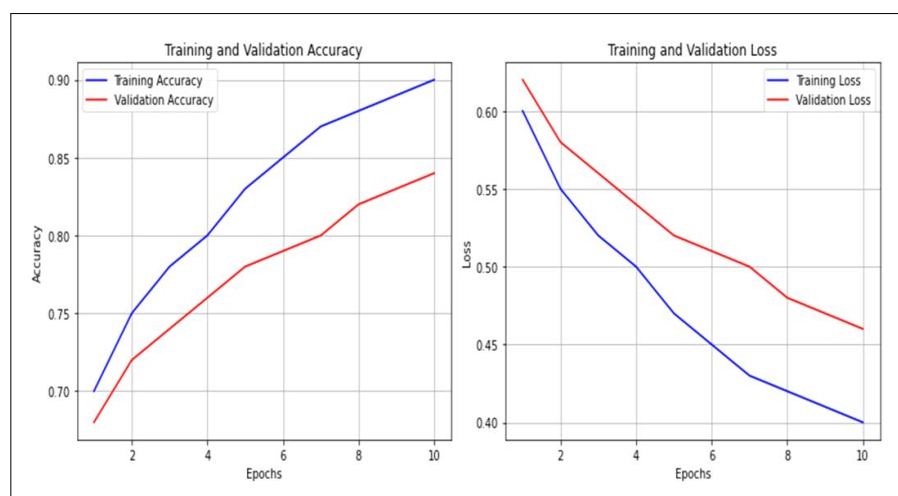


Fig 4: Model loss and accuracy graph for training and validation.

resources. In conclusion, VGG9-based plant disease identification offers a highly efficient, scalable and automated solution for precision agriculture. By integrating this deep learning model with IoT devices, drones and mobile applications, farmers can detect plant diseases early, reduce pesticide overuse and improve overall crop health. Future research should focus on enhancing model robustness, optimizing real-time processing and expanding datasets to ensure effective disease detection across different agricultural landscapes. With continued advancements in AI-driven agriculture, farmers can move towards sustainable and data-driven farming practices, ensuring higher productivity and food security.

CONCLUSION

The utilization of a plant disease detection model employing pre-trained CNN has yielded encouraging outcomes. The model effectively used pre-trained features from the ImageNet dataset and modified them to classify different plant diseases in the PlantVillage dataset by utilizing Transfer Learning. The model's performance was greatly improved by the application of image preprocessing techniques, such as scaling, normalization and data augmentation. This led to an amazing accuracy of over 95% on the test set. These results demonstrate how deep learning techniques may automate and enhance plant disease identification accuracy, giving farmers and other agricultural professionals useful tools. Plant diseases can be identified early and accurately, allowing for prompt interventions that reduce crop loss and promote sustainable farming methods.

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.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish, or preparation of the manuscript.

REFERENCES

- Alatawi, A.A., Alomani, S.M., Alhawiti, N.I., Ayaz, M. (2022). Plant disease detection using AI-based VGG-16 model. *International Journal of Advanced Computer Science and Applications*. 13(4): <http://dx.doi.org/10.14569/IJACSA.2022.0130484>.
- Anjna, K., Kumar, A. and Gupta, R.K. (2020). Deep learning for plant disease detection: A review. *Plant Methods*. 16(1): 1-13. <https://doi.org/10.1186/s13007-020-00661-7>.
- Ayaz, A., Khan, M.A. and Zubair, M. (2019). Automated leaf disease diagnosis using artificial intelligence with IoT sensors methodologies. *Journal of Big Data*. 6(1): 1-15.
- Bosso, L., Russo, D., Febbraro, M. D., Cristinzio, G. and Zoina, A. (2016). Potential distribution of *Xylella fastidiosa* in Italy: A maximum entropy model. *Phytopathologia Mediterranea*. 55: 62-72.
- Burne, A.R. (2019). Pest Risk Assessment: *Halyomorpha halys* (Brown marmorated stink bug). Version 1, June 2019. Ministry for Primary Industries, New Zealand.
- Ferentinos, K.P. (2018). Deep learning models for plant disease detection and classification. *Computers and Electronics in Agriculture*. 145: 311-318.
- Ghosh, H. and Rahat, Irfan and Shaik, Kareemulla and Khasim, S. and Yesubabu, M. (2023). Potato leaf disease recognition and prediction using convolutional neural networks. *ICST Transactions on Scalable Information Systems*. 10.4108/eetsis.3937.
- Hemanthakumar R. Kappali, K.M. Sadyojatha, S.K. Prashanthi (2024). Computer vision and machine learning in paddy diseases identification and classification: A review. *Indian Journal of Agricultural Research*. 58(2): 183-187. doi: 10.18805/IJARE.A-6061.
- Hughes, D.P. and Salathé, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics through machine learning and crowd sourcing. *CoRR*, abs/1511.08060. Available at: <http://arxiv.org/abs/1511.08060>.
- Jafar, B., Bibi, F., Naqvi, S., Sadeghi-Niaraki, A. and Jeong, J. (2024). Plant disease detection methods, applications and their limitations. *Frontiers in Plant Science*. <https://doi.org/10.3389/fpls.2024.1356260>.
- Jung, M., Song, J.S., Shin, A.Y. *et al.* (2023). Construction of deep learning-based disease detection model in plants. *Sci Rep*. 13: 7331. <https://doi.org/10.1038/s41598-023-34549-2>.
- Kashyap, N., Kashyap, A.K. (2024). Artificial intelligence for plant disease detection. *Shodha Prabha*. 49(1): 85-96.
- Kashyap, N., Singh, D.K., Singh, G.K. (2019). Color Histogram and Smartphone-based Diabetic Retinopathy Detection System. In: *Engineering Vibration, Communication and Information Processing*. [K. Ray, S. Sharan, S. Rawat, S. Jain, S. Srivastava and A. Bandyopadhyay (Eds.)], Springer, Singapore. https://doi.org/10.1007/978-981-13-1642-5_58. pp 478-483.
- Liu, J., Wang, X. (2021). Plant diseases and pests detection based on deep learning: A review. *Plant Methods*. 17: 22. <https://doi.org/10.1186/s13007-021-00722-9>.
- Martinelli, F., Scalenghe, R., Davino, S., Panno, S., Scuderi, G., Ruisi, P., Villa, P., Stroppiana, D., Boschetti, M., Goulart, L.R., Davis, C.E., Dandekar, A.M. (2015). Advanced methods of plant disease detection: A review. *Agronomy for Sustainable Development*. 35(1): 1-25. <https://doi.org/10.1007/s13593-014-0246-1>.
- Mohanty, S.P., Hughes, D.P. and Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*. 7: 1419. doi:10.3389/fpls.2016.01419.
- Monigari, V. (2021). Plant leaf disease prediction. *International Journal of Research in Applied Science and Engineering Technology*. 9(7): 1295-1305. <https://doi.org/10.22214/ijras.2021.36582>.
- Nishant, S., Suraj, S., Shubham, S., Shreyash, D. and Kausar F. (2022). Plant disease detection using CNN. *ITM Web of Conferences*. 44: 03049 ICACC-2022.

- Nguyen, Thanh-Hai, Thanh-Nghia Nguyen and Ba-Viet Ngo. (2022). A VGG-19 model with transfer learning and image segmentation for classification of tomato leaf disease. *Agri Engineering*. 4(4): 871-887.
- Patel, S., Jaliya, P. (2020). A survey on plant leaf disease detection. *International Journal of Modern Trends in Science and Technology*. 6(5): 129-134.
- Sankaran, S., Mishra, A., Ehsani, R., Davis, C. (2010). A review of advanced techniques for detecting plant diseases. *Computers and Electronics in Agriculture*. 72(1): 1-13.
- Sharma J., Lager P., Yogesh Kumar (2024). Techniques for detection and diagnosis of plant Viruses: A review. *Agricultural Reviews*. 45(2): 274-281. doi: 10.18805/ag.R-2378.
- Shoaib, M., Shah, B., El-Sappagh, S., Ali, A., Ullah, A., Alenezi, F., Gechev, T. (2023). An advanced deep learning models-based plant disease detection: A review of recent research. *Frontiers in Plant Science*. 14: 1282443.
- Shivappa, M., Metagar, Gyanappa A. Walikar (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.
- Singh, M., Rajesh, K., Rana, Sarang Monga, Rajbir Singh (2022). Organic and natural farming- A critical review of challenges and prospects. *Bhartiya Krishi Anusandhan Patrika*. 37(4): 295-305. doi: 10.18805/BKAP569.
- Yang, Y., Yang, Y., Liu, X. and Zhang, J. (2024). A novel plant type, leaf disease and severity identification framework using CNN and transformer with multi-label method. *Scientific Reports*. 14: 11664.