Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 05, May-2025

# Deep Learning Architectures for Late Blight and Early Blight Disease Detection on Potatoes

Samiksha Madan More
Assistant Professor Department of Computer Science and Engineering

Manjiri Virendrasinh Shisode
Lecturer Department of Computer Science and Engineering

Virendrasinh Udaysinh Shisode
Lecturer, Electronics and Telecommunications, CSMSS College of Polytechnic

G.M. Solanke
Assistant Professor at Department of Technology, Shivaji University, Kolhapur, Maharashtra, India

***Abstract***
**Potato is the fourth largest agricultural food crop after rice, wheat and maize. However, a large part of potato crop becomes spoiled due to diseases. In an early stage potato leaf disease detection is challenging because of variations in crop species, crop disease symptoms and environmental factors. Early detection of potato leaf diseases becomes difficult by such factors. Therefore, the manual diagnosis of these diseases becomes very challenging. Automatic potato leaf disease classification can be helpful in improving the quantity and quality of the crop yield. It may also be a helpful tool for pricing and crop quality evaluation. Numerous machine learning methods have been developed to identify diseases of the potato leaf. In this paper a deep convolutional neural network model is implemented to identify and diagnose diseases in potato plant from their leaves. At the first stage a novel potato leaf disease classification has been developed using a convolutional neural network to detect the early blight and late blight potato diseases. The proposed method was trained and tested on the PlantVillage dataset with more than 14000 images and less resources and with data augmentation techniques. The proposed method has a high testing accuracy of 98.83% with a good training accuracy of 96.88%. It had a minimal number of parameters i.e. 314,819 and was simpler than the state-of-the-art methods, saving a substantial computational cost and speed. In comparison with VGG16 and InceptionV3, accuracy is improved. Therefore, the proposed techniques can be used as a good tool for potato leaf disease detection.**

*Keywords:* **Potato disease classification, Deep learning, Crop health, Convolutional Neural Network, Transfer learning**

## 1. INTRODUCTION

Across the world, potato is the fourth largest agricultural food crop after rice, wheat and maize. India produces 48.5 million tons of potatoes annually and rank 2nd largest country in the production of potato. Potato is grown almost in all states of India. However, the major potato growing states are Himachal Pradesh, Punjab, Uttar Pradesh, Madhya Pradesh, Gujarat, Maharashtra, Karnataka, West Bengal, Bihar and Assam. According to the Agricultural and Processed Food Products Export Development Authority (APEDA), Uttar Pradesh is the nation's top producer of potatoes, contributing more than 30.33% of the nation's total output [1]. The nutrients potassium, vitamins C and B6, and fibber are abundant in potatoes.The Food and Agriculture Organization Report (FAO) projects that by 2050, there will be about 9.1 billion people on the planet. Approximately 70% of the expansion in food production is needed to provide a stable food supply.

Plant diseases may be diagnosed using a variety of techniques, one of the most common and simple being visual estimate. Traditional methods of identifying plant diseases rely primarily on the experience of farmers, which is very unpredictable and inaccurate.

In contrast to traditional methods for identifying plant diseases, the researchers havedeveloped a spectrometer th at allows them to distinguish between healthy and diseased plant leaves. [3] Another technique is to use the polymerase chain reaction [4], or real-time polymerase chain reaction [5], to extract the DNA from the leaves. The development of automated plant leaf disease detection systems is made possible by recent advancements in

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 05, May-2025

Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision (CV) technology. Without human assistance, these methods may quickly and effectively identify illnesses of the plant leaves. It has been noted that the most common application of DL has been in agriculture [6]. It helps in the significant efforts made to encourage, control, and improve agricultural production.

On the other hand, deep learning is the core of smart farming by adopting new devices, technologies, and algorithms in agriculture [7]. Deep learning is a popular method for solving challenging issues including image categorization, feature extraction, transformation, and pattern analysis [8]. Many researchers utilized deep learning techniques for identifying crops diseases [9-11].

Recently, many varieties of deep learning architecture have been presented recently for the categorization of plant diseases. Convolutional Neural Network is the most prominent technique. A Convolutional Neural Network is a supervised deep learning model inspired by the biological nervous system and vision system which performs noticeably better than previous models. As compare to the Artificial Neural Network (ANN), CNN requires a larger training dataset than an ANN, but it requires fewer neurons and multilayer convolution layers to learn the features [12-13].

## 2. RELATED WORKS

The implementation of proper techniques to identify healthy and diseased leaves helps in controlling crop loss and increase productivity. This section includes many existing machine learning techniques for the identification of plant diseases.

### 2.1 Identification Based on Shape and Texture

In [14] the authors identified three different soybean diseases using different colour and texture features. [15] identified diseases using tomato leaf images. They used different histogram based and geometric features from segmented diseased portions and applied an SVM classifier with different kernels. [16] They introduced a method name as Bacterial Foraging optimization based on Radial Basis Function Neural Network (BRBFNN) for identification and classification of plant leaf diseases automatically. In [17] used a feed-forward neural network and back propagation to identify plant leaves diseases.

### 2.2 Identification Based on Deep Learning

In [18], the authors used Alexnet and GoogleNet CNN architectures in the identification of 26 different plant diseases. [19] used different CNN architectures for the identification of 58 different plant diseases, the authors reported high levels of classification accuracy. They also tested on real-time images. [20] Used Caffe DL framework to perform CNN training and designed a DL architecture to identify 13 different plant diseases. In [22], the authors proposed a nine-layer model to classify plant diseases. They utilized the PlantVillage dataset and data-augmentation methods to expand the data size for testing, and they performed performance analysis. The accuracy reported by the authors was superior to that of a conventional machine-learning-based method.

[24] authors identified 10 different diseases in plants using six different pre-trained network (AlexNet, VGG16, VGG19, GoogLeNet, ResNet101 and DenseNet201) and they achieved the highest accuracy rate of 97.3% using GoogleNet. Performance was assessed using four different colour spaces: RGB, HSV, YCbCr, and grayscale. When utilizing RGB pictures, the best classification accuracy of 99.4% was attained. In [26] applied deep forest technique to classify maize leaf diseases from healthy leaves. Using a variety of deep-forest hyperparameters related to the quantity of trees, forests, and grains, they examined their method and contrasted the outcomes with conventional machine-learning models including SVM, RF, LR, and KNN. [27] examined several deep-learning architectures for the purpose of identifying plant diseases. [28] applied a transfer-learning-based strategy on pretrained deep-learning models to increase the model's accuracy.

In addition to working on potato crop diseases, a large number of researchers trained their models using the PlantVillage dataset. [29] Proposed a Feed-Forward Neural Network (FFNN) to detect early blight, late blight diseases along with healthy leaves. [30] Proposed a self-build CNN (SBCNN) model to detect the potato leaf diseases. [31] developed a CNN methodology to classify early blight, late blight disease of potato and a healthy class. They trained a model on PlantVillage dataset to detect diseases of specific region. [1] utilized a pre-trained model, VGG19, to extract the features, and used different classifiers, including neural networks, KNNs, and SVMs, were employed for classification. Lee [32] proposed a CNN model to identify early and late blight diseases and healthy leaves of potato. Islam [33] developed a segment-based and multi-SVM-based model to detect potato diseases, namely early blight, late blight and healthy leaves. Their model also used the PlantVillage dataset and also needs to be improved in terms of accuracy.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 05, May-2025

## 3. DEEP LEARNING FOR IMAGE CLASSIFICATION

In this section, we briefly explain two most popular architectures for image classification namely VGG16 and InceptionV3. These architectures have been primarily used for object recognition tasks in images. However, they are sufficient at other tasks, such as video classification, semantic segmentation, region of interest extraction, image indexing and retrieval, etc., with the help of transfer learning and tuning parameters. In the experimental findings we used VGG16 and InceptionV3 for potato disease classification. We will give a quick description of each here.

### 3.1 Dataset

To generalize the proposed model, it was trained on the PlantVillage [35] dataset. The database consisted of JPG colour images with 256 × 256 dimensions. It had 38 classes of diseased and healthy leaves of 14 different plants. The focus of this research was on the potato crop only. Therefore, 1000 leaves for late blight, 1000 leaves for early blight and 152 images of healthy leaves were selected for the experiment. Then the dataset was divided into 80%, 10% 10% ratios for train, validation and test sets.

### 3.2 VGG16 deep learning architecture

VGG16 is a convolutional neural network is also known as a ConvNet which is a kind of artificial neural network. A convolutional neural network has an input layer, an output layer, and various hidden layers. This architecture consisting of 16 layers. These layers fall under different categories including convolutional layers, Max Pooling layers, Activation Layers and fully connected layers. The 16 in VGG16 refers to16 layers that have weights. In VGG16 there are 13 convolutional layers, 5 max pooling layers and 3 dense layers, total 21 layers. A soft-max classifier follows two completely connected layers, each with 4096 modes. On the other hand, VGG16 has 140 million parameters.

The pre-trained VGG16 model has been trained on a very large image dataset (ImageNet) and can be used as a transfer learning model to solve similar problems in image recognition as shown in Fig.1.

### 3.3 InceptionV3

InceptionV3 is Convolutional Neural Network that is 48 layers deep that makes several improvements including using label Smoothing, factorized 7x7 convolutions, and use of an auxiliary classifier. The Inception V3 also used batch normalization for layers in the side head. The architecture of InceptionV3 has been shown in Fig. 2. In the InceptionV3 model, there are total 24 million parameters. Out of which, there are trainable 55,299 and 21,802,784 non trainable parameters.

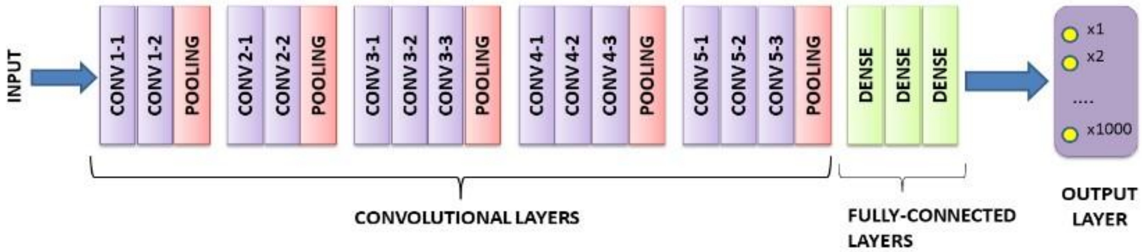


Fig. 1 VGG16 Layer Architecture

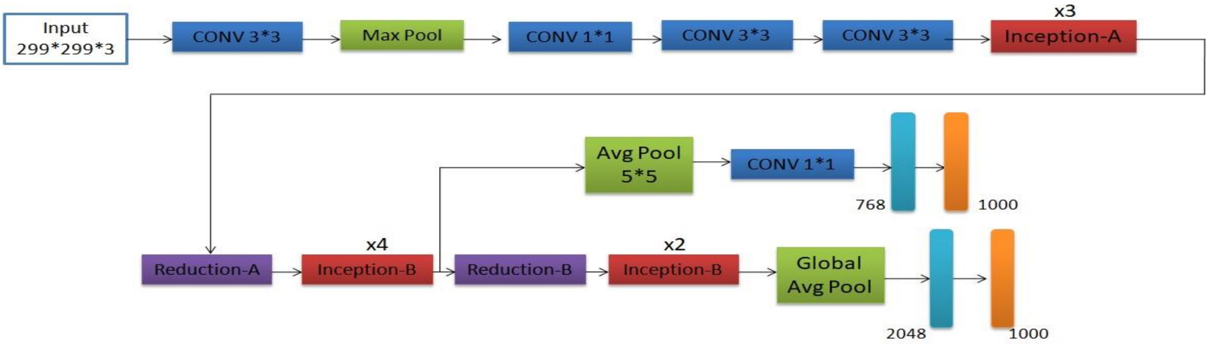


Fig. 2 Inception V3 Layer Architecture

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 05, May-2025

### 3.4 Proposed Model

By using the intuition of above two models our proposed model is shown below. The Fig. 3 shows the schematic flow diagram of the proposed model. First we apply training input data to our proposed model. The input volume and weights were convolved throughout the convolution process. Depending on the padding and stride, the convolved matrix might expand. In the backward pass, the model's weights, or parameters, are adjusted in order to back propagate the error that is computed using the expected and predicted values. The training process is repeated over a finite number of iteration called epochs. The model is transferred to the disk and its accuracy is recorded once training is finished.

Fig. 4 shows the architecture of proposed deep learning model for potato leaf disease classification. These proposed model consist of total 9 layers out of these 6 are convolutional and 3 are fully connected layers (dense layers). Convolution, pooling, and regularization operations performed at various stages of a signal processing pipeline can make convolutional neural networks an effective tool for handling image classification challenges. We used an RGB picture with 256 × 256 pixels as input for training. The convolutional layer of the model has a 3x3 kernel size. Max pooling is a technique commonly used in CNN for reducing the special dimensions of an input feature map. The proposed model has been trained over more than 14 thousand images of potato leaf diseases. Eventually, the trained model accepts an image and can label with disease class. Or with healthy if it matches with this class. The activation functions used in the convolutional layer are ReLU (Rectified Linear Unit) and Leaky ReLU. The activation function used in the dense layers is ReLU.

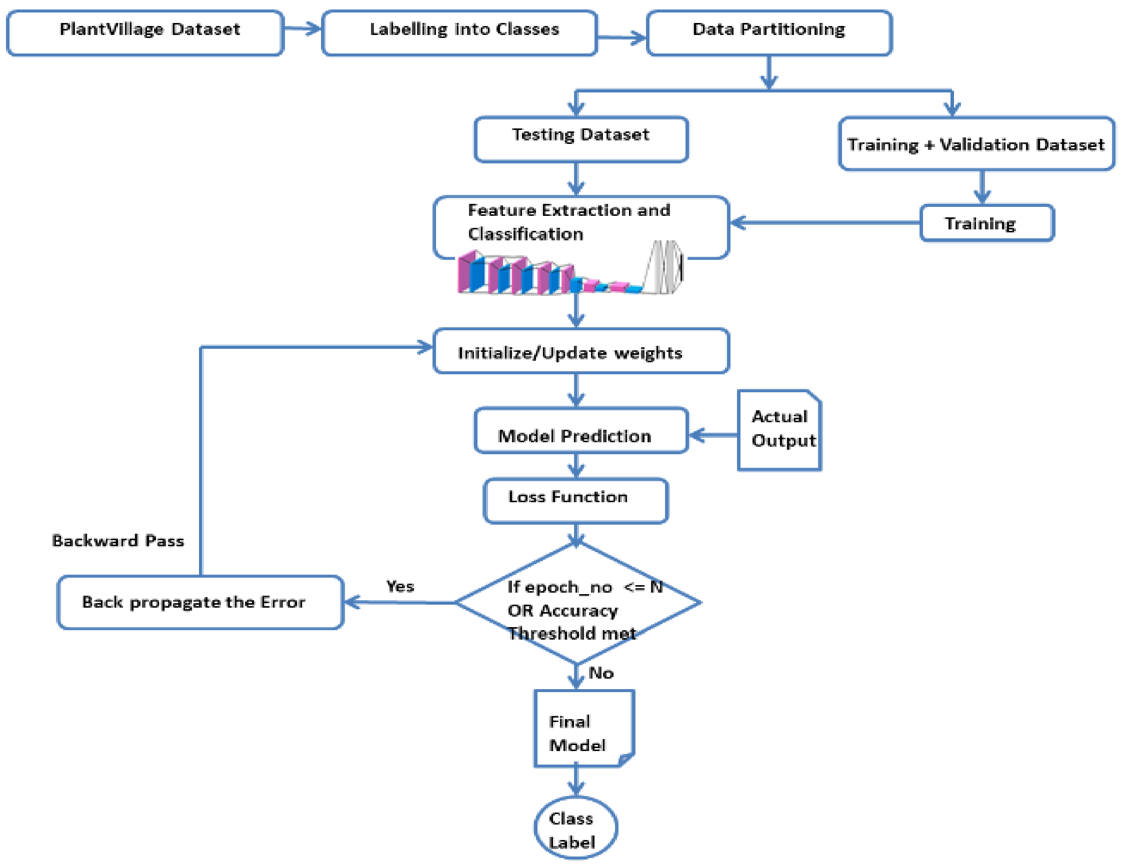


Fig. 3 Flow diagram of the proposed model

There are three fully connected layers which are then followed by a SoftMax classifier and dropout (0.2). The optimizer used is Adam. The convolutional stride used is of one pixel. The width of the network begins at an estimation of 32 and increases by a factor of two after each pooling layer. The proposed architecture learns around 3,14,819 parameters. Only the convolution layers and the fully connected layers have trainable weights. The input image has been reduced using the max pooling layer, and SoftMax is used to determine the final result. The convolution and pooling layers help in feature identification, while the dense layers for learning and prediction follow next. Nodes in each layer train using the output from the layer before it. As a result, nodes in successive layers are capable of to identify characteristics that are becoming complex and detailed.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 05, May-2025

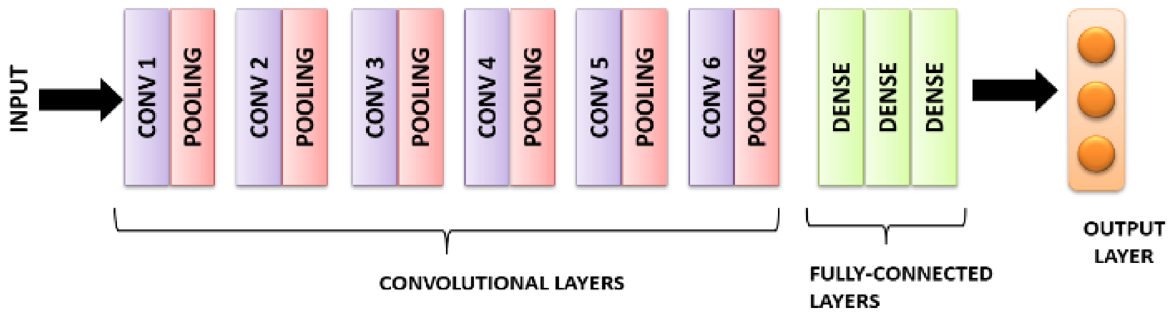


Fig. 4 The Architecture of Proposed Deep Learning Model

There are three fully connected layers which are then followed by a SoftMax classifier and dropout (0.2). The optimizer used is Adam. The convolutional stride used is of one pixel. The width of the network begins at an estimation of 32 and increases by a factor of two after each pooling layer. The proposed architecture learns around 3, 14,819 parameters. Only the convolution layers and the fully connected layers have trainable weights. The input image has been reduced using the max pooling layer, and SoftMax is used to determine the final result. The convolution and pooling layers help in feature identification, while the dense layers for learning and prediction follow next. Nodes in each layer train using the output from the layer before it. As a result, nodes in successive layers are capable of to identify characteristics that are becoming complex and detailed.

## 4. RESULTS AND DISCUSSION

The proposed model experiments were implemented using the Keras open source libraries, Tensor-Flow framework and Python programming language. Experiments were carried out on a computer having an Intel i3, 4GB RAM and windows 10 operating system. The network was trained up to 25 epochs. It utilised the Adam optimizer with default learning rate, 32 batch size and sparse categorical cross-entropy loss function for training. The entire training process completed around 7 to 8 hours.

The results of the proposed model focused on:

1. Differentiating the potato leaf images into early blight, late blight, or healthy.
2. The PlantVillage dataset using data augmentation and without data augmentation techniques on the training set.
3. Measured the performance of the proposed model by using confusion matrix.
4. To compare & evaluate the results with other state-of-the-art methods, such as VGG16 [36], InceptionV3 using the transfer learning.

### 4.1 Performance of Proposed Model on PlantVillage Dataset

The experiments were conducted to evaluate the performance of the proposed model. In the first of experiments, we applied groups of data augmentation techniques to the PlantVillage dataset's training set. Secondly all experiments used the Adam optimiser, sparse categorical cross-entropy loss function, 32 batch size, 25 epochs and the default learning rate. It confirmed that, as we increased the training samples using more data augmentation techniques, the accuracy also increased. At last, the dataset containing 2152 images was used for training and testing the proposed model. Furthermore, the size of the augmented dataset is more than 14000 images.
The following Table 2 shows all classes with the number of augmented images for each class that were used by the disease identification model. By using Data augmentation, we achieved the highest accuracy because we increased the training samples using the seven data augmentation techniques. The results showed that the proposed model required a vast amount of training samples for training.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 05, May-2025

**Table 2 classes with the number of augmented images**

| Data Augmentation Used | No of Images | | |
|---|---|---|---|
| | Early Blight | Healthy | Late Blight |
| horizontal_flip, vertical_flip, | 2000 | 250 | 2000 |
| width_shift_range, height_shift_range, | 2000 | 250 | 2000 |
| rotation_range, | 1000 | 125 | 1000 |
| shear_range, | 1000 | 125 | 1000 |
| zoom_range, | 1000 | 125 | 1000 |
| **Total** | **7000** | **875** | **7000** |

Table 3 showed the results achieved in data augmentation techniques achieved. It attained 98.83% average accuracy on the PlantVillage datasetThe results showed that the proposed method achieved excellent identification rates on the PlantVillage dataset using the data augmentation techniques applied to the training set.

**Table 3 Classification accuracies, precision, recall and F1-Score of the proposed PoLeD CNN model**

| | Performance Measures | Early Blight | Late Blight | Healthy | Average |
|---|---|---|---|---|---|
| **With Data Augmentation** | **Accuracy** | 97.49% | 96.89% | 95.23% | 98.83% |
| | **Precision** | 99% | 99% | 97% | - |
| | **Recall** | 97% | 99% | 99% | - |
| | **F1-Score** | 99% | 99% | 99% | - |
| **Without Data Augmentation** | **Accuracy** | 92.87% | 85.47% | 93.25% | 91.23% |
| | **Precision** | 88% | 94% | 90% | - |
| | **Recall** | 94% | 85% | 89% | - |
| | **F1-Score** | 95% | 92% | 94% | - |

The proposed method is further examined by calculating the test set's precision, recall and F1-score. It also observed that the proposed model's performance achieved excellent results using the data augmentation techniques applied to the training set of the PlantVillage dataset, as shown in Table 2. The Table 3 demonstrated that the proposed model achieved 99%, 99% and 97% precision scores on early blight, healthy and late blight and attained 97%, 99% and 99% recall scores on early blight, healthy and late blight. The proposed model achieved 99%, 99%, 99% F1-scores on early blight, healthy and late blight. The results showed excellent performance on all the classes. Fig 6 shows the accuracy and loss plot of VGG16 on PlantVillage dataset.

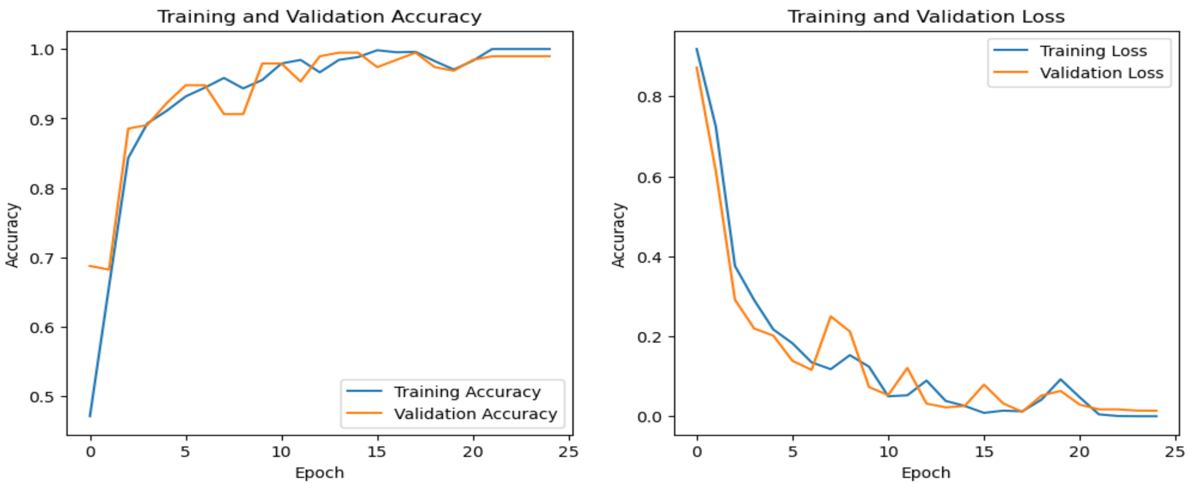


Fig. 5 (a) Accuracy and Loss graph of proposed model on PlantVillage using data augmentation

In Table 4 the proposed approach's performance is compared to that of three standardized models. The results show that the proposed model outperforms the other classical models having total parameter which is less than the other two models and added extra layer in the model. Fig 7 shows the accuracy and loss plot of Inception V3 on PlantVillage dataset.

Table 4 Accuracies Comparison of Proposed Method with different model

| Sr. No. | Model | Accuracy Rate | Total Params | Training Params | Non-Trainable Params |
|---|---|---|---|---|---|
| 1. | VGG16 | 79.52 | 14,789,955 | 75,267 | 14,714,688 |
| 2. | Inception V3 | 64.25 | 21,858,083 | 55,299 | 21,802,784 |
| 3. | Proposed PoLeD CNN | 98.83 | 314,819 | 314,819 | 0 |


**Fig. 5 (b) Accuracy and Loss graph of proposed model on PlantVillage without using data augmentation**

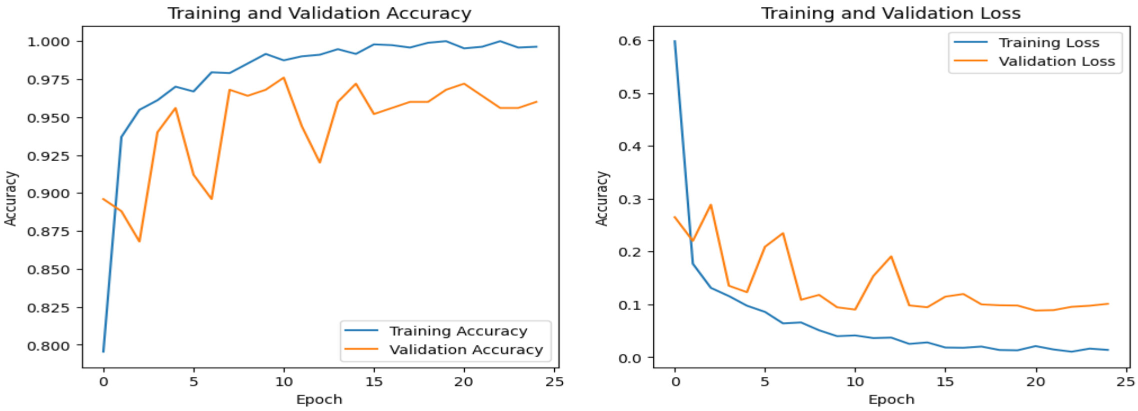


**Fig. 6 Accuracy and Loss graph of VGG16 on PlantVillage Dataset**

4.2 Comparison with the other State-of-the-Art Methods

To evaluate the performance of the proposed model, we performed transferred learning on VGG16 and InceptionV3 models with the proposed model on PlantVillage dataset. For purpose, we have made sure; the experiments had the same setup and same data augmentation techniques. Table 4 shows the accuracy achieved by the state of the art deep learning techniques. The VGG16 model achieved 79.52 % accuracy InceptionV3 gained 64.25% accuracy and the proposed model accomplished 98.83% accuracy on the PlantVillage dataset. The performance demonstrates that the proposed model achieved the highest accuracy 98.83% and InceptionV3 carried off the worst accuracy (64.25%). The proposed model has less training parameters than the VGG16 and InceptionV3. The state-of-the-art models had a large number of training parameters as compared to the proposed model i.e. 14,789,955 and 21,858,083 parameters for VGG16 and InceptionV3 model respectively as presented in Table 4. In contrast, the proposed model had only 314,819 parameters which saved a lot of computational costs and needed less time to train the model than the state-of-the-art models. The proposed model had fewer convolutional layers, and fewer layers mean fewer parameters and less computational cost.

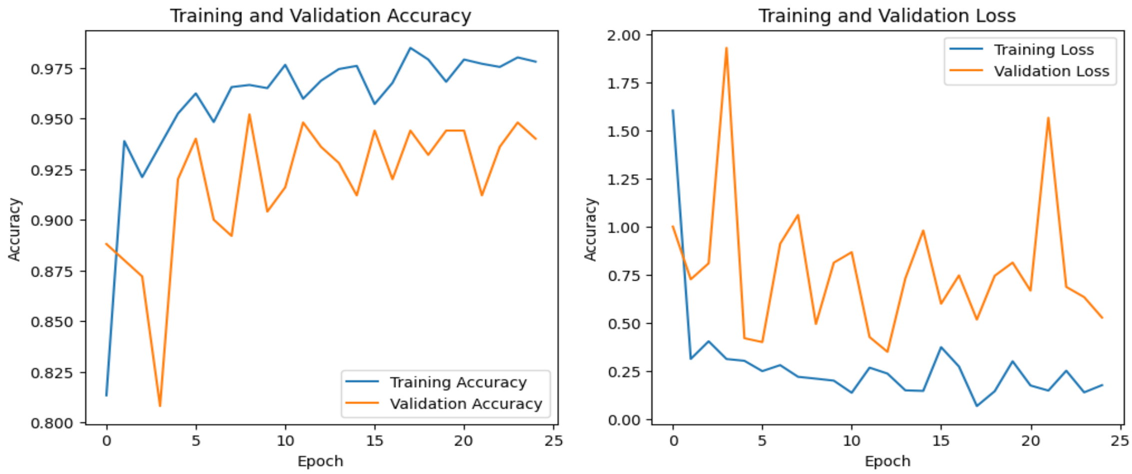


**Fig. 7 Accuracy and Loss graph of InceptionV3 on PlantVillage Dataset**

4.2 Comparison with the other State-of-the-Art Methods

To evaluate the performance of the proposed model, we performed transferred learning on VGG16 and InceptionV3 models with the proposed model on PlantVillage dataset. Table 4 shows the accuracy achieved by the state of the art deep learning techniques. The VGG16 model achieved 79.52 % accuracy InceptionV3 gained 64.25% accuracy and the proposed model accomplished 98.83% accuracy on the PlantVillage dataset. The performance demonstrates that the proposed model achieved the highest accuracy 98.83% and InceptionV3 carried off the worst accuracy (64.25%). The proposed model has less training parameters than the VGG16 and

InceptionV3. The state-of-the-art models had a large number of training parameters as compared to the proposed model i.e. 14,789,955 and 21,858,083 parameters for VGG16 and InceptionV3 model respectively as presented in Table 4. In contrast, the proposed model had only 314,819 parameters which saved a lot of computational costs and needed less time to train the model than the state-of-the-art models. The proposed model had fewer convolutional layers, and fewer layers mean fewer parameters and less computational cost.

4.3 Accuracies Comparison of Proposed Method with Existing Studies
To represent the proposed approach's generalization, we had compared the proposed techniques performance with the state-of-the-art models, as exhibited in Table 5. The proposed model performance was compared to the existing potato leaf disease detection techniques from the literature. The results showed that the proposed method achieved the highest accuracy 98.83% compared to others as shown in Table 5. The proposed model outperformed the existing studies as [1] achieved 97.80% accuracy, but pre-trained models were employed having a large number of trainable parameters, i.e., 143,667,240. [37] reported 98.00% accuracy possessing 14 layers' architecture with higher computational cost. [32] performed 99.00% accuracy, but it had 10,089,219 trainable parameters and used the PlantVillage dataset, which possesses imbalanced classes and a smaller number of parameters. The proposed model achieved 98.83% accuracy with fewer parameters, i.e., 314,819, leading to a lower computational cost and the highest accuracy compared to existing models.

**Table 5 Comparison with existing studies**

| **Existing Study** | **Total Parameters** | **Accuracy** |
|---|---|---|
| Sanjeev *et al.,* | - | 96.50% |
| Tiwari *et al.,* | 143,667,240 | 97.80% |
| Khalifa *et al.,* | - | 98.00% |
| Lee *et al.,* | 10,089,219 | 99.00% |
| Rashid *et al.,* | 8,578,611 | 99.75% |
| PoLeD CNN | 314,819 | 98.83% |

## CONCLUSION

Deep learning techniques perform significantly in plant leaf disease detection to improve crop productivity and quality by controlling the biotic variables that cause severe crop yield losses**.** However, there is still no effective commercial solution that can be used to identify the diseases. In our work, a fast and straightforward deep learning model for potato leaf disease recognition was proposed to classify the potato leaves diseases. The proposed model performed significantly well on the potato leaf images collected from open access PlantVillage dataset, with and without augmentation. The proposed model performance was compared with the state-of-the-art techniques, and existing studies were used for potato leaf disease detection. The proposed method was trained on the PlantVillage dataset with more than 14000 images and less resources and with data augmentation techniques, with a good training accuracy of 96.88 %, whereas the average testing accuracy is reported to be 98.83 %, high precision, recall and F1-score. It had a minimal number of parameters i.e. 314,819 and was simpler than the state-of-the-art methods, saving a substantial computational cost and speed. In comparison with VGG16 and Inception V3, accuracy is improved. Therefore, the proposed techniques can be used as a good tool for potato leaf disease detection.

## REFERENCES

1. Tiwari, D., Ashish, M., Gangwar, N., Sharma, A., Patel, S., & Bhardwaj, S. (2020). Potato Leaf Diseases Detection Using Deep Learning. Proceedings of the International Conference on Intelligent Computing and Control Systems, ICICCS 2020, 461–466.
2. Sasaki, Y. Okamoto, T. Imou, K. Torii, T. (1998). Automatic diagnosis of plant disease Spectral reflectance of healthy and diseased leaves. IFAC Proc. 31, 145–150.
3. Henson, J.M.; French, R. (1993). The polymerase chain reaction and plant disease diagnosis. Annu. Rev. Phytopathol. 31, 81–109.
4. Koo, C.; Malapi-Wight, M.; Kim, H.S.; Cifci, O.S.; Vaughn-Diaz, V.L.; Ma, B.; Kim, S.; Abdel-Raziq, H.; Ong, K.; Jo, Y.K.; (2013). Development of a real-time microchip PCR system for portable plant disease diagnosis. PLoS ONE, 8, e82704.
5. Singh, U.P. Chouhan, S.S. Jain, S.Jain, S. (2019) Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease. IEEE Access, 7, 43721–43729.
6. Ferentinos, K.P. (2018) Deep learning models for plant disease detection and diagnosis. Comput. Electron. Agric., 145, 311–318.
7. Aamir, M.; Irfan, M.; Ali, T.; Ali, G.; Shaf, A.; S, A.S.; Al-Beshri, A.; Alasbali, T.; Mahnashi, M.H. An Adoptive Threshold-Based Multi-Level Deep Convolutional Neural Network for Glaucoma Eye Disease Detection and Classification. Diagnostics 2020, 10, 602
8. Chen, S.W.; Shivakumar, S.S.; Dcunha, S.; Das, J.; Okon, E.; Qu, C.; Taylor, C.J.; Kumar, V. Counting apples and oranges with deep learning: A data-driven approach. IEEE Robot. Autom. Lett. 2017, 2, 781–788.

ISSN: 2278-0181
Vol. 14 Issue 05, May-2025

9. Ubbens, J.; Cieslak, M.; Prusinkiewicz, P.; Stavness, I. The use of plant models in deep learning: an application to leaf counting in rosette plants. Plant Methods 2018, 14, 6.
10. Dias, P.A.; Tabb, A.; Medeiros, H. Multispecies fruit flower detection using a refined semantic segmentation network. IEEE Robot. Autom. Lett. 2018, 3, 3003–3010.
11. Golhani, K. Balasundram, S.K. Vadamalai, G. Pradhan, B. (2018) A review of neural networks in plant disease detection using hyperspectral data. Inf. Process. Agric 5, 354–371.
12. Aamir, M.; Irfan, M.; Ali, T.; Ali, G.; Shaf, A.; S, A.S.; Al-Beshri, A.; Alasbali, T.; Mahnashi, M.H. An Adoptive Threshold-Based Multi-Level Deep Convolutional Neural Network for Glaucoma Eye Disease Detection and Classification. Diagnostics 2020, 10, 602
13. Kaur, S.; Pandey, S.; Goel, S. Semi-automatic Leaf Disease Detection and Classification System for Soybean Culture. IET Image Process. 2018, 12, 1038–1048.
14. Mokhtar, U.; Ali, M.A.; Hassanien, A.E.; Hefny, H. Identifying two of tomatoes leaf viruses using support vector machine. In Information Systems Design and Intelligent Applications; Springer: Berlin/Heidelberg, Germany, 2015; pp. 771–782.
15. Chouhan, S.S.; Kaul, A.; Singh, U.P.; Jain, S. Bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards plant pathology. IEEE Access 2018, 6, 8852–8863.
16. Babu, M.P.; Rao, B.S. Leaves Recognition Using Back Propagation Neural Network-Advice for Pest and Disease Control on Crops. Available online: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.110.3632&rep=rep1&type=pdf (accessed on 1 May 2021).
17. Mohanty, S.P.; Hughes, D.P.; Salathé, M. Using deep learning for image-based plant disease detection. Front. Plant Sci. 2016, 7, 1419.
18. Ferentinos, K.P. Deep learning models for plant disease detection and diagnosis. Comput. Electron. Agric. 2018, 145, 311–318.
19. Sladojevic, S.; Arsenovic, M.; Anderla, A.; Culibrk, D.; Stefanovic, D. Deep neural networks based recognition of plant diseases by leaf image classification. Comput. Intell. Neurosci. 2016, 2016, 1–10.
20. Kamilaris, A.; Prenafeta-Boldú, F.X. Deep learning in agriculture: A survey. Comput. Electron. Agric. 2018, 147, 70–90.
21. Geetharamani, G.; Pandian, A. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Comput. Electr. Eng. 2019, 76, 323–338.
22. Jadhav, S.B.; Udupi, V.R.; Patil, S.B. Identification of plant diseases using convolutional neural networks. Int. J. Inf. Technol. 2020, 1–10.
23. Rangarajan Aravind, K.; Raja, P. Automated disease classification in (Selected) agricultural crops using transfer learning. Autom. Casopis Autom. Mjer. Elektron. Raˇcunarstvo Komun. ˇ 2020, 61, 260–272.
24. Rangarajan, A.K.; Purushothaman, R. Disease classification in eggplant using pre-trained vgg16 and msvm. Sci. Rep. 2020, 10, 1–11.
25. Arora, J.; Agrawal, U. Classification of Maize leaf diseases from healthy leaves using Deep Forest. J. Artif. Intell. Syst. 2020, 2, 14–26.
26. Lee, S.H.; Goëau, H.; Bonnet, P.; Joly, A. New perspectives on plant disease characterization based on deep learning. Comput. Electron. Agric. 2020, 170, 105220.
27. Ghazi, M.M.; Yanikoglu, B.; Aptoula, E. Plant identification using deep neural networks via optimization of transfer learning parameters. Neurocomputing 2017, 235, 228–235.
28. Sanjeev, K. Gupta, N.K. Jeberson, W. Paswan, S. (2020) Early Prediction of Potato Leaf Diseases Using ANN Classifier. Orient. J. Computer. Science. Technology., 13, 2–4.
29. Barman U., Sahu D., Barman G. G., & Das J. (2020). Comparative Assessment of Deep Learning to Detect the Leaf Diseases of Potato based on Data Augmentation. International Conference on Computational Performance Evaluation, ComPE.
30. Rozaqi, A.J.; Sunyoto, A. Identification of Disease in Potato Leaves Using Convolutional Neural Network (CNN) Algorithm. In Proceedings of the 2020 3rd International Conference on Information and Communications Technology (ICOIACT), Yogyakarta, Indonesia, 24–25 November 2020; pp. 72–76.
31. Lee, T.Y.; Yu, J.Y.; Chang, Y.C.; Yang, J.M. Health Detection for Potato Leaf with Convolutional Neural Network. In Proceedings of the 2020 Indo–Taiwan 2nd International Conference on Computing, Analytics and Networks (Indo-Taiwan ICAN), Rajpura, India, 7–15 February 2020; pp. 289–293.
32. Islam, M.; Dinh, A.; Wahid, K.; Bhowmik, P. Detection of potato diseases using image segmentation and multiclass support vector machine. In Proceedings of the 2017 IEEE 30th canadian conference on electrical and computer engineering (CCECE), Windsor, ON, Canada, 30 April–3 May 2017; pp. 1–4.
33. Fang, Y.; Ramasamy, R.P. Current and Prospective Methods for Plant Disease Detection. Biosensors 2015, 5, 537-561.
34. Hughes, D.; Salathé, M. An open access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv 2015, arXiv:1511.08060.
35. Simonyan, K.; Zisserman, A. Very deep convolutional networks for large-scale image recognition. arXiv 2014, arXiv:1409.1556.
36. Khalifa, N.E.M.; Taha, M.H.N.; Abou El-Maged, L.M.; Hassanien, A.E. Artificial Intelligence in Potato Leaf Disease Classification: A Deep Learning Approach. In Machine Learning and Big Data Analytics Paradigms: Analysis, Applications and Challenges; Springer: Berlin/Heidelberg, Germany, 2021; pp. 63–79.