

## Optimized Deep Learning Model for Disease Prediction in Potato Leaves

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### Abstract

Food crops are important for nations and human survival. Potatoes are one of the most widely used foods globally. But there are several diseases hampering potato growth and production as well. Traditional methods for diagnosing disease in potato leaves are based on human observations and laboratory tests which is a cumbersome and time-consuming task. The new age technologies such as artificial intelligence and deep learning can play a vital role in disease detection. This research proposed an optimized deep learning model to predict potato leaf diseases. The model is trained on a collection of potato leaf image datasets. The model is based on a deep convolutional neural network architecture which includes data augmentation, transfer learning, and hyper-parameter tweaking used to optimize the proposed model. Results indicate that the optimized deep convolutional neural network model has produced 99.22% prediction accuracy on Potato Disease Leaf Dataset.

**Keywords:** Deep Learning, Artificial Intelligence, Machine Learning, Deep Convolutional Neural Network, Optimized Deep Convolutional Neural Network Model, Disease Prediction

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### 1. Introduction

In recent years, food production has been heavily impacted due to plant diseases. Plant diseases are caused by climate change, adverse impact on the environment, heavy usage of fertilizers and so on. Climate change has severely impacted potato yield due to a variety of diseases. The most destructive diseases in potato leaves are late blight and early blight. These diseases have largely emerged in the last few years [1] due to many reasons including climate change. The infections that damage plants, starting in the leaves before spreading to the entire plant, are the major causes of the yield decline in

potato production. Potatoes are a largely consumed food item in the world. According to a report published in Statista, over 376 million metric tons of potatoes were produced in 2021 which is down 2% from 2020 crop [2]. Farmers heavily rely on human inspection to identify potato leaves diseases which are time consuming and have a high chance of error. In the present technological era, the use of new age technologies such as artificial intelligence (AI), deep learning, and computer vision (CV) etc. are very advantageous to speed up the potato disease prediction process. AI and deep learning have witnessed immense surge in the agriculture domain due to its capabilities of image identification, processing, image classification and image prediction [3].

A kind of machine learning [4-6] called deep learning (DL) has been demonstrated to be particularly good at

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classifying images [5-9]. Convolutional Neural Network (CNN) is used in a variety of tasks, including object identification and image classification [10-13]. To predict potato leaf diseases, an optimized deep learning model is tuned in this work. It is also called an optimized deep convolutional neural network (ODCNN). The model performance is refined using methods including data augmentation, transfer learning, and hyper-parameter tuning after being trained on a dataset of potato leaf pictures. Metrics like performance accuracy and loss are used to assess the model performance [14-16]. Since early disease identification is essential for crop management, the requirement for an accurate and effective approach to predict potato leaf disease is the driving force behind our research. The suggested methodology is used for the management of potato fields and the early identification of illnesses in potato plants. The article is structured into distinct sections, with section 2 providing an overview of related literature, section 3 outlining the methodology employed, section 4 analysing the obtained results, and section 5 presenting the conclusion and potential avenues for further research.

## 2. Related Work

CNN has proven beneficial in a number of applications, including object recognition and image recognition. In several research studies, CNNs have demonstrated remarkable accuracy and resilience in the categorization of plant diseases. In recent years, disease prediction in potato leaves has received significant scientific attention, several strategies and procedures have been put forth to increase the precision and effectiveness of disease detection. Using DL models, which have proven to be incredibly successful in image-based illness prediction tasks, is one of the most often used strategies.

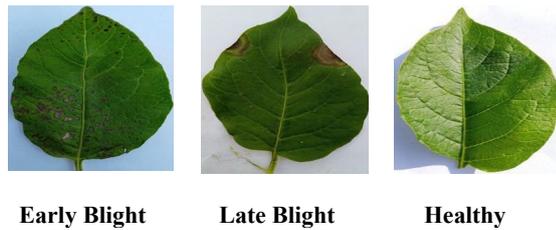
Several researchers have conducted investigations pertaining to illnesses affecting potato crops, while simultaneously employing the PlantVillage dataset to train their models. Khalifa et al. (2021) introduced a Convolutional Neural Network (CNN) model for the identification of early blight (EB), late blight (LB) disorders, as well as a healthy class. The model was trained on the PlantVillage dataset (PVD), which was limited to crops particular to certain locations [17]. Sanjeev et al. (2021) introduced a Feed-Forward Neural Network (FFNN) [18] as a means of identifying EB, LB diseases, as well as healthy leaves. The approach under consideration was trained and evaluated using the PlantVillage dataset. Rozaqi and Sunyoto (2020) introduced a convolutional neural network (CNN) model designed for the classification of EB, and LB illness in potato leaves. The algorithm was trained using the PlantVillage dataset in order to identify diseases within a certain geographic area [19]. Barman et al. (2018) introduced a self-build CNN (SBCNN) model for the purpose of detecting EB, LB, and healthy classes of potato leaf diseases. The PVD was utilised throughout the training and assessment of the considered strategy. To classify EB and LB diseases in potato

leaves, Rozaqi and Sunyoto (2020) presented a convolutional neural network (CNN) model. The system for disease detection in a given region was trained using the PlantVillage dataset [19]. In order to distinguish between the EB, LB, and healthy categories of potato leaf diseases, Barman et al. (2018) presented a self-build CNN (SBCNN) model. The model was fine-tuned with regionally specific data from the PlantVillage dataset. Unfortunately, the researchers didn't put their model to the test with any novel data [20]. Lee et al.'s (2020) CNN model was developed to identify potato plants with early blight, late blight infections, and healthy leaves. The researchers also made use of a PVD specific to a certain region. Evaluation of the model did not include testing on novel data [21]. Using a segment-based method and a multi-SVM architecture, Islam et al. (2017) presented a model for the detection of a variety of potato diseases, including EB, LB, and healthy leaves. The researchers' methodology incorporated PVD but needs additional precision improvements [22]. For their feature extraction, Tiwari et al. (2020) used a VGG19 model that has already been pre-trained. After that, they used a number of classifiers like Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and neural networks to sort the data. To further improve its ability to detect EB, and LB infections in potato leaves, the model was trained with data collected from the PlantVillage dataset. The effectiveness of the researchers' model was not assessed using novel data [23]. A comprehensive summary of deep learning model to classify potato disease on PLD is presented in Table 1.

Table 1: Summary of deep learning model to classify potato disease on PlantVillage dataset

Algorithm	Disease Name	Accuracy (%)	Reference
Deep CNN	Multiple	96.46	[24]
ResNet50	Multiple	98	[25]
Modified MobileNet	Multiple	98.34	[26]
CNN	EB, LB	98	[17]
FFNN	EB, LB	96.6	[18]
CNN	EB, LB	99	[21]
SVM, KNN and ANN	EB, LB	97.8	[23]

In conclusion, current research has demonstrated that convolutional neural networks or deep learning models, have been particularly successful in identifying illnesses of potato leaves. It has also been demonstrated that using transfer learning enhances the effectiveness of these models. In this article, authors have explored to make a model by utilizing transfer learning, deep CNN, and optimized model performance by hyperparameter tuning.



**Figure 1.** Sample image of potato leaves of each class.

### 3. Methods

#### 3.1. Dataset

This research work has used potato leaf images from an open source Kaggle dataset repository [27, 28]. Images of both healthy leaves and leaves afflicted by the two major potato illnesses, LB, and EB, are included in the collection. Plant pathology specialists assigned labels to the images indicating the late blight, early blight or healthy [29]. This research work used two datasets namely PlantVillage [27] and Potato Disease Leaf Dataset (PDL) [28]. The PlantVillage dataset comprises 2162 well-labeled images of potato leaves in the three categories viz a viz early blight, late blight, and healthy whereas PDL consists of 4071 labeled images of potato leaves. A total of 80% of the data is used for training, 10% for validating, and 10% for testing. The sample size of the datasets is shown in Table 2 and Table 3. Figure 1 depicts a sample image of potato leaves of each class.

**Table 2.** Sample size and train-validation-test-split of PlantVillage dataset

Category	Label	Number of Images
Early Blight	1	1000
Late Blight	2	1000
Healthy	3	162

**Table 3.** Sample size and train-validation-test-split of PDL dataset

Category	Label	Number of Images
Early Blight	1	1627
Late Blight	2	1424
Healthy	3	1020

#### 3.2. Data pre-processing

The dataset size was expanded using techniques for data augmentation including random horizontal flipping, and random rotation for model performance enhancement. The VGG19 model is applied for feature extraction. The VGG19 method was developed by K. Simonyan and A. Zisserman [30] and is built on convolutional neural networks. ImageNet, a collection consisting of over 15 million annotated high-resolution pictures across 22,000 categories, was used to train this model. This model used 1.3 million training pictures, 50 thousand validation images, and 100 thousand test images while being learned for the ImageNet LargeScale Visual Recognition Competition (ILSVRC) [30]. VGG19 [31] performs a simple preparation step, which consists of removing the mean RGB value from each pixel. When compared to AlexNet, the VGG19 model's improved categorization accuracy can be attributed to the fact that it swaps out all the massive kernel-sized filters for a collection of smaller ones measuring just 3\*3. Pooling is performed over 2\*2 frames with a stride size of 2. This model ends with a softmax layer. The ReLU function has been used to add non-linearity across all of the model's hidden levels. The 1\*1 filters necessary for linear translation were incorporated into the model as well. One pixel is padded around each edge to keep the spatial resolution constant. The spatial sharing is performed only on the last 5 convolution layers.

#### 3.3. Architecture of CNN

Artificial neural networks, of which Convolutional Neural Networks [32] are one type, have found widespread application in a variety of fields, including categorization, picture processing, segmentation, etc. Convolution is a filter learning technique where the filter is dragged over the picture to pick up on key characteristics. Because we know that a picture is just a grid with some numbers in it, represented by the letter I. Figure 2 shows how these filters, denoted by the letter K, are convolved over the incoming picture to assist with learning the crucial information or features. The resulting feature map values are computed using the formula expressed in equation 1, where f represents the input image, h represents our kernel, and m and n represent the indexes of rows and columns, respectively, of the result matrix.

$$F[m, n] = f * h [m, n] = \sum_i \sum_j h[j, k] f[m - j, n - k] \dots\dots(1)$$

The "hidden" layer of a CNN consists of various types of processing units, including convolutional layers, pooling layers, fully connected layers, and a normalisation layer. where the activation function is provided with data from the buried layers. The activation function boosts the network's performance, allowing it to express non-linear, complex, arbitrary functional mappings between inputs and outputs and to learn more intricate structures from data. We used a nonlinear activation to create nonlinear mappings from inputs to outputs. The model employs ReLU activation for the hidden layers and softmax activation for the output layers.

Convolution is something we've already discussed. Downsampling, often known as pooling, is a method for decreasing the dimensionality of an input representation. Minimal pooling, maximum pooling, and average pooling are only a few examples of the many pooling methods available. The functions of these classes are indicated by their names. The terms min-pooling and max-pooling refer, respectively, to retrieving the least and maximum values from a matrix of a given dimension. In Figure 3, we see a 2\*2 window example of maximum pooling.

To average pool is to calculate an average of all the numbers in the given matrix. When a layer is fully linked, all of the neurons in the subsequent layer receive the weights from the one below. By using the normalization layer, we can guarantee that the average activation of the layer below is very near to 0.

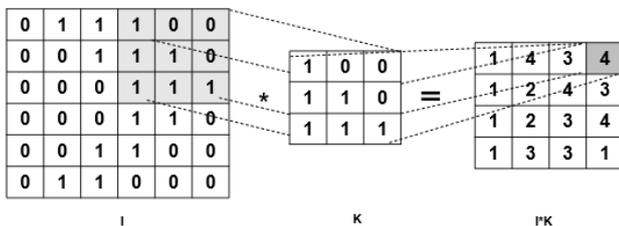


Figure 2. Convolution 3x3 filter over the image

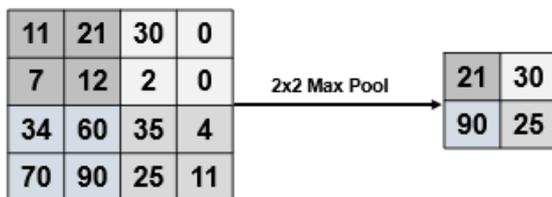


Figure 3. Max Pooling from 2x2 window

### 3.4. Optimized Deep Convolutional Neural Network Model

Deep CNN (DCNN) is used a lot these days in fields like medicine, agriculture, and more [33]. In this work, we employed a VGG19 pre-trained model to pull out the important features of the image. This way, we can use what we've learned before instead of starting from scratch. This is also called transfer learning. There are models that have already been trained, like VGG19 [31] and InceptionV3 [34]. Model extracts features from images by feeding them into models like VGG19 which had already been trained. Figure 4 presents feature extraction using transfer learning. Now the features are extracted by the VGG19 model and fed into the DCNN model, and the model is optimized. Figure 5 shows the workflow of the proposed optimized DCNN model. There are several methods applied to optimize DCNN. These methods consist of:

#### Data augmentation

To expand the training dataset and lessen overfitting, data augmentation entails adding different modifications to the pictures such as rotation, scaling, and flipping [35].

#### Dropout

It is a regularization method that, in order to avoid overfitting, randomly eliminates (i.e., sets to zero) a certain proportion of the neurons during training [36].

#### Batch normalization

This method standardises neuronal activations across layers to improve training consistency and efficiency [37].

#### Early stopping

Using this strategy, training is stopped as soon as the model's performance on a validation dataset begins to deteriorate [29].

#### Hyper-parameter tuning

It entails employing methods like grid search or random search to get the ideal settings for the model's numerous hyper-parameters e.g., learning rate, number of filters in the convolutional layers, etc. [33-35].

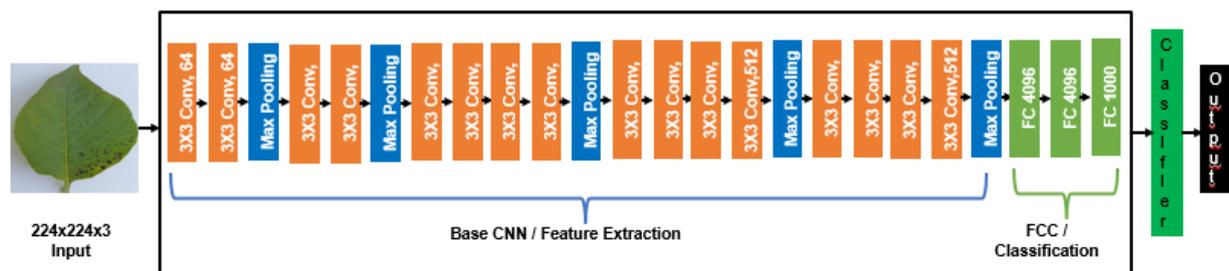


Figure 4. Feature extraction using VGG19 model.

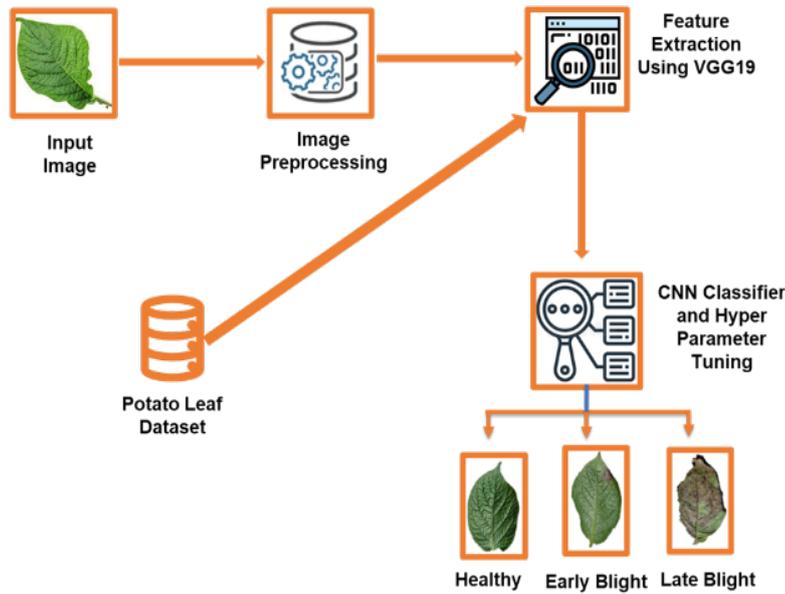


Figure 5. Workflow of proposed optimized DCNN model.

Table 4. Performance Evaluation Metrics of ODCNN Model

Dataset	Training Accuracy (%)	Training Loss	Validation Accuracy (%)	Validation Loss	Prediction Accuracy (%)	Prediction Loss
PlantVillage	99.88	0.0042	98.96	0.0116	98.26	0.0257
PDL D	98.99	0.0284	99.22	0.0360	99.22	0.0325

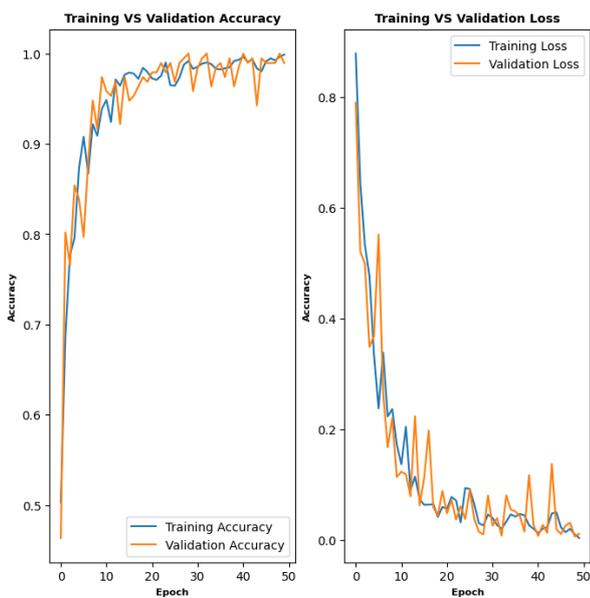


Figure 6(a). Training VS Validation Accuracy and Training VS Validation Loss for Plant Village dataset

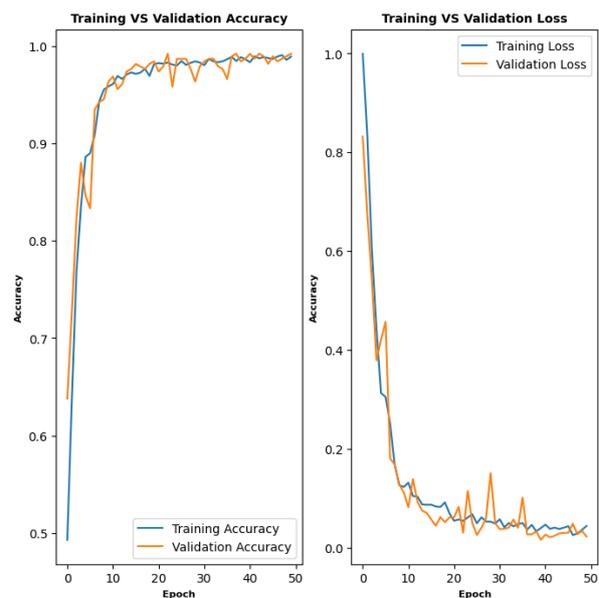


Figure 6(b). Training VS Validation Accuracy and Training VS Validation Loss for PDL D

Table 5. Performance comparison with others work

Reference	Model	Dataset	Accuracy (%)
[36]	VGG16, VGG19	PlantVillage	91
[37]	CNN	PlantVillage	98
Proposed Work	VGG19, ODCNN	PlantVillage, PDL D	98.26, 99.22

## 4. Results and Discussion

The ODCNN model is trained on PVD [27] and PDL D [28] datasets. The PlantVillage [26] dataset includes 1000 images of EB, 1000 images of LB, and 162 images of healthy potato leaves. Similarly, PDL D [28] consists of 1626 images of EB, 1424 images of LB, and 1020 images of healthy potato leaves. For feature extraction, the pre-trained model VGG19 [19] was employed. The proposed ODCNN model was trained on both the datasets. The accuracy of the model's predictions was measured by comparing data from the validation set and the test set. The model utilized strategies like data augmentation, dropout, batch normalization, and early stopping, the model improved as it is being trained. Additionally, hyper-parameter tweaking was performed to determine the ideal values for the model's numerous hyper-parameters (e.g., learning rate (0.001), number of filters in the convolutional layers, epochs etc.). Finally, the test set was used to predict the disease in the potato leaves. To assess the model performance on unobserved data, utilize the test set and k-fold validation employed to make sure that the model performance is resilient and generalized. The ODCNN achieved the best accuracy 99.22% on 50 epochs. The performance metrics, training accuracy, training loss, and validation accuracy were computed to assess the effectiveness of the model (refer Table 4). Table 5 shows a comparison with others' work, and it delineates that the ODCNN has better accuracy than the model proposed by Sholihati et al. [36] and Krishna et al. [37].

## 5. Conclusion and Future Work

In this work an optimized deep CNN is designed to predict disease in the potato leaves. Transfer learning is applied for feature extraction then the proposed ODCNN model is optimized, and hyper tuning is applied to achieve the best performance of the model. The model is trained and tested on two datasets namely PlantVillage [26] and Potato Disease Leaf Dataset (PDL D) [31]. The proposed model delineates prediction accuracy of 98.26% and 99.22% on PlantVillage, and PDL D dataset respectively. The data augmentation procedure improves the robustness of the

CNN model. This model can assist farmers in identifying illnesses in potato leaves at an early stage, Hence, increasing crop yields.

In future work, researchers would like to design a mobile-based application in which the ODCNN model will be used to predict Potato leaf images. Farmers can take leaf pictures from a mobile camera and the model will predict the disease in potato leaves and also recommend appropriate medicine to control the disease.

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