

# Potato Disease Detection Using Convolutional Neural Network and LSTM (Long Short-Term Memory) Algorithm

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**Abstract** - Potato diseases are one of the primary causes of decreased agricultural production quality and quantity. With ongoing changes in potato structure and cultivation techniques, new diseases are constantly arising on potato leaves. In this work, we have reviewed many CNN articles on detecting potato disease detection. CNN models are trained on image data are the most effective method for detecting early leaf detection. But here we work upon a specific plant disease i.e. potato plant disease like – early blight, late blight. In this study we use CNN models for feature extraction and segmentation, where we can get the CNN model as a pre-trained deep learning model. Here we also use a model for classification i.e. LSTM (long short-term memory) which is an updated version of RNN model. The experiments are carried out using the popular publicly available dataset Plant Village dataset and potato leaf disease dataset which has about 2152 images of early blight, Late blight and healthy leaves.

**Keywords:** CNN, Convolutional Neural Network, ANN, Artificial Neural Network, LSTM, long-Short Term Memory, RNN, Recurrent Neural Network, VGG-16, InceptionV3, PlantVillage Dataset, Potato disease, Early Blight, Late Blight.

## I. INTRODUCTION

One of the most critical areas of precision agriculture research is detecting diseases in potato leaves via image analysis. The traditional method of recording the severity of potato diseases is based on the visual examination of potato tissues by trained experts. Expert systems in cultivation and management have become widely used due to the widespread adoption of digital cameras and the advancement of information technology in agriculture, considerably increasing plant production capacity. However, pest and disease extraction and description characteristics in expert systems mainly depend on experts' expertise, resulting in high costs and low efficiency. With the evolution of computer vision, there are numerous ways to resolve the detection issues for potatoes, since the infection spots are initially seen as spots

and patterns on leaves. Researchers have proposed several techniques to accurately detect and classify potato infections. Some use traditional image processing techniques that incorporate hand-crafted—that is, manual—feature extraction and segmentation. The most common techniques are the K-nearest neighbors (K-NN), logistic regression, decision tree, support vector machine (SVM), and CNN. These techniques are used with different image pre-processing techniques to promote the extraction of features. With the advent of machine learning and deep learning techniques, the progress made in plant disease recognition has been enormous and represents a massive breakthrough in research. In recent times, convolution neural networks (CNNs) have gained wide attention for their recognition and classification abilities, which work by extracting low level complex features from images. Hence, CNNs are preferred for the replacement of traditional methods in automated potato disease recognition as they achieve better outcomes compared different CNN architectures for disease detection in potato a shallow CNN model achieving 90.85% accuracy. The best outcome is likely to be achieved by training the deep-learning model using a large dataset. Although very good outcomes have been attained in the previous studies, improvement in the diversity of the image databases is still required.

## II. METHODOLOGY

This study used potato leaf data from the Plant Village dataset, where potato leaf images and corresponding segmented potato leaf are provided. CNN is an evolution of simple ANN that gives better result on images. Because images contain repeating patterns of particular thing (any image). Two important functions of CNN are convolution and pooling. Convolution is used to detect edges of patterns in an image and pooling is used to reduce the size of an image. As explained earlier, the paper has three different studies: binary classification of healthy and unhealthy segmented leaves using combining model structure of CNN and LSTM and other two models are VGG-16 and InceptionV3. The paper also explored different variants of CNN segmentation models to investigate

the best segmentation network for leaf segmentation from the background. The classification is done using CNN networks that have been comparatively successful in previous publications by the authors.

### 2.1 Dataset description

In this study, PlantVillage potato leaf images and corresponding leaf mask dataset were used, where 2152 potato leaf images and corresponding segmented leaf masks are available. The dataset was used for training the tomato leaf segmentation models and classification models as well. All images were divided into 3 different classes, where one class is healthy and the other two classes are unhealthy (such as Early blight, Late Blight). Some sample potato leaf images, for healthy and different unhealthy classes, and leaf masks from the PlantVillage dataset are shown. Moreover, a detailed description of the number of images in the dataset is also shown in Table-1, which is useful for classification tasks discussed in detail in the next section.

Table 1: Dataset Description

Class	Plant name	Healthy or Diseased	Disease Name	Images (Numbers)
C_0	Potato	Diseased	Early Blight	1000
C_1	Potato	Diseased	Late Blight	1000
C_2	Potato	Healthy	-	152

### 2.2 Model Description

As we are work over 3 models, we describe here a detailed description of CNN- LSTM model, VGG-16 model and InceptionV3 model. Descriptions are below here-

#### 2.2.1 CNN-LSTM

This model is a hybrid architecture combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) layers, designed for plant disease classification across three categories. It begins with a `resize_and_rescale` preprocessing layer that ensures all input images are uniformly sized and normalized. The CNN portion consists of six consecutive Conv2D layers with 64 filters each and ReLU activations, interleaved with MaxPooling2D layers to progressively reduce spatial dimensions while extracting hierarchical features from the images. After flattening the output of the final convolutional block, the model uses `RepeatVector(10)` to reshape the flat feature vector into a sequence suitable for temporal modeling by the LSTM layers. Two LSTM layers follow: the first with 128 units and `return_sequences=True` to pass the sequence to the next LSTM, and the second with 64 units to produce a compact representation of the temporal features. The network ends with

a dense layer of 64 ReLU-activated neurons for further feature abstraction and a final softmax layer to output probabilities across three plant disease classes. This architecture is particularly effective when the spatial features captured by CNN layers benefit from sequential modelling via LSTM, simulating dependencies in structured data like time-series-like representations of image patches.

Table 2.1: CNN-LSTM training Parameters

Parameter	Values
Epochs	50
Batch Size	32
Image Size	256
Activation in middle Layers	ReLu
Activation in Final Layers	Softmax

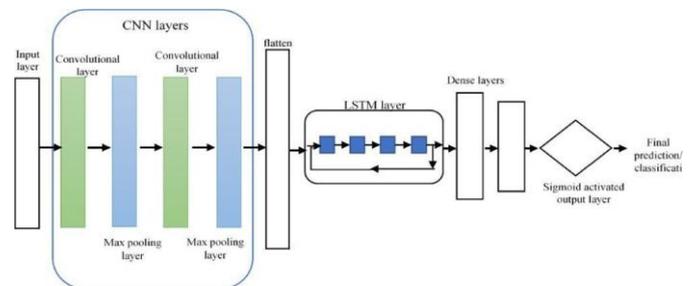


Figure 1: CNN-LSTM Model Structure

#### 2.2.2 VGG-16

This model leverages transfer learning using the pre-trained VGG16 architecture as a fixed feature extractor for plant disease classification into three categories. The VGG16 model is initialized with imagenet weights and excludes its top classification layers (`include_top=False`), retaining only the convolutional base. All layers of the base model are frozen to preserve the learned features from ImageNet, which are effective for extracting general visual patterns. Two additional convolutional layers are added to allow the model to learn more task-specific features; each is followed by batch normalization, ReLU activation, and max pooling to stabilize training and reduce spatial dimensions for feature extraction. On top of this frozen base, a custom classification head is added: the output of the convolutional base is flattened into a 1D vector, followed by a dense layer with 512 ReLU-activated neurons that introduces non-linearity and task-specific learning. A Dropout layer with a rate of 0.5 is applied to reduce overfitting by randomly disabling half of the neurons during training. The final layer is a Dense layer with softmax activation that outputs class probabilities for the three target categories. This architecture is particularly efficient when training on limited data, as it benefits from the strong feature extraction of a proven CNN model while fine-tuning only a small number of parameters in the classification head.

Table 2.2: VGG-16 Training Parameter

Parameter	Values
Epochs	50
Image Size	224
Activation in middle Layers	ReLu
Activation in Final Layers	Softmax

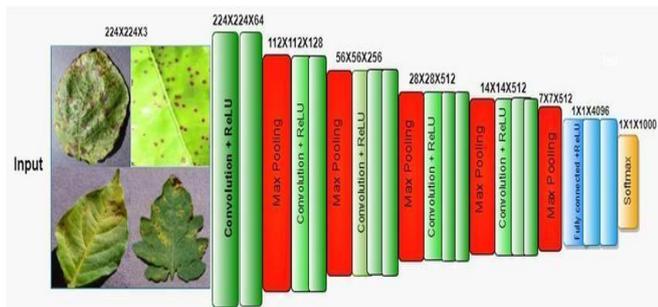


Figure 2: VGG-16 Model Structure

### 2.2.3 InceptionV3

This model is built using transfer learning with the InceptionV3 architecture as the foundational feature extractor for classifying images into three plant disease categories. The pre-trained InceptionV3 model, loaded with ImageNet weights and excluding its top layers (include\_top=False), serves as a powerful backbone capable of capturing complex, multi-scale features from input images of shape (IMAGE\_SIZE, IMAGE\_SIZE, CHANNELS). All layers in the base model are frozen to retain their learned weights, preventing updates during training and thereby speeding up convergence while reducing overfitting. Instead of flattening, the output from InceptionV3 is passed through a GlobalAveragePooling2D layer, which efficiently reduces the spatial dimensions by computing the average across each feature map—maintaining key spatial information and improving generalization. A custom classification head follows, comprising a dense layer with 32 ReLU-activated units to introduce non-linearity, a Dropout layer with a 0.5 rate for regularization, and a final softmax-activated dense layer that outputs class probabilities across the three defined categories. This architecture strikes a balance between high-level feature reuse and task-specific

fine-tuning, making it highly effective for plant disease detection tasks with limited data availability.

Table 2.3: InceptionV3 Training Parameter

Parameter	Values
Epochs	50
Image Size	299
Activation in middle Layers	ReLu
Activation in Final Layers	Softmax

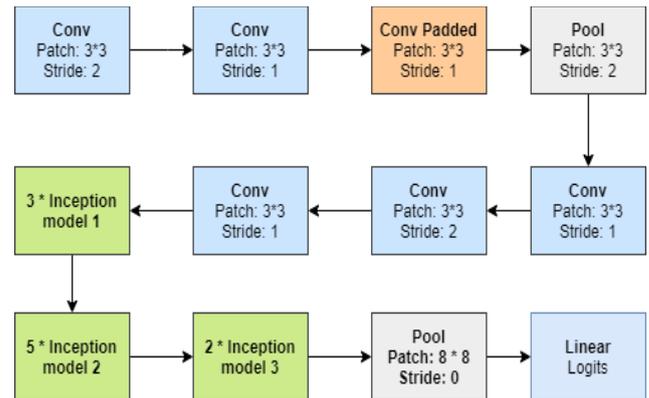


Figure 3: InceptionV3 Model Structure

## III. RESULTS AND DISCUSSIONS

This study shows the importance of plant disease detection in these days. This model were developed using 3 different Deep Learning models in python. 10% images from PlantVillage potato dataset were used to test the accuracy of this model and 10% for validation. These images are from 3 different classes. 10% of each class randomly. The CNN-LSTM model give us more than 100% accuracy on those images as well by telling either leaf is healthy or diseased. Testing dataset gives accuracy more than 99%. Now if we look at the other model, like VGG-16, it also gives us a good accuracy of 93% on the same potato leaves dataset and the InceptionV3 model gives us accuracy of 68% which comparatively very low from the other two models. In discussions we can say that, CNN+LSTM is a lightweight, task-specific model tailored to the potato leaf dataset. In contrast, InceptionV3 and VGG16 are may include redundant or non-optimal layers for agricultural image classification.

Table 3: Model's Training and Testing Accuracy

Model	Dataset for Training	Dataset for Testing	Dataset for Validation	Training Accuracy	Testing Accuracy
CNN- LSTM	PlantVillage (80%)	PlantVillage (10%)	PlantVillage (10%)	100%	99%
VGG-16	PlantVillage (80%)	PlantVillage (10%)	PlantVillage (10%)	94%	93%
InceptionV3	PlantVillage (80%)	PlantVillage (10%)	PlantVillage (10%)	67%	68%

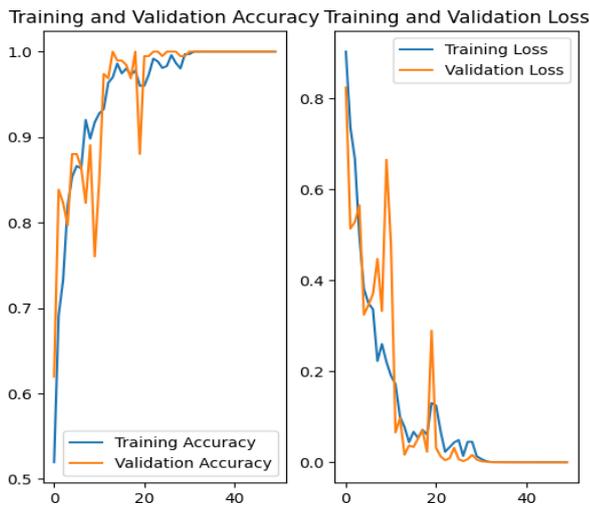


Figure 4: Testing and validation accuracy of CNN-LSTM Model

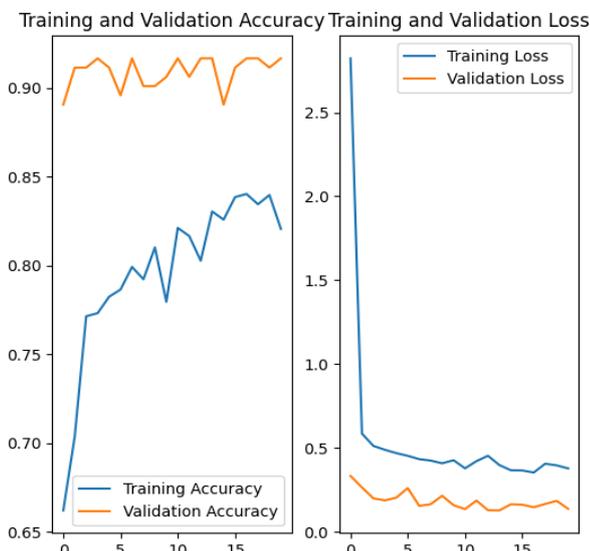


Figure 5: Testing and Validation Accuracy of VGG-16 Model

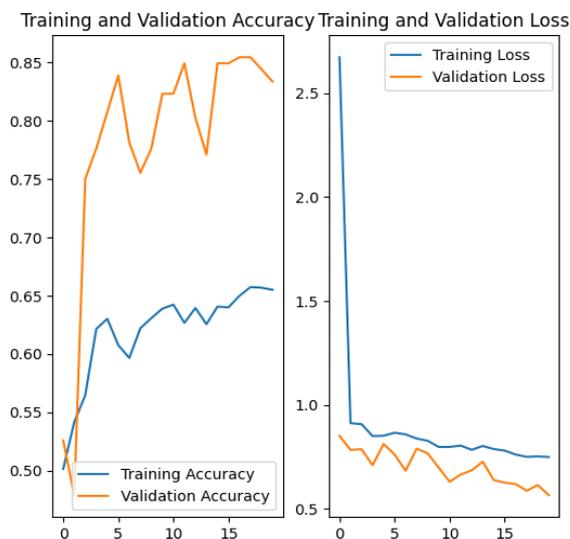


Figure 6: Testing and validation Accuracy of InceptionV3 Model

#### IV. CONCLUSION

This study has utilized deep learning capabilities to achieve automatic plant disease detection system. This study is based on a simple classification mechanism and also a comparative study which exploits the feature extraction functionalities of CNN. For prediction finally, the models utilize the fully connected layers. The research was carried out using the publicly accessible collection of 2152 potato images. The CNN-LSTM system has achieved an overall 99% testing accuracy, which is highest than other models, on publicly accessible dataset. It is concluded from accuracy that CNN-LSTM is highly suitable for automatic detection and diagnosis of potato plants. This system can be integrated into mini-drones to live detection of diseases from potato plants in cultivated areas. Though this system is trained on Plant Village dataset with only 3 classes it could tell if the plant has a disease or not as somehow symptoms are same in all kinds of plants. In addition, more actual environment images can be added to the dataset to improve the accuracy on real-condition images of leaves and classify more plant types as well as disease types. The future of plant disease detection can be significantly enhanced by integrating CNN and LSTM models with emerging technologies and broader agricultural systems. Real-time data from IoT sensors—such as temperature, humidity, and soil moisture—can provide environmental context, improving prediction accuracy. Mobile apps can make disease detection more accessible for farmers in remote areas by allowing them to upload leaf images for instant analysis. Incorporating climate models will help detect emerging diseases linked to changing conditions, while integration with farm management systems can centralize operations for more efficient and informed decision-making.

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