



## Research articles

**Disease identification in crops using deep learning models**

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**ABSTRACT**

Food is one of the most fundamental necessities and is crucial for survival. Loss of the food source due to pest infestation attributes towards destroying one-fifth of the yearly worldwide crop yield. The past few decades have witnessed a burgeoning trend of using computerized methods for discerning various diseases found in crops. The main advantage of digitizing the detection process is that it eliminates the errors and miscalculations associated with manual detection. With the advent of Object Detection and Artificial Intelligence, malady detection has not only been rapid but has also maintained the expected level of accuracy. The concepts and models of deep learning have been efficaciously applied and used to identify as well as classify plant diseases. In the scope of this research paper, we present a comprehensive digitized approach to detect plant diseases by utilizing image detection, computer vision, and deep learning models like the Convolutional neural networks, Inception model, and the Visual Geometry Group (VGG16) model. In addition to this, the performance of the above-mentioned models has been evaluated by the virtue of metrics like f1 score, accuracy, precision, and recall.

**Keywords:** Convolutional neural networks, Disease identification, Inception model, VGG16 model

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**INTRODUCTION**

India is an agrarian economy.<sup>[1]</sup> Agriculture contributes towards 17% of GDP and is the major source of income for about 70% of Indian households.<sup>[2]</sup> Agriculture is the backbone of the Indian economy, thus boosting crop production has been one of the prime objectives of the Indian government.<sup>[3]</sup> The techniques used in amplifying the crop yield eventually resulted in the Green revolution.<sup>[4]</sup> As a consequence of the green revolution, increased use of fertilizers and pesticides were promoted to increase crop yield.<sup>[5]</sup> The shift from traditional subsistence farming techniques to commercial, labor-intensive, monoculture-based agriculture with heavy chemical fertilizers has exposed Indian farming to the ravages of plant diseases.<sup>[6]</sup> The monopoly of commercial crops in the Indian sowing seasons like Rabi (in November - April) and Kharif (May - October) has increased the probability for plant disease-causing agents to proliferate.<sup>[7]</sup> The major causes of plant diseases are pathogenic microbes like fungus, viruses, and bacteria.<sup>[8]</sup> Infected plants have a change in their physical appearance, which is a telltale sign of plant diseases.<sup>[9]</sup> Common symptoms include Leaf spot (Septoria brown spot), Chlorosis (yellowing of leaves), leaf spot with a yellow halo, Canker, and Crinkled leaves.<sup>[10]</sup> Although it's easy to

identify that a plant is infected, it is hard to pinpoint the exact disease.<sup>[11]</sup> In India, smallholder farmers generate more than 80% of the agriculture production. For the farmers, a loss of such magnitude due to pests is devastating. This makes crop disease a major threat to food security.<sup>[12]</sup> Classic examples of a collapse in the food chain supply inadvertently, resulting in the downfall of the economy and society are the Irish potato blight (1845 to 1852) and the Bengal potato famine (1943).<sup>[13]</sup> Hence, timely and correct identification of a disease when it first appears is critical for efficient disease management.<sup>[14]</sup> Currently, disease detection in plants depends on the skills and expertise of only an individual or a group of specialists. This method of analysis is exhaustive and completely unreliable especially for a bigger zone of the ranch.<sup>[15]</sup> The present method of disease detection is inefficient, time-consuming, and hard to scale.<sup>[16]</sup> Moreover, diseases identification might be challenging due to the lack of necessary lab infrastructure.<sup>[17]</sup> In this research paper, we propose a digital method for disease detection in plants using Deep Learning tools. This method when scaled can aid in the digitalization of monitoring crop health, which in turn might lead to significant amelioration in the agriculture yield.

## Literature review

This paper provides an in-depth study of the application of deep learning in the agriculture domain.<sup>[18]</sup> It surveys 40 research endeavors and examines their findings, methodology based on questions like data type used, performance on real-world data, whether or not data augmentation techniques are used or not, etc.<sup>[19]</sup> The paper also compares deep learning with other prevalent techniques. Finally, the paper concludes that the application of deep learning techniques in agriculture seems to be promising making crop analysis more affordable and accessible to all.<sup>[20]</sup>

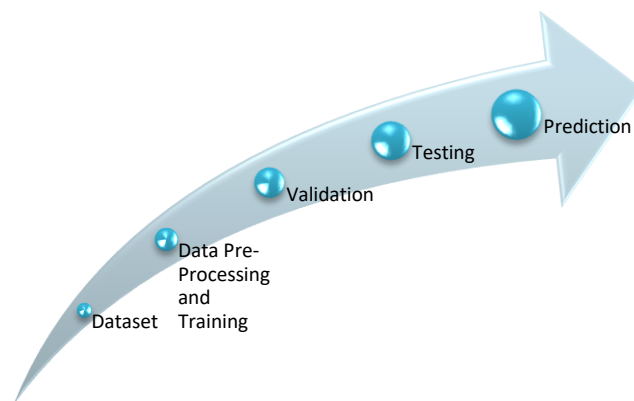
In this paper, the author aims to improve on a major drawback of current deep learning models that perform well on test data but have a considerable loss in accuracy and performance when applied on previously unseen or real-world images.<sup>[21]</sup> Instead of using full-size images, the author uses segmented images that result in a significant increase in the accuracy of the model when exposed to real-world data.<sup>[22]</sup> The author concludes that pre-processing of images or data can be crucial to increase a CNN model performance.

This paper depicts a new concept for using data mining in the field of farming, as it involves using largely employed data mining systems over agricultural information sets. Data mining can be defined as a technique of separating crucial information from wide-ranging databases by the advent of diverse tools and methods. According to the author, different data mining practices like K-Means, K-Nearest Neighbor (KNN), Artificial Neural Networks (ANN), Support Vector Machines (SVM), Bi-clustering, etc.<sup>[23]</sup> Have found their applications in the field of agriculture. Data mining in agriculture is an imminent research field. The author of this paper

discusses her opinions about efficacious techniques that can be refurbished and altered for working out multifaceted agricultural problems.<sup>[24]</sup> The author also provides proposals for upcoming research innovations in agriculture-related fields.

## MATERIAL AND METHOD

Figure. 1: Steps involved in disease prediction using a deep learning model



### Dataset Description

A Dataset is an integral and crucial facet of any research study. The dataset used to train our neural network model has been obtained from Kaggle, a web community of knowledge scientists and machine learning practitioners.<sup>[25]</sup> We chose the Plant village dataset, Which is an open-source dataset from Kaggle exclusively, made for a Disease detection system. This dataset comprises 15 different categories as shown in Figure. 2 and contains 20,639 images. Note that, these data accompany predefined training and test subsets. Following the loading of the dataset and installation of all the required packages, we segregated the dataset into testing and training sets respectively.<sup>[26]</sup>

Figure. 2: kaggle dataset directories

|                                        |                                    |                                       |                                      |                                         |
|----------------------------------------|------------------------------------|---------------------------------------|--------------------------------------|-----------------------------------------|
| Pepper_bell__Bacteria...<br>997 files  | Pepper_bell__healthy<br>1478 files | Potato__Early_blight<br>1000 files    | Potato__Late_blight<br>1000 files    | Potato__healthy<br>152 files            |
| Tomato_Bacterial_spot<br>2127 files    | Tomato_Early_blight<br>1000 files  | Tomato_Late_blight<br>1909 files      | Tomato_Leaf_Mold<br>952 files        | Tomato_Septoria_Leaf_s...<br>1771 files |
| Tomato_Spider_mites_T...<br>1676 files | Tomato__Target_Spot<br>1404 files  | Tomato__Tomato_Yello...<br>3209 files | Tomato__Tomato_mosai...<br>373 files | Tomato_healthy<br>1591 files            |

### Data Pre-processing

Data preprocessing can be defined as the technique of priming the raw data and making it optimal for a Machine learning/ deep learning model.<sup>[27]</sup> Applied and everyday data commonly contains noises in the form of missing values, or perhaps in an unusable format that cannot be immediately used for training the machine learning/Deep learning models. Data preprocessing is a necessitated task for preparing the data and making it optimal for a deep-learning model, which consequently also intensifies the accuracy of a deep-learning model. Some of the techniques used in data preprocessing are:

- Data cleaning: It refers to filling the inconsistencies in the data, de-noising it, identifying outliers, and solving irregularities.
- Data integration: It involves consolidating data from multiple sources into one coherent data warehouse.
- Data transformation: Data transformation can involve functions like normalization, smoothening, aggregation, and generalization.
- Data reduction: This is achieved by either reducing the volume of the data or the number of attributes.

The pre-processing done in our model comprises procedures like cropping of the images, flipping horizontally/vertically, varying other parameters like contrast, saturation. We have cropped the images in the chosen dataset to a uniform size. Furthermore, we have also applied Data augmentation, which aids in creating new training data from existing training data as the efficacy of deep learning neural networks often improve with the amount of data available. In addition to this, we have also used image augmentation, which comprises creating transformed versions of images in the training dataset <sup>[28]</sup>.

### Deep learning Models used

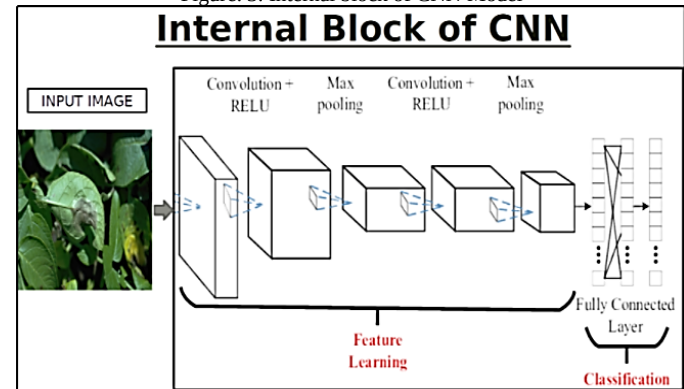
As a part of our research, we have included results of 3 different trained models namely, a Convolutional Neural Network model, Inception Model, and VGG 16 model. <sup>[29]</sup>

- Convolutional Neural Network model

A convolutional neural network is a kind of neural network, which is most recurrently harnessed to solve image-processing issues.<sup>[30]</sup> A convolutional neural network comprises an input layer (takes input in numerous forms), an output layer, and a hidden layer (performs calculations on data). The output layer then delivers the result of the calculations. Convolutional neural networks handle the information as spatial. Rather than the neurons being coupled to every neuron in the preceding layer, they are only linked to neurons that are within proximity. The simplification within the connections means that the network upholds the spatial facet of the information set. Every layer encompasses neurons that are associated with the neurons in the former layer and each neuron has its weight. A convolutional neural network is composed of the convolutional layer

and the pooling layer in addition to a RELU (rectified linear unit layer) and a fully connected layer<sup>[31]</sup> depicted by Figure. 3. The RELU layer can be thought of as an activation function, safeguarding non-linearity as the data progresses through each layer in the network. In the absence of it, the data being fed into each layer would lose some of its dimensionality. The fully connected layer aids in performing classification functions on the data set.

Figure. 3: Internal block of CNN Model



A filtering process takes place inside a convolutional neural network. The convolutional layer places a filter over an array of image pixels. This creates a convolved feature map.<sup>[32]</sup> A pooling layer is used to down sample the size of a feature map. Down sampling makes the processing more efficient and faster due to the reduction in the number of parameters that need to be processed by the network. The result of this function is a pooled feature map. There are two methods to achieve this: max pooling (takes the maximum value of every cluster of neurons situated at the previous layer), and average pooling (uses the average value instead).<sup>[33]</sup> The amalgamation of these steps results in feature extraction. With the advent of feature extraction, the network formulates a picture as per its own mathematical rules. A fully connected layer then performs the classification.

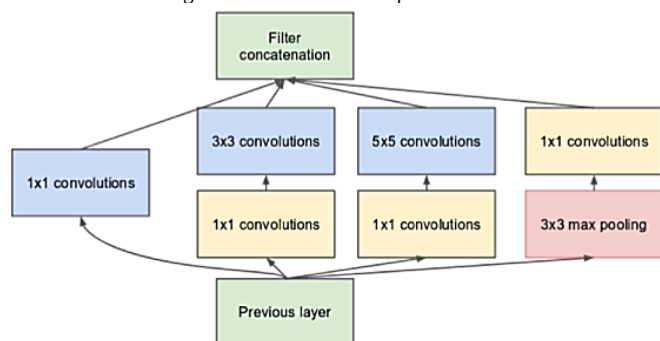
- Inception Model

Inception is a notably maneuvered CNN-based image detection model.<sup>[34]</sup> It is a deep learning model with a structural design that comprises reiterating components known as Inception modules. An Inception Module consists of the following components:

Input layer

- 1x1 convolution layer (used to reduce dimensions & filters and learn patterns)
- 3x3 convolution layer and 5x5 convolution layer (pick up spatial patterns across all dimensional constituents like height, width, and depth of the input)
- Max pooling layer (A pooling layer is used to downsample the size of a feature map.)
- Concatenation layer (amalgamates the result from previous layers.)

Figure. 4: Structure of Inception model

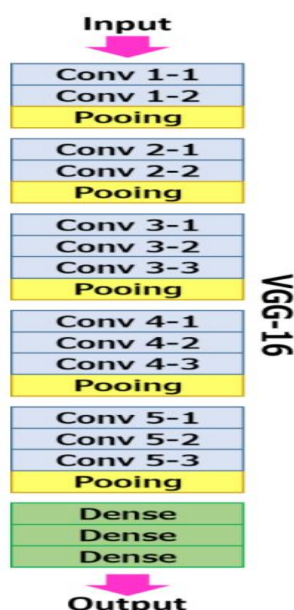


The inception module can be thought of as a set of parallel convolutional layers with various sized filters (1×1, 3×3, 5×5) and a 3×3 max-pooling layer, the outputs of which are then concatenated (Figure. 4).<sup>[35]</sup> This is a very straightforward and efficient architecture, which facilitates the model to learn parallel filters of varying sizes. This enables learning at multiple scales. The inception module can be directly implemented using the Keras functional API.

- VGG16 Model

VGG16 is a type CNN model that was propositioned by K. Simonyan and A. Zisserman from the University of Oxford. VGG16 constitutes 3×3 kernel-sized filters with a stride of 1. It was trained for weeks via NVIDIA Titan Black GPUS.

Figure. 5: Structure of VGG 16 model



VGG16 models always use the same padding and max pool layer, which is of a 2x2 filter with a stride equivalent to two. This arrangement is customarily followed throughout the VGG16 model's entire architecture (Fig 5). The last part of the model has two Fully Connected layers. These fully connected layers are then followed by SoftMax, which aids in the computation of the output. A VGG16 model has sixteen layers. All these layers have weights associated with them.

## RESULT AND DISCUSSION

The classification models' efficiency and competency have been quantified by the means of metrics like accuracy, precision, recall, and F1 score. The above models have been implemented using Python 3 and trained on Google Collab's NVIDIA Tesla K80 GPU.

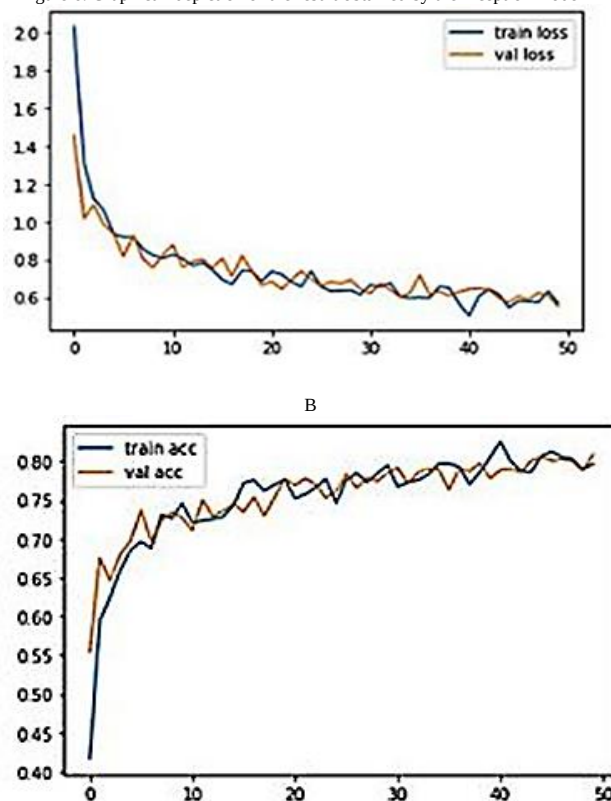
### Inception Model

The concept of transfer learning was used to facilitate the training of this model. The weights were downloaded from image net. The model was trained for 50 epochs and had a batch size of 32. Adam optimizer was used. The results obtained by same are as follows (table 1, figure 6):

Table 1. Evaluation metrics obtained by the inception model

|                 |         |
|-----------------|---------|
| Precision Score | 0.068   |
| Recall Score    | 0.069   |
| F1 Score        | 0.067   |
| Accuracy        | 86.70 % |

Figure 6. Graphical depiction of the result obtained by the inception model A



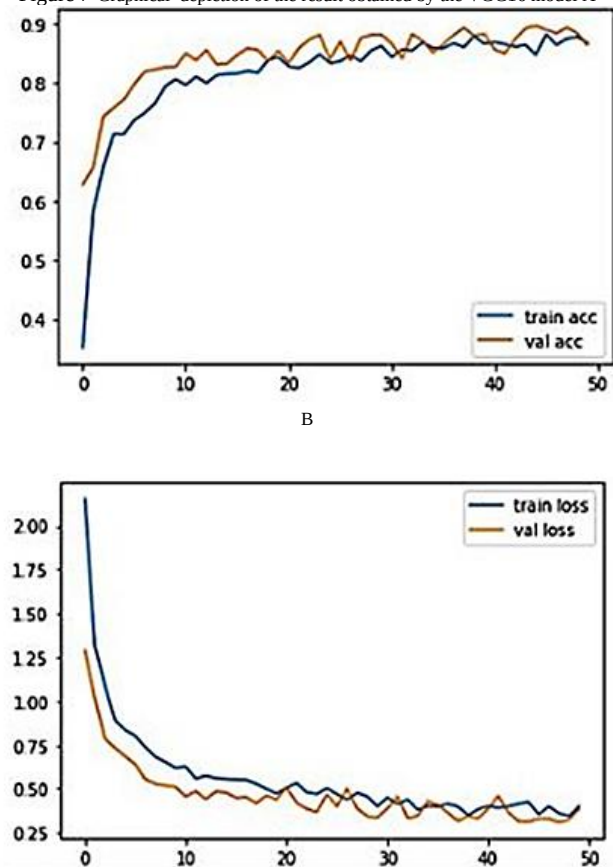
### VGG16 Model

The concept of transfer learning was used to train the VGG16 model and the weights for the same were downloaded from image net. The model was trained for 50 epochs. The Batch size was 32 and Adam optimizer was used. The results obtained by same are as follows (table 2, figure 7):

Table 2. Evaluation metrics obtained by the VGG16 model

|                 |         |
|-----------------|---------|
| Precision Score | 0.068   |
| Recall Score    | 0.067   |
| F1 Score        | 0.067   |
| Accuracy        | 80.39 % |

Figure 7 Graphical depiction of the result obtained by the VGG16 model A



### CNN Model

The CNN model was trained from scratch for 50 epochs and had a batch size of 32. Adam optimizer was used to increase the efficacy of the model. The results obtained by same are as follows (table 3):

Table 3. Evaluation metrics obtained by the CNN model

|                 |       |
|-----------------|-------|
| Precision Score | 0.062 |
| Recall Score    | 0.066 |
| F1 Score        | 0.063 |
| Accuracy        | 83.62 |

### CONCLUSION

Diseases in crops are a chief hazard to the food supply, as they have a detrimental effect on both the quantity and quality of the agricultural yield. A plant disease detection system can function as a comprehensive detector, recognizing anomalies on the leaves and can facilitate monitoring of large fields. This Methodology provides a possibility to unearth these diseases at a preliminary stage, thus significantly reducing the chances of massive outbreaks of crop diseases. Our paper exhibits the technical practicability of the deep learning model for predicting plant diseases. All the aforementioned models were successful in predicting the affliction with notable accuracies. The most optimal results were obtained with trifling computational efforts, which is a testament to how far computer vision, image recognition, and classification technologies have come.

### CONFLICT OF INTEREST:

The authors declared no conflict of interest.

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