Comparison and Analysis of CNN based Algorithms for Plant Disease Identification

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Abstract.

High crop yield is an important feature that impacts the field of agribusiness and farmers financially, socially, and in every perspective. At different stages of a crop's growth, it is important to keep a close eye on it so that early infections can be found. Manual examination of the crops cannot help because humans are always prone to errors, and the risk of false predictions is high, and it is very time consuming as well. Also, when the paradigm shift is towards smart agriculture these years, automation of every aspect of crop growing and monitoring is important. Therefore, in this work, we have analyzed the appropriateness of automated approach for the classification of diseases in plants. Two algorithms one based on a CNN, and other based on VGG-16 approach has been compared and analyzed in conditions of precision and loss. The performance has been verified with the plant village dataset and the precision given by first trained model of CNN (convolution neural network) was 96.77% and the VGG based trained model with batch normalization is 94%.

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INTRODUCTION

Agribusiness is one of the main occupations in India. It is the foundation of India's economy. 60% of the population is dependent on agriculture. There is large variety for selecting acceptable crops and locating appropriate insecticides for them. Consequently, harm to the crops will increase the loss in the output rate as well as influence the country's economy. Crop development and results are important characteristics that impact the area of agribusiness along with farmers economically and socially. So, it is necessary to closely examine different phases of harvest growth to detect diseases on a timely basis. However, human detection may not be adequate in some cases. Therefore, automatic identification and grouping of different diseases of a particular harvest are important for exact recognition [1]. Automatic identification of plant diseases is essential to recognize the signs of disease in the initial stages when they show on developing in leaves or any part of the plant. This research work presents a relative study of the CNN (convolution neural network) based algorithms for exact recognition and detection of plant disease. The simulations are carried out using the plant village dataset.

LITERATURE REVIEW

Research studies attempted by a number of experts in the recent years have shown that the convolutional neural network classifier identifies or detects wide range of plant diseases with high validity or accuracy. K-means and multi – Support Vector Machine based methods also has given exact results and have consumed very less time to complete the task [2]. A convolution neural network strategy has achieved an accuracy of 88.80% [3].

The Gabor filter is utilized to extract the feature from the gathered leaves along with grouping of leaf infection by utilizing a pre-trained DENSENET [4]. The offered technique is viewed as finest when evaluated against the existing / current investigations. CNN technique functions well when it works with a single kind of plant leaf or fruit. CNN utilizes training from scratch & provides finest classification exactness. Preprocessing in the HSV space and using an ELM classifier to train the model on the dataset and has observed an improved precision of 84.4% [5]. CNN used to identify the disease along with affected part of the plant. A fresh arithmetical activation function is built as well as compared with some current activation functions. Using new mathematical activation function has enhanced the precision of convolution neural network by 95% [6].

Systematic soybean disease detection technique is used in which the author have used pretrained Alex Net along with Google Net CNN. In offered system 649 pictures of infected and 550 of healthy soybean leaves are used. Where Alex Net gives 98.75% of accuracy and Google Net gives 96.25% of accuracy [7]. Convolution neural network method used for plant disease detection. A CNN based model is developed and trained with 3663 number of pictures. This model obtains the accuracy of 88.7% [8]. Deep CNN based model is developed. The developed model was trained with 70295 pictures and 17572 validation pictures. This work includes total 38 different types of plant leaf pictures. The offered methodology gives 99.80% of accuracy [9].

Used a minor variation of CNN method known as LeNet to classify & detect disease. The primary goal of this study is to detect Tomato leaf disease by utilizing easiest approach. The approach used in this study provides 94-95% of accuracy which shows the working possibility of the offered method under desirable conditions [10]. A CNN strategy is offered by using the method of transfer learning. Data augmentation method used. The offered method obtains accuracy of 97.61% [11]. The main concentration of [12] is on identifying plant disease that will keep track of plant disease and help in increasing crop production. The offered work will detects and identify the plant disease at initial phase by utilizing DL methods. The offered work utilizes deep convolution neural network method to identify and detects the disease. This work gives the accuracy of 96.50%. [13] Worked on data set that includes different images of plant leaves of both healthy and infected leaves. CNN method is utilized to train the model. The offered method predicts the health of plant leaves with the accuracy of 85%.

Number of CNN and DL based structures has been offered in this papers that have given promising results. The outcome of this study/ literature review shows that deep models especially Convolution neural network method outflanks the traditional handcrafted methods. In this offered work we have compare the CNN and VGG16 method.

TABLE 1- Types of CNN models [9]

Models	No. of layer's	Parameters	Size
LeNet	7	-	-
Alex Net	8	60	-
Res Net 152	-152	50	132MB
Res Net 101	-101	44	171MB
Mobile Net - V1	28	4.2	16MB
Mobile Net - V2	28	3. 37	14MB
Inception V1	-27	7	-
Inception V3	-42	27	93MB

There are many different types of Convolution neural network models. Table1 involves those different types of CNN models. Such as Let-net, Alex-net, Res-net.

Dataset

The dataset used for analysis of the algorithms in this work is the plant village dataset. Table 2 shows that dataset involves around 20,639 total pictures, in which 15 types of healthy and diseased plant leaves are included.

TABLE 2- Plant Village Dataset [14]

Plant	Disease Name	Training Image	Validation Image
Pepper	Bacterial – Spot	790	207
	Healthy	1081	397
Potato	Early-Blight	795	205
	Healthy	122	30
	Late-Blight	803	197
Tomato	Target- Spot	1173	231
	Tomato-Mosaic-Virus	297	76
	Tomato-Yellow-Leaf Curl Virus	2788	421
	Bacterial-Spot	1811	316
	Early-Blight	794	206
	Healthy	1185	406
	Late-Blight	1503	406
	Leaf-Mold	816	136
	Septoria-Leaf-Spot	1400	371
	Spider- Mites-Two-spotted spider-mite	1320	356

METHODOLOGY

The images are resized to a standard size of 256X256. Augmentation is performed by Rotation and shifting as well as a batch- size of 32 is selected. The architecture based on the CNN structure is given in Fig.1 and VGG-16 based architecture in Fig.2

The experiment now runs for 5 epochs (an epoch is calculated as quantity of training iterations where specific NN has made a full-pass through entire training dataset) to train the CNN model. To check the accuracy of the trained CNN model, it was made to run through the validation image dataset.

4.1 CNN(convolution neural network) Based Approach

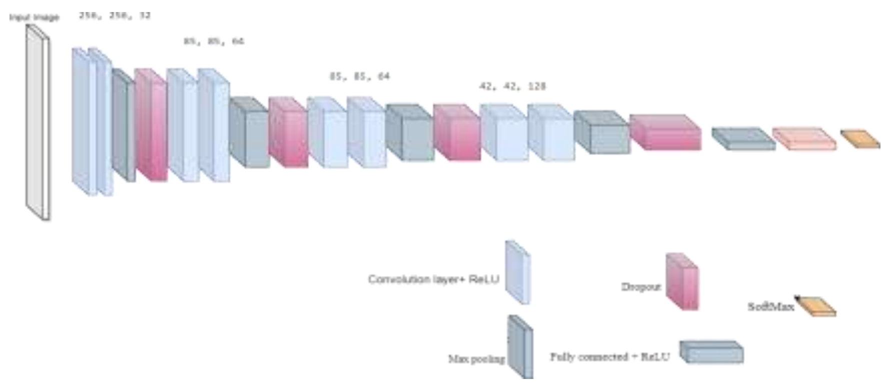


Figure 1. CNN model architecture [15]

CNN are a type of DNN that can detect and classify significant picture features and are commonly used in image analysis techniques. The convolution neural network receives picture as input, processes it, analyses it, and produces outcome values that indicate how confident it is that the picture is of a specific object.

The convolution layer is the very first layer, which extracts the various traits and properties. In figure 1 there are 4 convolutional layers with 32, 64, 64 and 128 filters correspondingly in the different layers. Result of convolution layer is the feature map, which contains picture information like corners and edges. The outcome feature map is then used as input to further layers. After a convolutional layer, relu layer is applied ReLU is known as Rectified Linear Unit for a non-linear operation. The output is $f(x) = \max(0, x)$. After relu layer, max pooling is added to reduce the dimension of the convolution feature map to lessen computational expenses. Based upon mechanism, different types of pooling methods exist. The FC layer, i.e., a fully connected layer, connects the neurons between two layers and is made up of weights and biases. The Adam optimizer with the binary entropy loss function is used with accuracy as the performance metric. Choice of training-testing/validation set distribution is made to be 80% for training, 20% for testing/validation. 16,678 are used as training images and 3961 images were tested. This used a training image dataset of 16677 image files belonging to 15 classes. The CNN model architecture used in this approach extracts a total of 58,102,671 parameters and from total 58,099,791 are trainable parameters and 2,880 are non-trainable parameters [15].

4.2 VGG-16 Based Approach

VGG-16 is basically a type of convolution neural network. The model summary of the VGG-16 based architecture is given in Figure3. The dimension of each image is (224, 224, and 3). Keras adds an additional dimension for the purpose of processing numerous batches, or in other words, for the purpose of training multiple pictures at each step of a single epoch. 'None' is used to indicate the size of a batch since it may be of any size. As a result, the input shape becomes (None, 224, 224, 3). Output with the size (222, 222) is produced when an image with the dimensions (224, 224) is convolved with a filter with the dimensions (3, 3), having both the strides and the dilation rate set to 1, and having 'valid' padding = (224 – 3 + 1, 224 – 3 + 1). Due to the fact that both the amount of filters used in this convolution layer and the amount of channels used in its output are 32, the result, therefore, is: (222, 222, 32). The Max-Pooling kernel in its default configuration has a shape of (2, 2) with strides of (2, 2). The outcome of applying that to an image with the coordinates (222, 222) is an image with the form (((222-2)//2) + 1, (222-2)//2) + 1)) = (111, 111). This pattern may be expanded to include all of the Conv2D and Max-Pooling layers. The Flatten layer converts each pixel along each channel into a 1D vector. The input value (26, 26, 128) is thus converted to (26 * 26 * 128) = 86528 values. The subsequent levels are dense, with the first layer containing 256 units and the second layer containing 15 units.

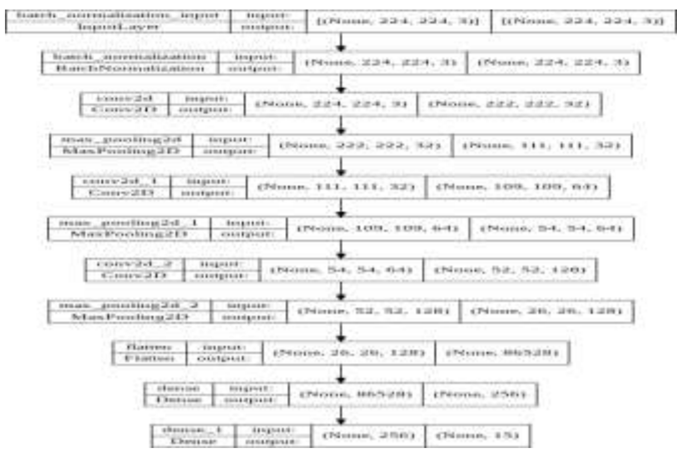


Figure 2. Model summary [17]

RESULTS AND DISCUSSION

Plant-Village dataset of 54,306 photos covering 38 categories of 14 kinds of crops and 26 diseases, the dataset used for this study was limited to 15 classes and a total of 20639 images. The accuracy achieved was 96.4% with CNN based approach and 94% with U Net model. Notably, although the training of the model requires a significant amount of time the classification itself is very rapid and can thus be readily implemented on a smart phone. This demonstrates the future scope for smart phone-assisted worldwide crop disease diagnosis. However, there are certain drawbacks at this level that must be tackling in upcoming research. Initially, when evaluated on collection of photographs captured under unique settings from those utilized for training, models precision drops significantly, a more diversified collection of training data is still required to improve the adaptability of the algorithm.

Figure 3. Training and validation /testing precision (CNN Based approach)

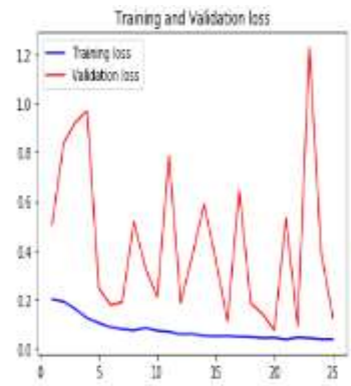
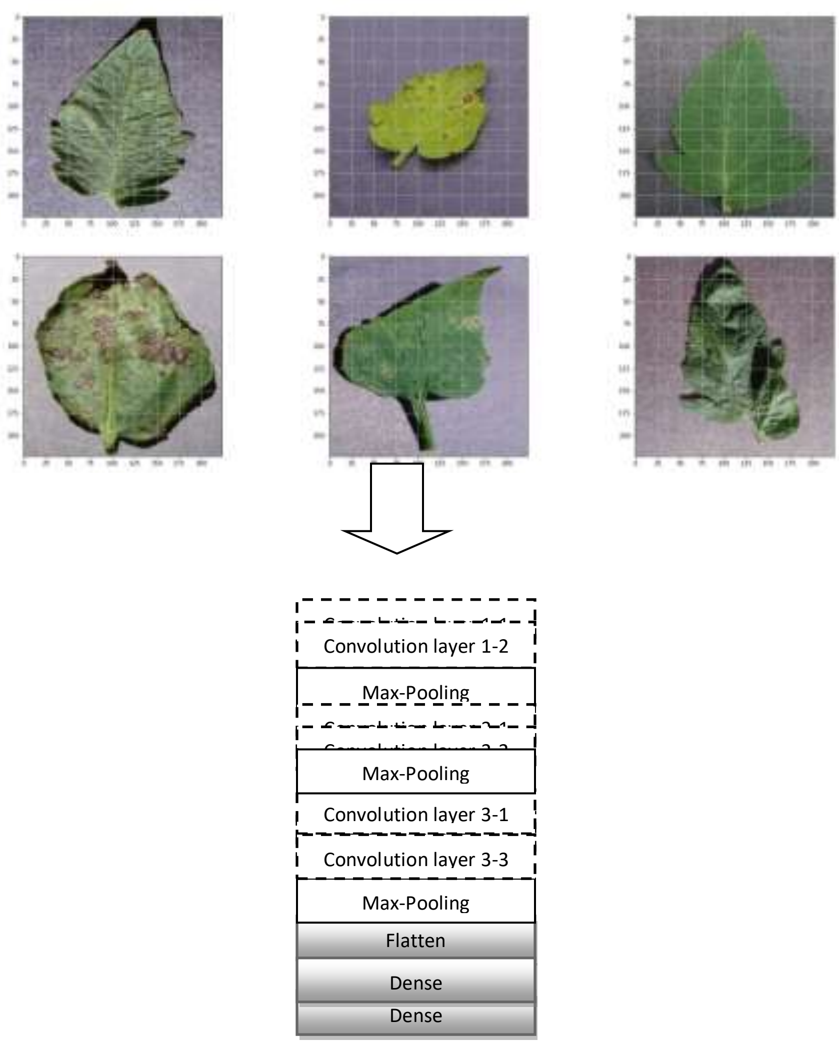


Figure 4. Training and validation /testing loss (CNN Based Approach)

In figures 3 and 4, the graphs show training and testing accuracy, loss. In figure 3 x-axis show the epoch used and y-axis show the accuracy. In figure 4 x-axis show the epoch used and y-axis show loss.



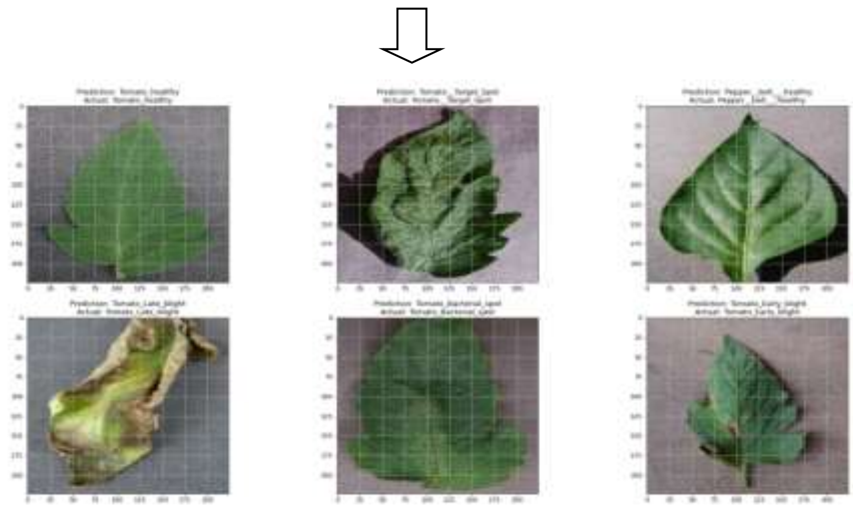


Figure 5 Actual vs. predicted [17]

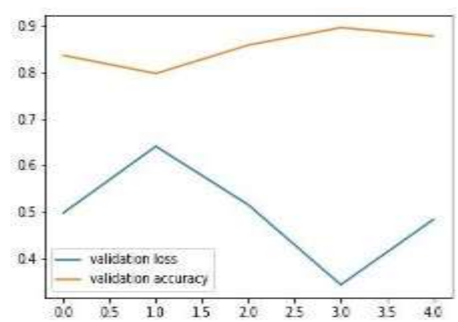


Figure 6. Training loss and accuracy

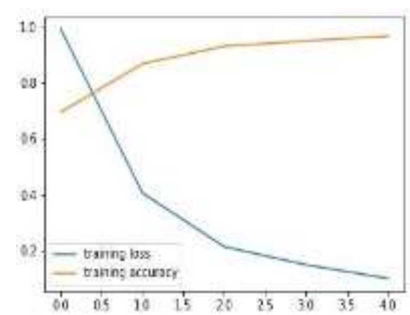


Figure 7. Training loss and accuracy

In figures 3 and 4, the graphs show training and testing accuracy, loss. In figure 6 shows validation loss and accuracy the blue line shows the loss and red one shows the accuracy. In figure 7 shows training loss and accuracy the blue line shows the loss and red one shows the accuracy.

CONCLUSION

Plant diseases are a matter of serious concern in the agricultural sector and must be diagnosed before they lead to a total loss of the crop. But, often, farmers are unable to differentiate among identical signs that indicate distinct illnesses. In this study, a DL-based system for automatically classifying and detecting this from leaf images was investigated. The models considered for the study are CNN and theVGG16, the first trained model gives 96.45% and the second trained model 93% of accuracy. DL models outperform the traditional algorithms and can be appropriate for automation of crop monitoring in smart agriculture.

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