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Detection and Classification of Different Leaf Diseases in Solanum torvum using Deep Learning

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Abstract *– Fungal disease is a serious threat for plant life. Detection of this fungal disease under laboratory is a time consuming and laborious work. Image processing techniques can be used for early detect of these diseases. This paper discusses the detection of Early Blight and Late Blight diseases in Solanum torvum species. Early Blight is caused by Alterneria Solani and Late Blight is caused by Phythphora Infestens. Both fungal pathogens are identified in the laboratory of department of Botany, Madhabdev University, Assam. After identification of fungal disease image processing is carried out with the help of Convolution Neural Network. In this study, by using the EfficientNetB0 model CNN architecture, initially 98.75% accuracy has been observed and after fine-tuning 100% of classification accuracy has been achieved.*
Index Terms *– Convolutional Neural Network (CNN), Deep Learning, Digital Image Processing, Solanam torvum.*

1. INTRODUCTION

Solanum torvum, which is also known as Turkey Berry or Wild Eggplant in English, is a wild edible plant species belonging to Solanaceae family. The traditional medicine system from ancient civilization utilized the Solanum torvum due to its diverse pharmacological properties like antioxidant, antimicrobial, anti-inflammatory, promote digestive health and so forth. However, the Solanum torvum is not only used as a resource of medicine but is also popular as a food with high nutritional values. Though, this plant species is considered as a wild plant however, in West Indies & Africa the cultivation of Solanum torvum has started.

In view of the contribution to the human civilization, the sustainable utilization and conservation of the Solanum torvum plant species became a very important aspect. Therefore the early detection and diagnose of plant diseasesin this plant is an important aspect for the conservation.

The Convolutional Neural Network (CNN) is a very popular deep learning framework which has shown a very significant success in the field of image recognition. Therefore, in this study, detection and classification of different fungal diseases of Solanum torvum from leaf image is performed with the help of Convolutional Neural Network (CNN). The EfficientNetB0 [15] architecture as the base model and with the help of transfer learning and fine-tuning, the leaf image of Solanum torvum is classified in three classes namely Healthy, Early-Blight and Late Blight.

2. RELATED WORK

Different literatures by several authors have been surveyed where different techniques are proposed with the help of digital image processing for accurate identification of plant diseases based on leaf. It has also been observed that with the emergence of Convocational Neural Network (CNN) the accuracy of image classification has significantly increased. Thus, the prediction percentage of accurate disease detection based on leaf image has also increased significantly.

Dheeb Al Bashish et al. [1] proposed an image-processing model for detection of five diseases of leaf and stem namely Late scorch, Early scorch, Tiny whiteness, Cotton mold, and Ashen mold. In this model after image acquisition phase the segmentation of image is done using K-Means clustering method which is followed by feature extraction phase where the texture analysis of infected leaf and stem has been done using Colour Co-occurrence Method (CCM). The classification is done by using a Back propagation algorithm where around 93% of disease prediction result has been obtained.

Another image processing technique for Tomato leaves disease detection has been presented by Usama Mokhtar et al. [2] where two types of diseases namely Early blight and Powdery mildew are considered. After Pre-processing and Feature Extraction phase using Gabor wavelet transformation the output feature vectors are used as input for classification phase, where Support Vector Machine(SVM) with three kernels are used to properly identify the disease class.

Using K-mean clustering and color and texture analysis Sabah Bashir et al. [3] presented an effective algorithm for identifying the leaf diseases of Malus Domestica. Here, for texture analysis and color analysis the Co-occurance matrix algorithm and K-means clustering algorithm has been used respectively.

By utilizing a custom Convocational Neural Network model in deep learning approach Ahmad Garba et al [4] proposed a model for detecting tomato leaf diseases. Due to the use of large dataset of healthy and diseased tomato leaf image the model give a high accuracy result in distinguishing the healthy and diseased tomato leaves.

Mohanty et al. [5] develop and train a deep convocational neural network by using a public dataset containing 54,306 images of healthy and diseased leaf images. The model identify 14 crop species and 26 different diseases and gain a prediction accuracy of 99.35%.

In a study, Huang [6] presented an application of image processing and neural network for detecting and classification of one of most popular orchids namely Phalaenopsis seeding diseases. The application try to classify the input image in four classes that are Bacterial soft rot (BSR), Phytophthora blactrot (PBR), Bacterial brown spot (BBS) and Healthy. Gray level co-occurrence matrix(GLCM) has been used to evaluate the texture features and back-propagation neural network was used as classifier . 97.2% of detection accuracy without classification as well as 89.6% of detection and classification accuracy has been reported in the study.

Khirade et al. [7] describe a disease detection model where Otsu threshold algorithm, Artificial Neural Network (ANN), Support Vector Machine (SVM) & Back propagation network has been used for detection and classification of diseases based on digital images.

97% of efficiency has been achieved by the image processing technique introduced by Ramakrishnan et al. [8] for Groundnut plant disease detection where the author try to detect the two diseases of Groundnut plant leaf namely Early leaf spot and Late leaf spot. In the study the RGB leaf Image are first converted to HSV color images then using co-occurrence matrices technique the color and texture features extraction has been done. Then using two phases in black propagation algorithm namely Propagation and weight update the author try to classify and recognize the accurate diseases of Groundnut plant.

An image processing technique for orchid leaf disease detection has been proposed by Fadzil et al. [9] where the two type of diseases mostly found on orchid namely Black Leaf spot and Sun scorch are considered. In this model, the Region of Interest (ROI) is added on a Graphics User Interface (GUI) and based on the selected ROI of the orchid leave image the analysis has been done using Border Segmentation Technique which is developed using MATLAB.

In the study conducted by Mohanty et al. [10] deep learning model has been proposed using Alexnet and GoogleNet CNN Architecture where the PlantVillage dataset has been used. Using AlexNet the proposed model find an accuracy of 99.27% whereas 99.34% of accuracy has been achieved while using GoogleNet.

Using AlexNet and GoogleNet, Pawara et al. [11] proposed a deep learning plant disease detection model where they experiment the model using three different dataset namely: AgriPlant, LeafSnap and Folio. With the AgriPlant dataset the model find an accuracy of 96.37% while using AlexNet CNN architecture and 98.33% while using GoogleNet CNN architecture. In the other hand, in LeafSnap dataset the model found accuracy of 89.51% and 97.66% with AlexNet and GoogleNet CNN architecture respectively. 97.67% and 97.63% of accuracy has been obtained in AlexNet and GoogleNet CNN architecture respectively while using Folio dataset.

Ferentinos [12] proposed a deep learning plant disease detection model using a custom dataset of 87848 numbers of images where AlexNetOWTBn and VGG CNN architecture has been used. The model achieved an accuracy of 99.49% and 99.53% respectively using AlexNetOWNTBn and VGG CNN architecture.

Mishra et al. [13] proposed a real time deep Convolutional Neural Network model for recognition of Corn plant disease where the author create a custom dataset where bulk of images are taken from plant village dataset and some of the images are directly captured from different corn plantation in Raebareli and Sultanpur District under Uttar Pradesh. The proposed model achieved an accuracy of 88.46% during recognition of corn leaf disease.

A deep learning CNN model proposed by Geetharamani et al. [14] was trained and tested using plant village dataset with data augmentation. The dataset is divided in training, testing and validation set which included 55636, 1950 and 3900 number of images respectively after data augmentation. The proposed system achieved a classification accuracy of 96.46%.

3. PORPOSED MODEL

In this study, we proposed a model for detection and classification of diseases of Solanum torvum plant species based on leaf image. Mainly, two type of disease has been considered in this study namely Early Blight and Late Blight.

The initial stage is called the image acquirement phase. In this phase, publically available large image dataset containing different leaf images of Solanum torvum healthy leaf as well as infected leaf images of early blight and late blight is collected. As, such a large leaf image dataset of Solanum torvum is not readily available as on date, therefore we prepare a new leaf image dataset of Solanum torvum consist of 336 healthy leaf images, 332 early blight infected leaf images and 332 late blight infected leaf images of Solanum torvum. The images are collected from different geographical part of Lakhimpur District, Assam which are captured uniformly in a white background on daylight using Oneplus 11R smart phone in a dimension of 1836 x 4096 Pixels. The dataset containing total 1000 numbers of different leaf images are categorized into 3 different labels namely Healthy, Early Blight and Late Blight. Figure 1 shows an example of Healthy, Late Blight and Early Blight leaf image captured during data acquirement phase.

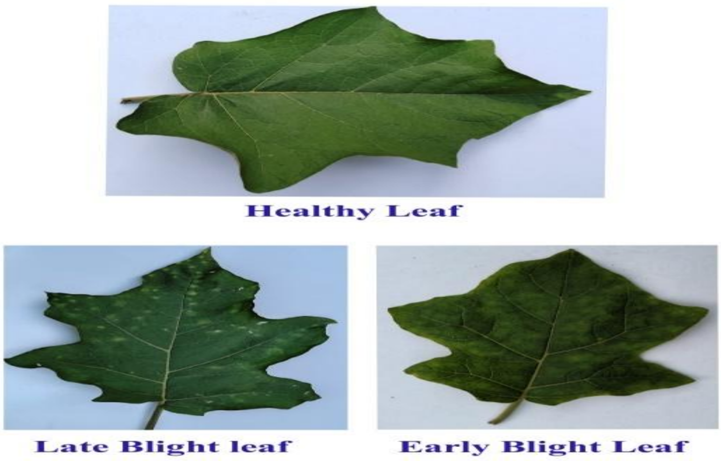

Figure 1 An example of (a) Healthy (b) Early Blight and (c) Late Blight Leaf Image captured during data acquirement

The dataset is further divided into three subset that are Training, Testing and Validation, where 70% images are stored in Training dataset and 15% images are stored in Testing and another 15% in Validation dataset. Figure 2 shows different leaf images belonging to three different classes namely HEALTHY, LATE_BLIGHT and EARLY_BLIGHT under training dataset.

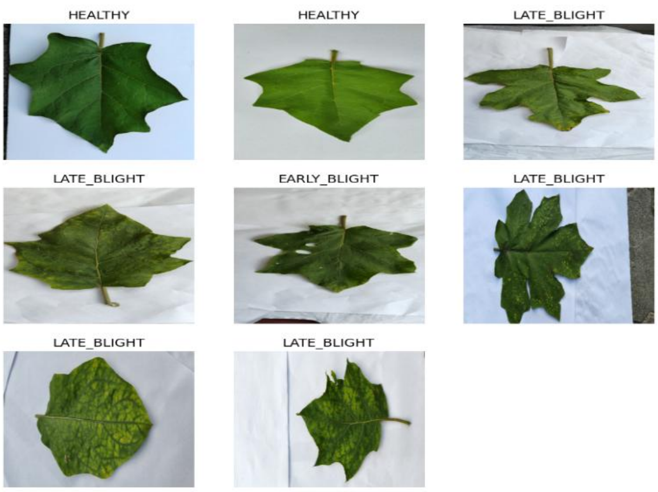

Figure 2 Leaf images of three different classes of training dataset

The number of images available in training and testing of our proposed dataset is shown in Table 1.

Class	Number of Images for Training	Number of Images for Testing	Number of Images for Validation

HEALTHY	200	67	67
EARLY_BLIGHT	200	66	66
LATE_BLIGHT	200	66	66
Total:	600	200	200

Table 1 Dataset for Image Detection and Classification of Solanum torvum leaf

After the image data acquirement phase we move to the image pre-processing phase which is considered as a very crucial step for preparing the images for Convolutional Neural Network model. It is already mentioned that due to the lack of publicly and readily available large leaf image dataset of Solanum torvum plant species we have to prepare a new dataset where we collect different images of healthy and infected leaf of Solanum torvum from different geographical area of Lakhimpur district, Assam. The dataset we have prepared consist of only 1000 images. Due to some advantages like improvement of generalization, robust feature learning, reduce over fitting and so forth, a large dataset is always preferable for use in convocational neural network model. Therefore in the image pre-processing phase of this study we use data augmentation which overcome the limitations of our small dataset during training of our proposed Convolutional Neural Network (CNN) model. Among different techniques of data augmentation, in this study we use some techniques of data augmentation like image rescaling, shear transformation, horizontal flipping and random zooming. Here we use a rescaling parameter of 1./255, which normalize the image pixel value range from [0,255] to [0,1]. For shear transformation and random zooming we use shear intensity value and zoom factor value of 20%. Also, the horizontal flipping parameter is set to true.
Figure 3 shows a image of a leaf of Solanum torvum after rescaling, shear transformation, Zooming, Horizontal flipping.

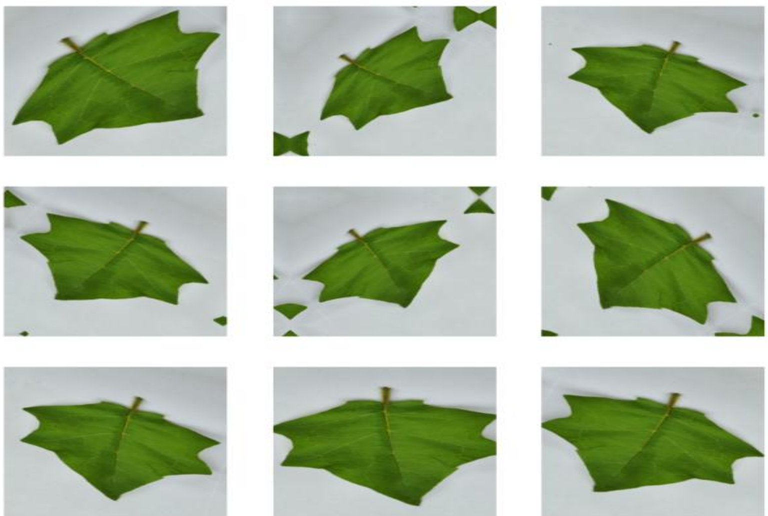

Figure 3 An example of rescaled, sheared, zoomed and flipped leaf image

After pre-processing of images classification of images is carried out. For this, a sequential Convolutional Neural Network has been prepared based on the architecture of a EfficientNetB0. The model summary has been illustrated in Table 2. The model architecture of our proposed model is shown in Figure 4.

Layer	Output shape	Parameter
input_layer_2 (Input Layer)	(None, 528, 528, 3)	0
resizing (Resizing)	(None, 224, 224, 3)	0
efficientnetb0 (Functional)	(None, 7, 7, 1280)	40,49,571
global_average_pooling2d (Global Average Pooling 2D)	(None, 1280)	0
dropout (Dropout)	(None, 1280)	0

dense (Dense)	(None, 3)	3,843

Total Parameters: 40,49,571
Trainable Parameters: 38,44,191
Non-trainable Parameters: 2,09223

Table 2 Summary of the proposed Model

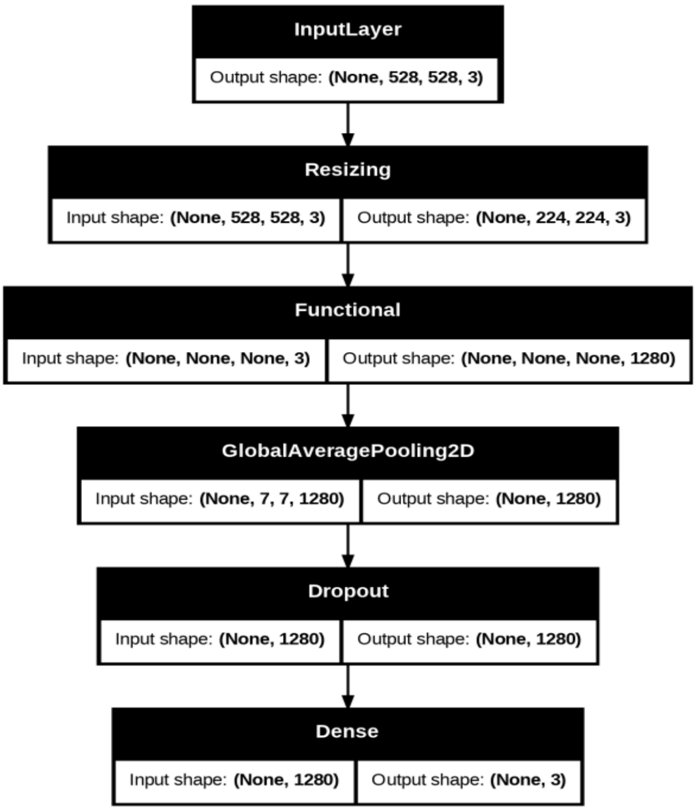

Figure 4 Proposed Model Architecture

Figure 4 and Table 2, clearly illustrate the architecture of our proposed CNN model based on EfficientNetB0. The base model we have used is a lightweight Convolutional Neural Network which ensures higher accuracy even with limited resources. In the first layer that is in the Input and initial processing layer the image input size has been defined with a height and weight of 528 and the input image is in RGB color format. The input image is further resized to 224 x 224. To improve the training stability and ensure consistency the input image is also rescaled from [0, 255] to [-1, 1]. Further, in the stem layer, an initial 2D convolution layer is use for low level features detection in the input image which is followed by batch normalization. The activation function ReLU (Rectified Linear Unit) has been used after the batch normalization process. If x is considered as the input to the neuron then the ReLU function f(x) can be written mathematically as

$$f(x)=max(0,x)$$

The stem layer is followed by a series of blocks where the each block consist of multiple convolution layer with different filters and kernels, squeeze-and-excitation layers along with batch normalization, and activation functions.

In the final layer i.e. the output layer of the model, a convolutional layer has been deployed for final features extraction which is followed by batch normalization and activation. To reduce the spatial dimensions that reduce the risk of outfitting, the global average pooling has been performed. Before the final prediction, the model applies dropout for regularization. Finally, the dense layer produce the final output which is the prediction of disease of leaf image.

4. RESULTS AND DISCUSSIONS

This study was carried out on a windows system, which is equipped with an Intel(R) Core(TM) i5-8250U@1.60 GHz CPU and Intel(R)UHD Graphics 620 GPU with 8 GB RAM.

We propose a CNN model to recognize the leaf diseases of Solanum torvum carried out with a new dataset which we have created with a collection of 1000 different types of leaf images of Solanum torvum plant species. All the images are collected from different geographiccaly area of Lakhimpur district, Assam.

The dataset consist of three different classes namely HEALTHY, EARLY_BLIGHT and LATE_BLIGHT, where 600 images are of healthy Solanum torvum leaves another 200 images of Early Blight Leaf and 200 images of Late Blight leaf. All the images are of size 1836 x 4096 pixels which are further converted to 528 x 528 pixel during preprocessing phase.
In this study the image are preprocessed and provided as input for the proposed CNN model.
The proposed model provides a classification accuracy of 98.75% with epochs value of 10 without fine-tuning as shown in Figure 5.

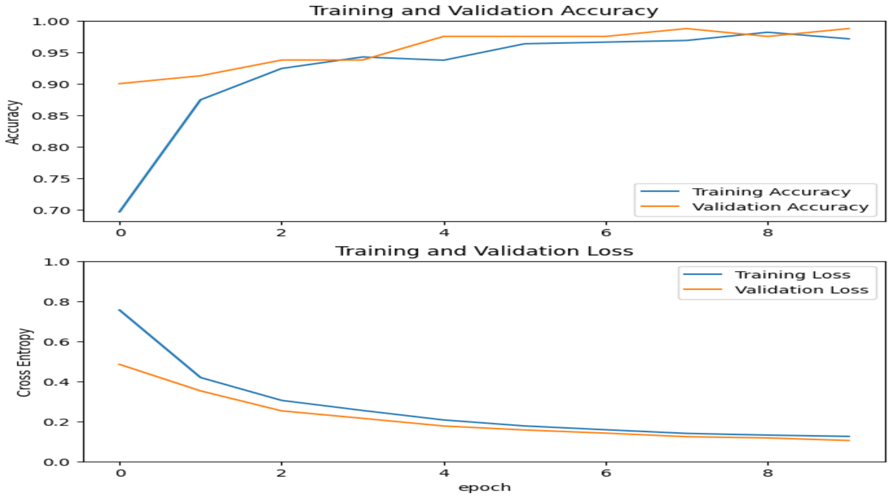

Figure 5 Initial model accuracy using epochs 10 (without Fine-tuning)

Further, we fine tune the proposed model and found 100% classification accuracy in training, validation as well as testing. The training and validation accuracy according to the given epoch is given in Table 3.

epochs value	Training accuracy	Validation accuracy	Validation loss
11	82.98%	93.75%	15.72%
12	90.47%	97.50%	4.72%
13	93.66%	96.25%	7.25%
14	97.10%	91.25%	18.48%
15	95.33%	95.00%	10.71%
16	96.92%	100.00%	0.31%
17	98.96%	98.75%	1.17%
18	98.70%	100.00%	0.94%
19	98.84%	100.00%	0.22%
20	100.00%	100.00%	0.17%

Table 3 Training and Validation accuracy and loss of the proposed Model

Figure 6 illustrate the training and validation accuracy of the proposed model after fine tuning.

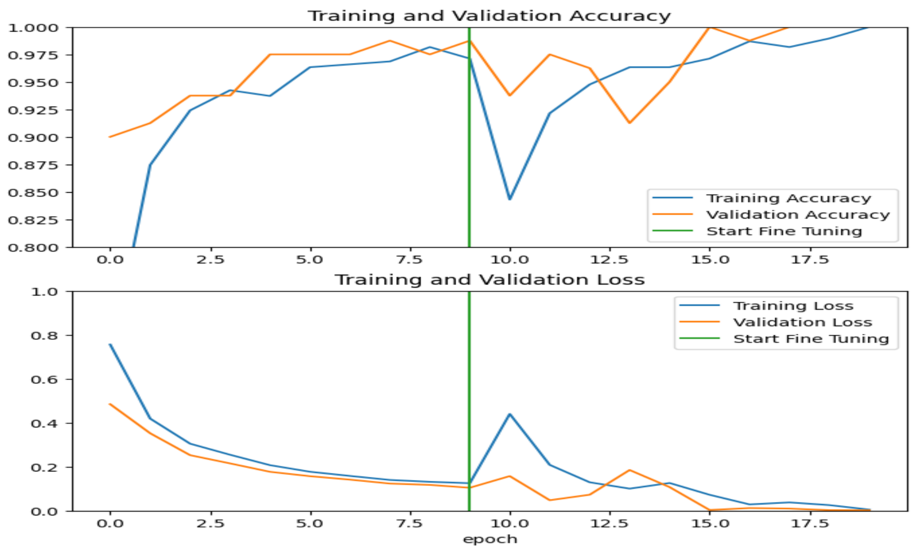

Figure 6 Training and Validation Accuracy after fine tuning

Finally, the model of our study is evaluated by retrieving a batch of random images from the testing set and evaluates the prediction values and label values where 100% accuracy has been achieved as indicate below:

Predictions:

[1 2 0 1 0 2 2 2]

Labels:

[1 2 0 1 0 2 2 2]

Figure 7 shows the model prediction of the leaf images taken from testing set for final evaluation.

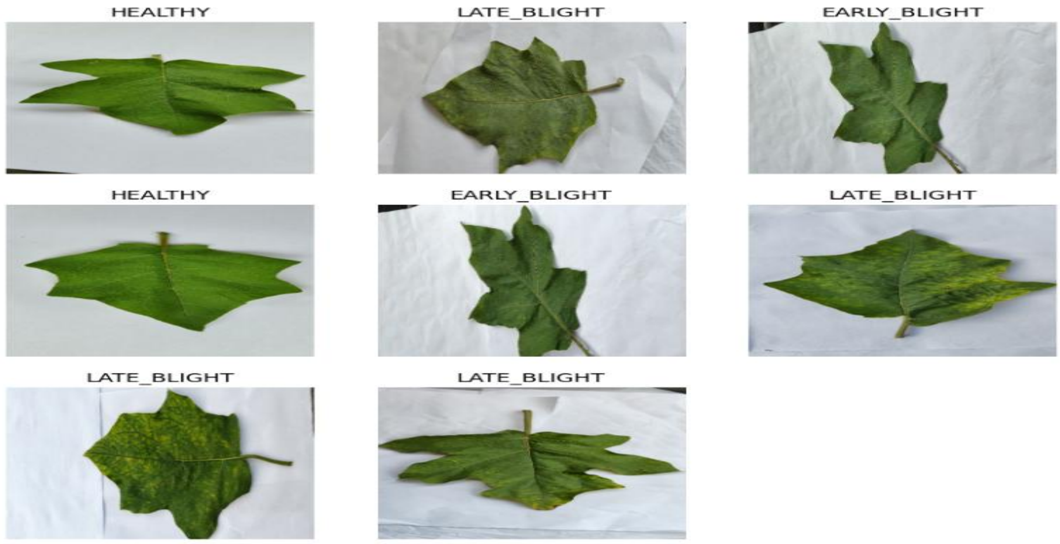

Figure 6 Model prediction of leaf images

5. CONCLUSION

This paper discussed the application of Convolutional Neural Network in wild relative crop plant Solanum torvum which is a significant ethno-medicinal plant, where abnormalities during life process can be detected. Early detection of these diseases by using CNN can prevent damage and serious threat of the plant. Not only it gives significant information about the plant life's but also play a major role in the economy of the aborigine people. In this paper, the identification of fungal disease of Solanum torvum by using CNN shows 100% accuracy. Further, application of CNN can also be used for other fungal, bacterial as well as viral disease identification of different plant. Besides traditional methods of image processing CNN have more potentiality in classification and identification of plant diseases.

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