

Plant Disease Detection using Convolutional Neural Network

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Abstract - Agricultural productivity highly influences the economy of any country, especially in India where agriculture makes up about 20% of the country's GDP. In such situations, if the plant is affected by diseases and it is not treated properly at the right time, it will lead to economic losses and also increases the global food problem. To prevent this from happening, plant diseases must be detected and treated early so as to prevent serious consequences. The existing manual method of detecting plant diseases is time-consuming and not very pocket-friendly to farmers and may sometimes result in incorrect diagnosis as well.

Thus, we can make use of technologies like image processing and deep learning to successfully detect the diseases affecting the plant in the early stages. Most of the plant diseases can be visually seen, so it is convenient to apply image processing techniques to detect and classify them. In our approach, we use the technique of Convolutional Neural Network using Keras which uses the concept of hidden layers to classify the different diseases that affect the plants. Our model is successfully able to classify the diseases mentioned in the Potato, Pepper and Tomato subsets of the Plant Village dataset with an accuracy rate of 95.8%.

Key Words: Plant Disease Detection, Deep Learning, Convolutional Neural Networks

1. INTRODUCTION

Agricultural productivity of a country highly influences its economy. Especially in a country like India, where agriculture provides employment to about 60% of the population and contributes to about 20% of the country's GDP. In this scenario, the health of the plants becomes a major point of concern. If the plant diseases are not identified at the right time, it could lead to crop and hence to large economic issues. In order to prevent this from happening, the plant diseases must be correctly identified on time and proper preventive measures must be taken.

The existing manual method, where farmers consult plant doctors for cure of plant diseases is time consuming and usually involves manual work. Sometimes, the consultation fees is very high, which the farmers cannot afford. To overcome these drawbacks, we have built a plant detection system using Convolutional Neural Networks which predicts the plant disease based on the image uploaded by the farmer. This proposed work is less time-consuming, free of cost and provides good accuracy, which makes it appropriate to be used in real-time.

2. LITERATURE SURVEY

Nilam Bhise *et al.* in paper [1] talks about the identification and detection of diseases of plants as one of the main points which determine the loss/gain of the yield of crop production and agriculture. The studies of plant disease is the study of any visible points in any part of the plant which helps us differentiate between two plants, technically any spots or color shades. So, in this paper the Deep Learning algorithm i.e. Convolutional Neural Network is used with a goal to detect the diseases in the crops. The model is basically tested on some types of plant species with some types of plant diseases. The model was made using Tensorflow and Keras framework and the system is implemented on Android. The overall system results show that the Mobile Net model works better as compared to the other models and provide better accuracy in detecting the diseases. As an extension to the project the number of classes of plants and its diseases will be increased. Also, the model will be further improved by increasing the parameters for training and test.

S. Gopinathan *et al.* [2]'s paper is based on the plant leaf disease detection research work on good healthy agriculture and the economic growth of Indian farmers. Agricultural growth is the forming of good vegetables and fruits. The plant leaves are the most common features to reflect the plants and healthy agriculture modules. The classification of multiple plant leaves was identified using the model leaf structure and disease. It trained 21 labels using the 50 epoch iteration feed-forward model to a different part of plant diseases. It recognizes the plant diseases most of the time in multiple leaves. The Tamil Nadu agricultural weather conditions and plant virus diseases are different from other states/countries. This trained digital image model on the Tamil Nadu live image dataset has a accuracy level of 93.99 % in the levels. The future scope of the trained model is to find the live digital video processing for the identification of plant leaves, disease detection using drone mapping and pest control suggestions.

Mohit Agarwal *et al.* in paper [3] discusses about how tomato is the most popular crop in the world and in every kitchen, it is found in different forms irrespective of the cuisine. After potato and sweet potato, tomatoes are crops which are cultivated worldwide. India ranked 2 in the production of tomatoes. In the proposed work, they have developed a CNN based model to detect the disease in tomato crops. In the proposed CNN based architecture there are 3 convolution and max pooling layers with varying number of filters in each layer. For the experiment, we have

taken the tomato leaf data from the PlantVillage dataset. In the dataset there are 9 disease classes and classes which have healthy images. As the images inside the class are not balanced, data augmentation techniques have been applied to balance the images inside the class. Experimentally, it is observed that the testing accuracy of the model ranges from 76% to 100% for the classes. Moreover, the average testing accuracy of the model is 91.2%. The storage space needed by the proposed model is of order of 1.5 MB whereas pretrained models have storage space needs of around 100 MB thus showing the benefit of the proposed model over pretrained models.

Sammy V Milante[4] In his paper, uses CNN architecture for disease classification and identification. The methodology in the study involves three key stages: acquisition of data, pre-processing of data and image classification. Steps used in this methodology are - Input Dataset, Image Acquisition, Image pre-processing and Classification. A 96.5% accuracy rate was achieved using 75 epochs during the training of the model. The model also achieved a maximum accuracy rate of 100% when testing random images of plant varieties and diseases.

Suma V in paper [5] uses CNN with Artificial Neural Networks (ANN) and Machine Learning Algorithms (Image processing techniques using 5000 datasets). The Network is trained using the images taken in the natural environment and achieved 99.32% classification ability. This shows the ability of CNN to extract important features in the natural environment which is required for plant disease classification. Image classification, Image Categories, Feature Extraction, and Training Data is carried out. The algorithm is implemented with training data and classification of given image dataset. The test input image is compared with the trained data for detection and prediction analysis. From the results, it is clear that the model provides reliable results.

Md. Arifur Rahman[6] mainly focuses on implementing an improved segmentation technique using a combination of thresholding and morphological operations. For classification, they have used the deep neural network. This method includes four important stages namely: enhancement, segmentation, feature extraction and classification. Their proposed method has achieved 99.25% accuracy in the Plant Village database.

S.Santhana Hari in his paper[7] talks about detection of plant disease by leaf image. Disease identification is done by using a deep learning method. All the classification was done based upon the images of the crop's leaf, which contains both the healthy and affected leaf. This model has produced an accuracy of about 96.3%. Deeper Network architecture is implemented for the grading of plant species. Their result produced an accuracy of 86.2% which is less accurate.

Mercelin Francis[8] uses Convolutional Neural Network and deep learning models(image-processing approach). This

paper implements a convolutional neural network to detect and classify whether the leaf is diseased or healthy. Apple and Tomato plant leaves are used to detect whether the plant is healthy or affected by the disease. The achieved accuracy is 88.7 with minimum number of parameters i.e., 45K when compared to other existing models. Creating and training a CNN model from scratch is a tedious process when compared to the usage of existing deep learning models for various applications to achieve maximum accuracy. So, depending on the application various models can be used or retrained. Therefore, in the future work it is planned to utilize a model efficient than VGG and other existing architectures, such that it gives higher accuracy with minimum size and complexity, so that it can be used in mobile or any other embedded applications.

Andre da Silva Abade *et al.*[9] talks about how crop diseases are a major threat to food security, but their rapid identification remains difficult in many parts of the world due to the lack of the necessary infrastructure. The combination of increasing global smartphone penetration and recent advances in computer vision made possible by deep learning has paved the way for smartphone-assisted disease diagnosis. Using a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions, we train a deep convolutional neural network to identify 14 crop species and 26 diseases (or absence thereof). The trained model achieves an accuracy of 99.35% on a held-out test set, demonstrating the feasibility of this approach. When testing the model on a set of images collected from trusted online sources - i.e., taken under conditions different from the images used for training - the model still achieves an accuracy of 31.4%. While this accuracy is much higher than the one based on random selection (2.6%), a more diverse set of training data is needed to improve the general accuracy. Overall, the approach of training deep learning models on increasingly large and publicly available image datasets presents a clear path towards smartphone-assisted crop disease diagnosis on a massive global scale.

Sharada Prasanna Mohanty *et al.* in paper [10] talks about how plant diseases are considered one of the main factors influencing food production and to minimize losses in production, it is essential that crop diseases have fast detection and recognition. Nowadays, recent studies use deep learning techniques to diagnose plant diseases in an attempt to solve the main problem: a fast, low-cost and efficient methodology to diagnose plant diseases. In this work, they propose the use of classical convolutional neural network (CNN) models trained from scratch and a Multichannel CNN (M-CNN) approach to train and evaluate the PlantVillage dataset, containing several plant diseases and more than 54,000 images (divided into 38 diseases classes with 14 plant species). In both proposed approaches, their results achieved better accuracy than the state-of-the-art, with faster convergence and without the use of transfer learning techniques. Their multichannel approach also

demonstrates that the three versions of the dataset (colored, grayscale and segmented) can contribute to improve accuracy, adding relevant information to the proposed artificial neural network.

3. METHODOLOGY

3.1 Technologies Used

3.1.1 Backend Model

The proposed Convolutional Neural Network model is built using Python with TensorFlow and Keras library. Both TensorFlow and Keras are specially used to handle deep learning networks. Keras works as an interface for TensorFlow library.

3.1.2 Frontend

The backend model has to be made accessible to the users by providing a suitable interface for them to interact with. We have made use of the Flask framework, which is written in Python. It is simple framework which helps us to build web-based applications.

The image submitted by the user for consultation, is converted into proper format(arrays) and send to the backend for classification using the Flask API. These requests and responses are communicated using AJAX. The frontend webpages are built using simple HTML and CSS.

3.2 Implementation

In our proposed work, we aim to detect and classify the plant diseases using the concept of Convolutional Neural Networks (CNN). Convolutional Neural Networks is a class of artificial neural network that works on the concept of hidden layers and is most widely used to in image processing and recognition.

The basic framework or flow of our project consists of 5 steps, namely: Image Acquisition, Image Pre-processing, Image Segmentation, Feature Extraction and Classification.

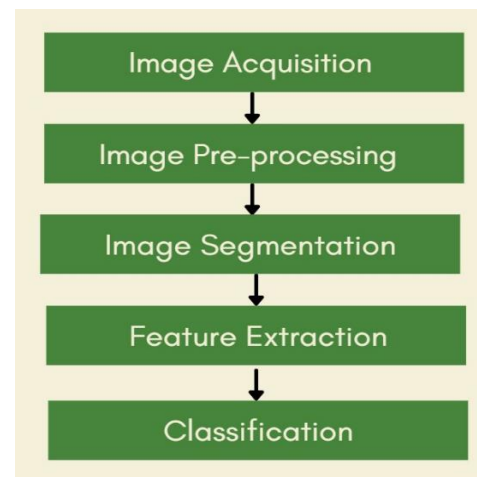


Fig -1: Framework of Proposed System

3.2.1 Image Acquisition

The first step of image classification is image acquisition. The dataset which is selected to build the model plays a very important role in the result observed from it. In image-oriented datasets, the images must be properly labelled, and it must be made sure that no such images exist which do not have labels.

For our CNN model we have made use of PlantVillage dataset. This dataset has a collection of 15 directories of healthy and diseased plant leaves of 3 different plants namely Bell Pepper, Potato and Tomato. With a total of 20,639 images, this dataset houses the following directories of plant leaves:

- Pepper Bell Bacterial spot
- Pepper bell healthy
- Potato Early blight
- Potato Late blight
- Potato healthy
- Tomato Bacterial spot
- Tomato Early blight
- Tomato Late blight
- Tomato Leaf Mold
- Tomato Septoria leaf spot
- Tomato Spider mites Two spotted spider mite
- Tomato Target Spot
- Tomato Yellow Leaf Curl Virus
- Tomato mosaic virus
- Tomato healthy



Fig -2: PlantVillage Dataset

3.2.2 Image Pre-processing

The images which are acquired cannot be directly fed into the Convolutional Neural Network. Since, the computer does not understand anything other than binary numbers, the images also must be converted into machine understandable format. This is done by converting the images into array format. The images of the dataset are converted into 256 x 256 size arrays where each block represents the pixel value. The acquired images may have noise and other discolorations which are not ideal for image processing. All of these ambiguities have to be handled. This is carried out using the process of image segmentation, where the images are divided into smaller segments to map out the areas of interest and to avoid the areas which are less important, and which may cause disruptions to the accuracy of the system.

3.2.3 Feature Extraction

After the images are processed into proper format and divided into segments, the next very important step is feature extraction. This step in Convolutional Neural Network is done by using activation function followed by max-pooling layers.

3.2.3.1 Activation Function

The main purpose of using an activation function in a CNN is to decide which combination of weights and input will fire the next neuron. The activation function used in our CNN model is the ReLU activation function or Rectified Linear Unit activation function. This is very simple mathematical function, which outputs the input as long as the input is greater than zero, otherwise outputs zero. It can be represented as $y = \max(0, x)$ where x is the input and y is the output.

Using this activation function helps the model to learn faster and perform better because it does activate all the neurons at once.

3.2.3.2 Max-Pooling Layers

In CNN, usually every activation function layer is followed by a pooling layer. Pooling layers are used to reduce the dimensions of feature maps. They are 3 types of pooling – average-pooling, max-pooling and global-pooling. We have made use of max-pooling technique because it enhances the features of the images by taking the maximum of the values present in that region. At the end of this operation, we obtain the most prominent features of the image. This step helps in avoiding over-fitting and also reduces noise distortion.

Other than these 2 techniques used for feature extraction of an image, dropout layer is used to reduce over-fitting of the model, where the neurons are dropped at random. Flatten layer is used to convert the output into one long feature vector which is given as input into the next layer.

A summary of the model is shown:

```
model.summary()
```

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 256, 256, 32)	896
activation_1 (Activation)	(None, 256, 256, 32)	0
batch_normalization_1 (Batch Normalization)	(None, 256, 256, 32)	128
max_pooling2d_1 (MaxPooling2D)	(None, 85, 85, 32)	0
dropout_1 (Dropout)	(None, 85, 85, 32)	0
conv2d_2 (Conv2D)	(None, 85, 85, 64)	18496
activation_2 (Activation)	(None, 85, 85, 64)	0
batch_normalization_2 (Batch Normalization)	(None, 85, 85, 64)	256
conv2d_3 (Conv2D)	(None, 85, 85, 64)	36928
activation_3 (Activation)	(None, 85, 85, 64)	0
batch_normalization_3 (Batch Normalization)	(None, 85, 85, 64)	256
max_pooling2d_2 (MaxPooling2D)	(None, 42, 42, 64)	0
dropout_2 (Dropout)	(None, 42, 42, 64)	0
conv2d_4 (Conv2D)	(None, 42, 42, 128)	73856
activation_4 (Activation)	(None, 42, 42, 128)	0
batch_normalization_4 (Batch Normalization)	(None, 42, 42, 128)	512
conv2d_5 (Conv2D)	(None, 42, 42, 128)	147584
activation_5 (Activation)	(None, 42, 42, 128)	0
batch_normalization_5 (Batch Normalization)	(None, 42, 42, 128)	512
max_pooling2d_3 (MaxPooling2D)	(None, 21, 21, 128)	0
dropout_3 (Dropout)	(None, 21, 21, 128)	0
flatten_1 (Flatten)	(None, 56448)	0
dense_1 (Dense)	(None, 1024)	57803776
activation_6 (Activation)	(None, 1024)	0
batch_normalization_6 (Batch Normalization)	(None, 1024)	4096
dropout_4 (Dropout)	(None, 1024)	0
dense_2 (Dense)	(None, 15)	15375
activation_7 (Activation)	(None, 15)	0
=====		
Total params: 58,102,671		
Trainable params: 58,099,791		
Non-trainable params: 2,880		

Fig -3: Backend Model Summary

3.2.4 Classification

After the layers of the Convolutional Neural Network are decided, we compile the model. The dataset is divided into training and test datasets, we have used 20% of the dataset for validation. We have an epoch value of 25, where epoch value is the number of passes that the model makes over the dataset. Real-time image processing functions are used to capture the different features of the image. Once, the model is trained, it is tested on the validation dataset.

4. RESULTS

After compiling our model and training it on the train data with an epoch value of 25 and then plotting the training and validation accuracy and the training and validation loss, the following graphs can be observed. From these graphs, it can be concluded that at the end of the 25 epochs, both the accuracy and loss of the training and validation dataset tend to converge at one point.

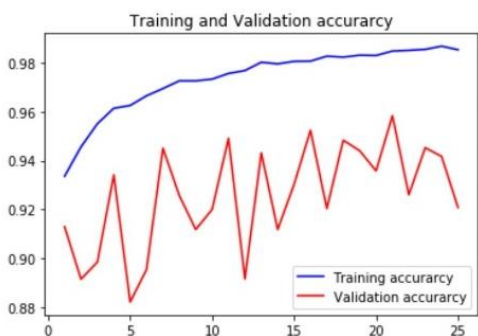


Fig -4: Plot of Training and Validation Accuracy

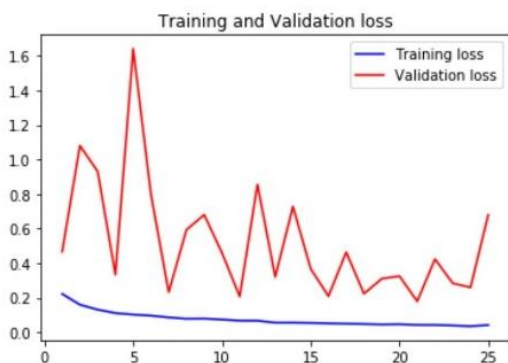


Fig -5: Plot of Training and Validation Loss

The accuracy of the built model is observed to be 95.82%.

```
print("[INFO] Calculating model accuracy")
scores = model.evaluate(x_test, y_test)
print(f"Test Accuracy: {scores[1]*100}")
```

[INFO] Calculating model accuracy
591/591 [=====] - 1s 2ms/step
Test Accuracy: 95.82628506896056

Fig -6: Accuracy of Trained Model

On connecting the backend model to the frontend and deploying it on the server, the users can simply upload the pictures of the affected plant leaves and get the consultation for it at the click of a button.

Plant Disease Diagnosis



Fig -7: Uploading picture for detection

Plant Disease Diagnosis



Result: Potato__Early_blight

Fig -8: Prediction of Disease

5. CONCLUSIONS

Based on the results observed after implementing our Convolutional Neural Network model, it can be safe to say that our model is able to identify and classify the various plant diseases present in the dataset with good accuracy. Furthermore, the accuracy of our model can be increased by increasing the epoch value but at the loss of processing time. To make the plant disease detection process cater to more plants and diseases, it would be more useful to increase the

size of our dataset by collecting images of more plants and their diseases.

Commercialization of our product can include deploying of a mobile app where users can click pictures of the plant diseases in real time and upload it, to get a consultation instantly. Furthermore, the state of the plants can be tracked around the clock using hyper spectral imaging.

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