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A distinctive Approach for Early detection of Plant Disease for Sustainable Agriculture

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Abstract. Agriculture has always been the primary resource in producing food. Plant disease has been a major factor influencing the food production. If there are low yields and less stock of food, and a disease epidemic occurs then food shortage can easily develop resulting in worst effects on human society. So, it is essential to deal with the identification of the plant diseases as early as possible to avoid low crop yield because of diseases. Because of the rapid development of the Smart Farming, the identification of the plant disease becomes data driven enabling smart analyses. In this context, Deep Learning algorithms is used for disease identification. So, a mathematical model of plant disease classification and its findings are proposed. The proposed work consist of two layers namely Pre-processing Layer and Fully Connected Layer (FC). The Pre-processing Layer is for Feature Map extraction and the Fully Connected Layer is Neural Network. The model is trained using larger dataset of diseased leaves and healthy leaves and it is tested against random samples. The proposed model obtained 97% of accuracy in classification and recognition of various plants.

Keywords: Deep Learning, Pre-processing, Convolutional Neural Network, Fully Connected Layer, Feature Map

1 Introduction

A major portion of national income comes from agriculture. It provides raw materials for industries and plays a crucial role in international trade. It is an attempt to recognize and take early precautions to reduce major crop crisis. Difference between rate of productivity of crops and rate of human consumption is increased in 21st century. Environmental and biological hazards are the prime factors in agriculture for plant diseases. The average production of the tomatoes is 181 million Tonnes per year out of which 34% of crop is lost due to various diseases and pests. Similarly, the average production of corn is 1.15 billion Tonnes per year and 6.8% of crop is lost due to various diseases. The mean economic loss due to reduced yield caused by corn diseases from 2017 to 2020 is US$ 55.99 per acre only in United States and Canada. Preventing the losses in crop can be done by taking proper measures.

For traditional based methods, conservative processing algorithms and classifiers are often used. These kinds of algorithms can be affected by properties of plants, appropriate illuminations. This may help in reducing the complexity of algorithm implemented, increases the application cost. Due to this complete elimination of scene changes by classic algorithms cannot be expected. In above conditions, the traditional classical algorithms has many drawbacks to produce an optimum accuracy. A deep learning model may assist in classifying and detecting the plant diseases even in harsh environments. Thus, the primary focus of this research is to implement a Convolution Neural Network (CNN) model which is capable of detecting the various types of plant disease, so that efficient preventive measures can be taken immediately by the farmers to reduce the crop losses.

2 LITERATURE REVIEW

Economic status of India majorly focusses on production rate of crops. This rate is highly depends on the diseases and pest in agronomy [10]. A findings on pathogen analysis using remote sensing images were applied to study and relate the various methods. There is a huge loss for the farmers due to these bioagressors [11]. One of the principal crop of our country is rice, its cultivation rate highly depend on factors like pest and diseases. It develops an autonomous methods to analyze the plant diseases [13]. CNN model is developed for detection of pest and diseases. It majorly focuses on drawbacks in processing the major parameters which affects the performance of efficiency [2]. CNN uses convolution and regression and pooling to reduce the size of the image and enhance the size of the image and reduce the pixel size which helps to make the exact size [3]. From the above literatures it is evidently proven that there is a lot of research undergoing in the field of Artificial Intelligence for Smart Farming. There has been significant improvement in the accuracies of the models with the improvement in the technologies. As Deep Learning is out performing all the existing technologies it would be beneficial to develop a mathematical model using this technology.

3. Model Development Using Deep Learning

A Machine Learning model is proposed to identify 9 different plant types namely Corn Healthy, Corn Common Rust, Cherry Powdery Mildew, Cherry Healthy, Tomato Spider Mites, Tomato Bacterial Spot, Tomato Healthy, Strawberry Leaf Scorch Healthy, and Pepper Bell Healthy. The first stage is acquiring of the image dataset from Google Drive. All the dataset is uploaded to the Google Drive and model has to mount to the Google Drive folder where the dataset is there. For doing this package drive should be imported. All the images in the dataset are of size 256 x 256 x 3. After the fetching of the dataset from the Drive, the next level is cascaded layers of combination of Convolution and Pooling. In our model 4 Cascaded Layers of Convolution and Pooling is defined. The size of the Kernels in all the Convolution Layers is 3 x 3. The proper learning rate is to be used and the weights are changing relatively. It is not good to make a jump so large that optimal value for a given weight may get skipped. Here the learning rate is considered as 0.001. The way the error is moving towards minima in both cases big learning rate and small learning rate.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) \left[\frac{\delta L}{\delta w_t}\right] \quad \textbf{(1)}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) \left[\frac{\delta L}{\delta w_t}\right]^2 \quad \textbf{(2)}$$

m_t and v_t are mean and uncentered variance of the gradients respectively.

$$\widehat{m}_t = \frac{m_t}{1-\beta_1^t} \quad \textbf{(3)}$$

$$\hat{v} = \frac{v_t}{1-\beta_2^t} \quad \textbf{(4)}$$

The parameters are updated which yields the Adam update rule:

$$w_{t+1} = w_t - \widehat{m}_t \left(\frac{\alpha}{\sqrt{\hat{v}_t} + \varepsilon}\right) \quad \textbf{(5)}$$

This loss function performs the same type of loss categorical cross entropy loss but works on integer targets instead of one-hot encoded ones.

$$-Y_a * \log (Y_p) \quad \textbf{(6)}$$

The classification report of the model gives information about three important parameters namely precision, recall and f1 score.

i) Precision

Precision is the ability of a classifier not to label an instance positive that is actually negative.

$$\text{Precision} = TP / (TP + FP) \quad \textbf{(7)}$$

ii) Recall

Recall is the ability of a classifier to find all positive instances. The formula for recall is shown in equation 4.8.

$$\text{Recall} = TP / (TP+FN) \quad \textbf{(8)}$$

iii) F1 Score

The F1 score is a weighted harmonic mean of precision and recall.

$$\text{F1 Score} = 2*(\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision}) \quad \textbf{(9)}$$

In this research work, the dataset contains 11792 images of plant leaves and 9 classes are allocated. All these images are resized into 256 X 256 pixels. Further, 11792 images are divided into training and testing datasets. Where, training dataset contains 9543 images and testing dataset contains 2249 images. Detailed classification of images in dataset according to crop-disease pair is given in Table 1.

Table 1: Training and Testing Dataset Details

Crop Disease pair	Training data	Testing data
Cherry plant Healthy	872	147
Cherry plant with Powdery Mildew	900	152
Corn plant Healthy	962	200
Corn plant with Common rust	1002	190
Pepper plant healthy	1173	305
Strawberry plant with leaf scorch	929	180
Tomato plant healthy	1241	350
Tomato plant with bacterial spot	1168	350
Tomato plant with spider mites	1296	375
Total Training Images	9543	2249

Each class of the training set has around 1000 images to bring balance to the dataset. So that no bias is shown towards a single class and model is trained equally for all classes. The Test dataset is used to evaluate the model. It is only used once a model is completely trained using training dataset

5. Results & Discussions

This summarizes the results obtained for the model. The results include output images of each layer and graphs for loss and accuracy are plotted. The classification report and model summary are tabulated. The input image which is used to test the trained model. The first stage of the convolution layer contains 16 kernels. The output images of the first convolution stage and max pooling is shown in figure 1.

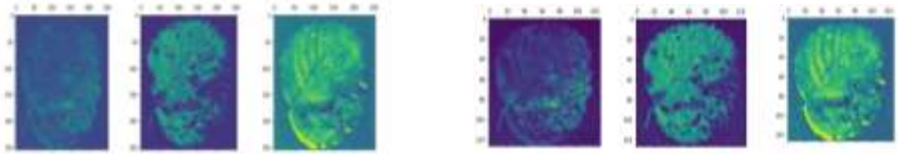

Figure 1: First Convolution and First Max Pooling Layer outputs

The second stage of convolution contains 32 kernels and the outputs of second stage convolution and pooling is shown in figure 2.

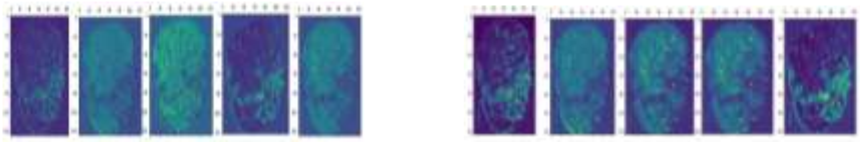

Figure 2: Second Convolution and Max pooling Layer outputs

The third stage contains 64 kernels and the output images of the third stage convolution and max pooling are shown in figure 3.

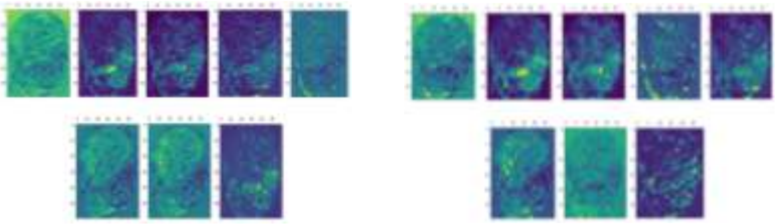

Figure 3: Third Convolution and Max pooling Layer outputs

Finally, the fourth stage contains 64 kernels and the output images are shown in figure 4.

Figure 4: Fourth Convolution and Max pooling Layer outputs

The classification report talks about Precision, Recall, F1 Score and Support for every class available. Support is the number of images available to calculate all these parameters. Classification report is generally calculated for test data set. Table 2 discusses about classification report of the testing dataset.

Table 2: Classification Report of the testing dataset

Class	Precision	Recall	F1-score	Support
0	1.00	1.00	1.00	200
1	0.99	0.98	0.99	190
2	0.98	0.98	0.98	152
3	0.86	0.99	0.92	147
4	0.97	0.98	0.98	375
5	0.93	0.99	0.96	350
6	0.96	0.99	0.98	350
7	0.98	0.89	0.94	180
8	0.99	0.84	0.91	305

The model has achieved a training accuracy of 99.16 % and testing accuracy of 97.42 %.

6. Conclusion

The people around the world rely on the agriculture sector as one of the most important sectors where crops are the basic source of food. Early recognition of the diseases is crucial to the agriculture industry. A deep learning-based CNN model is developed for plant disease classification and detection using TensorFlow and Keras framework. The model is trained and tested against 9 different classes of plant leaves. It is trained using 9543 training images for 10 epochs. It has achieved an accuracy of 97% in classifying and detecting the plant classes. With this accuracy the model can assist farmers to detect plant diseases. Since the runtime has some limitations in loading the dataset, the model is trained to detect only 9 classes. The model which can detect a greater number of plant types can be developed using higher efficient runtimes. By increasing the number of features and the dataset count to the neural network, the performance of the Neural network can be enhanced. This model can be developed into an android application or website, which gives the disease of the plant just by uploading the photo of a leaf. So, it will be much useful to the agriculture sector. The accuracy of the model can be increased by using the advanced architectures of the CNN.

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