Proceedings of the Fifth International Conference on Computing Methodologies and Communication (ICCMC 2021)
IEEE Xplore Part Number: CFP21K25-ART

Analysis of Effectiveness of Augmentation in Plant Disease Prediction using Deep Learning

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2021 5th International Conference on Computing Methodologies and Communication (ICCMC) | 978-1-6654-0360-3/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICCMC51019.2021.9418266

Abstract:* Crop diseases pose a significant threat to food production. Because of the widespread adoption of smartphone technology, it is now technically feasible to use various image processing techniques to identify the type of plant disease from a single picture. Detecting illness early will lead to more effective interventions to reduce the impact of crop diseases on the food supply. Image classification is the most important step required for disease prediction in plants and deep learning techniques are the most optimal techniques used for image classification in the current scenario. This paper analyzes three major transfer learning techniques namely InceptionV3, DenseNet169 and ResNet50 using augmentation and without augmentation for image classification and thereby plant disease detection. After applying the above mentioned techniques we analyzed the efficiency of the algorithm with the help of various quality metrics: precision, recall, accuracy, F1-score.The best model with highest accuracy is ResNet50 with 98.2 percent accuracy with augmentation and 97.3 percent accuracy without augmentation.

Keywords:* Plant disease, prediction, convolution neural network, transfer learning, training, testing, validation, augmentation, dropout.

1 .INTRODUCTION

Plant illnesses in agriculture have often been an essential source of concern, as they reduce crop quality and thus yield. Plant diseases can affect agricultural economy of developing countries which rely on a single or a few crops. Severe damage to entire areas of planted crops [23], resulting in high financial loss and having a significant effect on the agricultural economy of developing countries [1].

Agriculture is the backbone of Indian economy. The agricultural outcome is declining year by year in India due to various crisis [3]. Indian population is increasing day by day the agriculture productivity also should be increased to meet the requirements of the huge population. Rice, Potato and Tomato are major crops which are used by majority of the Indian population irrespective of the economic class they belong. The productivity of these crops is affected by diseases like common scab, early blight, fusarium dry rot, black dot, late blight, silver scurf, black scurf and pink rot etc. [25,26]. These diseases can be due to bacteria or fungi.

As soon as the plant is infected by any disease the leaves starts showing various symptoms like change in their shape, colour as well as texture etc. Slowly it will start affecting other parts of the plants and the productivity will come down. If the plants are carefully monitored in regular intervals the diseases can be identified in the early stage and necessary action can be taken to avoid further loss[24]. Various strategies for diagnosing disease have been established to avoid significant losses. The precise identification of causal agents is possible method developed in molecular biology and immunology. Many farmers, however, are unable to use these methods because they require extensive domain awareness or a substantial amount of time and money to incorporate.

Due to the above mentioned reasons, extensive research has been conducted to develop reliable and available methods for most farmers to enhance the yield and disease diagnosis [24]. Machine learning and deep learning are the two major techniques used in the current scenario to classify the diseases in plants without human intervention. The major disadvantage of machine learning is feature engineering labeling and pre-processing of data. Process of extracting important features from the data to describe the problem properly and the get high accuracy in classification is called feature engineering. It needs a great amount of domain knowledge as well as it is time consuming. Another major problem of machine learning is preprocessing of data and the requirement of labeled data. In deep learning labeled data is not required and many image pre-processing steps can be skipped because the model is capable of working with unstructured data.

The major challenges in the area of plant disease prediction is complex backgrounds with different real-conditions, detection of multi-infection in the full single or multiple leaves sample, computational time complexity, segmentation sensitivity towards region of interest, infection level of disease and life cycle of plant on the basis of infection [23], lack of photographs collected and labeled from real-life scenarios in currently available datasets [23].

Deep Learning technology can detect the presence of pests and disease in farms with pinpoint accuracy [23] by overcoming all the above issues. The main problem with deep learning is the need for huge data size. If it doesn't have enough data and if there are many classes, then there is a chance of over fitting while doing tuning of hyper parameter and it will get set to local minima. But with the emergence of digital technology huge amount of data can be easily collected and optimal decisions are made in terms of identification of various diseases in plants using various deep learning techniques. So, this paper focuses on deep learning techniques for the classification of plant disease.

Deep learning and computer vision has helped to conduct a lot of research in the domain of plant disease prediction. Various computer vision algorithm like sift, hog surf, haar, image segmentation, K-means, K-Nearest Neighbours (KNN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN).AlexNet, VGGNet, GoogleNet etc are widely used for plant disease prediction.

II. RELATED WORK

The fact traditional manual visual inspection method followed by the farmers is practically impossible when it comes to many acres of land and it is very much time consuming, tedious and expensive. This is the key reasons why researchers are exploring alternative methods. Several methods for machine learning and deep learning are used by researchers to solve this problem with high precision while reducing the expense of subjectivity.

The authors of [7] proposed to distinguish between healthy rice seedling infected with Bakanae using SVM classifications. The authors have concluded that the approach proposed is superior to traditional naked-eye inspections, since it was less time consuming and easy to implement. Four different forms of soyabean plant diseases have been used in other investigations, and applied three different classification techniques called Support Vector Machine,K Nearest Neighbour and Probabilistic Neural Network[8]. The authors stressed the importance of feature extraction and segmentation in this paper.

The writers of [14] examined aphids in wheat fields. Their results show that the detection rate and the weather conditions under which the images were made were significantly affected by color, density, and position. [15-21] in this paper comparison of KNN, NB, SVM, DT and recurring neural networks, the SVM was found to be the most effective classification of the five tests.[76] in this paper the authors use image enhancement, feature extraction and image segmentation technique to identify the diseased part in a leaf. Next canny and sobel filters are used to identify the edges. [28] used diseased rice plant leaf images and Image segmentation techniques using K means algorithms to identify affected area of the leaf. Later the region of interest which is got as a result of segmentation is used to classify the healthy and unhealthy leaves using Convolutional Neural Network with a softmax layer.

[29] in this paper authors are masking the green pixels by calculating threshold using otsu's technique and other pixels with red, blue and green values and nearby pixels of these are removed. [30] in this paper as initial image preprocessing technique image enhancement is done, after that image segmentation is done with the help of neural networking technique. If the segmented region of interest is having a yellow birder then it is concluded that the plant is infected bacterial blight disease. [31] Perform color space conversion and image enhancement image segmentation using K-means clustering and then feature extraction and classification using SVM classifier. [32] used transfer learning and CNN architecture also they have tried fine tuning of hyper parameter to get a very accurate result.

The performance of these algorithms is greatly affected as the conditions change. Deep Learning (DL) has shown high potential and productivity in many fields already, and these concepts can provide good solutions to agricultural problems. Since its breakthrough in the fields of automatic game playing, the processing of natural languages, autonomous and much more, DL studies inspired researchers to explore the use of a wide variety of applications and promising results in agriculture.

III. PROPOSED METHOD

In this paper we are using transfer learning concept for classification purpose. In transfer learning we are able to use a model which is already trained for a similar kind of problem by customizing it. The major advantage of transfer learning in deep learning is that it helps to use the knowledge what is achieved already while this will reduce our work and will help to make use of previous knowledge and avoids starting from the beginning. Transfer learning concept is used for image classification using pre-trained models. A model which is trained on an already established standard data set and it can be used to solve a problem which is similar to the problem which is already solved The three models used in our study are Inception v3, DenseNet169 and ResNet50. The flowchart of the proposed model is given in Figure 1

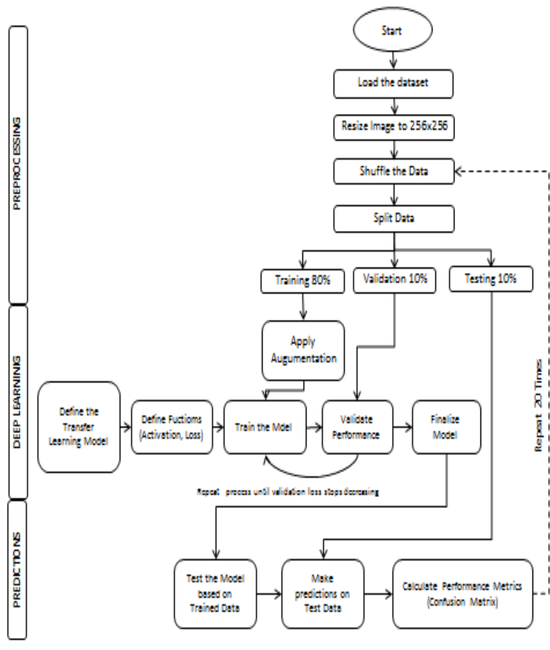

Figure 1 :Flowchart of proposed model

A. Dataset

A public data set from plant village where there is a total of 10000 leaf images of diseased and healthy plants. The plants included in the study are grape, pepper, mango, strawberry tomato and potato. The diseases included in this study are both of bacterial and fungal category, so the class is labeled as crop: disease Figure 2 shows sample data set. Early Blight, Late Blight, Yellow Leaf Virus Curl, Bacterial Spot, Tomato Mosaic, Septoria Leaf Spot, Bacterial Leaf Bight, Anthracnose, Powdery Mildew and Flag Smut are the various disease considered in our study.

B. Image Preprocessing

Convolutional neural network requires inputs of fixed size so all the images in the data set is resized to 256x256 which is a suitable size which avoids loss of any information from the image. If the fixed size is large enough then shrinking is not required so that the features can be preserved, and this will increase the accuracy of the classification. But if the size of the image is too large it will increase the time sand space complexity also an appropriate size 256x 256 is selected for resizing in this paper. Another major preprocessing technique used in our paper is image augmentation which explained in the coming section.

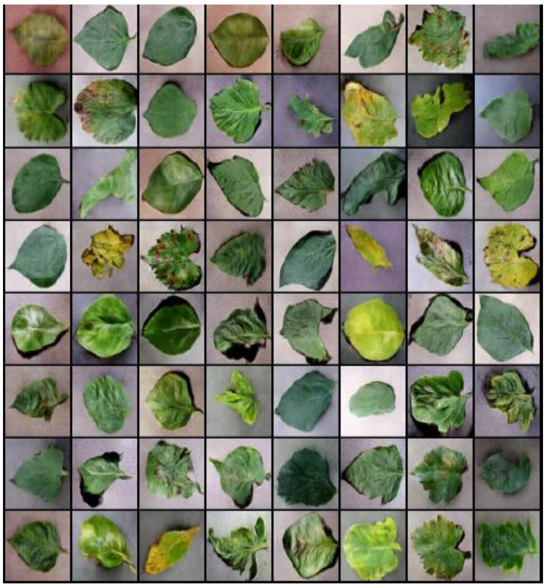

Figure 2: Sample data set used

C. Image augmentation techniques

Overfitting is a major problem in deep learning techniques which indirectly reduce the accuracy of classification, to overcome this problem we had done data set augmentation[33]. The 80 percent data which is used for training is augmented with the help of various augmentation techniques after the splitting process. It is done with the help of Keras library in Python which is used for implementing deep learning. Image rotation, image noising, image contrast and brightness enhancement are commonly used augmentation techniques. The degree of rotation is between 0 to 45 and it is chosen randomly with help of augmentation the number of images increased between 1500 to 3500 in each class and it helped to achieve a balance in the distribution of samples. It also helps to avoid overfiitting in the model. Augmentation technique applied is illustrated in Figure 3.

Figure 3: Augmentation A)Original Image B) Rotation C) Noising D)Contrast

D. Deep Learning Architecture

For the classification purpose the entire data set is divided into train, test and validation sets.80 percent data is used for training, 10 percent for testing and 10 percent for validation. As mentioned earlier in this paper we use transfer learning architecture models Inception v3,ResNet 50, and Densenet169.The models are fine turned by adding 3 more convolution and pooling layers. In this model number of classes used is 10 which contains 6 types of crops and 10 different diseases. The loss function and activation function used are binary cross-entropy and Relu. Since it is a binary classification problem the activation function used in last layer was sigmoid. To avoid the model to getting stuck in local optima we have used drop out technique between layers .

E. Optimization

In an iterative process of deep learning were there are many number of parameters to fine tune it very important to complete the process of iteration as fast as possible. The most commonly used optimization algorithms are min-batch gradient descent, adam optimizer, stochastic gradient descent and min-batch gradient[34].In this paper the method used for optimization is stochastic gradient descent. In this method the updation of weight is done during each iteration and due to this reason, this method is said to be the fastest one.

F. Dropout

There are many techniques available in deep learning to overcome the problem of over fitting. Dropout is one such technique where the randomly chosen neurons are dropped out during the process of iterative training. This will help to remove the neurons temporarily in the forward iteration and updates of weight does not happen in backward pass. As a result of this network will not be so much sensitive to weight of neurons.

G. Feature Map Visualization

Even though deep learning neural networks helps to make very useful predictions and classifications users were not able to see the progress of the training and they were not aware how the predictions are made. The kind of features detected by the model can be understood by looking into the activation map output of the convolution layer. Feature maps helps to understand the progress of the model in each layer .It also helps to tune the hyper parameter because we will understand the error has occurred. In Figure 4 feature map visualization at fifth layer is shown.

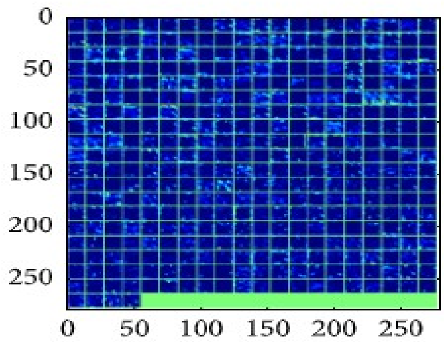

Figure 4:Feature Map Visualization of fifth layer after applying con

IV. RESULT ANALYSIS

In this section the results of the deep learning models are evaluated with the help of various quality metrics. The misclassifications of the various models are evaluated with help of confusion matrix. To calculate these values confusion matrix is generated.

Confusion matrix is a table is used to evaluate the performance measure of machine learning classification model. Confusion matrix contains 4 fields. They are True Positive (TP), False Positive (FP),,True Negative (TN),False Negative (FN).True Positive value represents the true positive predictions. False Positive value represents wrong positive predictions. True Negative value represents true negative predictions. False Negative value represents wrong negative predictions.

The class which is predicted properly is represented by row of the confusion matric and the original class is represented with columns. The classes classified properly are mentioned in the diagonal position. The quality metrics used for evaluating the result are specificity, accuracy, precision, recall,F1-Score and sensitivity.

A. Accuracy

The ratio of true predictions with respect to total number of predictions. Accuracy is calculated with the help of following equation

$$Accuarcy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

B. Recall

Recall is also called as Sensitivity which is True Positive Rate. It is the ratio of true positive predictions with respect to total number of actual positive predictions .The equation used for finding Recall is given below

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (2)$$

The classification model which is more sensitive will have sensitivity value one Specificity (SP). The classification model which is insensitive will have sensitivity value zero.

C. Specificity

Specificity helps to determine correctly identified actual negative values; it's also called as True negative Rate. It is the ratio of correct negative prediction with respect to total number of actual negative. The equation used to calculate specificity is given below.

$$\text{Specificty} = \frac{\text{TN}}{\text{TN+FP}} \quad (3)$$

D. Precision

It is the ratio of true positive predictions with respect to total number of predicted positive values. The equation used for finding Recall is given below

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (4)$$

E. F1-Score

F1-Score is calculated using precision and recall.it is considered as harmonic mean of precision and recall. The equation used to find F1-Score is given below.

$$\text{F1} - \text{Score} = 2 * \frac{\text{Recall}*\text{Precision}}{\text{Recall}+\text{Precision}} \quad (5)$$

The evaluation metrics generated with the help of confusion matrix for each class of ResNet50 model with augmentation is given in the Figure 5. In this study totally 20 epochs are done. In the Figure 6 loss vs epochs graph plotted is given. To evaluate the final result of all the three deep learning architecture Inception v3, ResNet50, and DenseNet with augmentation the parameters called accuracy, F1 Score, recall and precision are calculated, the result is shown in the Table 1. To evaluate the final result of all the three deep learning architecture Inception v3, ResNet50, and DenseNet without augmentation and with augmentation the parameters called accuracy, F1 Score, recall and precision are calculated, the result is shown in the Table 2.

Class	Precision	Recall	F1-Score
0	0.95	0.77	0.87
1	0.95	0.97	0.95
2	0.95	0.92	0.94
3	0.95	0.91	0.91
4	0.95	0.97	0.95
5	0.96	0.95	0.95
6	0.98	0.96	0.95
7	0.97	0.97	0.95
8	0.93	0.93	0.93
9	0.95	0.97	0.95
Average	0.95	0.93	0.94

Figure 5: Evaluation Metrics

Table 1 : Performance measure of the deep learning models with augmentation

Evaluation Metrics	InceptionV3	ResNet50	DenseNet
Accuracy	0.95	0.982	0.96
Precision	0.92	0.95	0.925
Recall	0.93	0.93	0.921
F1-Sore	0.92	0.94	0.934

Table 2 : Performance measure of the deep learning models without augmentation

Evaluation Metrics	InceptionV3	ResNet50	DenseNet
Accuracy	0.93	0.973	0.945
Precision	0.905	0.94	0.91
Recall	0.918	0.91	0.90
F1-Sore	0.91	0.92	0.915

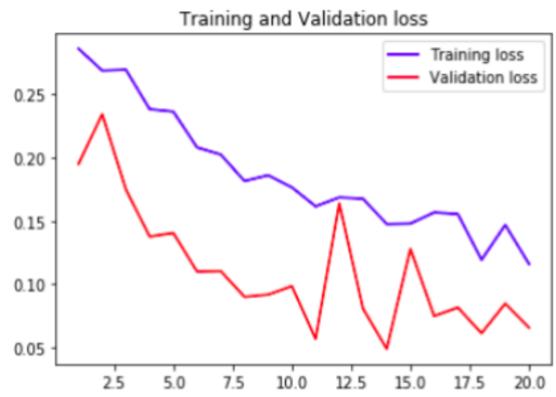

Figure 6: Loss vs epochs

V. CONCLUSION

Plant diseases have been a major threat to Indian agriculture for years. Application of machine learning and deep learning algorithms in agriculture has helped in early detection of diseases and thereby minimizing the economic loss of farmers. Optimal machine learning algorithms and recent advanced deep learning algorithms provide solutions with near accuracy in the field of plant disease prediction. This paper propose a comparative study of three transfer learning techniques Inception v3, ResNet50, and DenseNet with augmentation and without augmentation. Along with augmentation to optimize the result dropout technique is also applied.

This method of predicting plant disease in the early stages does not require pre-processing, infected area segmentation, and background removal steps. In this study a public data set with a total of 10,000 images both diseased and healthy is considered for classification. The efficiency of three transfer learning techniques Inception v3, ResNet50, and DenseNet are analyzed to classify 10 diseases of 6 various crops. The comparative analysis shows that the ResNet50 gives highest accuracy when compared to other models with augmentation as well as without augmentation. It gives an accuracy of 98.2 percent with augmentation and 97.3 percent without augmentation.

In this paper the author has done a comparative study on the effectiveness of augmentation technique on various transfer learning techniques. The sample screen shot of developed model is given in the Figure 7. This study helped us to understand the efficiency of transfer learning techniques and the result proved that transfer learning technique shows high performance when proper optimization and augmentation techniques are done. The result of the study proved that this ResNet50 transfer learning model can be used to classify healthy and unhealthy leaves in the data set with high accuracy.

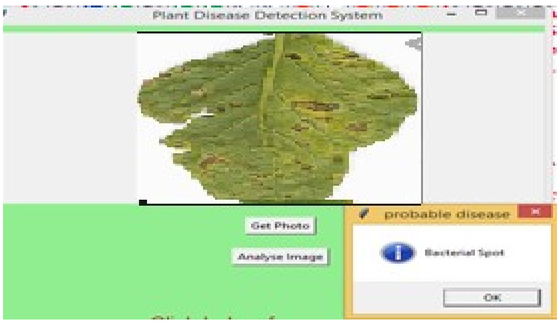

Figure7: Developed disease detection prototype

In the future size of the data set will be increased and optimization of feature selection will be done which helps to improve the overall precision of the model. Along with that various factors which affect the accuracy of transfer learning model like batch size and aspect ratio will be taken into consideration for improving the performance of the model

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