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Comparative Study using Deep Learning for Detecting PlantType and Leaf Disease

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***Abstract*— Plant diseases are growing significantly in the recent years due to severe climatic changes and a lack of immunity in the plants. Large-scale crop destruction results from this, which reduces the cultivation and ultimately affects the farmers money. Identification and treatment of the disease have become quite difficult due to the rapid development in the number of diseases and the inadequate understanding by human. On the other hand, various studies say that the texture and visual resemblance of the leaves are characteristics that help for the disease type identification. Hence the solution to this challenge can therefore be found by combining deep learning and computer vision. We proposed a model based on deep learning in the present work. It is trained on public datasets that contain pictures of both healthy and damaged plant leaves. The model accomplishes this goal bycategorizing photos of sick leaves.**

***Index Terms*— Deep Learning, Image classification, Plant disease, Transfer Learning, InceptionV3, MobileNet.**

I. Introduction

Everyday and for every generation of human beings, agriculture is provider of food, raw resources, and fuel for building a nation's economic growth. Approximately 66% of the people are dependent on agriculture, either directly or in some way. Agriculture is having trouble keeping up with demand because of the enormous rise in global population. Food security is still in threat from a number of issues, including changing climate, a decline in pollinators, plant diseases, a deficit of irrigation, etc. Plant disease decreases both food quality and output. Crop diseases have negative effects on small-scale farmers whose livelihoods depend on proper cultivation, in addition to having an impact on global food security. Automatic detection of plant diseases is a key topic of research because to the capability of monitoring vast fields of plants and automatically identifying disease symptoms as soon as they appear on leaf tissue [6].

The purpose of this paper is to present an application that, using leaf textural similarity, predicts the type of crop disease. The model is trained using a publicly accessible dataset of both healthy and sick plant leaves. Early detection of agricultural diseases can be used to stop additional crop damage, which is beneficial for maintaining cultivation.

The rest of the paper is organized into the following segments. The related research done in this particular field is

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included in Section 2. The proposed model and the approach taken to solve the problem are covered in Section 3. The tests done to address the topic at hand and the results that were found are covered in Section 4. The results are then summarized, including a comparison of several models and their potential application in the future.

II. LITERATURE SURVEY

Before we can identify the class of illness, we must first identify the plant species. In the research, Abdul Kadir employed pixel values for the leaves to create colour attributes like the mean, standard deviation, skewness, and lastly the kurtosis. The author has combined all the different features that are obtained from the Grey Level Co-occurrenceMatrix (GLCM) operations [1], and then pinpointed the image texture. He developed a GLCM which yields the statistical data through measuring the different pairs of pixels with some specific values in a spatial association which appears in the picture.

According to M.R.Naik [2] the disease has been detected by using a neural network. In this paper if the leaf is contaminated, then some additional processing is carried out in order to determine the disease. In their paper they have used the combination of both SVM and a genetic algorithm for minimizing the loss and determined the type of disease. This study presents a genetic algorithm-based method for loss function optimization that is analogous to the principle of natural selection, which holds that only robust parameters endure. Also in the following papers [7][11][12] uses the SVM classification approach towards the identification and categorization of the leaf diseases for grape, tomato, cucumber different plant leaves. Here, the sick region is being first identified by the authors using segmentation through K-means clustering, and then their texture and colour features have been extracted. Using the above classification technique, the type of plant diseases has been determined.

Semi-supervised learning is being utilized in the paper [3] for categorizing the images using the Generative Adversarial Networks. Here, the discriminator has been transformed into a multi-class classifier where the type of learning and the generator has been employed only for the discriminator training. In paper [4], the Inception-V3 model has been utilized for content-based image suggestions, and transfer learning has created the neural networks. In papers [8],[9],[10] the authors have provided an inventive method for the automatic classification of plant leaf diseases by utilizing the image segmentation methodology. Here, the image segmentation has been the key step for disease identification in the plant leaf disease, which has been accomplished by using the genetic algorithm. It also gives a general review of the many disease classification techniques that can be used to identify plant leaf diseases.

III. PROPOSED METHODOLOGY

In order to execute our work in this paper we have taken into consideration the following steps and those steps are, We have collected and prepared the dataset,training has been carried out by using the Convolution Neural Network (CNN) model for recognizing the crop type, then the training CNN for detecting the disease, and validating the model based on the different findings.

A. Dataset

Plant Disease Expert, an open source dataset with 60,129 photos of crop leaves divided into 41 categories, is used. The collection includes 29 different disease categories and 17 different plant species. There are two fields in each class that contain the names of the plant and the disease. Before any additional processing, all of these photos are segmented, shrunk to 224 by 224, and made into grayscale images.

B. Image Preprocessing

The photographs in the collection feature uneven illumination, which influence the application's accuracy. The segmentation of the image and noise removal during pre-processing are crucial for enhancing the quality of the CNN model. Therefore, segmentation is carried out to excerpt only the pertinent part of the image. Thus, all of the leaf photos with correct brightness level are acquired after segmentation. In addition, segmented photos are transformed to greyscale images and sent on for additional processing in order to deal with the uneven illumination circumstances. Figure 1 displays images that were obtained after preprocessing the strawberry leaves as available in the dataset.

C. *Detecting and Classifying Plant disease*

The categorization of a disease is carried out in following steps. Firstly, identify the plant type and the second of which is to identify the disease type. These jobs are performed using Deep CNNs. The ImageNet dataset is for providing the training in the deep learning model which is created by using the transfer learning process. In the deep learning technique which is being known as the transfer learning, we have taken an existing model has been trained on a task and then it is applied to another related task. For solving the issues rapidly and sustainably, we have proposed the method which builds neural networks for analogous tasks by using a pre-trained neural network. These pre-trained networks are developed through training process on different enormous datasets which included a wide range of different image types. Such existing models are created by many research organizations, and they take weeks to train on the most cutting-edge hardware. These existing models are instantly incorporated into new models which are meant for dealing with problems of a same sort after being made accessible for reusing it. These pre-trained models are able to be further enhanced if the nature of the new dataset and the existing dataset on which it was being trained. The different kinds of scenarios, the top layer of the network is being trained, after which the tuned network can be immediately deployed for dealing with the issues. If the existing dataset size is large enough, then the pre-trained model can again be re-trained with fresh data, andin this case, the neural network is initialized by using weights from the pre-trained model. Through transfer learning among the numerous pre-trained models like VGG16, VGG19, Xception, ResNet50, MobileNet, etc., InceptionV3 and MobileNet are employed for implementation. As seen in Figure 2, InceptionV3 has approximately 23,851,784 parameters and a depth of 159 layers, while MobileNet has approximately 4,253,864 parameters and a depth of 88 levels.

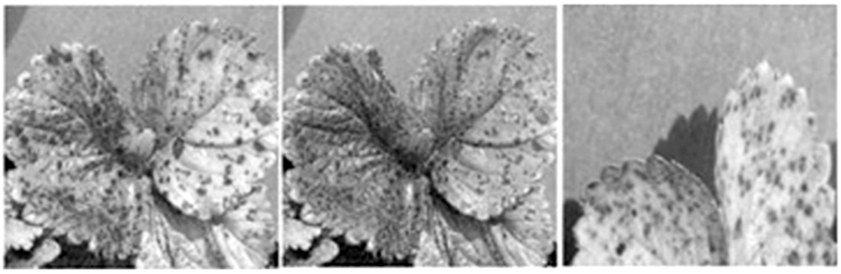

Figure 1. Plant leaf preprocessing i) Original ii) Grey Scale iii) Segmented (brightness)

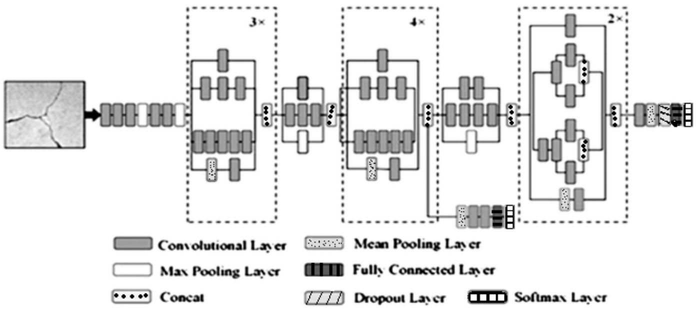

Figure 2. InceptionV3 Architecture

We have taken an existing dataset of 6000 photos from Kaggle featuring 12 different types of plants which has been used to fine-tune these existing new models.

These models are further initialized using the weights from the previously trained model. The dataset is preprocessed and divided at a ratio of 80% to 20% into training and testing data. Label encoding is used to transform output into a category type.

The image data generator is being used to provide the input photos with more variety. The dense layer with softmax activation function is added for retrieving the outcome of the model. The optimizer used in the model serves as the loss function, and the categorical cross entropy is used. These pre-trained models are then retrained for some abstract epochs using an approximate batch size in order to produce the required model for our paper. There is a dropout of 1e-3 which is added for avoiding the over-fitting problem. The created model is put to the test by using a testing dataset for ascertaining the validity of the validation. The performance of both the models is being assessed based on their training accuracy, training loss, and validation accuracy, validation loss per epoch. In order to detect the disease specific for a particular plant, then a deep convolutional neural network is used for the comparable plant recognition techniques that are being deployed by us. For disease identification, various models are created, and each one matching to a certain plant variety.

The aforementioned model determines the type of plant, which determines which disease detection model should be given the image in order to determine the type of disease.
The models developed for disease detection are evaluated in terms of training accuracy, training loss, and validation accuracy, validation loss per epoch using testing datasets.

IV. RESULTS

This section discusses the findings and observations from the experiments conducted using both models[13-18]. The segmented images model outperformed the colour and grayscale image models once thetrained model was put to the test. Both MobileNet and InceptionV3 models perform well in experiments for plant type detection, with accuracy rates of 99.7% and 99.77%, respectively (Figure 3-6).
The initial phases of accuracy growth shows an significant increase, which later-on converges. Rapid initial learning is indicated by an exponential reduction in the loss function.
It has been found that the InceptionV3 model outperforms MobileNet for the plant identification

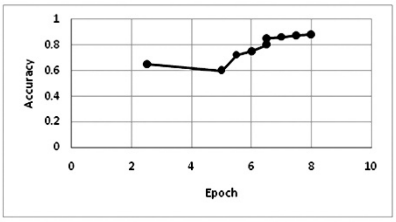

Figure 3. MobileNet, Plant identification-Accuracy Vs Epoch

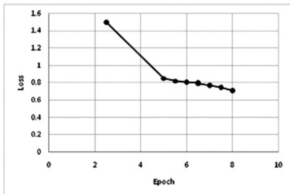
Figure 4. MobileNet, Plant identification-Loss Vs Epoch

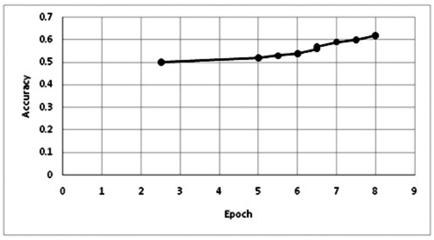

Figure 5. InceptionV3, Plant identification-Accuracy Vs Epoch

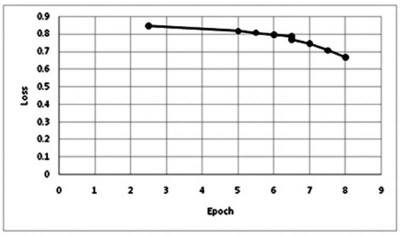

Figure 6. InceptionV3,Plant identification -Loss Vs Epoch

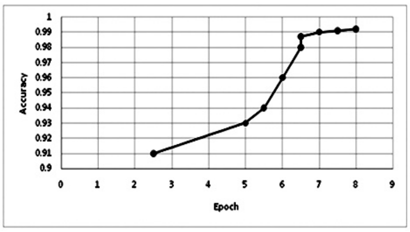

Figure 7. MobileNet, Disease identification-Accuracy Vs Epoch

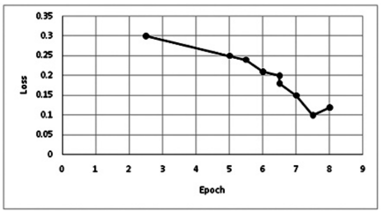

Figure 8. MobileNet, Disease identification-Loss Vs Epoch

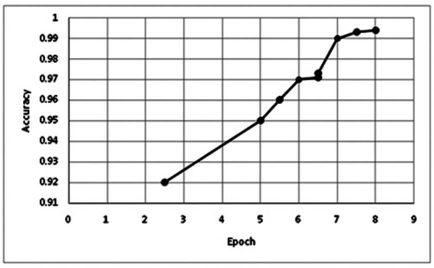

Figure 9 InceptionV3, Disease identification-Accuracy Vs Epoch

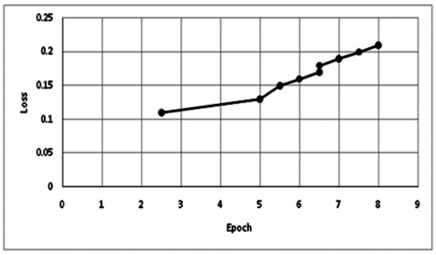

Figure 10. InceptionV3, Disease identification-Loss Vs Epoch

In Figure 7-10, the crop disease identification is shown, with the MobileNet and InceptionV3 model showing consistent growth and accuracy rates respectively. Between the seventh and eighth epochs, the InceptionV3 model's accuracy shows a very minor drop. The enhanced performance of InceptionV3 in the task of disease identification is supported by the value of the loss function at the end of the twelfth epoch.

V. CONCLUSION

In our work we have explored the different applications of Deep Convolutional Neural Networks in Anaconda Environment with the explicit goal for classifying the crop species and disease identification on the plant pictures, respectively. The proposed methodology has been simulated using Anaconda Environment from the samples from three distinct types of plant diseases and five different plant categories.

The experimental results show that the InceptionV3 model is the best than the existing MobileNet model in terms of accuracy and validation loss. The continuation of this study will include the categorization of pictures with many orientations and images not captured in a disciplined environment. Additionally, the variety of crop classes and their diseases can be expanded further. This technology can be combined with smartphone programmes that would offer an intuitive user interface and ease of use for it. In our future work we will optimize the working of InceptionV3 through cloud computing.

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