Efficient Deep Learning Models for Tomato Plant Disease Classification Based on Leaf Image

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***Abstract* — Tomato is grown in outdoor fields, greenhouses, and net houses in almost every country around the world. However, unfortunately, many diseases on these tomato plants have caused a considerable loss to the quality and the quantity of production that has affected the economy of the country. Accurate and faster detection of diseases in tomato plants could help to develop an early treatment technique while significantly reduce economic losses. Computer technology is playing a vital role in the study of visually observable patterns on the plants. Recently various image processing and pattern classification techniques are used to implement computer vision systems that are capable of detecting and classifying visual symptoms of plant diseases easily. The main objective of this study is to present an efficient and accurate model for the classification of tomato diseases, which will eliminate human error in the identification of tomato diseases based on naked-eye observation. This study has trained several deep learning models by building a CNN from scratch and fine-tuning VGG16, Inceptionv3, MobileNet architectures that are more efficient in visualizing the spots of tomato disease during their complete cycle of occurrence. Tomato leaf images belonging to 10 different diseased classes with a resolution of 256x256 were collected from the Internet to train, validate, and test the model. Images were normalized, and the image augmentation techniques were applied for the collected images to expand the size of the data set. To get the best optimal models, they were tested for many cases by changing the parameters. The proposed CNN model achieved an accuracy of 90% while other fine-tuned models VGG16, MobileNet, and Inceptionv3 achieved an average accuracy of 94%, 97%, 95% respectively. Experimental results show that our proposed system can effectively recognize ten different types of tomato diseases.**

Keywords — Computer vision systems, Tomato disease classification, Deep learning models

I. Introduction

Agriculture is the primary occupation of many developing countries. A significant percentage of the population in these countries still depend on agriculture. Globally, annual fresh tomato production amounts to about 160 million tons which is three times more than potatoes and six times more than rice worldwide. According to the Census and Statistics Department Sri Lanka, the size and production of tomatoes grew by 25 percent and 71 percent respectively in 2000, and by 2010. In the tomato production, 80 percent is confined to six districts, with Badulla, Nuwara Eliya, Kandy, Matale, Anuradhapura, and Rathnapura. There was 7,261 ha of land planted in 2010, and a 75,335mt tomato harvest was achieved. This suggests a growing increase over the years in the production of tomatoes. However, unfortunately, many diseases on tomato plants have caused a considerable loss to the quality and the quantity of agricultural productivity, which has directly impacted the economic[1].

Each year tomato cultivators have faced severe losses. Thus, protecting the tomatoes from these diseases is the biggest challenge for increasing agricultural production. To monitor the health of tomato plants, knowledge of expertise is a must. Naked eye observation by experts is the most traditional way of monitoring plant diseases by looking at the leaf. Nevertheless, it takes excessive processing time as continuous and constant observation of the fields is a necessity of this method [2]. In some cases, farmers in remote areas need to travel long distances to get the assistance of an expert. It takes time, as well as an extra cost. If the expert has lacked knowledge, the mistakes are often, and there is a high possibility that prediction goes wrong. Due to the complexity as some diseases do not have visual symptoms and a large number of cultivated plants and existing pathological problems, even experienced agronomists and plant pathologists often fail to detect diseases [3]. So, it is not a good habit to rely entirely on an expert, agronomists, or plant pathologists.

There are many advances in computer technologies that help to recognize and classify plant diseases automatically. It eliminates the need for professional personals to continuous observation of fields, which takes time and cost [4]. Recent case studies show that soft computing models like Neural Networks, Decision trees, Support vector machine, and Naïve Bayes have been applied for the automatic plant disease classification. Deep learning has dominated computer vision over the last few years. The combined factors of widespread smartphone penetration, HD cameras, and high-performance processors in mobile devices and advances in computer vision paved by deep learning has led to a situation where disease diagnosis is based on automated disease recognition. A deep neural network is made up of the combination of deep learning and neural network, which mimics the general principles of the brain. The architecture of a deep neural network includes an input layer, several hidden layers, and an output layer. The layers will be trained to figure out the best filter weight values. Convolutional Neural Network has had ground-breaking performance over the past decade in several fields linked to pattern recognition. Many other deep learning architectures like VGG16, Inceptionv3, MobileNet, AlexNet, DenseNet, and GoogleNet also have been proposed recently.

II. Objectives

The main objective of this study is to evaluate different architecture models that can be used for plant disease classification and identify the best model. With the application of these models, the ultimate goal is to present an accurate model for classifying plant diseases that can be used for further improvements in this field. In Sri Lanka, around 15% of the tomato loss is due to the diseases. Continuous monitoring of the crop is required throughout the growing stage to identify the plant diseases because if they do not control at the appropriate time, they can damage the tomato plant so much that most of them are lost. If the gardeners or start-ups are lack experience, they will not be able to identify the diseases at an early stage accurately. Rather than offering a guess, this study can at most give a definite answer on how the accuracy has varied with the different architectures.

III. METHODOLOGY

The methodology of this study is divided into the following steps:

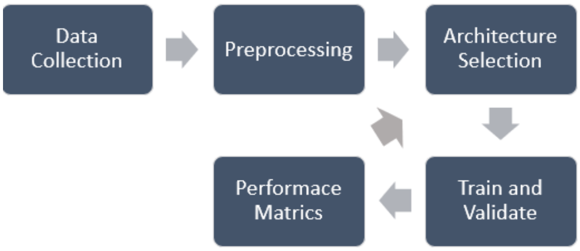

Fig. 1. Main steps of the methodology

A. Data Collection

Diseased tomato leaf images belonging to 10 different classes with a resolution of 256x256 were collected from the Internet. The entire dataset was divided into three main directories as train, validate and test where 17184, 4585, and 1161 images belong to each directory, respectively. Altogether there were 22930 images in the main directory. The purpose of using two different datasets for testing and validating is to ensure how the model performs with unseen data. Test data measure the performance of the final model while validate data was used to measure how the model performs during training.

Table 2. Summary of the dataset

Disease	**Train dataset**	**Validate dataset**	**Test dataset**
Bacterial spot	1684	425	54
Early blight	1761	480	159
Late blight	1713	463	138
Leaf Mold	1753	470	129
Septoria leaf spot	1682	436	63
Spider mites	1537	435	204
Target Spot	1659	457	168
Mosaic virus	1700	448	90
Yellow Leaf Curl Virus	1868	490	93
Healthy	1863	481	63
Total	17184	4585	1161

B. Image Pre-processing

Image pre-processing is a technique that is applied to enhance the input image for further processing by ensuring the relevant features are emphasized for further processing. In this study normalization and data augmentation techniques were applied within the pre-processing stage. A large number of different images are needed to construct an accurate classifier. But it is practically difficult to find such an amount of massive data. But by using data augmentation techniques, it is possible to generate new data by making changes to current data. Rotation, shear, zoom, horizontal and vertical flip are the augmentation options applied in this study.

C. Architectural Design

The success of the deep neural networks lies in the well-designed architecture. So, it is critical to identify which design gives the best results and under which circumstances they can be used. Here VGG16, MobileNet, inceptionv3 is used other than the CNN built from scratch.

1) Convolutional Neural Network (CNN)

CNN is a type of artificial neural network which is typically designed to extract data features by using high-dimensional data. The proposed CNN model comprises four convolutional blocks followed by batch normalization, max pooling, and dropout layers. Other than that, two dense and flatten layers were also included in the end. For each block, the Rectified Linear Unit (ReLU) activation function was used, but at the end, after the last dense layer, the SoftMax activation function was applied. A 0.001 fixed learning rate was used throughout the training. The number of epochs and the batch size was set to 15 and 27, respectively. The model was compiled by using the Adam optimizer and the categorical crossentropy loss function. The model was tested for many cases to identify the optimal set of parameters.

2) VGG16

VGG16 is a famous CNN model submitted by the researchers at the University of Oxford for the ImageNet Large Scale Visual Recognition Challenge (ILSCRC) in 2014 under the topic of image recognition [6]. In this study, a pre-trained VGG16 model was fine-tuned for the identification of plant disease. Pre-processing was applied before feeding the images to the input layer with the help of Keras VGG16 pre-process input function. The VGG16 model containing a total of 138,357,544 parameters was downloaded from the internet with the saved weights. The last layer of the model was removed, and a new fully-connected layer was added to make it fit for the requirements of this study. The same best set of hyperparameters on CNN were used in the VGG16 model.

3) InceptionV3

A team of researchers from Google has found the inception concept which belongs to the family of Deep Neural Network [7]. In this study, InceptionV3 is fine-tuned, which is the third version of the series. The model with 21,802,784 parameters was downloaded with Keras library. The specialty in this model is the addition of the global average pooling layer. Weights of the last layers were frozen, and the same set of hyperparameters were used like VGG16.

4) MobileNet

MobileNet belongs to the family of deep neural networks that are lightweight and faster. The size of a particular model mostly depends on the total number of parameters it has. The model was downloaded from the internet using Keras Library, and the images were pre-processed with the help of MobileNet pre-process function. When compared with other models, it usually applies less data augmentation. From the pre-trained model, the last five layers were removed, and a new dense layer was added with ten output nodes as there were ten disease types. The model was fine-tuned and the same best set of hyperparameters were used as in CNN.

D. Train and Validate

The fit () function was invoked by feeding the train images, validate images, setting epoch size, and steps for epochs. Finally, the performance metrics were evaluated, and the final model was predicted with the unseen data. These steps were followed iteratively by changing the parameter values until the best combination of the parameter was found to get the generalized accurate model.

IV. RESULTS AND DISCUSSION

This study is carried out to present an accurate model by evaluating the performance of various deep learning architectures in the tomato plant disease classification area that are commonly used today. A CNN, VGG16, MobileNet, and InceptionV3 has been built, fined tuned and trained successfully. The CNN model was implemented from scratch, and others were fine-tuned to make perfect for the study.

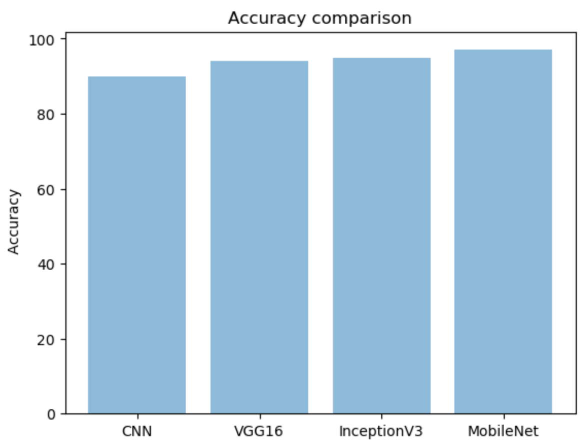

Fig. 2. Accuracy Summary

VGG16 model has taken a long time to train the model compared to the other two. That is because the total number of parameters used in those models were very high. So, we can conclude that when the parameters increase, the time that is taken to train the model also increases. When the complexity of the model was very high, the model tried to memorize all the information, which results in a poor generalization for unseen data. So, each model was tested for more cases before finalizing the model. The MobileNet is not too complicated when compared with the Inception and VGG16 models as it contains a smaller number of parameters. So, the training time of it was lesser than the other models. When compared with inceptionV3, MobileNet works better with size, latency, as well as accuracy. This model can be easily used in mobile devices and embedded vision applications in future improvements.

V. CONCLUSION

Deep learning models have shown significant improvement in the context of pant disease classification. This study is carried out to present an accurate, efficient model for tomato disease classification by understanding different architecture models that can be used within the study area. A CNN model was built from scratch and other deep learning models; VGG16, InceptionV3, and MobileNet were fine-tuned. They have shown an average accuracy of 90%, 94%, 95%,97% respectively. All the models were able to classify ten different types of tomato diseases. With regard to the results, we can conclude that MobileNet is perfect for the study as it is lightweight, faster, and can be easily run on mobile devices. Future work includes extending this study to other crops and developing a complete decision support system run on smart mobile devices.

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