Identification of Tomato Plant Diseases Using Convolutional Neural Network

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Abstract—*Tomato is highly grown vegetable all over the world. Tomato is highly susceptible to diseases and considerable amount of crop is wasted due to diseases caused by virus, bacteria and fungi. Disease identification of Tomato is a major problem faced by farmers. The proposed system helps farmers to identify four tomato diseases namely Anthracnose, Blossoms End Rot, Late Blight and Powdery Mildew. Convolutional Neural Network (CNN) has been applied in the study to predict the disease from the images. The implementation of CNN from scratch demands high computational resources and considerable amount of image data. Therefore, transfer learning approach has been applied with the MobileNet model which is trained on the ImageNet classification dataset. This research work was conducted by changing the number of images, training models and hyperparameters to experiment the accuracy of the system. The system gained 99.16% of training accuracy, 98.89% of validation accuracy and 98.96% of test accuracy with 0.0001 learning rate, 0.9 momentum, batch size as 32 and 3200 training images.*

Keywords— **Tomato Diseases, Deep Learning, Transfer Learning, Convolutional Neural Network (CNN), MobileNet**

I. INTRODUCTION

Tomato (Solanum lycopersicum) is a horticultural plant and it is one of the mostly cultivated vegetable in the world. According to environmental conditions prevailing in Sri Lanka, tomato can be cultivated in every region except the wet zone. It is an exporting crop in Sri Lanka and is considered as a commercial product which has a considerable exporting potential. Tomato has high market value in USA, European Union (EU) and Middle East markets. According to FAOSTAT results, in Sri Lanka about 80, 839 tons of tomatoes have been produced in 2017 and there is a reduction of the productivity in Tomato when compared to previous years ("factfish Tomatoes, production quantity world statistics and data," 2018).

Even though, Sri Lankan environmental condition is favourable for tomato cultivation, average productivity in Sri Lanka is considerably less when compared to the world average production (komahan and Prasannath, 2017). Limiting factor for the production in Sri Lanka is mostly diseases caused by fungi, virus and bacteria. These diseases cause serious damage to the crop and reduce the productivity. Main tomato plant diseases that can be seen in Sri Lanka are Anthracnose (Colletotrichum spp), Early Blight (Alternaria solani), Late Blight (Phytophthora infestans) and Powdery Mildew (Leveillula taurica). These diseases are caused by bacteria and Blossoms End rot is a disorder of the fruit caused by calcium deficiency.

Figure 1: (a) Anthracnose, (b) Early Blight, (c) Late Blight, (d) Powdery Mildew, (e) Blossoms End Rot
Source: Google Images

These diseases should be correctly identified before treating. Most challenging issue in cultivation is identification of diseases correctly at the early stages of the diseases. In Sri Lanka, this identification is done by a human expert. In this process, farmers must inform their issue to the agricultural instructors and then they will give advices based on the symptom explanation of the farmer. This process cannot be totally trusted. In some instances, agricultural instructors visit the field. sometimes this process may take days. Therefore, this process cannot be considered as the most appropriate method to identify tomato plant diseases.

This research is focused on solving these problems with an automated system. Most common and easiest method in identification of plant pathogens is by visual symptoms. Identification of plant diseases by visual symptoms can be automated using computer vision techniques. This paper discusses how to identify the diseases in the fruit and leaf by using an image of the defected area. Both tomato fruit diseases and leaf diseases are to be identified by this system.

This research has been conducted to identify tomato plant diseases using machine learning algorithms. The idea of neural networks emerged in 1943 (“History of Neural Networks,” n.d.) and believed that this network will act as a human brain and it would be able to convert a given continuous input into a discrete output. Later, Artificial Neural Networks (ANNs) were used in image classification. In ANN features of the classifying images should be extracted manually and fed into the network. After the deep learning algorithms were introduced in late 2000s (“Timeline of machine learning,” 2019), image classification became more easier by using Convolutional Neural Networks (CNN) which is a deep learning algorithm. In CNN features of the images are extracted by the network and perform classification. In the model development process transfer learning technique is used.

First section of this paper introduces the problem and the technology used in the study. Related works discusses in the second section and a brief introduction on CNN includes in the third section of the paper. Methodology adapted and the results gained in this study discuss in fourth and fifth sections respectively. Final section of the paper concludes the study.

II. LITRETURE REVIEW

Artificial Neural Networks (ANN) with image processing techniques and deep learning algorithms can be applied in the image classification. Transfer learning technique with pre-trained models are used in the development of deep learning models.

Kanjalkar et al., (Kanjalkar and Lokhande, 2018) have used ANN and image processing techniques to identify 3 Soybean diseases and 1 Cotton leaf disease. Image data acquisition was the first step in the development of the system and they have transformed RGB (Red, Green, Blue) image into HSI (Hue, saturation and Intensity) image. They have found out only Hue images gave clear discrimination on diseased spots. Then they performed segmentation and feature extraction process on the Hue images. Classification was done by an ANN and gained average of 80% accuracy for soybean diseases and 70% for Cotton leaf disease.

ANN and image processing techniques were used by Ranjan etal., (Ranjan et al., 2015) to identify cotton leaf diseases. After data gathering, they have performed pre-processing techniques to enhance the required features on obtained data. Then they have extracted features by converting RGB image into HSI image and extracted features. They have achieved 80% accuracy in their system.

Transfer learning was used by Krishnaswamy et al., (Krishnaswamy Rangarajan et al., 2018) to classify tomato leaf diseases. They have used AlexNet and VGG16 models for their classification. They were able to obtain 97.49% and 97.23% accuracy rates for AlexNet and for VGG16 model respectively. They have found out that accuracy of the model can be changed with number of images used and values given to hyperparameters.

Atabay (Atabay, 2017) was able to identify 9 tomato leaf diseases and a healthy class using VGG model and yielded 99.89% accuracy rate. He has found out that this classification can be done by using a regular PC with less training time with this model and transfer learning technique. Similar method was followed by Arivazhagan and Ligi (Arivazhagan and Ligi, 2018) using VGG16, VGG19 and AlexNet to identify 5 mango leaf diseases. They have gained 96.67% accuracy and found out that the accuracy rate can be increased by increasing number of images.

Wallelign et al., (Wallelign et al., 2018) used LeNet model in classifying 5 classes of Soybean diseases and gained 99.32% accuracy rate. They have performed experiment on segmented images, colour images and gray-scale images. Using image augmentation techniques and using colour images gave best accuracy rates in their study.

As Llorca et al., (Llorca et al., 2018) stated, image augmentation reduced overfitting problems and gained 88.9% of accuracy with Inception-V3 model.

Liu et al., (Liu et al., 2017) have generated pathological images of Apple leaf diseases and identified 4 types of leaf diseases with 97.62% of accuracy level using AlexNet. Model parameters were reduced, and accuracy was increased by generating pathological images. Same model was used by Adhikari et al., (Adhikari et al., 2018) and gained accuracy of 89% for 4 leaf diseases.

Rajmohan et al., (Rajmohan et al., 2018) have done a research by combining CNN and Support Vector Machine (SVM) to identify rice plant diseases. Model gained 87.50% of accuracy in identifying Rice plant diseases.

Existing studies have proved that deep learning algorithms increases classification accuracy and transfer learning reduces the training time and increases the efficiency level of the system.

III. TECHNOLOGIES ADOPTED

CNNs are mostly applied for computer vision problems. Computer vision is the ability of digital computers to identify and understand digital images and videos. Deep learning algorithms encourage this process with greater speed and accuracy. CNN is a deep learning algorithm which is mostly used in image classification.

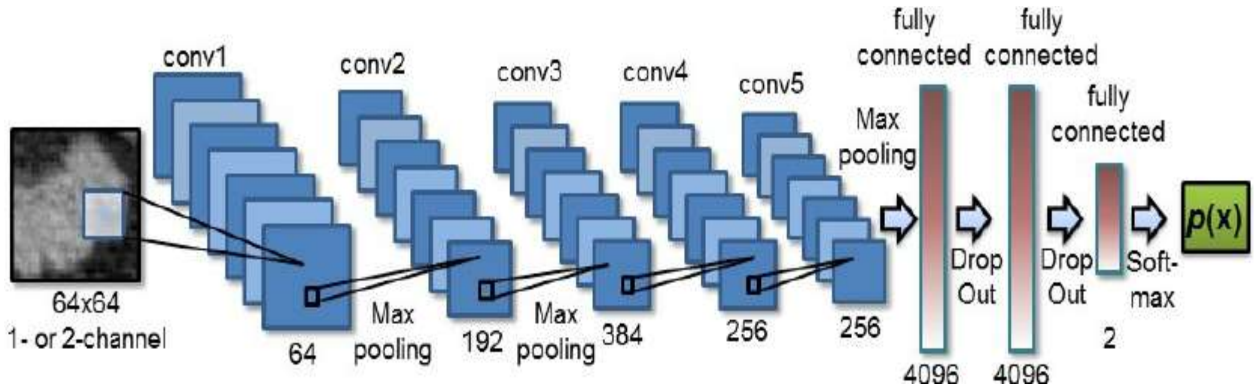


Figure 2: CNN Architecture

Source: Multi-level Deep Convolutional Networks for Automated Pancreas Segmentation

CNNs are made up of neurons collectively with learnable weights and biases. Inputs which are given to the neurons in the network, goes through an activation function and responds with an output. CNNs are built in layers and classification is done by the performance of these layers. ("Convolutional Neural Network (CNN) Tutorial In Python Using TensorFlow," 2018). Layers of CNN are;

1. Convolution layer
2. ReLU (Activation Function) layer
3. Pooling layer
4. Fully Connected layer

A. Convolutional Layer

This is the first layer in the network. In image classification an image is considered as a matrix of pixels. In this layer input matrix is multiplied with a kernel (filter) matrix and obtain an output matrix (Arunava, 2018).

B. ReLU (Activation Function) Layer

Rectified Linear Unit (ReLU) is mostly used activation function which activates only when the input value is above a certain value. If the input value is zero, output is also, zero. This will show a linear relationship with the dependent variable when the input value is above a certain threshold value. This layer removes all the negative values and keep the positive values as same. Input is smoothened and reduced the noise by this layer.

C. Pooling Layer

In this layer, the output gained by activation layer is shrunk into a smaller size. Image can be further reduced by applying above mentioned process again.

D. Fully Connected Layer

This is the final layer, where the classification happens. Output of the pooling layer is arranged into a single list. This process is called flattening. Classification is done by considering the flattened values obtained by the CNN.

IV. METHODOLOGY

This system is developed to identify five tomato plant diseases by using a CNN. disease identification is done by using images of defected areas of the plant.

A. General Overview of the system

General overview of the system is depicted in the following diagram.

B. Data Acquisition

The dataset contains images of four tomato plant diseases. Images for Late Blight leaves were taken from Plant diseases kaggle dataset ("Plant Diseases," 2018). Images for Anthracnose, Blossoms End Rot and Powdery Mildew were extracted from the internet. The images which were extracted from the internet were confirmed by an agricultural instructor for the accuracy of the disease.

C. Data Augmentation

To train a Convolutional Neural Network a large amount of data is needed. Therefore, gathered images were not enough to obtain a considerable accuracy. Data augmentation was performed on the collected images and expanded the image dataset. Data augmentation methods such as flipping, rotating an adding noise were performed on the dataset. 4080 images were obtained after the augmentation process. Dataset contained 1020 images for Anthracnose, 1020 for Blossoms End Rot, 1020 for Late

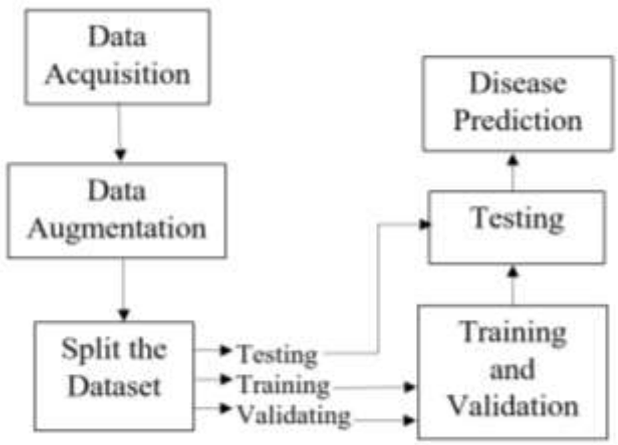


Figure 3: General Overview of the system

Blight and 1020 for Powdery mildew. Overfitting issue also was reduced by the process of data augmentation.

D. Split the Dataset

Dataset should be split into three parts namely testing dataset, training dataset and validation dataset. 80% of the dataset was considered as training data, 10% as validating data and the remaining 10% as testing data. Training dataset contains 3200 images, testing dataset contains 440 images and the validation dataset contains 440 images.

E. Model Development

Main purpose of this system is to classify tomato plant diseases using CNN. Model development is the most important process in the CNN since the training and image classification process is done by this developed model. Therefore, the most appropriate model which gives best results should be obtained in the model development process.

Model development is a very complex task. Therefore, in most of the deep learning systems they have adopted the Transfer Learning technique in developing the models.

1) Transfer Learning: Transfer learning technique is commonly used in deep learning systems. This is the process of using pre-trained models to train our own system. In this technique, a model which is developed for a particular task can be used for another task (Brownlee, 2017). This method is popular in Deep Leaning tasks as this method avoids the need of millions of data and reduces training time and resource consumption in training the network. Models which are used in Transfer learning, are trained on millions of data. These pre-trained models should be fine-tuned by using our training dataset. In this project, images of tomato diseases in the training dataset were used to fine-tune the model. This system is developed using MobileNet pre-trained model and it was trained on 1.4 million training images in ImageNet dataset.

2) MobileNet model: MobileNet architecture is a computationally efficient architecture with fewer parameters compared to other architectures. There are two main versions in this architecture. MobileNet V1 and MobileNet V2. Version 1 contains 4.24 million parameters while Version 2 contains only 3.47 parameters. For the development of this project, MobileNet V1 was used. Main feature of this architecture is Convolutional layers have been replaced by depthwise convolutions and pointwise convolutions. Depthwise convolution layer filters the input and pointwise convolution layer combines these filtered values to create new features. Full architecture contains 3 x 3 convolutions as the first layer. If 224 x 224 x 3 image is given as the input, then the output of the network will be 7 x 7 x 1024 feature map (Hollemans, 2019).

F. Training and Validation

This system was developed with Keras (“Home - Keras Documentation,” n.d.), using TensorFlow (“TensorFlow,” n.d.) as the backend. Model was trained on a normal PC with 8GB RAM and i7 CPU. Training was done for 5 epochs with batch size 32. By changing the learning rate, momentum, activation function, architecture and the number of images, different models were obtained, and best performing model was selected. System was trained with 3200 training images from the four classes.

Validation is a process of evaluating the system while tuning hyperparameters of the model, validation provides an evaluation how this model fits into the training dataset. This is a frequent evaluation. For the validation process 440 images were used.

G. Testing

After training process is completed the model should be tested with images which were not used in the training process or validation process. Before predicting images, accuracy of the network is measured by performing a test process. This system gained 98.96% of test accuracy for 440 defected tomato plant images.

H. Disease Prediction

Disease prediction is the main purpose of the system. This system has been trained to identify 4 tomato plant diseases. An image of a leaf or a fruit which belongs to one of these 4 classes is correctly predicted by the system.

V. RESULTS AND DISCUSSION

Tomato is highly susceptible to diseases. Disease identification has become a challenging factor in tomato cultivation. Since tomato diseases are visible to human eye, an image classification system can be developed to identify tomato diseases. In this project, a system which can identify 4 types of tomato diseases using Convolutional Neural Network is presented.

Deep neural network is a complex machine learning technique. Therefore, high level APIs are used to develop the deep learning models. This system was developed using Keras python library and TensorFlow was used as the backend. Data acquisition, result prediction, model training etc. can be done easily using TensorFlow.

Data is the most important fact in Deep Learning systems. Accuracy of this entire system is depending on the images and how they were trained. In this project, models were trained by changing hyperparameters and number of images. Augmentation techniques were applied on images to increase the number of images in the dataset. After training models, best model was selected by considering accuracy levels. Then the best performing model was used in developing the tomato plant disease detection system. Transfer learning approach was used, and the system was developed by using MobileNet model. System was trained with 3200 images, tested with 440 images and validated using 440 images. Learning rate is 0.0001 and momentum is 0.9. Softmax activation function was used in training the network and gained training and validation accuracies as 99.16% and 98.89%. after the training process system was tested and gained 98.96% accuracy.

Following graphs shows training and testing accuracies and loss.

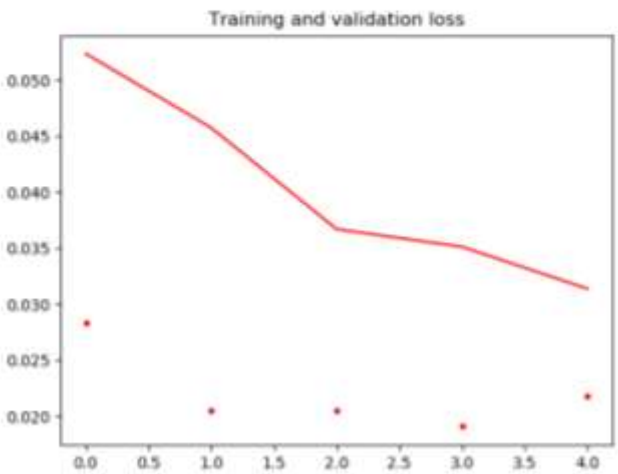


Figure 4: Training and Validation loss of the selected model

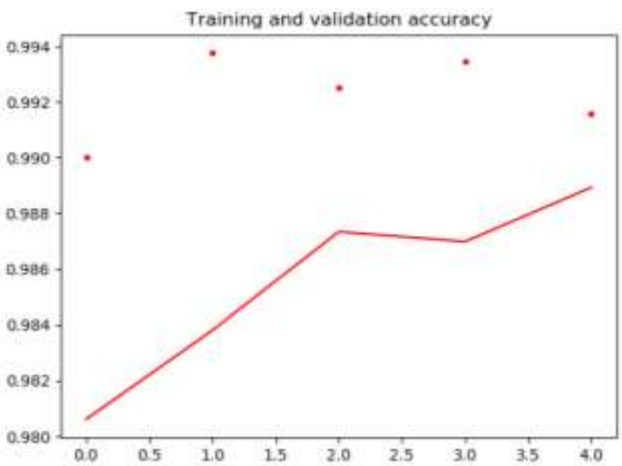
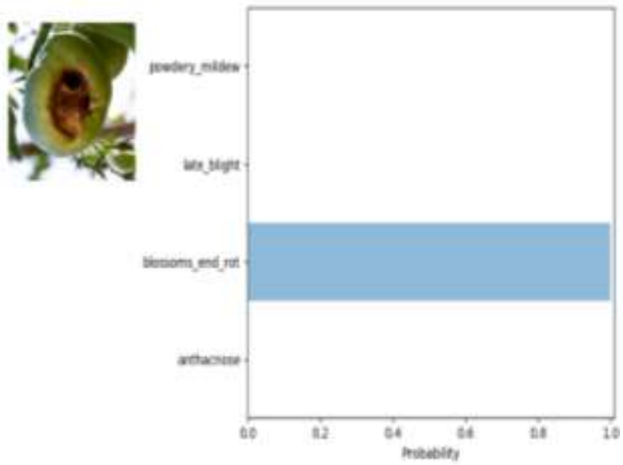


Figure 5: Training and Validation accuracy of the selected model

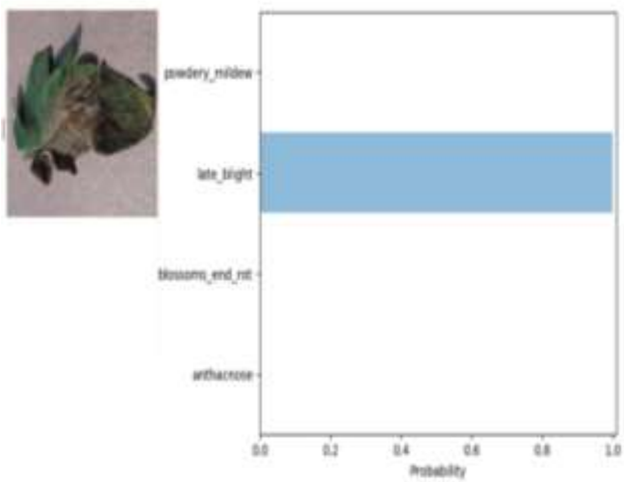


Final step is to predict the developed system. For the prediction, images which are unknown to the system should be provided. Results are predicted for these unknown images. This system was able to predict the diseases correctly.

Predicted results for a fruit disease and a leaf disease are

Figure 6: Predicted results for Blossoms End Rot image

given below.



VI. CONCLUSION

Deep Learning techniques are effectively used in image classification problems. Features of images can be learnt by a CNN and perform classification based on the learned features. In this proposed system, CNN is trained with diseased images of tomato leaves and fruits. Then this trained model identifies tomato diseases by an image provided to the system. Deep learning models are complex and need millions of data to train. This training process is

Figure 7: Predicted results for Late Blight image

computationally expensive, and it consumes a lot of time. Therefore, Transfer Learning approach is used in developing the Deep Learning model. Transfer learning technique with MobileNet model was used in this proposed system.

Performance of the system is depending on hyperparameters, activation function and the number of images used in the training process. This system was tested by changing the learning rate and momentum values. When the learning rate is increased and the momentum is decreased, changes were occurred in the accuracy of the system. Softmax activation function gained higher accuracy than ReLU activation function. Models were created using Inception V3 architecture and MobileNet architectures. According to this system, the highest accuracy gained with learning rate 0.0001, momentum 0.9, batch size 32 and 3200 training images with Softmax activation function and MobileNet architecture.

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