Tomato Leaf Diseases Detection Using Deep Learning

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Abstract. Early detection and diagnosis of plant leaf diseases is a major necessity in a growing agricultural economy, plant leaf diseases detection is considered crucial at a very early stage as it allows adopting predictive mechanisms that helps avoiding losses to the agri-based economy. Tomato is one of the most important crops that is produced in large quantities with high commercial value and contributes to food chain and security and a lucrative business for many farmers.

This study uses a deep convolutional neural network (CNN) to predict tomato leaf disease by transfer learning. InceptionV3 was used as the backbone of the CNN, the highest accuracy of 99.8% for identifying tomato leaf diseases is achieved on the PlantVillage dataset. And the final model was deployed as a web application on the cloud to be available.

The experimental results show that the proposed model is effective in identifying tomato leaf disease and could be generalized to identify other plant diseases.

Keywords: Deep learning; CNN; Classification; transfer learning; Plant disease.

1 Introduction

The world population is expected to increase by 2 billion people in the next 30 years, from 7.9 billion currently to 9.9 billion in 2050, developing methods for early detection of plant diseases serve the double purpose of increasing crop yield and reducing pesticide use [1]. In some countries of Asia and Africa over 50% of the population depends on agriculture production for their daily living [2]. According to FAO (Food and Agriculture Organization of the United Nations) pests and diseases are responsible for the loss of 40% of the global food production, which poses a threat to food security [3]. In 2019, around 20% of overall global crop productions were lost due to pests and diseases [4].

Tomato is a widely planted crop around the world, it contains rich nutrition and health effects, hence it plays an important role in global production and trade all over the world [5]. According to FAO, tomato is the second most important vegetable crop next to potato [6]. Given the importance of tomatoes in the economic context, thus it is necessary to maximize productivity and improve product quality by using available and evolved techniques. According to the last statistics, there are as many as 10 types of tomato leaf diseases that have sorely affected Tomato yield from both qualitative and quantitative aspects, this led to massive economic losses, consequently crop production has turned to be a nightmare for farmers due to such kind of diseases. Therefore, early diagnosis and treatment of tomato leaf diseases play an extremely important role in tomato production. Generally, it is possible for a person with high professional knowledge to accurately diagnose plant diseases, but smallholder farmers are not highly educated and do not have the required professional knowledge, so they usually have a low judgment rate of plant diseases.

In the last years, computer vision has provided an interesting and innovative approach for the accurate diagnosis of plant leaf diseases and paved the way for smartphone-assisted disease diagnosis [7][8]. Various techniques and applications have been made to reduce crop losses due to diseases, some methods have been proposed to identify plant diseases such as Convolutional Neural Networks CNN [9]. The successful identification of plant diseases is fateful to improve agricultural production and reduce the undesirable use of chemical treatment such as fungicide/herbicide. Therefore, disease detection is an important research field to advanced agricultural automation [10].

In the last few decades, Deep Learning has proved its ability of handling large amounts of data to recognize patterns, one of the most popular deep neural networks is the CNN. As CNN represents one of the most powerful techniques for modeling processes and performing pattern recognition in images [11]. Recently several convolutional neural network models have been proposed for plant diseases identifying, and some state-of-the-art architectures such as VGG, Inception-v3, ResNet, and DenseNet have shown promising results.

Few people go to train an entire convolutional neural network from scratch while the alternative approach and most common is using pre-trained models that are already trained on existing large datasets. One of the most common datasets is ImageNet that contains 1.2 million images with 1000 categories, this technique is called transfer learning, it helps to build accurate models in an efficient way [12].

The contributions of this study can be summarized as follows:

1. Presenting a deep learning model to identify tomato leaf diseases at a very early stage to avoid losses to the agri-based economy.
2. Presenting transfer learning as a significant technique to accelerate the training task and increase the accuracy and stability of the classification models.
3. Demonstrating how to improve model accuracy by hyper-parameters tuning and applying data augmentation.
4. Deploying the trained model on the web and make it available as a free app for smallholder farmers.

The rest of the paper is organized as follows: Section 2 analyses of the dataset used. Section 3 presents materials and methods like network architecture, transfer learning, data augmentation, and evaluation metrics. Section 4 provides and discusses the experimental results. Section 5 presents the deployment of the final model on the web. Finally, Section 6 summarizes the study and draws a conclusion.

2 Dataset

Generally, to develop accurate image classifiers for diagnosing plant disease, we need a large dataset of images for both diseased and healthy plants leaves. This type of dataset was not available short time ago. The PlantVillage project solved this issue as it addressed this problem and started to collect thousands of images from both healthy and diseased crop plants and made them open and free for public use [13]. From this dataset, we extracted only tomato leaf images that are classified in 10 classes. Figure 1 shows one example per each sample class. The total number of images in our dataset is 18,160, each having animage size of 256 x 256 x 3. a summary of our dataset is presented in Table 1.

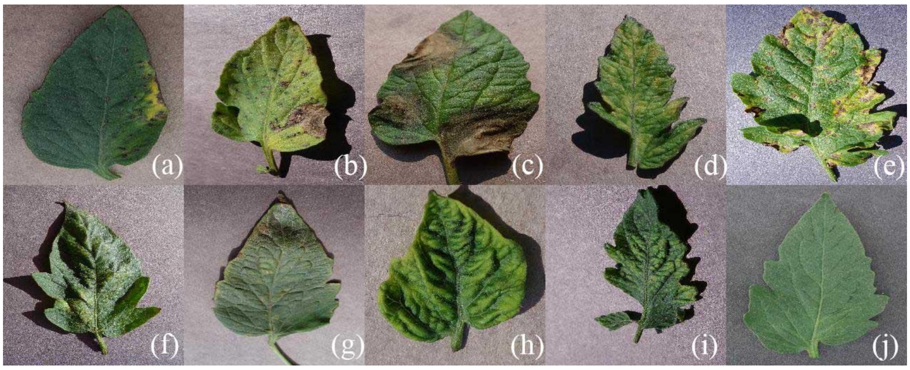

Fig. 1. Sample images tomato dataset: (a) Bacterial Spot, (b) Early Blight, (c) Late Blight, (d) Leaf Mold, (e) Septoria Leaf Spot, (f) Spider Mites, (g) Target Spot, (h) Yellow Leaf Curl Virus, (i) Mosaic Virus, and (j) Healthy

Table 1. Distribution of classes in Dataset

Class Name	Number of images
Bacterial Spot	2127
Early Blight	1000
Late Blight	1909
Leaf Mold	952
Septoria Leaf Spot	1771
Spider Mites	1676
Target Spot	1404
Yellow Leaf Curl Virus	5357
Mosaic Virus	373
Healthy	1591

3 Materials and Methods

This study concentrates on identifying tomato leaf disease using CNN. This section is based on five sub sections, first one displays deep learning-based proposed architecture for identifying tomato leaf disease. In the second and third ones we briefly introduced transfer learning and augmentation. After that training specification is presented. Finally, we explained in the last one the evaluation metrics used in this study.

3.1 Deep Learning Model

In this study, we use Inception-v3 architecture, which is a convolutional neural network architecture from the Inception family that is widely used for classification tasks. This architecture was originally introduced during the ImageNet Recognition Challenge [14]. The Inception V3 network has multiple symmetric and asymmetric building blocks, where each block has several branches of convolution layers, average pooling, max-pooling, concatenated, dropouts, fully-connected layers, and softmax [15]. Figure 2 represents the architecture of the Inception-V3 network for 256x256x3 image size and 10 classes.

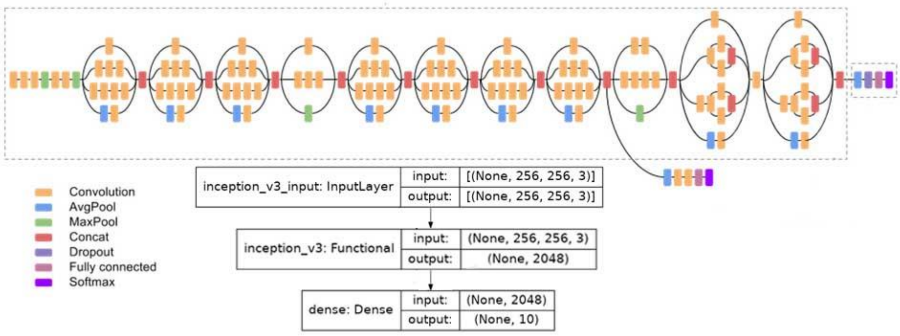

Fig. 2. Architecture of the Inception-v3 neural network

3.2 Transfer Learning

Transfer learning technique is a process that takes features learned on one problem, and leveraging them on another, problem. Transfer learning is usually used when you have small dataset to train a model from scratch [16]. Transfer learning enables us to train models with fewer size data. It can reduce training time and computing resources, see Figure3. Using transfer learning (pre-trained models) can boost accuracy without taking much time to converge compared to a model trained from scratch. Sometimes if models are trained from scratch without proper normalization, it can produce misleading results, which might mean that training from scratch is not optimal at all.

In this study, we use the Inception-V3 network already trained on more than a million images from the ImageNet (ImageNet is one of the most common datasets that contains 1.2 million images with 1000 categories).

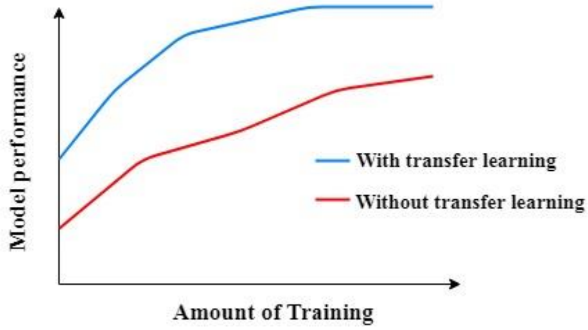

Fig. 3. The benefit of transfer learning

3.3 Data Augmentation

Usually, deep learning models need a lot of data for training, in general, the more the data, the better the performance of the model. But sometimes acquiring enormous amounts of data is considered a major challenge in deep learning. The problem of shortage of data is that the deep learning model might not learn the pattern from the dataset and hence it might not give a good performance.

basically, Data Augmentation (DA) technique is used to increase the amount of data by adding slightly modified copies of already existing data. It is one of the most practical approaches to enhance model performance without spending days manually collecting data [17]. In this study, some data augmentation techniques were proposed, such as shear, zoom, rotation, vertical flip, and horizontal flip to boost the training set for improving the model accuracy.

3.4 Training Specifications

In this study, the experiments are implemented using the Keras framework, and classification was done on Inception-V3 network. Transfer learning is used to increase the accuracy and stability of the model. Our model was first pre-trained on the ImageNet dataset then the model training was done in 30 epochs with a batch size of 16, the model was optimized via Adam optimizer [18] with a learning rate of 0.001, and Categorical CrossEntropy was used as a loss function [19]. To achieve higher accuracy, the learning rate has been reduced whenever a loss metric had stopped improving. The dataset was split into two sets: a training set and a validation set with a ratio of 80:20 respectively.

3.5 Evaluation Metrics

The performance of the model is generally evaluated by different metrics to analyse how well the model performs on test data. Sensitivity, Specificity, Accuracy, Precision, and F1-score metrics are used for evaluating our model.

Sensitivity (True Positive Rate) also known as recall refers to how many positives are correctly identified; this can be calculated by the following equation.

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

Where TP is the true positives that are the number of instances that are positive and are correctly identified, and FN refers to the false negatives that are the number of positive cases that are incorrectly identified as negative.

Specificity (True Negative Rate) refers to the probability of the negative label being true, this can be calculated using the following equation.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Where TN is the number of true negatives that are classified as negative, and FP is the number of false positives that refers to the negative instances that are incorrectly classified as positive cases.

Accuracy is the most commonly used metric to evaluate classification models. This metric calculates the proportion of samples that are correctly classified, the following equation is used to calculate accuracy.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Precision (Positive Predictive Value) is defined as the number of true positives divided by the number of true positives plus the number of false positives, is given by the following equation.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

F-score is defined as the harmonic mean precision and recall, as shown in the following equation.

$$\text{F} - \text{score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

4 Results and Discussion

The objective of this research was presenting a CNN model to classify tomato plant leaf diseases with high accuracy, our model showed statistically significant performance. Table 2 shows sensitivity, specificity, accuracy, precision, and F-score of Inception-V3.

Table 2. Performance results for Inception-v3

Model	Sensitivity	Specificity	Accuracy	Precision	F-score
Inception-v3	0.9969	0.9998	0.9978	0.9977	0.9978

And Figure 4 shows the Accuracy/loss curve for Inception-v3 model.

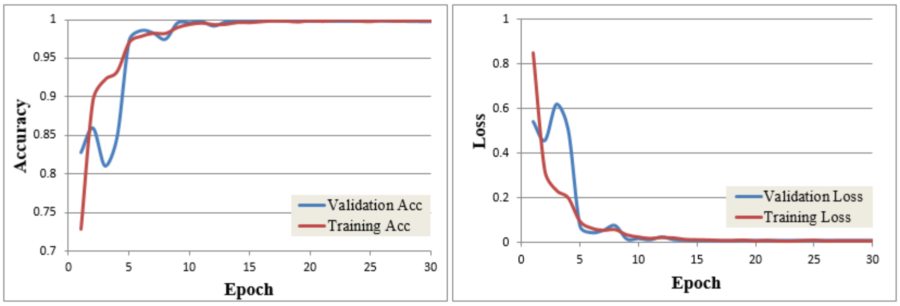

Fig. 4. Accuracy/loss curves of Inception-v3 model

Table 3 shows the confusion matrix of the model; it is possible to visually evaluate the performance of the model. The rows are related to the output classes. The diagonal cells are associated with the observations that are correctly identified, and the off-diagonal cells correspond to the incorrectly identified observations.

Table 3. Confusion matrix based on Inception-V3 model. (1) Bacterial pot; (2) Early Blight; (3) Late Blight; (4) Leaf Mold; (5) Septoria Leaf Spot; (6) Spider Mites; (7) Target Spot; (8) Yellow Leaf Curl Virus;(9) Mosaic Virus; and (10) Healthy

Predicted

Actual	1	2	3	4	5	6	7	8	9	10
1	425	0	1	0	0	0	0	0	0	0
2	0	196	4	0	0	0	0	0	0	0
3	1	0	380	0	0	0	0	0	0	2
4	0	0	0	190	0	0	0	0	0	0
5	0	0	0	0	354	0	0	0	0	0

6	0	0	0	0	0	335	0	0	0	0
7	0	0	0	0	0	0	281	0	0	0
8	0	0	0	0	0	0	0	1071	0	0
9	0	0	0	0	0	0	0	0	75	0
10	0	0	0	0	0	0	1	0	0	317

Among the ten classes, five classes produced 100% correct classification results since those diseases have distinctive features and appearance, which are Leaf Mold, Septoria Leaf Spot, Spider Mites, Yellow Leaf Curl Virus, and Mosaic Virus. The performance measures were calculated for each class and the obtained results are shown in Table 4.

Table 4. Performance results for each class

Class	Sensitivity	Specificity	Accuracy	Precision	F-score
Bacterial Spot	0.9977	1.000	0.9997	0.9997	0.9987
Early Blight	0.9800	1.000	0.9989	0.9989	0.9894
Late Blight	0.9948	0.9985	0.9981	0.9980	0.9964
Leaf Mold	1.000	1.000	1.000	1.000	1.0000
Septoria Leaf Spot	1.000	1.000	1.000	1.000	1.0000
Spider Mites	1.000	1.000	1.000	1.000	1.0000
Target Spot	1.000	0.9997	0.9997	0.9997	0.9998
Yellow Leaf Curl Virus	1.000	1.000	1.000	1.000	1.0000
Mosaic Virus	1.000	1.000	1.000	1.000	1.0000
Healthy	0.9969	0.9994	0.9992	0.9992	0.9980

5 Deployment Final Model on the Web

When a machine learning engineer develops a machine learning model using TensorFlow, PyTorch, Keras, etc. The definitive goal is to make the model available for production. Often when we work on a machine learning project, we focus a lot on Exploratory Data Analysis (EDA), preparing data, feature engineering, build model, hyperparameters, etc. But we forget that our major goal is to extract important values from the model predictions. Deployment of machine learning models means making models available to the end-users or systems. However, models deployment is sometimes considered tricky [20].

In this study, we build a web application from two parts: Front-end and Back-end. In the front-end, we used HTML and CSS to build a basic front-end with an input form for uploading images and build a back-end of the web application using a Flask framework, Flask is a web application framework used to develop web applications [21]. then we deployed the web application in DigitalOcean cloud [22], after deployment, the model became publicly available and can be accessed via web URL.

6 Conclusions:

Plant diseases had become a major concern in agriculture for years. Precision agriculture can help improving both environmental and economic issues, it reduces pesticides usage and obtain the disease information through computer vision effectively at a very early stage to avoid losses to the agri-based economy.

Deep learning has been successfully used in various fields, it showed promising results, and large potential. In agriculture, the role of deep learning has become inevitable due to its powerful deployment capabilities in disease detection, as disease diagnosis using deep learning can enhance the quickness of taking proper decisions to avoid crop losses due to diseases and pests. In addition, the small-holder farmers need such kind of reliable, efficient and cheap technique in their fight against plant disease.

Transfer learning reduces the time of execution drastically and provides various advantages like improving the accuracy of output and requires lesser training data. Although like every other technique, there are few limits to transfer learning, such as overfitting and negative transfer. The inception-V3 model proved to be very effective in image classification and showed great potential in identifying tomato leaf diseases through achieving high classification accuracy.

The main goal of this study was to improve the efficiency of automatic plant disease detection. Experimental results showed that the proposed model can successfully detect and classify tomato leaf disease with an accuracy of 99.8%. In future work, we will extend to focus on detecting diseases in various locations of the plant and at different phases of the disease.

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