Tomato Leaf Disease Detection Using Inception V3

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Abstract: Agriculture is one of our society's most critical fields, and it has been since the Middle Ages. Crop diseases are a significant threat to food security, but timely detection is difficult due to a complete lack of facilities in many parts of the world. Bacteria and fungi infect tomato plants in several ways. Early blight and late blight are two fungal diseases that affect plants. Bacterial spot is caused by four Xanthomonas species and can be found wherever tomatoes are grown. Smartphone-assisted disease detection is now possible thanks to rising global smartphone penetration and recent developments in machine vision made possible by deep learning. To distinguish different tomato leaves, we trained deep convolutional neural network diseases using a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions and choosing the images of tomatoes. Training deep learning models on increasingly broad and publicly accessible image datasets points to a direct path toward global crop disease diagnosis aided by technology.

Keywords: Early Blight, Late Blight, Bacterial spot, Leaf Mold, Septoria Leaf spot, Target Spot, Yellow Leaf Curl Virus, Mosiac Virus, Two Spotted Spider Mite

1. Introduction

Agriculture is one of the fundamental building blocks of every civilization. Growing vegetables like tomatoes are effective in India's diverse range of subtropical climates. A diseased plant has been hindered from achieving its normal state. A disease may also be described as interfering with a plant's yield and reducing its vitality. In India, diseases change with the seasons and are affected by environmental factors. Pathogens and the variety of crops grown during the season play a role in these diseases. Late Blight and Early Blight are two common tomato diseases [1]. They have the potential to damage tomato plants and agricultural lands. Spotting Late Blight and Early Blight on plant leaves is possible, but it takes a long time if performed manually. As a result, more recent changes are needed. With the aid of image processing and computer vision, there are many ways to detect objects and their unique features from images. The deep learning CNN model [2] is one of the most common approaches. The model, in our case, will detect disease based on the picture of the leaves.

Convolutional neural networks are image processing methods using jpg files to comprehend them [3]. Shift invariant is another name for them. Because of their weight-sharing architecture and translation invariance properties, this is the case. As a result, they've also been known as space-invariant neural networks. They're used in recommender systems, image and video recognition, medical image analysis, image detection, natural language processing (NLP) [4], brain-computer interfaces, and financial time series, among other items. They also rule a slew of different applications in a variety of fields. The paper is further classified into sections that discuss various viewpoints in analyzing tomato diseases' impact on Indian agriculture. Raw Dataset was used, and the detail extraction is discussed in section 3.1. The results, the accuracy, and their evaluation have been documented in section 4. The paper is finally concluded on a note with an evaluated conclusion and expectations of future scope in sections 5 and 6, respectively.

2. Related Work

The use of computer vision to identify agricultural diseases has become a hot subject. In the early years, traditional machine learning methods and external networks were commonly used in the agricultural sector.

Sannakki et al. [2] proposed using k-means-dependent clustering performed on each image pixel to isolate the infected location. Those who realized that the Grading System they created with machine vision and fuzzy logic is very useful in evaluating plant disease. Samanta et al. introduced a new histogram-based approach for detecting potato scab diseases, which relied on a color image segmentation technique to detect precise intensity patterns. With a classification accuracy of 97.5 percent, they came out on top. Pedro et al. used fuzzy decision-making and a fuzzy multicriteria decision-making approach to classify marijuana form, with an accuracy of 92.9 percent. Matson and Cheng used Support Vector Machine (SVM), Decision Tree, and Neural Network to classify rice and weed, with Decision Tree providing the highest accuracy of 98.2 percent. Sankaran and Ehsani used quadratic discriminant analysis (QDA) and k-nearest neighbor (kNN) to distinguish Huanglongbing (HLB)-infected citrus leaves and canker from healthy citrus leaves, with kNN providing overall accuracy of 99.9%. D. Tiwari et al. [3] used transfer learning and various pre-trained models and concluded that VGG 19 provided the best accuracy on the potato leaves image dataset. Backpropagation neural networks have a 92 percent accuracy rate, while support vector machines have a 95 percent accuracy rate. In their research, Melike Sardogan et al. [5] attempted to detect and classify tomato leaf diseases using a Convolutional Neural Network with a Learning Vector Quantization algorithm.

A. Pranathi et al. [6] proposed a small convolutional neural network model variant. To detect and diagnose illnesses in tomato leaves, researchers presented LeNet. Their planned research aims to develop a solution to the challenge of detecting tomato leaf disease using the basic strategy while employing the fewest computational power possible to produce results comparable to the best technologies available. Chittaragi et al. [6] suggested the use of automatic feature extraction in neural network models to assist in the classification of input images into disease classes. Their proposed solution attained an average accuracy of 94 - 95 percent, demonstrating the neural network approach's feasibility even under adverse conditions. U. Mokhtar et al. [7] proposed a method that uses the Gabor wavelet transform approach to extract essential elements from a tomato leaf image, as well as Support Vector Machines (SVMs) [8] with different kernel functions, to discover and diagnose the disease that affects tomato plants. They used actual samples of damaged tomato plants, isolated each leaf in a separate image, and used a wavelet-based feature approach to find the best feature subset. H. Hefny et al. [6] used a support vector machine classifier with several kernel functions such as Cauchy kernel [9], Invmult Kernel, and Laplacian Kernel to test the efficacy of this methodology to detect and identify where tomato leaves infected with Powdery mildew or early blight. Extensive testing shows that the proposed method gives good annotation with a 99.5 percent accuracy rate. The proposed approach's efficient results can lead to a tighter relationship between agriculture specialists and computer systems, resulting in more effective and dependable results.

3. Materials and Methods

This paper aims to use deep learning to detect tomato leaf diseases. Deep neural networks train the model to detect presence after acquiring features from inception v3 [7]. In the photos, you can see early blight and late blight. The Adam optimizer is used during classification to minimize training time and easily converge the loss [10]. Adam is a computer vision extension of SGD [11] that is now commonly used. The softmax activation mechanism is used to classify various labels [10]. The softmax activation function transforms a vector of n real values into a vector of n real values that add up to 1. The softmax [12] converts the input values into values between 0 and 1, allowing them to be interpreted as probabilities.

3.1 Raw Dataset

A dataset is the first step in writing a deep-learning document. It can be used to research and infer even more findings from the model and train it. The data set used in this project is from the Kaggle platform. The data set is named PlantVillage [13], a popular dataset in the Kaggle platform. Kaggle is an online platform for data scientists and machine learning engineers where they can compete in ML competitions and work on various datasets and notebooks. There are approximately 20000 photos of leaves from tomato plants, bell pepper plants, potato plants, and other plants in this Dataset. The images in the Dataset are in jpg/png format. This is a collection of data leaves that are both healthy and diseased. The diseased leaves are divided into early blight and late blight. For stable leaves, 80% of the Dataset is used for preparation, and the remaining 20% is used for testing; the same is true for diseased leaves. As a result, the model will be trained on more leaves and checked on fewer to achieve the highest accuracy during prediction and detection. Each plant has its directory, and each disease associated with that plant has its folder. The Tomato plant dataset is the subset of the Dataset we're working with. There are 1000 images of early blight leaf images, 1000 images of late blight leaf images, and 152 images of late blight leaf images in this Dataset.

Fig. 1 Sample images of the Dataset

3.2 Data Preprocessing

Since the data is in image format, to make it useful for the system to run, we first convert it into an image array with the help of Keras functions. Classification of diseases will only be performed appropriately if the image is colorful so that the model can differentiate between various conditions. So a 3D NumPy [14] array will be generated using RGB values.

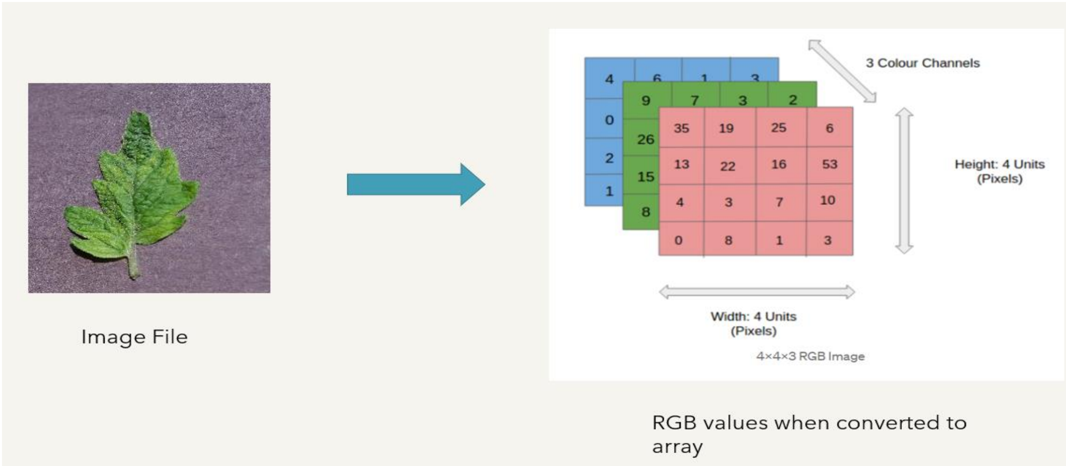

Fig. 2 Converting images to Numpy array

The Inception V3 model derives the learning algorithm from the ImageNet Dataset and uses that learning algorithm in the PlantVillage dataset. ImageNet is already a popularly known labeled image dataset of 14 million labeled images. So to improve the learning algorithm in our Dataset, we will provide labels to our data. After converting the images to arrays, we need to label the data so that the model will classify them in order of classes. Label Binarizer library is used so that the images will be properly labeled into categories with the names of the disease. LabelBinarizer will help classify the data during the training of data.

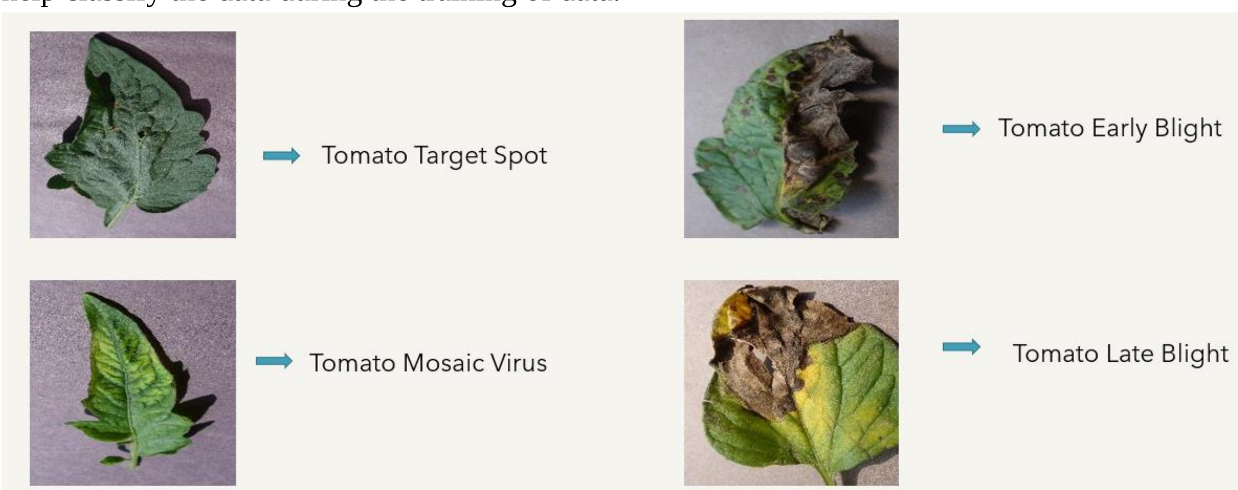

Fig. 3 Labeling Data

3.3 Data Augmentation

We have used CNN to perform classification in this research project. Deep neural networks train the model to detect the existence of early and late blight in the images after acquiring features from Inception v3. Further, we use Adam optimizer during classification to minimize training time and quickly stabilize the loss. Adam[9] is a machine vision extension of SGD [11] that is commonly used. The softmax activation function is used for the classification of different labels. The softmax activation function translates a vector of n absolute values into a vector of n actual values that add up to one. And although input values can be any number, the softmax converts them to a number between 0 and 1, allowing them to be used.

3.4 Deep Learning Models

All images are fed into the CNN model's input layer at the start. The images are then provided in the inception v3 architecture [8] for feature extraction. There are Deep neural nets that identify the images based on pre-trained information using feature-extracted images. The images are finally sent to the output layer. The model comprises a few layers that are first generated and then compiled together using TensorFlow library functions [8].

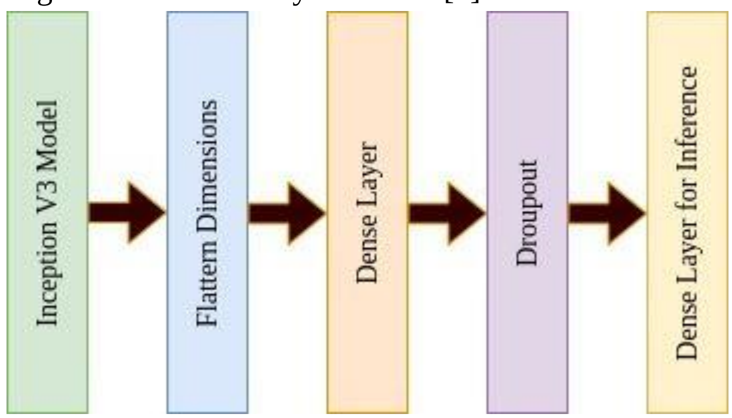

Fig. 4 Abstract form of Inception V3 model

4. Experimental Results and Discussions

The plant village dataset, which contains around 1000 leaf images of early blight and 152 images of healthy plants, was used to develop the model proposed in this paper. The Dataset for this model has been divided into two parts: the training set and the test set. The training set accounts for 80% of the Dataset, while the test set accounts for 20% of the total. Inception V3 is the pre-trained model used to extract features from this Dataset. Based on the training and testing performed, our CNN model offers an accuracy of about 84% for classification, which can be further improved if we are provided with resources to run ML models. Our data set's input images are 128 x 128 pixels, each with RGB colors with a density of 512. This accounts for the shape of our image to be a 3-dimensional matrix of 128 x 128 x 3. We use Label Binarizer for providing labels to the input image data. Label Binarizer library is used so that the images will be properly labeled into classes with the names of the disease. Performing an image prediction will result in an output of a 3D NumPy [14] array, which provides an image value. Classification of diseases will only be performed appropriately if the image is colorful so that the model can differentiate between various diseases. So a 3D NumPy [14] array will be generated using RGB values.

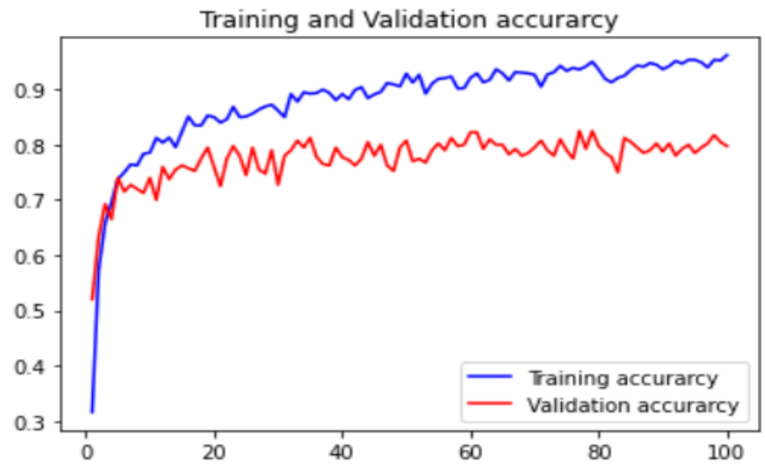

Fig. 5 Training and Validation Accuracy

With an epoch of 70, the training accuracy increases to greater than 90%. However, the validation accuracy (training accuracy subtracted loss) achieves a plateau at ~80 to 85%. With close analysis and evaluation of the model, we get a mean accuracy of 84%.

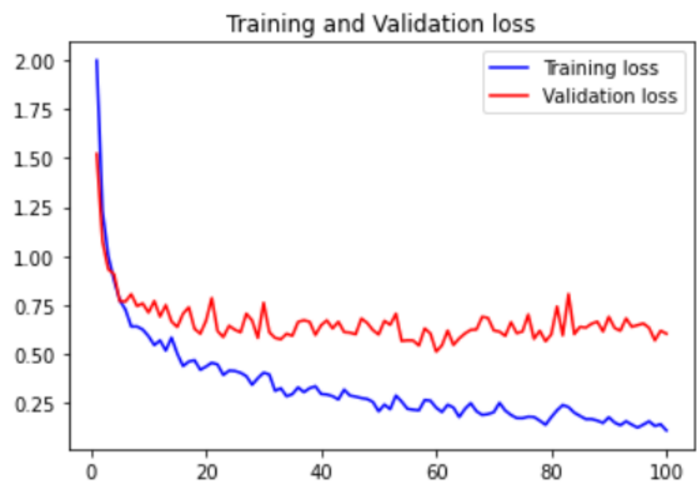

Fig. 6 Training and Validation Loss

With the iteration of every epoch, the model improves the learning method and minimizes the losses. We see an exponential fall in training loss with a conclusion training loss percentage of 10 to 15%. After evaluating the model, we find this mean decrease to 12%. As the training loss (referred to as val_loss) starts decreasing, the training accuracy (referred to as val_acc) increases. This inversely proportional relationship confirms that our model is learning and working as expected.

5. Conclusion

In this study, we used the Inception V3 architecture and Adam Optimiser [15] to create a CNN model to diagnose and identify diseases in tomato plants, such as early and late blight, with a classification accuracy of 90% over the test dataset. With the aid of our model, a farmer can construct a computer setup from which he can effectively track plant health issues, increase crop yield, and detect and diagnose diseases at an early stage.

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