



Classification of Tomato Leaf Disease using a Custom Convolutional Neural Network

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Abstract

A plant's genetic potential for crop production can only be realised if the plant is healthy. Infected plants produce less than their genetic potential when they are unhealthy and exposed to infection-causing agents of any kind. A disease can have an impact on a plant's metabolism. Manual checking of plant health is not feasible for anytime. Accurately identifying the disease as soon as it first manifests on the plant is crucial for controlling it in farms. Thus, taking the proper action to stop further crop and yield damage will depend heavily on an automated method of disease identification and precise disease relegation. This paper presents a convolutional neural network (CNN) model for diagnosing tomato leaf diseases. The findings are presented with an emphasis on accuracy as well as loss. About, 14240 numbers of tomato leaf image data representing nine distinct disease classes were utilized to train the model. On average, this classification was found to be 95.53 percent accurate.



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Introduction


The life of farmers is not easy, farmers have to do very hard work throughout the year but the efforts and time of farmers is most times devastated by the diseases which also leads to the financial loss of farmers. The disease detection system contains an automatic process to detect leaf illnesses, and smartphone users can access information about leaf diseases.²⁵ The disease detection system is capable of accurately detecting disease types. The disease detection system will be very useful for farmers to reduce the harm caused by the disease

in the initial stage of disease occurrence. Disease control and its management is described by the factors like surveys, monitoring, classification and identification. In order to make an accurate diagnosis of the disease, the first and most important step is to set up an appropriate leaf detection system. The crop yields can be increased with the utilization of precision agriculture. There are always variations in crop yields due to a number of factors like changes in climate conditions, type of fertilizer used and soil characteristics. Utilization of automation in the agricultural field will help to increase the

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production of good quality crop yields while reducing the resources utilizations. The precision in Smart agriculture is improving by implementation of deep learning algorithms.

A lot of research has been done on what role ANN can play in the emerging field of smart irrigation water management, and how to implement it. Crop irrigation relies heavily on accurate estimates of reference evapotranspiration (ET_o) for a variety of reasons, including but not limited to irrigation scheduling, precision farming, healthcare, etc. Agriculture management has changed a lot thanks to the Internet of Things.⁵ IoT technology connects all agricultural devices and gives real-time information that helps farmers make good decisions about irrigation and fertilizer application. Through wireless sensor networks, a variety of sensors can communicate and exchange data. The Internet of Things (IoT) works with cloud services to process and analyse the data from different sensors and make the best decisions in agriculture to increase crop yield.^{2,3,4} Many developing nations lose between 30 and 50 percent of their annual agricultural yield due to disease because of the lack of available control measures. It is possible that there won't be enough food to eat if pests and fungi destroy crops. But in other years, the losses are much worse, causing disaster for those who depend on the crop for food. Diseases that spread quickly through food crops have been the cause of famines and large-scale migrations throughout history. Diseases are currently detected using a visual recognition method, but this is a laborious and time-consuming process with unsatisfactory results. The environment in which grapes grow would be negatively impacted, as would the quality of the resulting fruit if this technique were used excessively. Many different spectroscopy methods have been used for plant disease monitoring and detection, but the high cost and low efficiency that come with using highly sensitive sensors and complicated instruments limit their usefulness.

Overview of Related Work

CNN architectures have been heavily researched and implemented in the field of plant leaf diseases. Rendering to those work and studies, CNN gets the innovative, strong feature of diseased images right from the original images instead of manually extracting or selecting the features, which is better

than the traditional methods of extracting features. But while using CNN, we have two main problems. One problem is that it takes a lot of data to train the models, and each disease on a grape leaf shows up at different times. This means that the time available for collecting images of the diseases is limited, which means that there are fewer grape images available for training the models. The second one is the hard job of classifying fine-grained images of grape leaf disease. The trained models with transfer learning did not have satisfactory achievements. Due to this design of an excellent CNN Structure for disease identification of grapes images is a formidable task.⁴ In the past decades, due to advancements in 3G or 4G and NB-IoT technology, the speed at which exchange of information and communication has increased.²⁴ This has led to an increase in the sharing of real-time data through IoT, which in turn has led to more accurate evaluations in the agricultural sector. On the other hand, the efficiency of data transmission is significantly reduced when it comes to 4G networks because of improvements in the quality of the data.⁵

An image classification system based on tomato leaf images is proposed in this study. When compared to machine learning, deep learning performs better in several key areas, including the accuracy of its categorizations and the breadth of its potential uses around the world. This paper makes a comparison between the ResNet50 and Xception architectures. Greater accuracy of 99% can be achieved using Xception Architecture in combination with the Adam optimizer and 0.0001-learning rate.¹ Otsu's segmentation technique was used in conjunction with a decision tree in the study carried out by Sabrol *et al.*⁷ to try and diagnose the disease that was present in tomato leaves. In this study, authors employ leaf phenotypic features such as shape, texture, and colour to learn about leaf diseases. Classification accuracy was 97.30% using the proposed method. Early blight as well as powdery mildew in tomato leaves were detected using Moth-Flame Optimization and MFO Rough Set by Hassanien *et al.*⁸ The proposed strategy is tested with the help of the GA and PSO rough set algorithms. The experimental findings show that the proposed method has better precision (85.7%), recall (86.0%), and F-score (85.7%) than the current method.

About three hundred and sixty leaf colour photos were divided into six classifications by Sabrol *et al.*^{7,9} five unhealthy and one healthy. Using standard image processing, RGB images were transformed to the CIE XYZ colour space model using the classifiers FIS, MLPNN, and ANFIS (ANFIS). With an accuracy percentage of 87.20%, MLPNN is the most accurate algorithm. Annabel *et al.*¹⁰ experimented with random forest algorithm and found useful to classify tomato leaf diseases like bacterial spot, late blight, tomato mosaic virus, and healthy leaf images. With the same dataset, the algorithm's 94.10% accuracy is the highest among those obtained by SVM (82.60%) and MDC (87.60%). The proposed classification method achieves 95% accuracy in experiments. Hlaing *et al.* in their work¹¹ used quadratic support vector machine to identify and classify diseased tomato leaves in plant-village datasets with seven classes. Pre-processing fills regions, assigns channel values, removes noise, etc.

Basavaiah and Anthony¹² identified the four most common tomato leaf diseases viz., mosaic virus, septoria spot, yellow curl virus, and Bacterial spot by combining data from various sources. Local binary patterns, color histograms, haralick moments, and more have been found in leaf samples by researchers. The decision tree and random forest algorithms use extracted features to classify data. Random forest outperforms decision tree in detection accuracy by 94%. An effort was made by Rangarajan *et al.*,¹³ to use a pretrained deep learning architecture that included transfer learning concepts, in particular AlexNet and VGG16, to extract characteristics from photos of tomatoes and categorize them as either healthy or unhealthy. In terms of accuracy in classification, AlexNet and VGG16 score 97.49% and 97.23%, respectively.

Traditional image processing methods like the Scale Invariant Feature Transform (SIFT), the Grey Level Co-occurrence Matrix (GLCM), and the Speeded Up Robust Features (SURF) all contribute respectably to disease identification through leaf pictures.¹⁶ However, this approach uses fewer datasets and produces conclusions that are more robust theoretically. Recently, there has been an uptick in research and development¹⁷ for Artificial Intelligence (AI) techniques that use computer vision to recognize and classify things. Using SqueezeNet and AlexNet,

Durmuş *et al.*¹⁸ were able to identify the tomato disease using photos of infected leaves pulled from the plantvillage database. When compared to AlexNet's 95.65% accuracy, SqueezeNet's results are slightly lower (94.30%).

Using leaf image-based GoogLeNet and AlexNet models, Brahimi *et al.*¹⁹ conducted experimental research to identify tomato plant disease. The outcome demonstrates that Google Net outperforms Alex Net, which has an accuracy of 98.60%, with a performance of 99.18%.

In order to evaluate the deep CNN model's efficacy in diagnosing tomato diseases, Suryawati *et al.*²⁰ conducted experiments. It was found that the VGGNet model, which has more layers, had the highest accuracy (95.24 percent) of all the models tested. GoogleNet, and AlexNet and baseline CNN models are also studied and compare with GoogleNet. Deep CNN modeling was used to create the embedded-based VegeCare tool to identify six tomato leaf diseases.²¹ In,²² Sardogan *et al.* put forward the idea that a deep CNN model that was based on learning vector quantization (LVQ) could be used to classify four distinct diseases that can affect tomatoes, besides a healthy class. The approach yields 86% accuracy.

As a matter of fact, the proposed method is able to obtain an 86% accuracy in classification. To better predict the disease status of ten different tomato varieties from the plantvillage dataset, For mobile devices, Elhassouny *et al.*²³ developed a MobileNet-based deep CNN model. To detect tomato illnesses with plantvillage datasets, Ma *et al.*²⁴ presented transfer learning, with impressive results: 97.29% and 97.49% recognition accuracies for VGG16 and AlexNet, respectively.

Methodology

This paper introduces a CNN-based tomato leaf disease recognition method. The ideal CNN structure for detecting tomato leaf disease is challenging to design. The method used in this paper is to detect tomato leaf disease using an improved CNN algorithm. In the proposed method, data from "plant village" is analyzed. Within this procedure, we considered 14240 files across 9 different categories using images sourced from the public domain website plant village. The data are

divided into a training and validation set. After this data augmentation applied for producing a larger dataset by incorporating slightly modified versions of an existing dataset. We used the publically available dataset of 14240 image files to train a CNN model from scratch. Throughout the course of the training's iterations, the model's performance will shift, signaling the need for gradual, incremental adjustments to the model's weights. For training purposes here, we used 20 epochs. To measure

how well an algorithm performs, a comprehensible measure of accuracy is used. After the model's parameters have been entered, the accuracy of the model is typically evaluated and displayed as a percentage. The precision of the model's forecast is measured against the actual data. The trained model may be later saved to a disc for processing. All the work done in web based computing platform jupyter notebook.

Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
sequential_1 (Sequential)	(32, 256, 256, 3)	0
conv2d (Conv2D)	(32, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(32, 127, 127, 32)	0
conv2d_1 (Conv2D)	(32, 125, 125, 64)	18496
max_pooling2d_1 (MaxPooling2)	(32, 62, 62, 64)	0
conv2d_2 (Conv2D)	(32, 60, 60, 64)	36928
max_pooling2d_2 (MaxPooling2)	(32, 30, 30, 64)	0
conv2d_3 (Conv2D)	(32, 28, 28, 64)	36928
max_pooling2d_3 (MaxPooling2)	(32, 14, 14, 64)	0
conv2d_4 (Conv2D)	(32, 12, 12, 64)	36928
max_pooling2d_4 (MaxPooling2)	(32, 6, 6, 64)	0
conv2d_5 (Conv2D)	(32, 4, 4, 64)	36928
max_pooling2d_5 (MaxPooling2)	(32, 2, 2, 64)	0
flatten (Flatten)	(32, 256)	0
dense (Dense)	(32, 64)	16448
dense_1 (Dense)	(32, 9)	585
Total params: 184,137		
Trainable params: 184,137		
Non-trainable params: 0		

Fig. 1: CNN Architecture summary

In this work, we used Keras Sequential API to construct a CNN model. Using the Sequential class, one can create an instance of a sequential model.

Layers can be convolutional, pooling, or dense, among others. Sequential model Finally, we'll use the summary method to get a snapshot of the full

CNN architecture as mentioned in the figure 1, and take into account all of the parameters.

Convolution, Pooling, Flatten, and Classification are the typical layers in a CNN's architecture.

In a CNN, the initial layer is a convolutional one. A CNN may consist of several convolutional layers. When images are fed into the first convolutional layer, processing can begin. The purpose of the convolutional layer is feature extraction while preserving local pixel context. CNNs also make use of a second type of layer called a pooling layer. In a CNN, the pooling layers can be nested. One pooling layer follows each convolutional layer. Therefore, layers of convolution and pooling are used in tandem with one another. The most salient characteristics are extracted by the pooling layer by maximizing or averaging the relevant numerical features.

Cut down on the number of pixels used in the output from previous convolutional layers, or the dimensionality. Reduce the amount of parameters that are used by the network. Remove any noise from previous convolutional layers' extracted features.

CNNs use a Multilayer Perceptron to assign a class label to the pooled feature map produced by the final pooling layer. The last layers of a convolutional neural network (CNN) are fully connected (dense) layers. A previously flattened layer is the input. It's possible for there to be more than one layer that shares connections with every other layer. Classification is performed by the last layer. In each fully connected layer, an activation function is applied. This layer is responsible for assigning a category label to the image features that have been detected.

Results and Discussion

Finding, understanding, and comparing data to make complicated ideas more easily communicated through visualization aids in-depth study and discovery of logical patterns. Many types of analytical work benefit greatly from the use of data visualization, such as data summaries, analysis of test results, and analysis of model outputs. Figure 2 represents random 15 images plotted to verify database

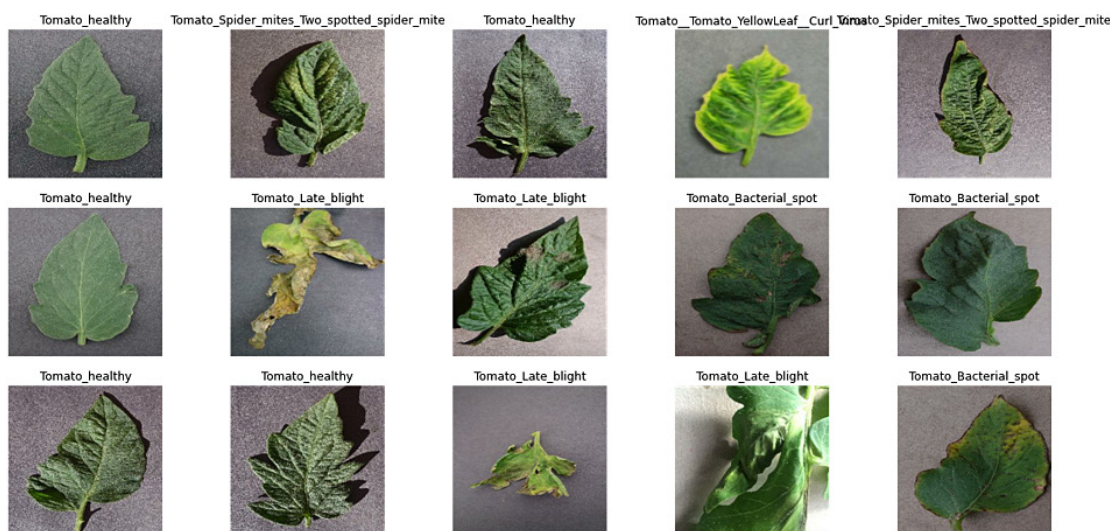


Fig. 2: Random visualization of 20 images from database

We have trained our model on tomato plant leaf diseases using custom Convolutional Neural Network to classify the diseases. We have trained

the Plant village data set of 9 classes. The code snippet in the figure 3 represent the 8 classes of tomato leaf disease and ninth class is healthy leaf.

```
In [5]: 1 dataset = tf.keras.preprocessing.image_dataset_from_directory(
2         directory=FILE_PATH,
3         shuffle=True,
4         image_size=(IMAGE_SIZE,IMAGE_SIZE),
5         batch_size = BATCH_SIZE,
6     )

Found 14240 files belonging to 9 classes.

2022-12-07 05:55:20.435459: I tensorflow/core/common_runtime/process_util.cc:146] Creating new thread pool with default inter o
p setting: 2. Tune using inter_op_parallelism_threads for best performance.

In [6]: 1 class_names = dataset.class_names
2         class_names

Out[6]: ['Tomato_Bacterial_spot',
'Tomato_Early_blight',
'Tomato_Late_blight',
'Tomato_Leaf_Mold',
'Tomato_Spider_mites_Two_spotted_spider_mite',
'Tomato__Target_Spot',
'Tomato_Tomato_Yellowleaf_Curl_Virus',
'Tomato_Tomato_mosaic_virus',
'Tomato_healthy']
```

Fig. 3: Code snippet representing class names

It is necessary to perform image preprocessing prior to using the data for model training. Size, rotation, and zoom are just some of the many alterations that may be made. We can perform more accurate

analysis if the image quality is improved through pre-processing. As a result, we split the data we use to train with into three categories: train (80%), and validate (20%).

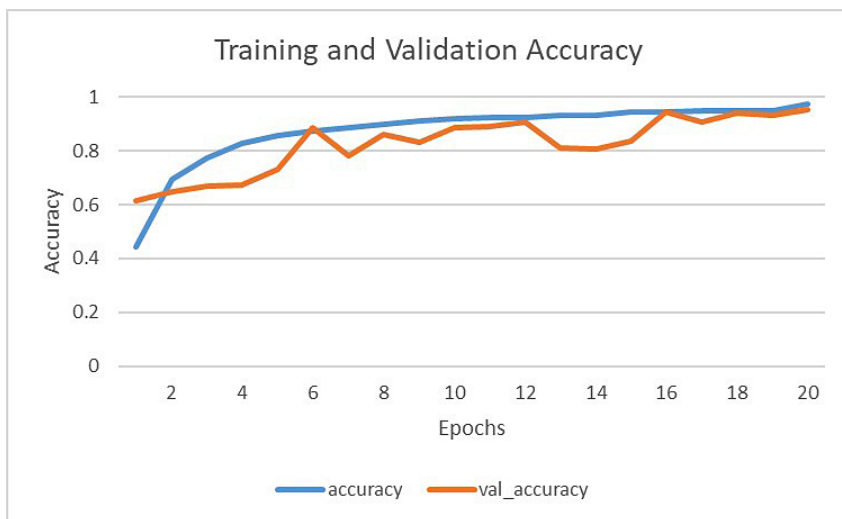


Fig. 4: Training and Validation accuracy plot

The model's performance is increasing with time, indicating that it is gaining knowledge through experience (learning). Figure 4 also shows that it expands initially, but eventually reaches a plateau, suggesting it can no longer learn. Figure 4 displays a plot of accuracy across 20 epochs, indicating that the accuracy reached 95.53% after the 20th epoch when applied to both the training dataset and the validation dataset.

Training loss shows how well the model fits training data, while validation loss shows how well it fits new data. Figure 5 depicts training and validation loss.

If you take a look at figure 6 and compare the real labels to the ones our model has assigned, you'll see that it makes accurate classifications. Every predicted image also has a confidence score.

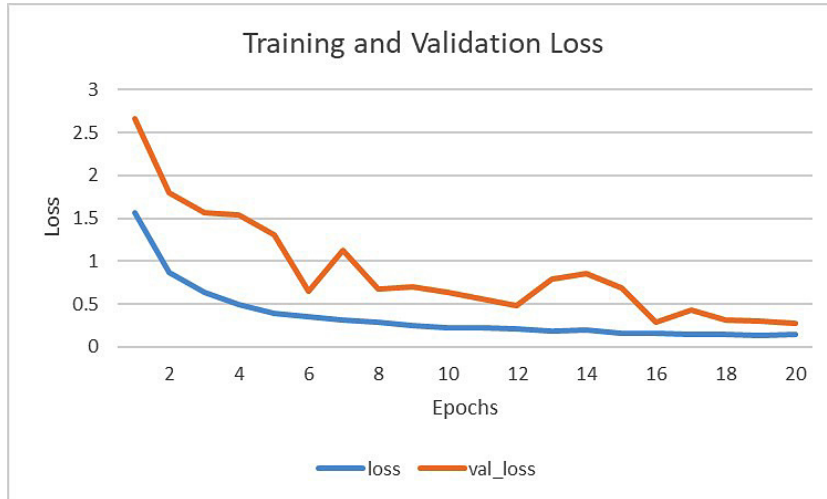


Fig. 5 : Training and Validation Loss plot

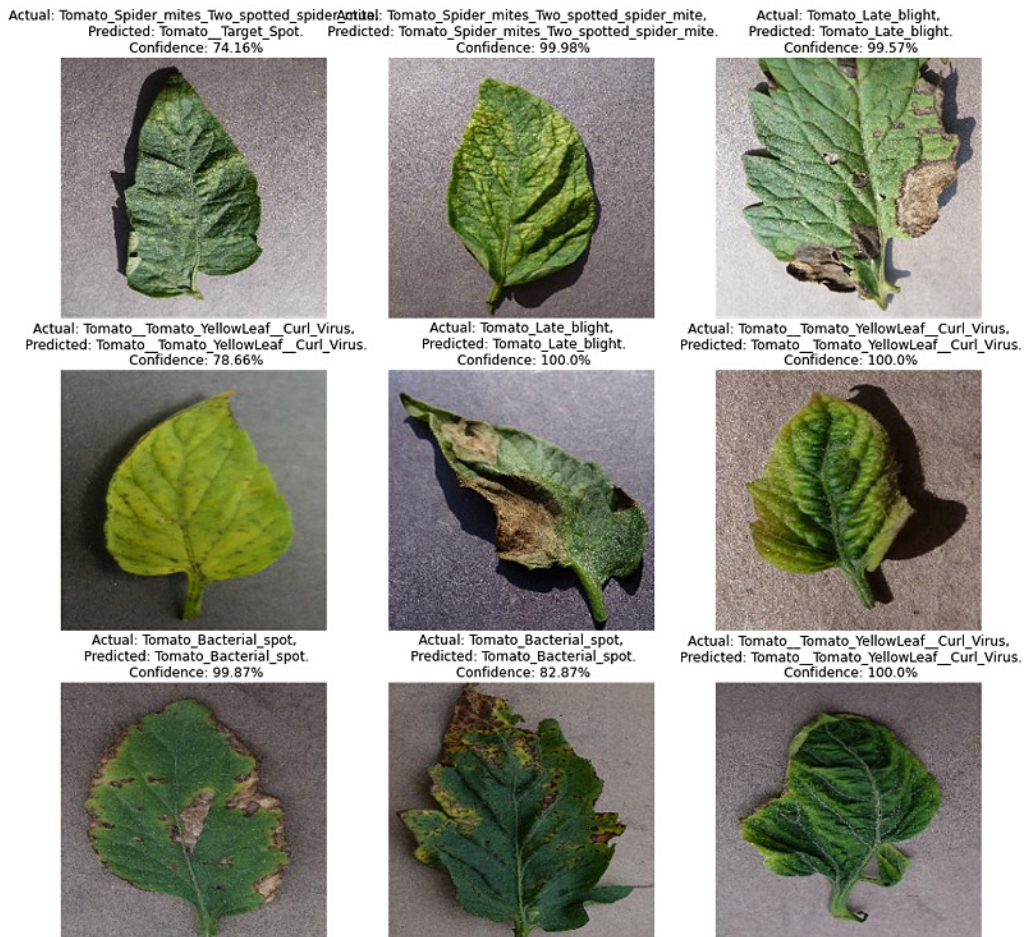


Fig. 6 : Prediction output

System flow for prediction is as shown in figure 2, we're using model. Load to load the model that to be saved in local disk. The trained model's result was obtained using prediction after the model had been loaded. In the prediction the different classes are defined as 0: 'Tomato_Bacterial_spot', 1:'Tomato_Early_blight', 2:'Tomato_Late_blight', 3:'Tomato_Leaf_Mold', 4:'Tomato_Spider_mites_Two_spotted_spider_mite', 5:'Tomato__Target_Spot', 6:'Tomato__Tomato_YellowLeaf_Curl_Virus', 7: 'Tomato__Tomato_mosaic_virus', 8:'Tomato_healthy'. The numeric values from 0 to 8 are represented in classification summary along with the precision, recall and f1 score of the respective class.

Conclusion

Classification of various plant leaf diseases has been analysed by various machine learning and other techniques. It is found that every technique has its own advantages and disadvantages depending on data availability and feature selection. Almost all the researchers presented outcomes for their experimentation for different databases with varied

quantity and disease types along with image type. Some researchers compare the same datasets for various algorithms and presented their results and found all of them useful for leaf disease classification. Experimental results show that the CNN model outperforms other classic models in terms of accuracy, reaching 95.53% showing improved robustness and good performance.

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Conflict of Interest

The author(s) has(have) no conflict of interest to declare.

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