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Plant Leaf Disease Detection Using CNN

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Abstract
Agriculture is the major area in several regions, including Pakistan and India, where roughly 55% to 60% of the inhabitant relies on it explicitly and implicitly. In agricultural countries, plant disease is a serious issue. Each year farmer faces loss due to the plant diseases and it is a difficult task to detect disease by a naked eye. The suggested approach intends to decrease agricultural losses. An automated plant identification and diagnosis is required for this. The proposed system helps to find and recognize disease at initial phase or at least diagnose the disease to avoid further degradation. AgriCure is a plant disease detector, an android application to detect disease in apple and tomatoes. This method overcomes the issues of cost, time, efficiency, restricted precision, and area for plant diagnosis because of traditional manual methods or naked eye inspections. The proposed system includes these modules i.e. disease detection, disease information, learn about diseases, add reminders and notes to remind tasks and show the weather forecast system. The system utilizes deep CNN method to diagnose and classify defect and show their descriptions. Such automated systems have been constructed in the past, but they generally have low accuracy or can’t manage a large range of plants. The system mainly focuses on the detection of diseases in apples into predefined categories like healthy apple leaf, apple scab, apple black rot, apple cedar rust, and in tomatoes predefined categories like healthy tomato leaf, bacterial spot, early blight, late blight, leaf mold, septoria leaf spot, tomato spider mites, tomato target spot, tomato yellow leaf curl virus, tomato mosaic virus. As a result, the suggested system is limited to some restrictions and difficulties. Team members of the project, on the other hand, would be working diligently to meet major milestones of the planned system. An automated and accurate plant disease detection system like AgriCure addresses a significant social problem by helping farmers reduce crop losses, ensuring food security, and promoting sustainable agriculture.

Keywords: Plant leaf disease, deep learning, convolutional neural networks (CNN), Feature extraction, Training, Classification.

Introduction

Farming is an essential part in every aspect of life including outfit, meal, medication, antibiotic cure and service. It is a basic origin of meal which is associated straightforward with the economic system. In the essential grouping of farming, the tomato is globally utilized vegetable [17], shows 16% of entire manufacturing of vegetation. If we talk about fruit [20], apple is one of the most famous and healthy fruits as it stands 3rd in the matter of production worldwide. Apple isn't always utilized as fresh, it's extensively utilized for making special merchandise like juices, jam, jellies, marmalade, cider. But what about infected tomatoes [39] and apples [40] as plant diseases [34] make contributions to production and manufacturing loss, which may be tackled with continuous monitoring. The disease of tomato or apple plants seems on plant stem, leaves or its fruit which makes it feasible to detect the disease from its outer surface instead of analyzing the plant DNA [29]. Physical monitoring of plant diseases [18] is exhausting and imperfect. Initial diagnosis of plant disorder via computer vision artificial intelligence (AI) or deep learning techniques [32] [28] that could assist to lessen the unfavorable outcomes of disorder and additional facilitates to triumph over the limitations of non-stop person tracking and observing. Due to the growth in demand for food and the rapid growth of the population, Agriculture performs a critical role. Not only feeding however additionally very critical for a better economy. As in Pakistan farmers are not much trained in disease detection So, for that reason they must ask for specialists, specialists must journey long distance, take time to discover however now no longer correct each time, then farmers have to pay them that is sometimes not affordable for the farmers. Moreover, Pakistan is an underdeveloped country [35] that is dealing with troubles and problems in food sufficiency and is ranked 92 out of 117 nations with-inside the Global Hunger Index 2021 with a score of 24.7 which is a serious level. The international tomato market is constantly developing to signify an important growth in its demand, manufacturing and production. Also, Pakistan produced 0.566 million lots because the 37th largest producer and biggest manufacturer within the globe as it is one of the most important vegetables in phrases of acreage, manufacturing and production, yield, industrial use, and consumption, that is used as food items on each day basis and forms a very completely critical component of food consumed in Pakistan. Apple is the biggest taxpayer with-inside the global [31], paying over $35 billion in company profits taxes within side the ultimate three years. Besides Pakistan, in apple production, it is at rank 25th. Disease in plants resulting from bacteria, viruses, and fungus has a great effect on low crop manufacturing and production as Pakistan is an agricultural country.

That's why, we need to control and manipulate disease in them to grow productiveness to enhance the economic rate [23]. There is a want for an automatic, fast, efficient and accurate system that is required to manipulate and control plant disease spread for a better crop manufacturing. So, AgriCure, a plant disease detector is proposed to hit upon and detect disease in plants [5]. The proposed system is dealing with tomato and apple leaf diseases. It will save the resources, time, and cost. It also helps to improve economy and food security.

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DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 3 No. 2 (February) (2025)

Farmers, general public, botanist, specialists, and consultants can use the proposed system for their benefits.

Literature Review

In 2015, S. Khirade et Al. tackled trouble of plant leaf disease detection through the usage of image processing [26] [21] [22] strategies and back propagation in neural network (BPNN). [11] Observer already explained unique strategies for plant diseases diagnosis through the usage of photographs of leaves. They had applied Otsu's thresholding observed by boundary detection and see a detection set of rules to section the inflamed element with-inside the leaf. Consequently, they had extracted the functions which include color, texture, morphology, edges, etc. for the category of plant disorder. BPNN applied for category i.e. to stumble on the plant disorder.
Garima Shrestha et Al. developed the CNN to hit upon leaf diagnosis. [30] Observer had efficaciously labeled twelve plant disorder. The dataset of three thousand high-decision coloured pics become utilized for research. The F1 rating is very low due to a high number of false-negative predictions.
The paper provides an overview of numerous kinds of diseases in plants leaf and various classification methods used in ML for detecting and classifying the different plant leaf diseases [9] such as bacteria, viruses and fungi. For classification, they consider some morphology features and some attributes or properties like color, intensity, and dimensions of leaves [3].
Disease of the stem plant detection is done in mentioned paper. A mobile app has developed for taking photographs of diseases effected jute plant stem. Send the picture to the server, and effected portion will be segmented using a threshold formula via hue-based segmentation. Features value will be match along-with the stored sample values and predict their disease using SVM classifier [27].
The paper mainly focuses on the papaya leaves. Random forest classifier is used to diagnose the healthy plant leaf with the unhealthy one with nearly seventy percentage accuracy. Numerous phases included int this paper like dataset creation, feature extraction, classifier training etc. [24].
Recently, numerous scientists investigate plant disease detection and identification based totally on deep learning techniques and methods.
The general leaf of apple sicknesses like rust, gray spot, and brown spot have been mentioned or located out along-with the assistance of deep learning algorithms and CNN. The data-set for unhealthy leaf become created, prepared, and gathered. A newly deep CNN version is planned for picking out small spots diseases.
In [16], Lu et al. suggested a unique identity technique for a rice disease depends totally on CNN. Utilizing 500 pix data-set of unhealthy and fine rice plants leaf and their stems. To diagnose ten rice general diseases, CNN technique was used. It achieves good accuracy.
In [33], Tan et al. established a CNN method for identifying the apple pathological pictures and automatically update or edit CNN parameters. Based on different analytics benchmark, prove that it is fairly effective approach than others.
In [12], a unique cucumber leaf disease detection device that is totally dependent on convolutional neural networks. The proposed CNN-primarily based totally device achieve an good accuracy rate in classifying cucumber leaves into healthy

and unhealthy class. The practical outcomes suggest that a CNN attain a performance of good classification.

The article [36] presented a deep learning-based approach leveraging CNNs for the efficient detection of plant leaf diseases. [37] proposed an AIoT-based intelligent system integrating predictive analytics for forecasting agricultural diseases. [38] developed a transfer learning-based model within an AIoT framework to enhance the accuracy of disease prediction in plants. These advancements collectively contribute to the precision and efficiency of plant disease identification, supporting early intervention strategies in modern agriculture.

In [32], Sladojevic et al. proposed a unique technique totally dependent on CNN to identify the plant diseases. For distinction the leaves of plant gathered in the environment, thirteen general varieties of plant diseases have been diagnosed via way of means of the proposed CNN model. All essential steps are also described in paper to implement the disease identification model.

This research displays that CNN had extensively implemented to the sector of crop and leaf disease identification, or acquired best results. But, on the side, that research simplest observe the CNN-primarily based model to discover crop and leaf diseases without enhancing the version. Additionally, on the alternative hand, so far, the convolutional neural network model has now no longer implemented for the identification of apple and tomato plants diagnosis; a unique convolutional neural network model made by our team members is implemented to come across apple [15] and tomato [4] leaf diseases having 13 categories in this paper.

Methodology

The methodology used to complete overall project is agile methodology [10]. To find out plant diseases there are a few steps which are required for this project i.e., pre-processing [25], feature extraction [13], training of classifier and testing. pre-processing of image brings all image size in to 100 X 100 or 256 X 256. In feature extraction step we will be extracting the features by applying different filters of colors on images which help of easily detecting object their outline and features.

Deep Learning Methodology

Artificial neural network is the model that generally work on the principles of brain functioning via neurons. The main feature is to ability to trained the model by using supervised learning algorithms. Deep learning [2] is a powerful machine learning [24] approach. CNN is the artificial neural network that mainly focuses on the image identification and recognition. Several architectures [6] of CNN have been developed.

The basic five CNN architecture and structure has been used to identify and detection of disease in image recognition i.e. plant disease detection from images of leaves. One is ALexNet, second is AlexNetOWTBn, third is GoogleNet, forth is Overfeat, and fifth is VGG [7] [14]. Torch machine learning [1] framework is used to implement the model and the training and testing process. Algorithms were implemented by using the GPU [8].

Dataset Description

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DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 3 No. 2 (February) (2025)

An open database having 38 different classes image with healthy and unhealthy leaves images that is used to implement the model of CNN. The dataset is collected from the PlantVillage dataset [19]. The figure 1 shows that some pictures taken from the dataset. Scope of proposed system is apple and tomato leaves having 14 categories. These 14 categories contain the healthy and unhealthy plants. Here is the link of dataset: https://www.kaggle.com/datasets/zarghammughal1/plant02.
The total images contain the 25292 images. The dataset is split into 2 datasets, the testing and the training set. Almost 4381 images are for the testing purpose and 20911 images are for training the model. The total images for training the model are shown in the below table:

Table 1: Information about Images

Plant name	Disease name	No. of Images
Apple	Apple Scab	600
Apple	Apple Black Rot	591
Apple	Apple Cedar Rust	245
Apple	Apply Healthy	1615
Tomato	Tomato Bacterial Spot	2097
Tomato	Tomato Early Blight	970
Tomato	Tomato Late Blight	1879
Tomato	Tomato Leaf Mold	922
Tomato	Tomato Septoria Leaf Spot	1741
Tomato	Tomato Spider Mites	1646
Tomato	Tomato Target Spot	1374
Tomato	Tomato Yellow Leaf Curl Virus	5327
Tomato	Tomato Mosaic Virus	343
Tomato	Tomato Healthy	1561

Figure 1: (a) Apple Black Rot (b) Tomato Leaf Mold (c) Tomato Bacterial Spot (d) Tomato Yellow Leaf Curl Virus

Measurement of Performance
It must be known that numerous photographs of the same leaf taken from multiple angles in PlantVillage data-set. Further for experiments we compute

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Vol. 3 No. 2 (February) (2025)

every evaluation metrices like precision, recall, F1 score, and support. In all approaches or described in this paper, we resize the image by 256 X 256 and 100 X 100 and apply the CNN is applied for classifying the diseases.

Approach

There are different approaches to classify and detection of diseases in leaves of plants. To get an idea of how our approaches will work on the new unseen data and also to determine the if any of our approach is over-fit or may be under-fit. We apply the CNN for the problem of classification and detection of disease because via CNN (convolutional neural network), maximum accuracy can be achieved and suitable to extract the features like texture, color, and edges. We work on different algorithms/architectures of CNN like Simple CNN, CNN with data augmentation, VGG-16 and VGG-19 with different epochs. We also build a model with an invalid cate- gory by using limited resources. We use a keras application that is deep learning model.

Table 2: Comparison of Models

No.	Model name	Activation Func.	Epoch	Accuracy
1	CNN	Softmax	50	70.71
2	CNN	Softmax	100	84.29
3	CNN with data augentation	Softmax	50	71.43
4	Modified CNN data aug	Softmax	50	72.14
5	VGG19	Softmax	11	75.71
6	VGG16	Softmax	10	78.32
7	VGG16	Softmax	13	79.89
8	VGG16 with invalid label	Softmax	11	74.45

The simple CNN model is developed in model 1. The target size and batch size is (100,100) and 20 respectively. Four convolutional layers and four max polling layers are used. 1st layer of convolutional layer has 128 filters, 2nd layer has 64 filter, 3rd layer has 32 filter and 4th has 16 filters. After every convolutional layer, 1 max polling layer is added. After this, 1 flatten layer and 2 deep neural network layers added. 1st has 512 units and 2nd which is output layer has 14 units which is fully connected to input layer. The input activation function is relu and output activation function is softmax. The loss is categorical crossentropy and adam optimizer is used. After training the model on 50 epochs we achieve an accuracy of 70.71%. The link of source code is https://www.kaggle.com/code/zarghammughal1/plant-disease- model01. The graphs of this model are shown below:

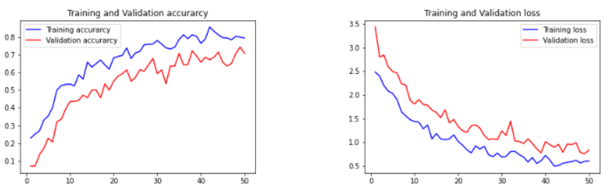

Figure 2: (a) Training vs Validation Accuracy (b) Training vs Validation Loss

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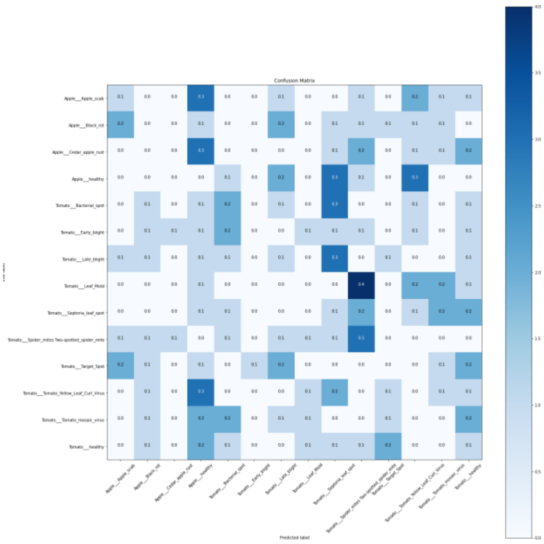

Figure 3: Confusion Matrix

The simple CNN model is developed in model 2. The target size and batch size is (100,100) and 20 respectively. Four convolutional layers and four max polling layers are used. 1st layer of convolutional layer has 128 filters, 2nd layer has 64 filter, 3rd layer has 32 filter and 4th has 16 filters. After every convolutional layer, 1 max polling layer is added. After this, 1 flatten layer and 2 deep neural network layers added. 1st has 512 units and 2nd which is output layer has 14 units which is fully connected to input layer. The input activation function is relu and output activation function is softmax. The loss is categorical crossentropy and adam optimizer is used. After training the model on 100 epochs we achieve an accuracy of 84.29%. The link of source code is https://www.kaggle.com/code/zarghammughal1/85-accuray. The graphs of this model are shown below:

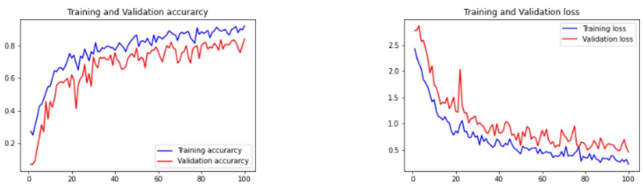

Figure 4: (a) Training vs Validation Accuracy (b) Training Vs Validation Loss

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DIALOGUE SOCIAL SCIENCE REVIEW

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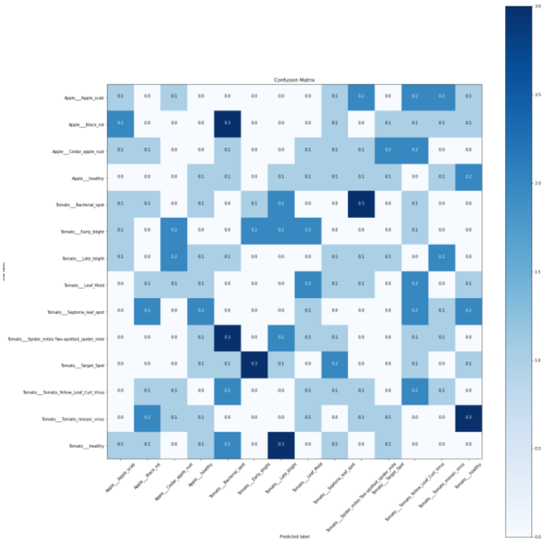

Figure 5: Confusion Matrix

The simple CNN model is developed but data augmentation also used in model 3. The target size and batch size is (100,100) and 20 respectively. We also use data augmentation like rescale, ro- tation, zoom range, shear range, shift range, and horizontal flip. Four convolutional layers and four max polling layers are used. 1st layer of convolutional layer has 128 filters, 2nd layer has 64 filter, 3rd layer has 32 filter and 4th has 16 filters. After every con- volutional layer, 1 max polling layer is added. After this, 1 flatten layer and 2 deep neural network layers added. 1st has 512 units and 2nd which is output layer has 14 units which is fully con- nected to input layer. The input activation function is relu and out- put activation function is softmax. The loss is categorical crossen- tropy and adam optimizer is used. After training the model on 50 epochs we achieve an accuracy of 71.43%. The link of source code is https://www.kaggle.com/code/zarghammughal1/plant-disease- model02. The graphs of this model are shown below:

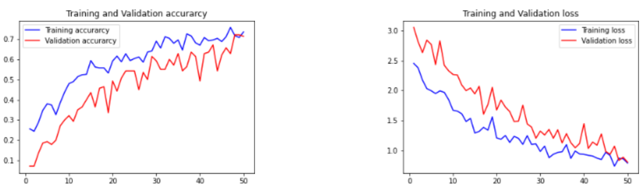

Figure 6: (a) Training vs Validation Accuracy (b) Training vs Validation Loss

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DIALOGUE SOCIAL SCIENCE REVIEW

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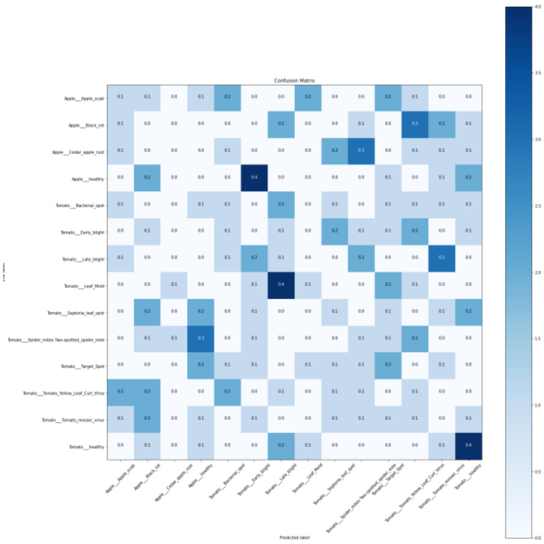

Figure 7: Confusion Matrix

The simple CNN model is developed but data augmentation also used in model 4. The target size and batch size is (100,100) and 20 respectively. We also use data augmentation like rescale, rotation, zoom range, shear range, shift range, and horizontal flip. Four convolutional layers and four max polling layers are used. 1st layer of convolutional layer has 128 filters, 2nd layer has 64 filter, 3rd layer has 32 filter and 4th has 16 filters. After every convolutional layer, 1 max polling layer is added. After this, 1 flatten layer and 2 deep neural network layers added. 1st has 512 units and 2nd which is output layer has 14 units which is fully connected to input layer. The input activation function is relu and output activation function is softmax. The loss is categorical crossentropy and adam optimizer is used. After training the model on 50 epochs we achieve an accuracy of 72.14%. The link of source code is https://www.kaggle.com/code/zarghammughal1/plant-disease-model02-improver-butsameacc. The graphs of this model are shown below:

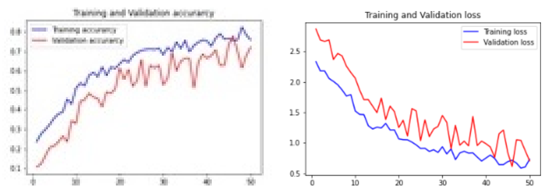

Figure 8: (a) Training vs Validation Accuracy (b) Training vs Validation Loss

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DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 3 No. 2 (February) (2025)

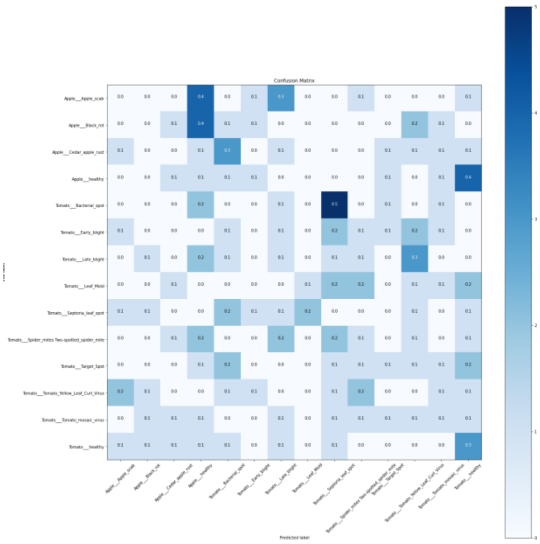

Figure 9: Confusion Matrix

The CNN architecture VGG 19 is developed, also data augmentation also used in model 5. The target size and batch size is (256,256) and 32 respectively. We also use data augmentation like rescale, rotation, zoom range, shear range, and horizontal flip. The activation function is softmax. The loss is categorical crossentropy and adam optimizer is used. We set the condition, model will stop when accuracy not improve after 2 epoch. After setting the 50 epochs, model stops on 11th epoch and achieve an accuracy of 75.71%. The link of source code is https://www.kaggle.com/code/zarghammughal1/plant-disease-modelvgg19. The graphs of this model are shown below:

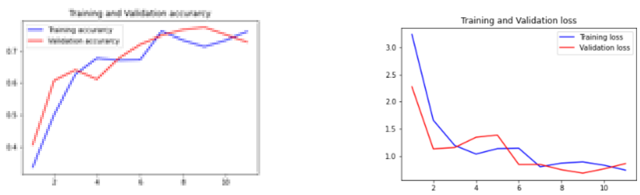

Figure 10: (a) Training vs Validation Accuracy (b) Training vs Validation Loss

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DIALOGUE SOCIAL SCIENCE REVIEW

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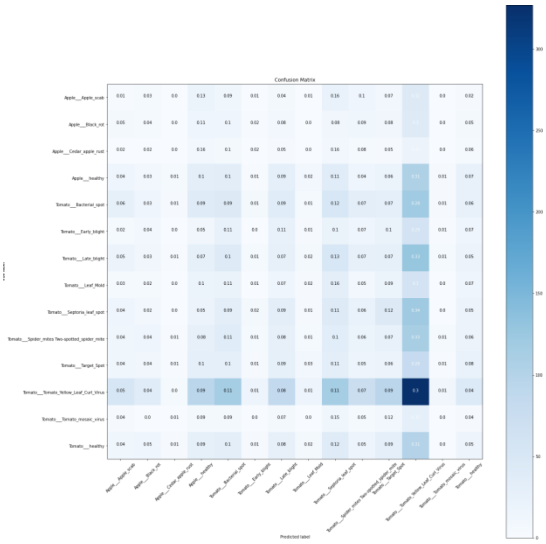

Figure 11: Confusion Matrix

The CNN architecture VGG 16 is developed, also data augmentation also used in model 6. The target size and batch size is (256,256) and 32 respectively. We also use data augmentation like rescale, rotation, zoom range, shear range, and horizontal flip. The activation function is softmax. The loss is categorical crossentropy and adam optimizer is used. We set the condition, model will stop when accuracy not improve after 2 epoch. After setting the 50 epochs, model stops on 11th epoch and achieve an accuracy of 78.32%. The link of source code is https://www.kaggle.com/code/zarghammughal1/vgg16. The graphs of this model are shown below:

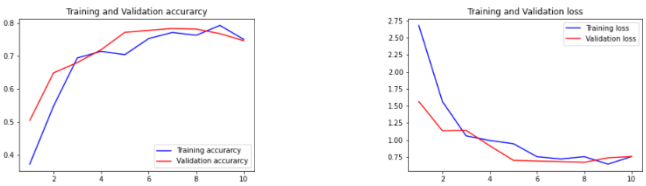

Figure 12: (a) Training vs Validation Accuracy (b) Training vs Validation Loss

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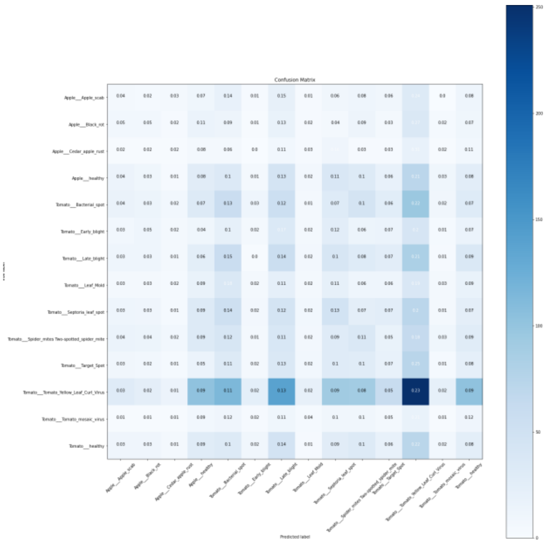

Figure 13: Confusion Matrix

The CNN architecture VGG 16 is developed, also data augmentation also used in model 7. The target size and batch size is (256,256) and 32 respectively. We also use data augmentation like rescale, rotation, zoom range, shear range, and horizontal flip. The activation function is softmax. The loss is categorical crossentropy and adam optimizer is used. We set the condition, model will stop when accuracy not improve after 2 epoch. After setting the 50 epochs, model stops on 10th epoch and achieve an accuracy of 79.89%. The link of source code is https://www.kaggle.com/code/zarghammughal1/for-tensor-flow-lite-file.
The CNN architecture VGG 16 is developed, also data augmentation is used in model 7. The target size and batch size is (256,256) and 32 respectively. We also use data augmentation like rescale, rotation, zoom range, shear range, and horizontal flip. The activation function is softmax. The loss is categorical crossentropy and adam optimizer is used. We set the condition, model will stop when accuracy not improve after 2 epoch. After setting the 50 epochs, model stops on 11th epoch and achieve an accuracy of 74.45%. The link of source code is https://www.kaggle.com/code/zarghammughal1/for-tensor-flow-lite-file. The graphs of this model is shown below:

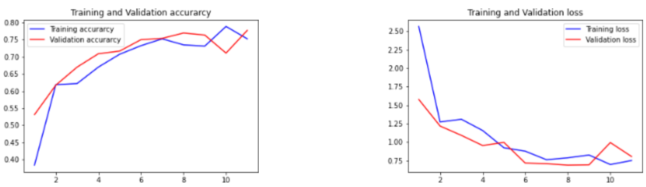

Figure 14: (a) Training vs Validation Accuracy (b) Training vs Validation Loss

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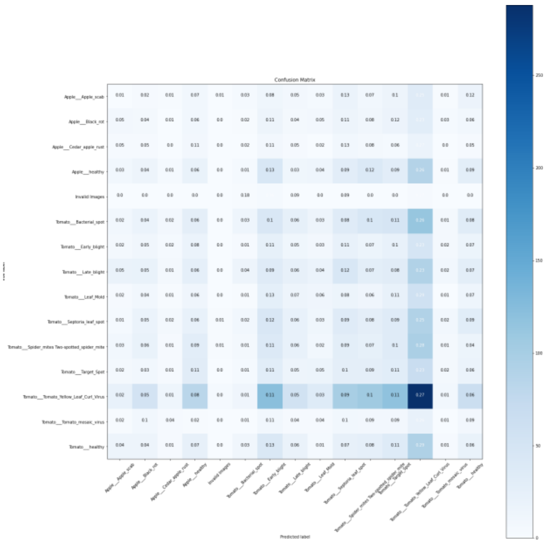

Figure 15: Confusion Matrix

1. Algorithm Description

We focus on the VGG 16. VGG 16 has 16 layers. It is the type of CNN architecture. 16 shows that vgg16 has 16 layers. Vgg16 gives us best accuracy result in all algorithms which we used in our model. If we talking about their architecture, you can see that vgg16 has total 16 layers where 13 layers are convolutional layers and remaining 3 layers are dense layers. 1st and 2nd convolution layer have 64 filters and then this will connect to max polling layer. Next 2 convolutional layers have 128 filters then max polling layer will be added. After these 3 convolutional layers will be added with 256 filters. After max polling, 3 convolutional layers added each layer has 512 filters with one max polling layer. Then again 3 convolutional layers added with 512 filters with one max polling layer. This will connect to flatten layer. After this flattening, layers will connect to neural network layer.

2. CONCLUSION AND RESULTS

As the above-mentioned figures and tables, we achieve an accuracy of approximately 85% that is actually 84.29%. But it has been noted that the confusion matrix of this model is not good. So, the VGG 16 and VGG 19 model also achieve an accuracy of approximately 80% that is actually 75.71% and 78/32% and 79.89%. We use VGG 16 model because it achieves a good accuracy and confusion matrix is also good as compared to other models. This model also predict more precisely than the other models and has a good accuracy rate. We applied the CNN for the problem of classifying and detection of disease because via CNN (convolutional neural network), maximum accuracy can be achieved and suitable to extract the features like texture, color, and edges.

3. FUTURE WORK

As we establish our system of plant disease detection, now we plan to use modern technologies to overcome the modern problems and also we can match our client's needs. There will always be room for more updates. We can expand our mobile application. Moreover, as we have created the whole system we can also add:

- **Extend the Scope:** Extend the scope will help people to detect disease in multi-plants.
- **Increase accuracy and prediction rate:** In the future, the system can be expanded and have more precise predictions without any doubts.
- **Developing web application:** As our mobile application is complete, our next step in the future is to develop a web application.
- **Plant Leaf Identification:** As we worked on plant identification with the limited resources but we will extend our scope and include more categories to check whether the provided image to the model is a leaf of plant or not.

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Vol. 3 No. 2 (February) (2025)

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