Deep Learning Models for Tomato Leaf Disease Detection

Gaurav Singh
Computer Science and Engineering
Rajkiya Engineering College Kannauj
Uttar Pradesh, India
gauravsinghgs8888@gmail.com

***Abstract*—Tomato is the most common vegetable widely cultivated in the agricultural fields in India. It is observed that production of agricultural products is going down nowadays due to the attack of diseases. Many farmers detect diseases by their previous experience or by taking help from experts. By this there is possibility of an inaccurate diagnosis of diseases having very large similarity in their symptoms. So, it is essential to move towards to new techniques for automatic diagnosis and controlling of disease. This is easily possible by machine vision system which is accurate and less expensive for tomato leaf disease detection. I have used Transfer learning technique to build my model, more efficient and effective. Also, I have compared different deep learning models with my proposed model in which my model ViT B16 gives highest accuracy of 96.20%.**

***Index Terms*—artificial intelligence; deep leaning; transformer; tomato diseases; transfer learning**

I. INTRODUCTION

Tomato is rich with nutrient and it is globally grown vegetable [1]. The production of tomatoes in India is reducing gradually over years because of major tomato leaf diseases. Due to this many tomato cultivators get a huge drop in their production and income. It is important to correctly identify plant diseases and classify them [2]. The problem of farmers will be solved if they know about the plants which are infected in early stages of their growth, so that they can use pesticides and save their crops from diseases. Artificial Intelligence becomes very popular in recent years such that it can automatically identify plant diseases from raw images [3], [4]. This research will help the farmers to recognize the tomato leaves which are fresh and diseased. In this project I have used the concepts of machine learning and deep learning.

Farmers detect diseases by their previous experience or by taking help from experts. By this there is a possibility of an inaccurate diagnosis of diseases having very large similarity in their symptoms. So, it is essential to move towards the new techniques for automatic diagnosis and controlling of disease. This is only possible by machine vision system which is accurate and less expensive for detection of disease from tomato leaf images. Plant leaf diseases may be accurately identified and categorized using image processing software and a classification scheme [5].

Due to various variety of diseases that affect tomatoes, the disease identification process of tomato is difficult. Deep learning is a strong technology which support for the computer-assisted detection of tomato diseases. Deep learning has deep neural networks, which learn complicated patterns. Convolutional neural network models can be used for disease detection and diagnosis in plants [6].

With Transfer Learning technique my ViTB16 model was build and I have compared my model with other pretrained models.

Around 160,000,000 metric tons of tomatoes are consumed annually across the globe [7]. People believe that tomato sales could help rural communities to earn income. The motivation for this project is to detect tomato diseases early. By detecting and managing diseases in a timely manner helps in healthy plant growth, maximizing crop productivity, and minimizing economic losses for farmers. Accurate diagnosis of tomato diseases is subjective and prone to errors. By using machine learning and computer vision techniques, my research aims to provide accurate and objective disease diagnosis. Traditional methods of disease identification involve visual inspection by experts, which is time-consuming. An automated system enable efficient and continuous monitoring of tomato crops, enabling the early identification of diseases.

The need of an automated technique to diagonise diseases that impact tomato plants is the key of this research. The following are some important contributions in this research that fill some of the gaps:

- Creating a new model with the help of Transfer Learning Technique.
- Increasing the accuracy of the model in comparison to other models.

II. LITERATURE REVIEW

In these years mostly CNN is used for diagonising plant diseases [8], [9]. Vani et al. [10], compare four models (LeNet, VGG16, ResNet, and Xception) and conclude that VGG16 model achieves the greatest performance (99.25% accuracy) when used to categorize nine distinct disorders. Researchers from different institutions have developed automated diseases detection systems using highly advanced technologies, such as machine learning and neural network designs like Inception V3, VGG 16, Xception and DenseNet121. They use highly accurate methods to diagnose tomato leaf diseases [11], [12]. Sabbir et al. [13], proposes a lightweight transfer learning based approach for detecting diseases from tomato leaves.

They combine a fine-tuned pretrained model and a classifier network. In this traditional augmentation approaches are replaced by runtime augmentation to avoid data leakage and address the class imbalance issue. Anil Bhujel et al. [14], designed a lightweight convolutional neural network by incorporating different attention modules to improve the performance of the models. The models were trained, validated, and tested using tomato leaf disease datasets split into an 8:1:1 ratio. Their proposed model outperformed the prevailing generic models used for plant disease detection in terms of accuracy and efficiency.

Naresh et al. [15], uses Convolutional Neural Network (CNN) to effectively define and classify tomato diseases. Google Colab is used to conduct the complete experiment with a dataset containing 3000 images of tomato leaves affected by nine different diseases and a healthy leaf. The proposed model predictions are 98.49% accurate. Changjian et al. [16], proposed a restructured residual dense network for tomato leaf disease identification. They use hybrid deep learning model which combines the advantages of deep residual networks and dense networks. Experiments show that there RRDN model can achieve satisfactory performance on the tomato dataset as high as 95%.

Mohit et al. [17], discuss Deep Learning based approach. They use Convolutional Neural Network for disease detection and classification. In their model, there are 3 convolution and 3 max pooling layers followed by 2 fully connected layer. The experimental results shows the efficacy of the proposed model over pre-trained model i.e. VGG16, InceptionV3 and MobileNet. The classification accuracy varies from 76% to 100% with respect to classes and average accuracy of the proposed model is 91.2% for the 9 disease and 1 healthy class. Iftikhar et al. [18], focuses on classification and identification of tomato leaf diseases using convolutional neural network (CNN) techniques. They consider four CNN architectures , VGG-16, VGG-19, ResNet, and Inception V3, and use feature extraction and parameter tuning to identify and classify tomato leaf diseases. They test these models on two datasets a laboratory-based dataset and self-collected data from the field. Their results is all architectures perform better on the laboratory-based dataset than on field-based data. They identified Inception V3 as the best performing algorithm on both datasets.

Belal et al. [19], trained a deep convolutional network to identify five (Bacterial Spot, Early Blight, Septorial Leaf Spot, Leaf Mold, Yellow leaf Curl Virus) tomato diseases. They use a public dataset of 9000 images of infected and healthy Tomato leaves collected under controlled conditions. Their trained model achieved an accuracy of 99.84% on a held-out test set. Prajwala et al. [20], adopts a slight variation of the convolutional neural network model called LeNet to detect and identify diseases in tomato leaves. There proposed system has achieved an average accuracy of 94-95%.

III. Methodology

In detection of tomato diseases via deep learning, at first tomato leaf picture dataset is collected from kaggle. The dataset contain various diseased and healthy leaves. Then after preprocessing, the dataset is used to teach a deep neural network, such as a CNN. After training, our model can categorize newly pictures as belonging to either the healthy class or one of the disease classes. Adjustments to the models parameters enhance the model performance and its accuracy. Model performance is tested by a test set of pictures.

A. Dataset

I have used dataset, consisting of 11,000 images of tomato leaves affected by 10 distinct diseases. Each class, contains 1100 images. Table I. displays the tomato leaf features. A sample each type of tomato leaf diseases is presented in Figure 1.

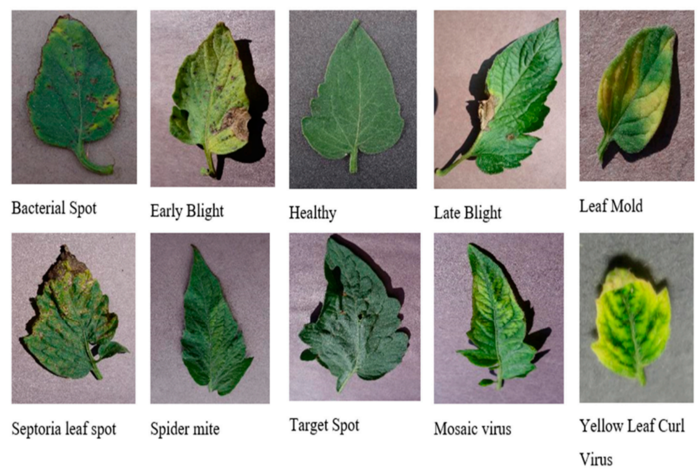

Fig. 1. Dataset Sample

B. Data Preprocessing

The data preprocessing step is important because it improves quality and performance of the classification methods used for image categorization process. In data preprocessing images noise and outliers are removed because negatively impact the models accuracy and also operations, such as image resizing and normalization are performed. Data preprocessing techniques results in a more consistent and high-quality dataset, which improve the model's accuracy.

C. Transfer Learning Algorithms

In transfer learning technique a model is trained on one task and then applied on a different but related task. It can save time and resources by using the knowledge and features learned from a pretrained model. Transfer learning improve model performance and allow to perform better on a new dataset. Transfer Learning reduce the need of labelled data and enhance the model performance.

TABLE I
TOMATO LEAF FEATURES

Class	Number of Samples	Description
Mosaic virus	1100	This disease symptoms are mosaic-like patterns, stunted growth, and deformed fruit.
Target spot	1100	This disease symptoms are concentric rings on leaves and stems. It can be managed by crop rotation and sanitation.
Bacterial Spot	1100	This disease symptoms are brown, sunken lesions on leaves and fruits. It can be controlled by using copper-based fungicides.
Yellow leaf curl virus	1100	This disease symptoms are yellowing and curling of leaf as well as distorted fruit. It can be managed by using insecticides.
Late blight	1100	Its symptoms are water-soaked lesions on leaves and stems. It can be managed by fungicide and removing infected plant parts.
Leaf mold	1100	Its symptoms are yellowing and brown lesions on the plant's lower leaves. It can be managed by fungicides and sanitation.
Early blight	1100	Its symptoms are concentric rings of dark brown spots on the plant's lower leaves. It can be managed by fungicides and cultural practices.
Spider mites	1100	It causes leaf yellowing and stunted growth. It can be managed by using predatory mites and insecticidal soaps.
Tomato healthy	1100	This class contains healthy tomato leaves for comparison with diseased leaves.
Septoria leaf spot	1100	Its symptoms are small, circular lesions with dark brown centers and yellow halos on the lower leaves of the plant. It can be managed by fungicides and crop rotation.

D. VIT Model

Vision transformer is a new architecture for image classification. VITs use transformer-based architecture. In VIT the input image is divided into a sequence of fixed-size patches. Each patch is then flattened into a 1D vector and passed through an embedding layer. ace. These patch embeddings are then fed into a transformer encoder. Fig2 shows VIT architecture.

E. Experiments

The models were trained, validated, and tested using a dataset that includes photographs of both healthy and sick tomatoes. The configuration for training the model was done on Google Colab. The TensorFlow and transformer architecture library was used for training the models. Both the training and testing sets were created from dataset. The dataset contain total 11000 images. Total 10 classes each having 1100 images. Training folder contains 8000 images and Validation folder contains 2000 images. Testing is performed on remaining 1000 images. The main goal of this division is to supply the deep learning models with a different set of images from which they learn and evaluates the models capacity to generalize their findings to new images.

F. Performance Measurement

To measure the performance of model, its accuracy is measured against a gold standard. It is a measure of the model predictive efficacy that may be calculated by dividing the number of accurate forecasts by the total number of predictions.

$$\text{Accuracy} = \frac{TP + TN}{FP + FN + TP + TN} * 100$$

The Precision or reliability of the model positive predictions is calculated by dividing the number of correct forecasts by the total number of correct predictions.

$$\text{Precision} = \frac{TP}{TP + FP} * 100$$

Recall provides a numerical representation of the fraction of the dataset positive instances that correspond to accurate positive predictions generated by the model. Recall calculates the number of true positive predictions as a fraction of the total number of positive cases included in the dataset.

$$\text{Recall} = \frac{TP}{TP + FN} * 100$$

F1 score is a way to balance the trade-off between precision and recall by taking the harmonic mean of the two metrics.

$$\text{F1 score} = 2 * \frac{Precision * Sensitivity}{Precision + Sensitiviy} * 100$$

where:
FP: False positive

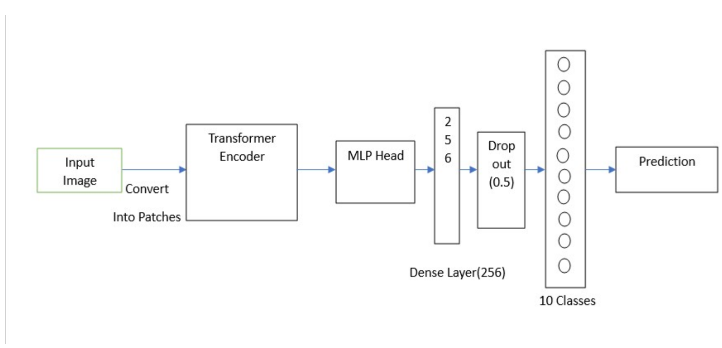

Fig. 2. ViTB16 Model Architecture

TP: True positive
FN: False negative
TN: True negative

A confusion matrix provides a detailed breakdown of the model's predictions compared to the actual labels. It shows the true positive, true negative, false positive, and false negative counts. The matrix helps analyze the model's performance for each quality class and can be used to calculate various metrics such as precision, recall,and accuracy.

IV. Result and Discussion

To detect tomato diseases via deep learning model, first I investigated different Deep CNN architectures and their performance. After that, I use Transfer Learning technique to build my model ViTB16. My model is based on ViT models which is a Transformer. Then, I compare the performance of my model with the existing DenseNet121, Xception, Inception V3 and VGG16 models.
Training graph of models like VGG 16, InceptionV3, Xception, DenseNet121 is shown in fig3-6. Comparison tableIV shows that VIT b16 model gives the highest accuracy of 96.20%. To achieve this accuracy I have added extra dense(256) layer and dropout(0.5) in my model. In figure7 confusion matrix provides detailed breakdown of the model prediction compared to the actual levels. The matrix helps to analyze the model performance for each quality class and can be used to calculate various metrics. Summarized result of ViTB16 model is shown in tableII This table shows the performance of disease classification on several metrics such as Precision, Recall, F-1 score. TableIII shows ViTB16 model parameters used to train the model. Our model model accuracy

Fig. 3. VGG accuracy

Fig. 5. Xception accuracy

Fig. 4. InceptionV3 accuracy

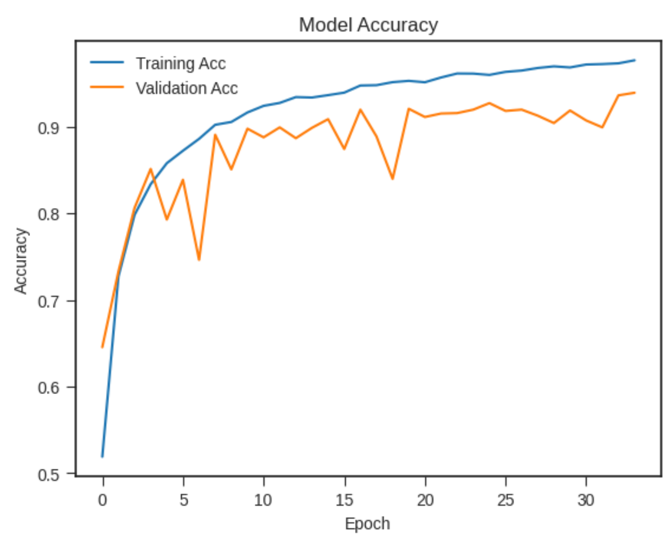

Fig. 6. DenseNet121 accuracy

and model loss is shown in fig8-9

TABLE II
RESULT OF VITB16

Class Name	Precision (%)	Recall (%)	F-1 Score (%)
Bacterial_Spot	92	96	94
Early_Blight	94	90	92
Late_Blight	98	97	97
Leaf_Mold	97	98	98
Septoria_Leaf_Spot	87	96	91
Two-potted_Spider_Mite	100	85	92
Target_Spot	79	88	83
Yellow_Leaf_Curl_Virus	88	100	94
Mosaic_Virus	100	90	95
Healthy	100	90	95

TABLE III
VITB16 MODEL PARAMETERS

Parameters	Value
Learning Rate	0.0001
Batch Size	10
Number_Epochs	34
Image Size	256

TABLE IV
MODELS COMPARISON

Model	Accuracy(%)
VGG16 [9]	85.00
InceptionV3 [10]	88.30
Xception [11]	89.15
DenseNet121 [12]	94.70
ViT B16	96.20

V. CONCLUSION AND FUTURE WORK

The purpose of my research is to analyze and apply different deep learning models to diagonise diseases that affect tomato plants. The dataset is collected from Kaggle. Dataset contains information of ten different diseases that might affect tomato plant leaves. Four CNN architectures was compared with ViT b16 architecure for disease prediction and classification in tomato plants using this dataset. Based on the results of my research, it can be concluded that deep learning models like DenseNet121, Xception, VGG16, Inception V3 and ViT16 are effective for tomato disease detection. Among these models, ViT B16 shows highest accuracy of 96.20% and DenseNet121 model show highest training accuracy of 98.64%.
In future for more accurate disease diagnosis we have to work on large dataset which could involve collecting dataset directly from field. Advanced segmentation techniques can be used to locate the infected regions before classification. Identifying multiple diseases on a single leaf is another challenging task for us. Finally, we can work on diseases from a broader range

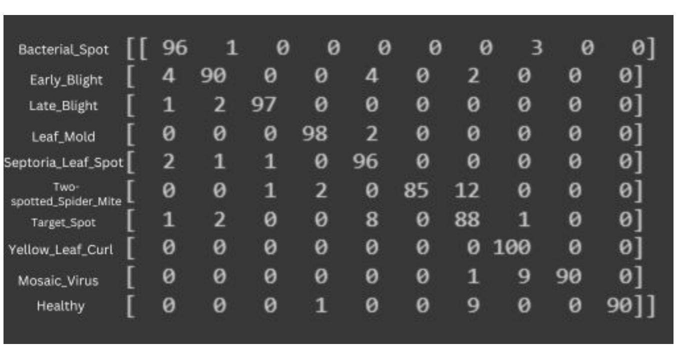

Fig. 7. Dataset Sample

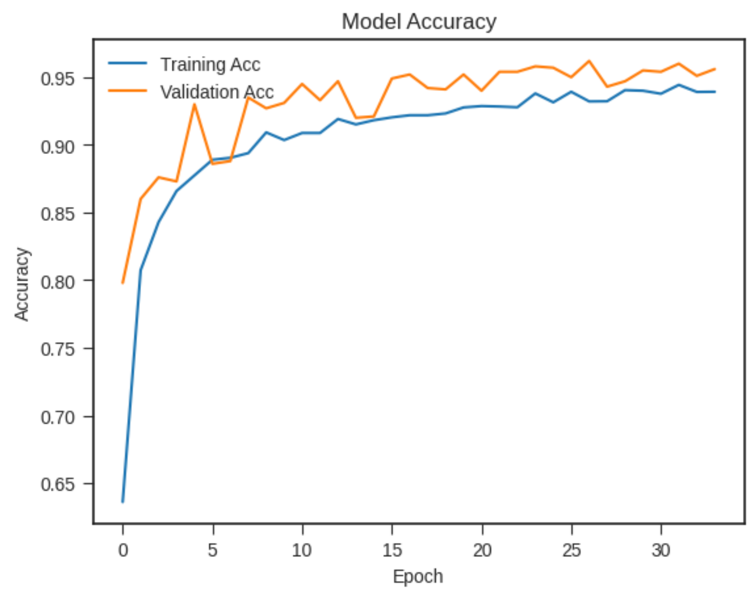

Fig. 8. VitB16 training and validation accuracy

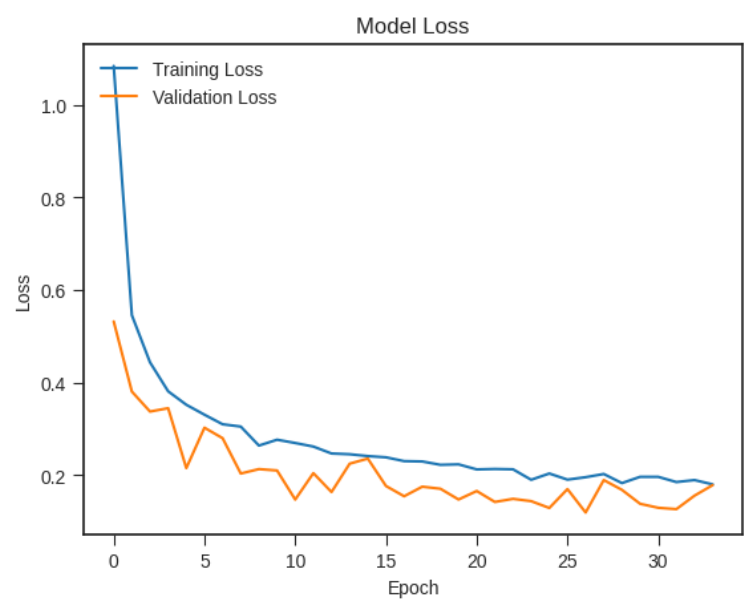

Fig. 9. ViTB16 training and validation loss

of crops.

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