BTP Project - B22RS01

CROP
DISEASE DETECTION

Under The Guidance of
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OUTLINE

- Introduction
- Motivation
- Problem Statement
- Literature review
- Present work
- CNN, Inception-V3, VGG16 Architectures
- Model Results Comparison
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INTRODUCTION

- Agricultural production rate plays a vital role in the economic development of a country.
- The identification of plant diseases at an early stage is crucial for global health and wellbeing. So, controlling on the diseased leaves during the growing stages of crops is a crucial step.
- Moreover, increasing crop production is essential to areas where food is scarce.

INTRODUCTION

- Loss of crops from plant diseases would result in reduction of income for crop producers, higher prices for consumers and significant economic impact.

- The access to disease-control methods is limited which results in annual losses of 30 to 50 percent for major crops in various countries. [1]

- Hence, detection of crop diseases is very crucial for economic development.

MOTIVATION

- Agriculture is a very important sector of the Indian economy.
- The share of agriculture in GDP increased to 20.2 per cent in 2020-21 from 18.4 per cent in 2019-20. [2]
- So, for the identification and detection of plant diseases, human raters are employed.

MOTIVATION

- This process is very time consuming and expensive and sometimes may lead to poorly identify the crop disease.

- Thus, continuous monitoring must be done which is a repetitive process which involves large group of experts costing very high when dealing with large farms.

- Therefore, this motivated us to automate the process and perform evaluation metrics, based on a deep learning classifier.

PROBLEM STATEMENT

- Detect the crop diseases.

- Differentiate between various crop diseases for a particular plant and then for many various plants.

- Using object detection algorithms to find the diseased area in the crop on the basis of the features such as color, wilt, leaf spots, unusual size of the leaf.

- Choosing appropriate neural network for classification.

OBJECTIVE

1. Our Main Objective is that given the images of a specific crop, it should classify it as a healthy crop or the disease it may be infected with.

2. We intend to use deep convolutional neural networks (D-CNN) and some concepts of image processing to reach our goal of identifying the disease of a plant using color, leaf spots, etc.

3. Also, if time permits, we are also planning to develop a web based application so that it can be used widely by large number of people to determine crop diseases.

PROCEDURE

Split the dataset into training and testing.

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Input images using the dataset

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Image Preprocessing (Image Augmentation)

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Building Neural Network Mode (input layers, hidden layers, output layers, activation)

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Training the Neural Network : Minimising loss function (Adam Optimizer - back flow propagation)

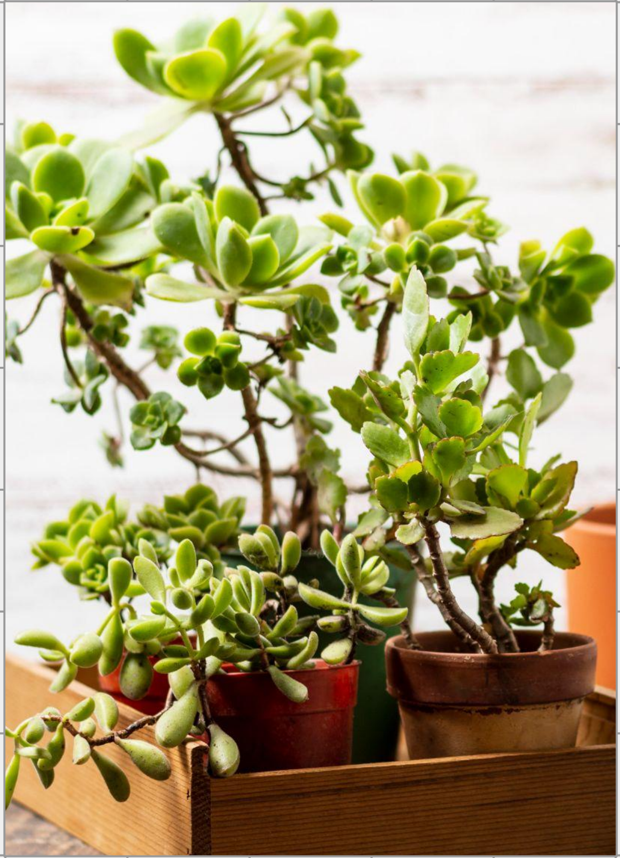
↓

Testing (Confusion Matrix)

↓

Output : Healthy or infected

LITERATURE REVIEW



Literature Review - Base Paper-1 [1]

AUTHOR AND YEAR	TITLE	METHODOLOGY	EVALUATION PARAMETERS	DRAWBACKS
Paymode, Ananda S., and Vandana B. Malode (2022) - ScienceDirect- ISSN 2589-7217	Transfer Learning for Multi-Crop Leaf Disease Image Classification using Convolutional Neural Network VGG [4]	1. Dataset (PlantVillage) 2. Image-processing using Picture filtering, grey transformation, picture sharpening, and scaling ..) 3.Image augmentation (flipping, cropping, rotation, colour transformation) 4.Transfer learning VGG	Accuracy (TP+TN)/(TP+FP+FN+TN) Accuracy for grapes crop : 1. Proposed VGG16 : 98.40% 2. Inception-ResNet-V2: 81.11% Accuracy for tomato crop: 1. Proposed VGG16 : 95.71% 2. Inception-ResNet-V2: 86.10%	1. Preparation of genuine datasets and applying to the deep learning models with multiple crops leaves images more than two is not done. 2. The use of Inception V3 and ResNet-based CNN models for much deeper analysis of crop images is an anticipation which is not done.

MODELS

We have implemented 3 models successfully on tomato plant.

1. CNN (with 3 different variants)

2. INCEPTION-v3

3. VGG-16

STATE OF ART - EXISTING ARCHITECTURE

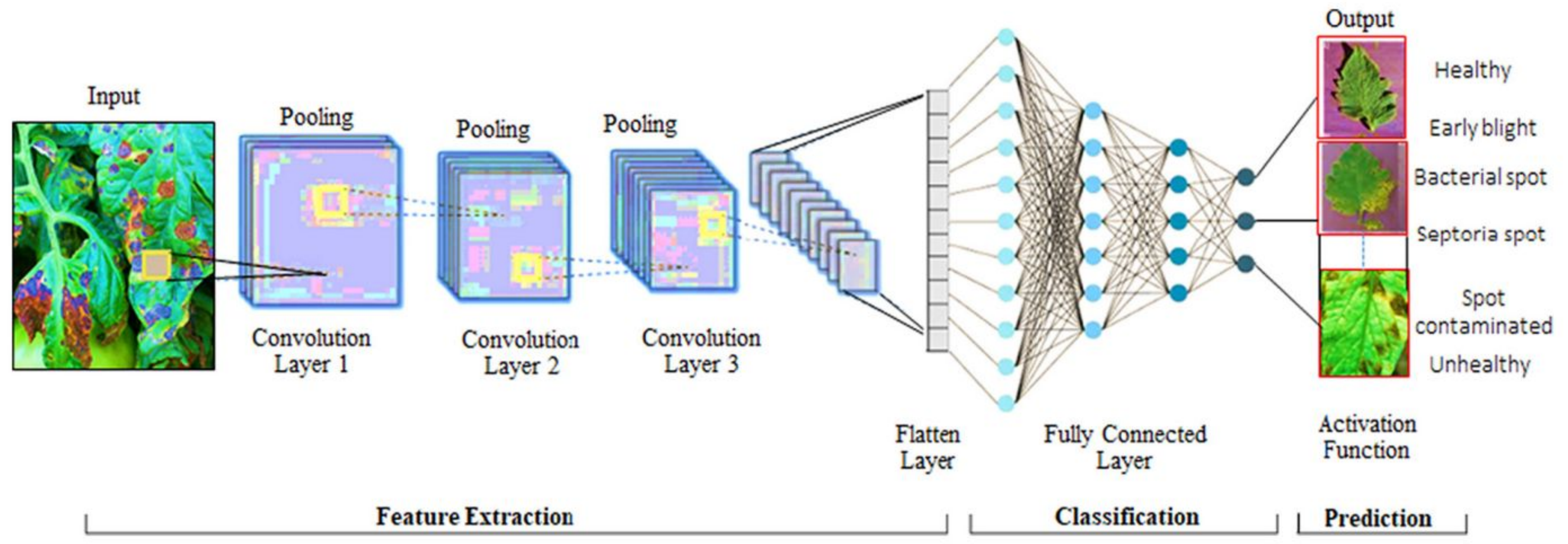


Fig 6. Proposed convolutional neural network CNN architecture.

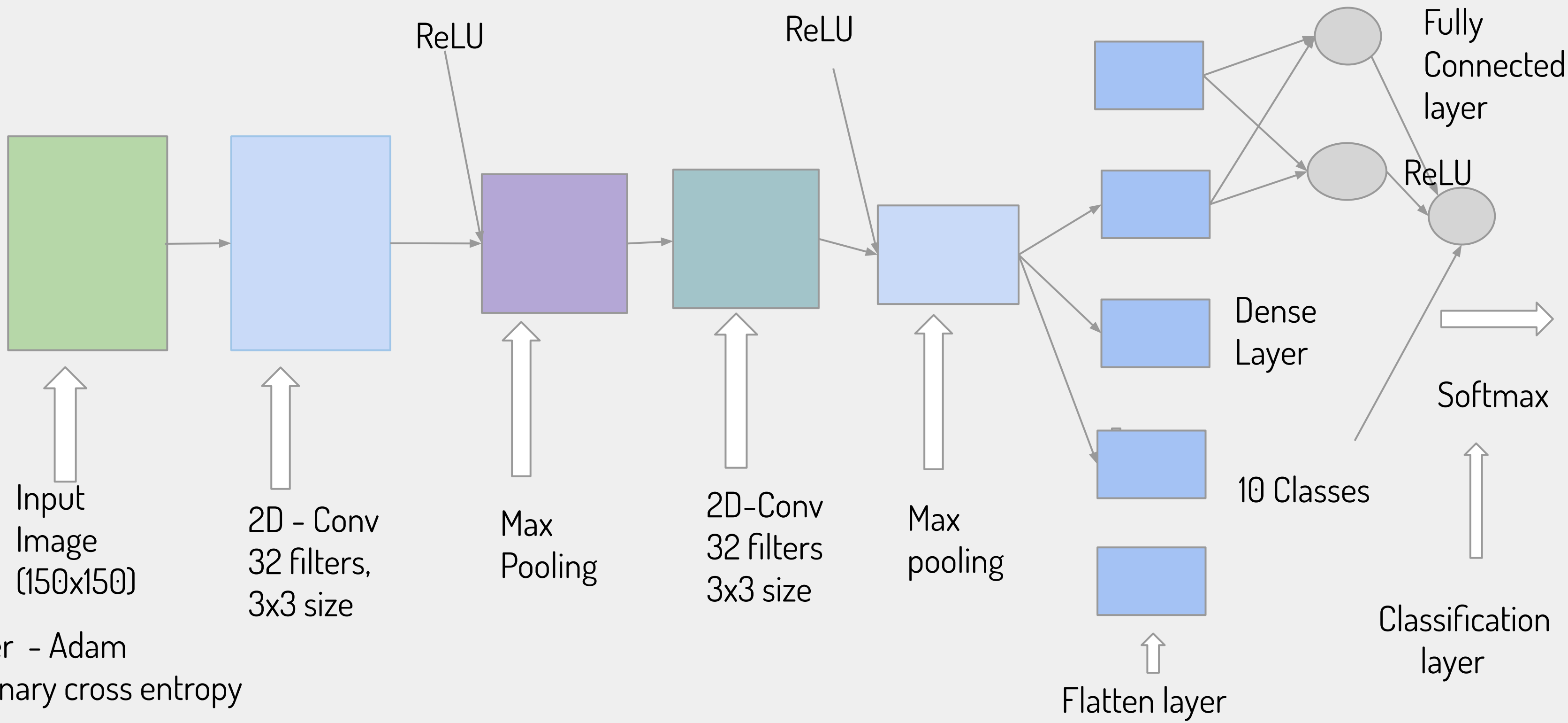
Base Paper 1 : [4]

DATASET

Classes(10)	Tomato___Bacterial_spot, Tomato___Early_blight, Tomato___healthy, Tomato___Late_blight, Tomato___Leaf_Mold, Tomato___Septoria_leaf_spot, Tomato___Spider_mites Two-spotted_spider_mite, Tomato___Target_Spot, Tomato___Tomato_mosaic_virus, Tomato___Tomato_Yellow_Leaf_Curl_Virus.
Total images	10000 images for training data 1000 images for testing data
Image Size	255 X 255
Other Information	● The data set contains the top 10 classes of diseases which are highly occured on tomato plant. ● The images had taken with different angles, with different backgrounds, and in different lighting conditions.

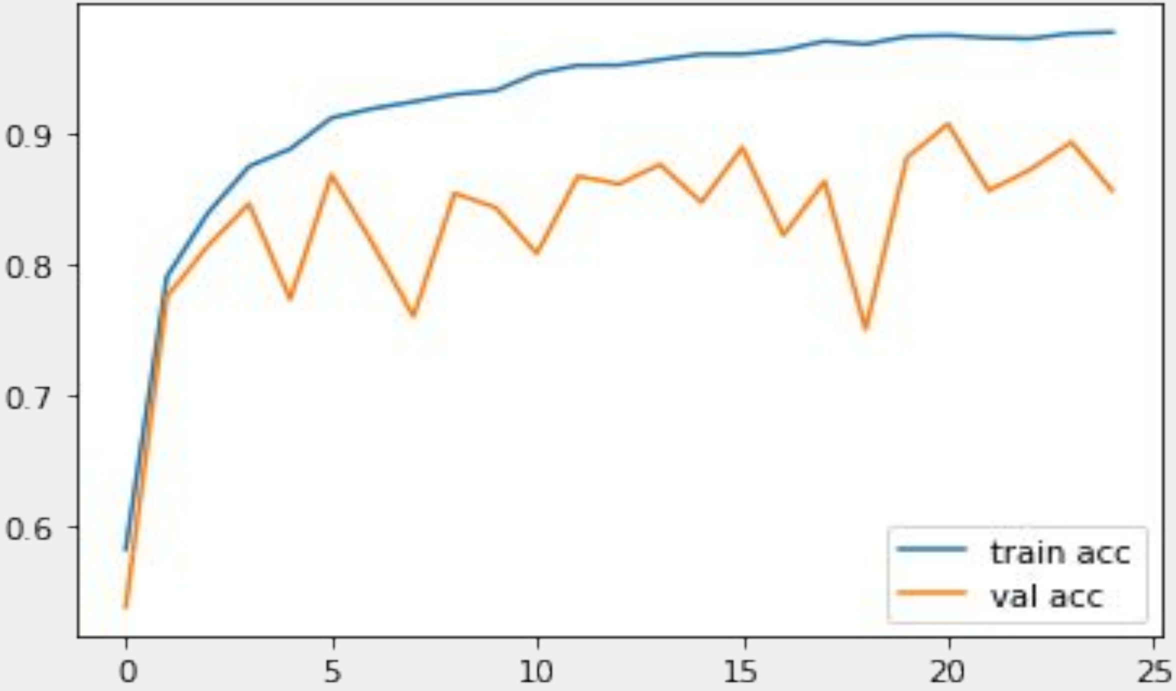
Dataset Link: https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf

CNN ARCHITECTURE -1 (OUR INITIAL MODEL)

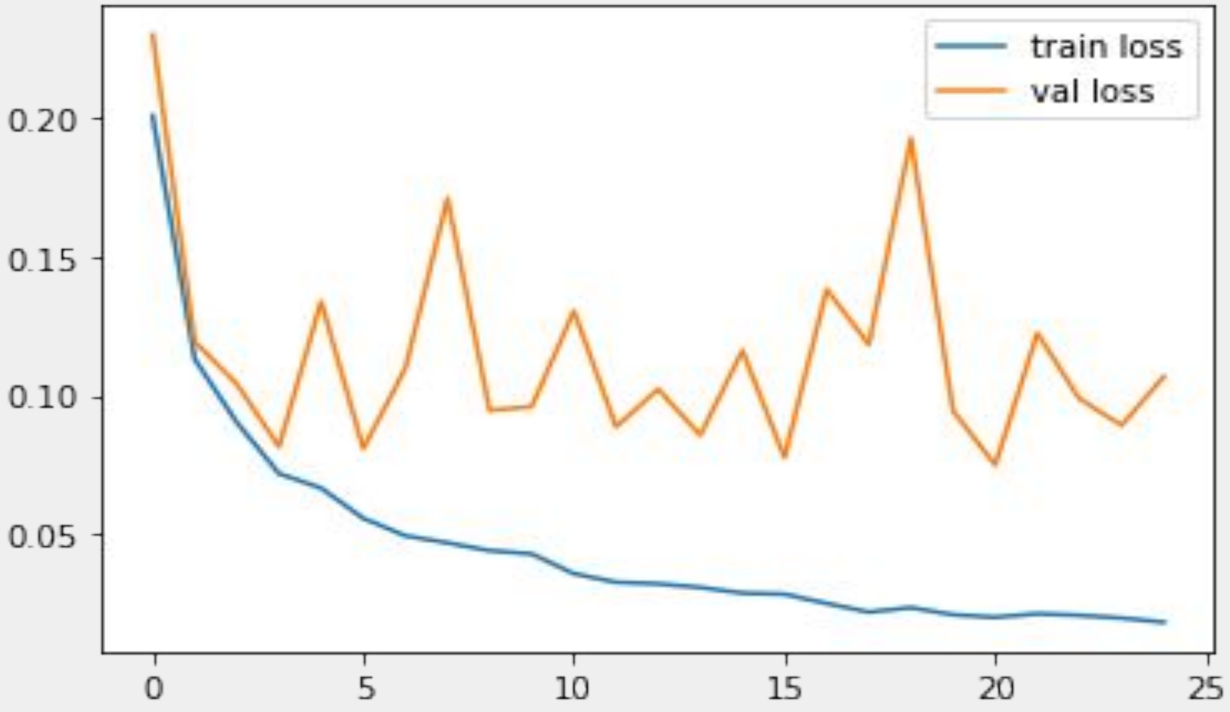


Optimizer - Adam
Loss - Binary cross entropy

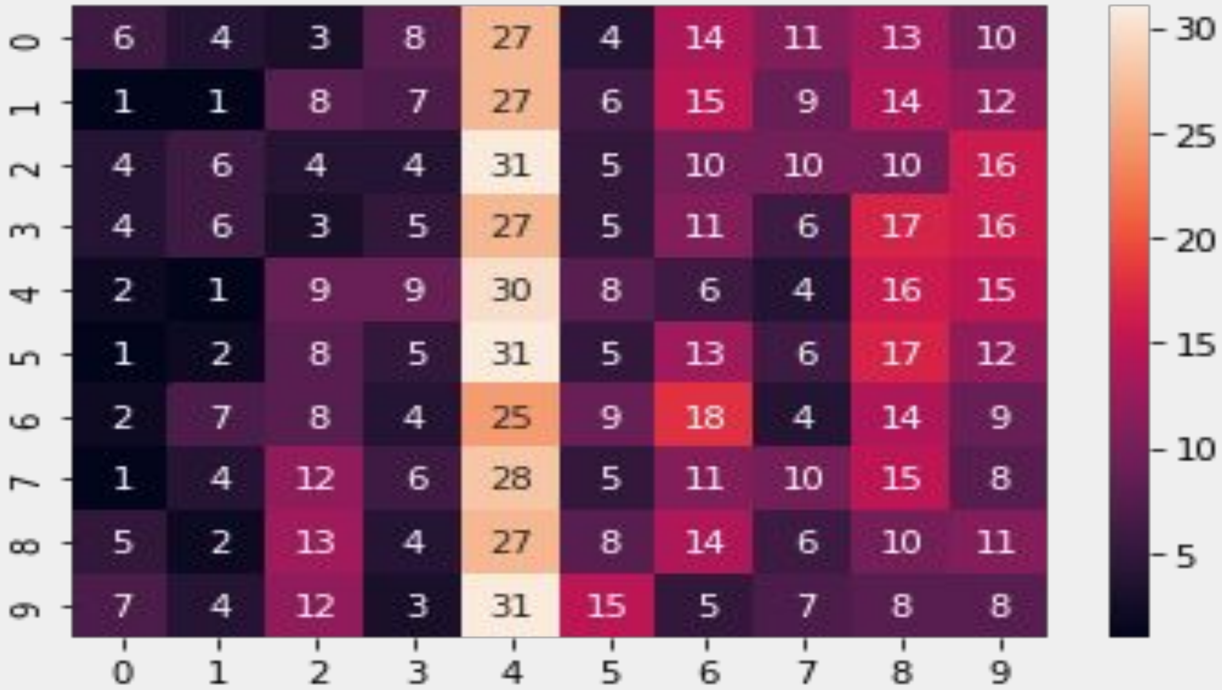
CNN1 RESULTS - TRAINING AND VALIDATION ACCURACY



CNN1 RESULTS - TRAINING AND VALIDATION LOSS



CNN1 RESULTS - CONFUSION MATRIX



CNN1 RESULTS- ACCURACY

DATASET NAME	TOTAL TRAINING IMAGES	TOTAL VALIDATION IMAGES
Tomato leaf disease detection	10,000	1,000

ACCURACY

Training accuracy - 98.119

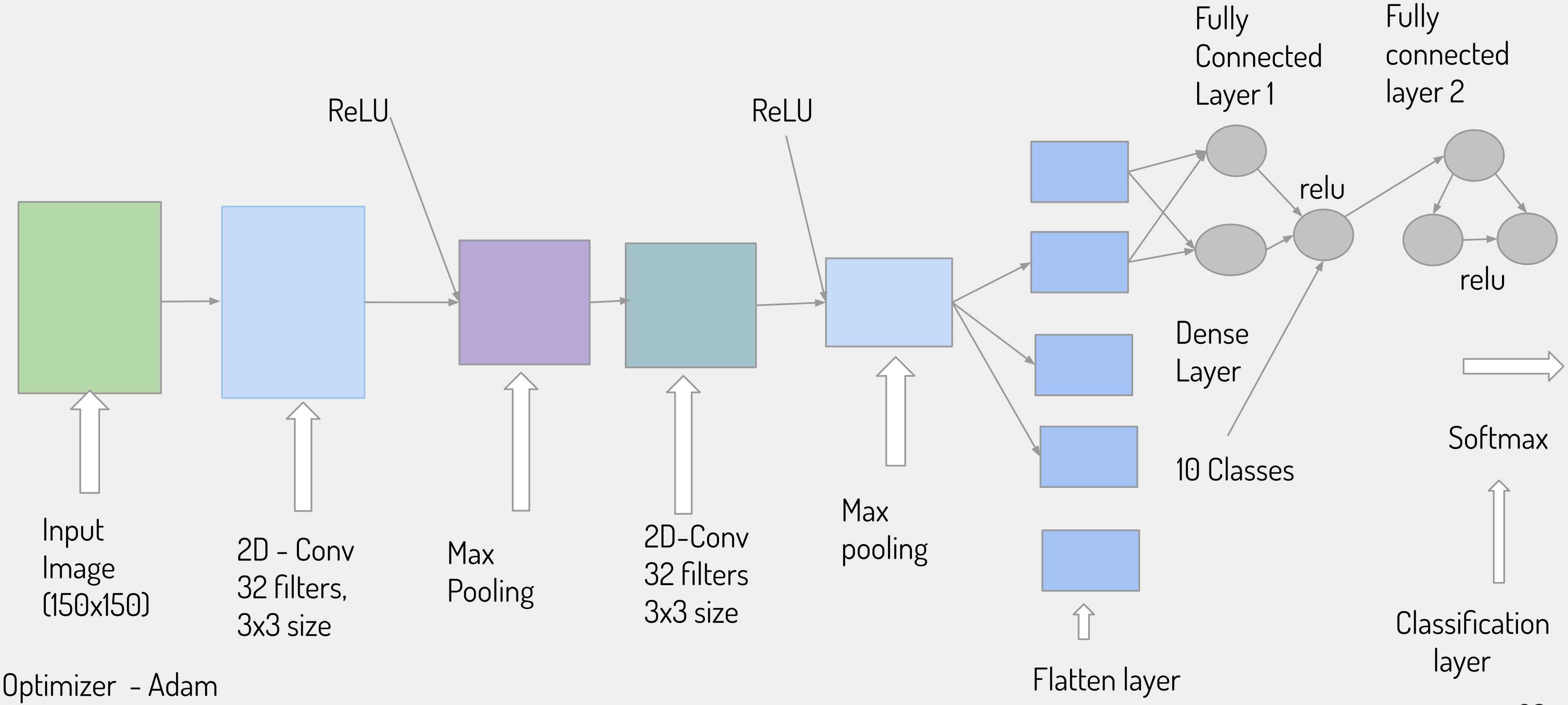
Validation accuracy - 85.60

LOSS

Training loss - 0.0167

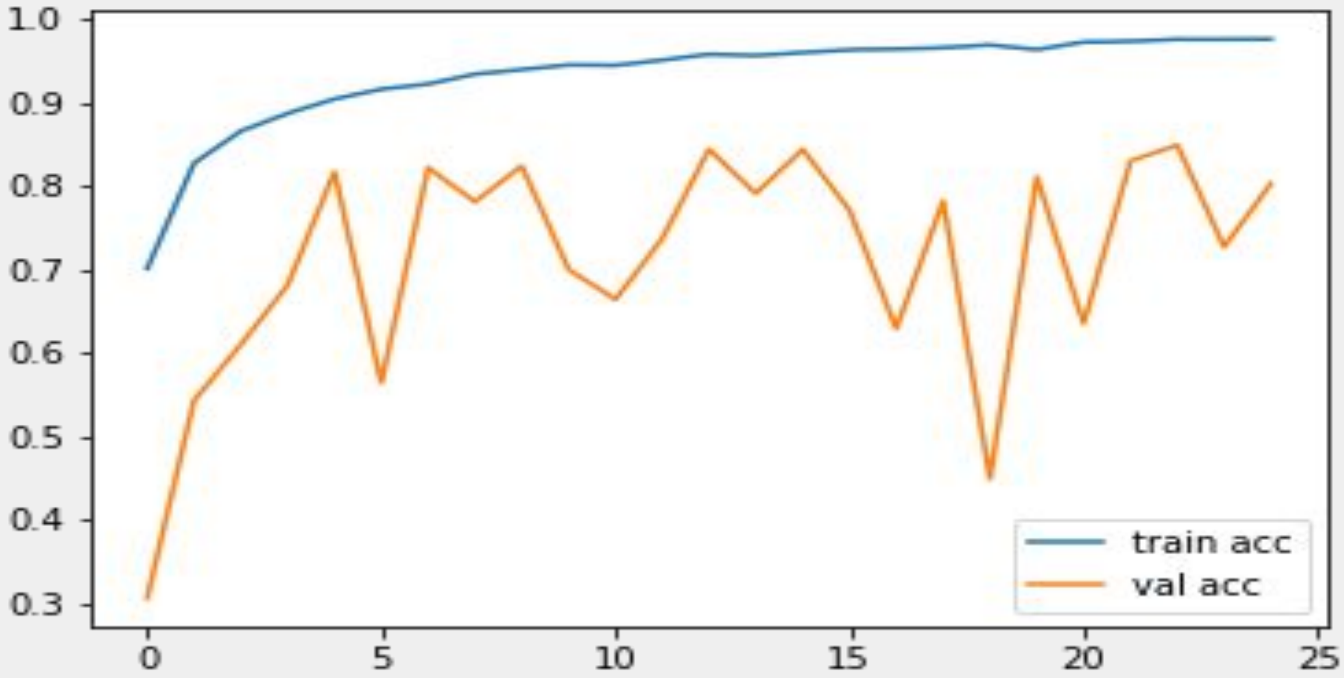
Validation loss - 0.1066

CNN ARCHITECTURE -2

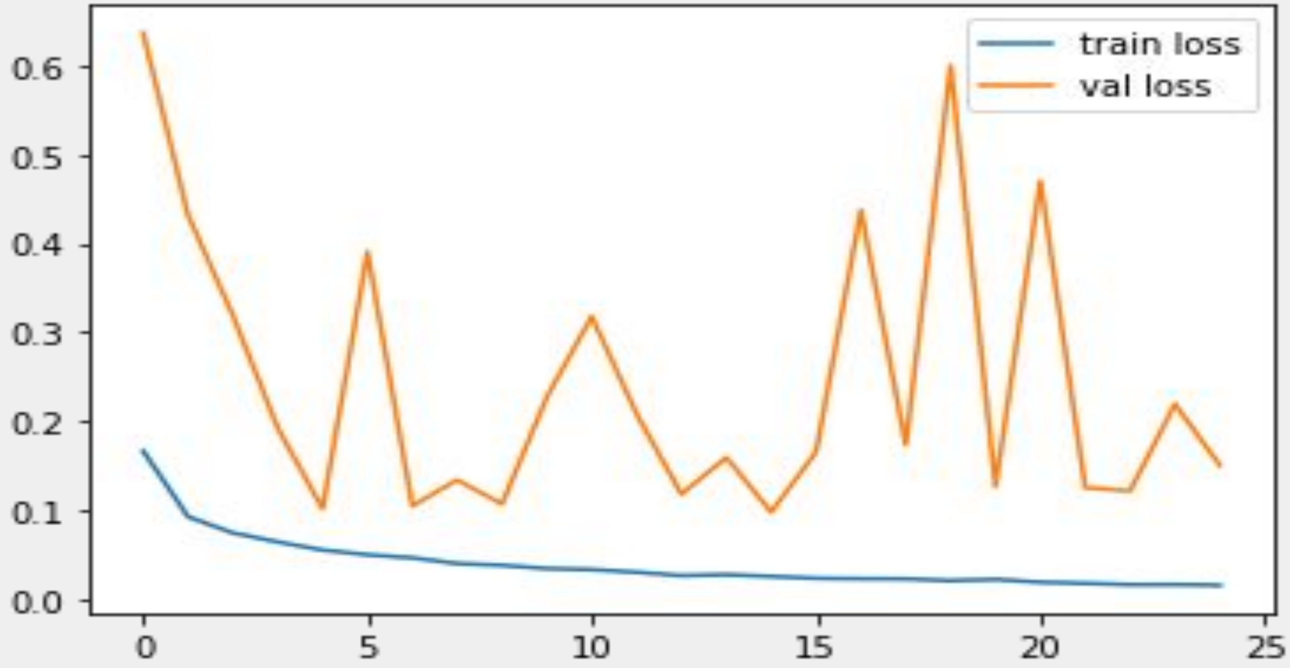


Optimizer - Adam
Loss - Binary cross entropy

CNN2 RESULTS - TRAINING AND VALIDATION ACCURACY



CNN2 RESULTS - TRAINING AND VALIDATION LOSS



CNN2 RESULTS - CONFUSION MATRIX

CNN2 RESULTS- ACCURACY

DATASET NAME	TOTAL TRAINING IMAGES	TOTAL VALIDATION IMAGES
Tomato leaf disease detection	10,000	1,000

ACCURACY

Training accuracy - 91.170

Validation accuracy - 80.290

LOSS

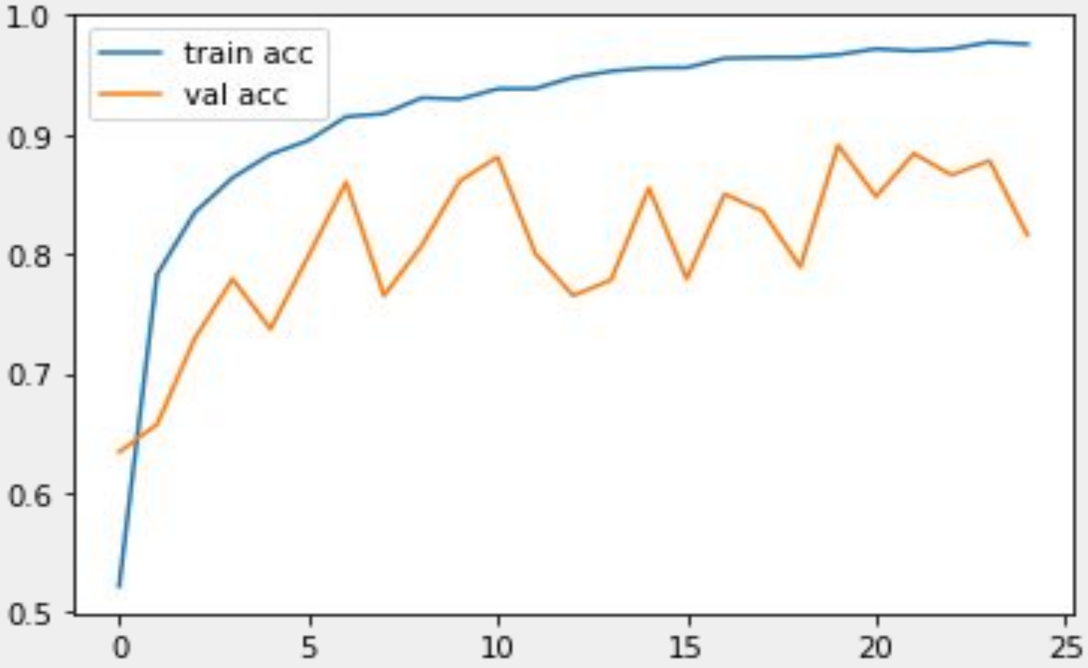
Training loss - 0.0540

Validation loss - 0.1509

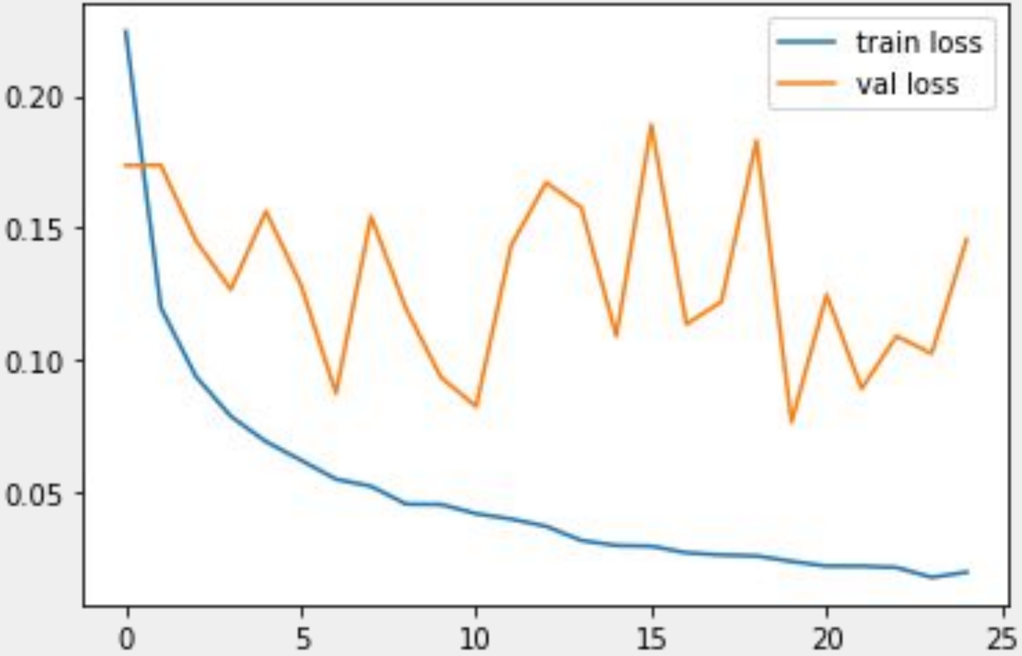
CNN ARCHITECTURE -3

- A convolutional neural network (CNN) is a type of artificial neural network used in image recognition and processing that is specifically designed to process pixel data.
- CNNs use image recognition and classification in order to detect objects, recognize faces, etc. They are made up of neurons with learnable weights and biases.
- Convolution is a mathematical operation on two functions that produces a third function that expresses how the shape of one is modified by the other.A CNN typically has three layers: a convolutional layer, a pooling layer, and a fully connected layer
- The Architecture contains the same layers as CNN1 but where fully connected layer of batch size 64 is taken (2 Conv Layers, 2 Max pooling, 1 Flatten Layer,1 Dense Layer, 1 Fully Connected Layer with batch size 64)

CNN3 RESULTS - TRAINING AND VALIDATION ACCURACY



CNN3 RESULTS - TRAINING AND VALIDATION LOSS



CNN3 RESULTS - CONFUSION MATRIX

CNN3 RESULTS- ACCURACY

DATASET NAME	TOTAL TRAINING IMAGES	TOTAL VALIDATION IMAGES
Tomato leaf disease detection	10,000	1,000

ACCURACY

Training accuracy - 97.64

Validation accuracy - 81.599

LOSS

Training loss - 0.0175

Validation loss - 0.1456

INCEPTION -V3 ARCHITECTURE

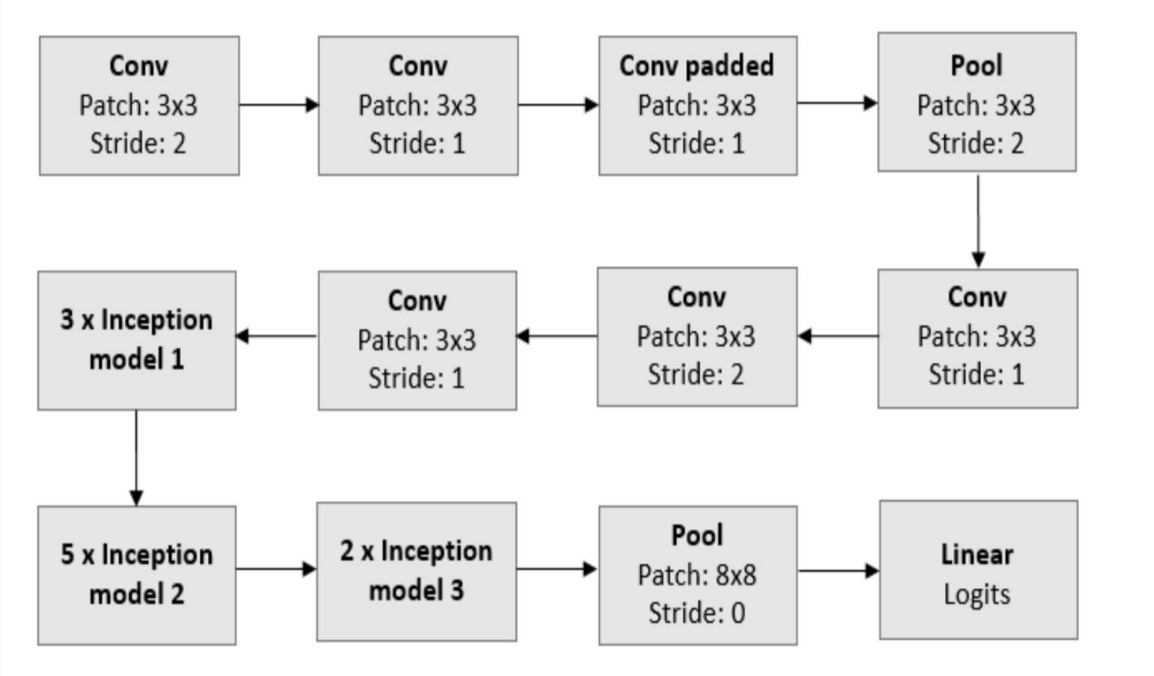
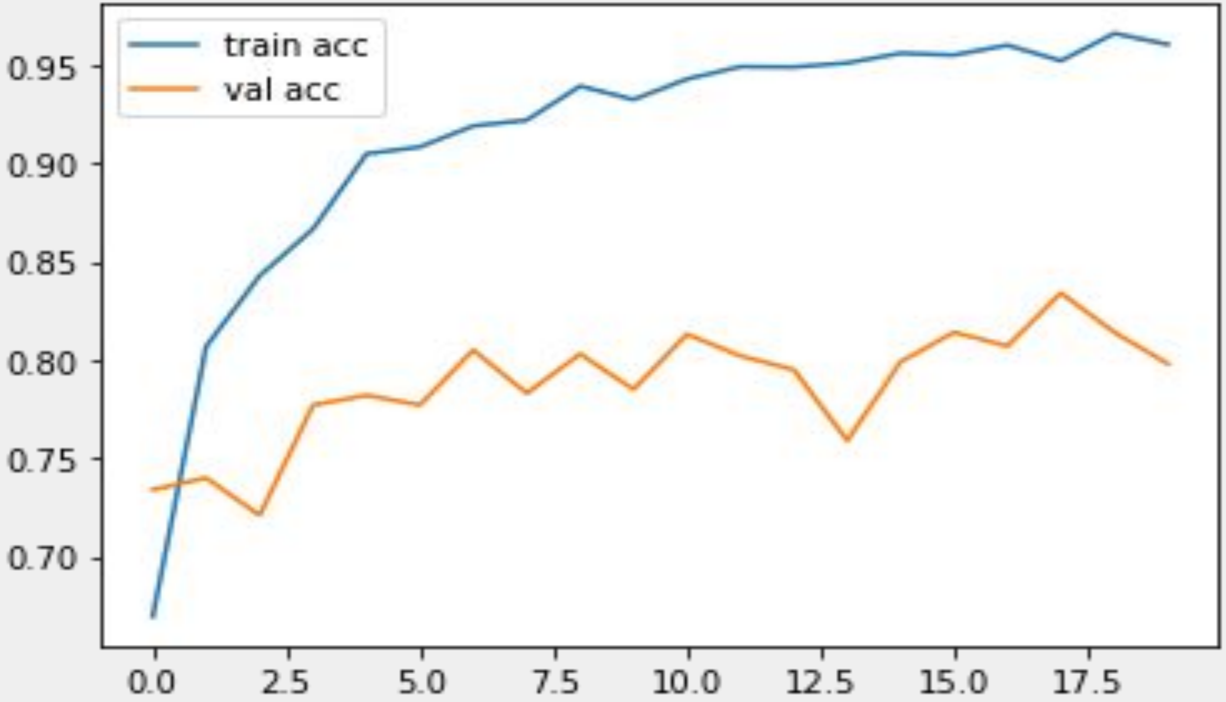
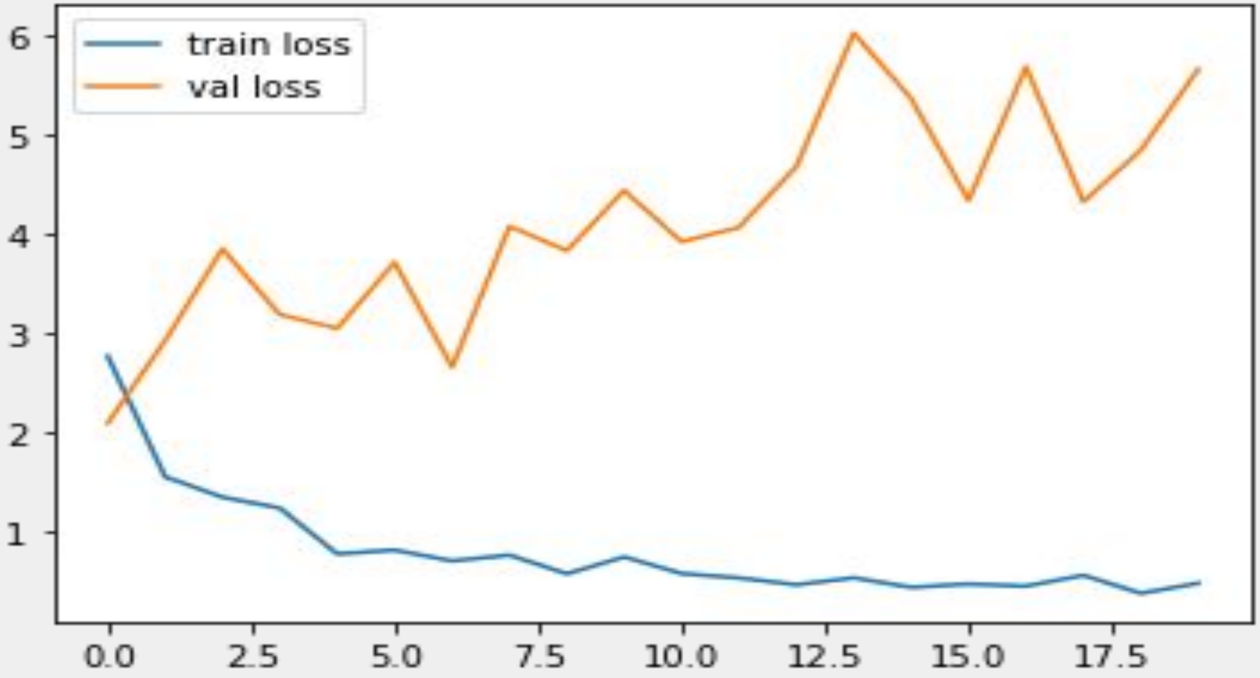


Image Credits: [8]

INCEPTION-V3 RESULTS - TRAINING AND VALIDATION ACCURACY



INCEPTION-V3 RESULTS - TRAINING AND VALIDATION LOSS



INCEPTION-V3 RESULTS- ACCURACY

DATASET NAME	TOTAL TRAINING IMAGES	TOTAL VALIDATION IMAGES
Tomato leaf disease detection	10,000	1,000

ACCURACY

Training accuracy - 95.490

Validation accuracy - 79.799

LOSS

Training loss - 0.6275

Validation loss - 5.6497

VGG-16 ARCHITECTURE

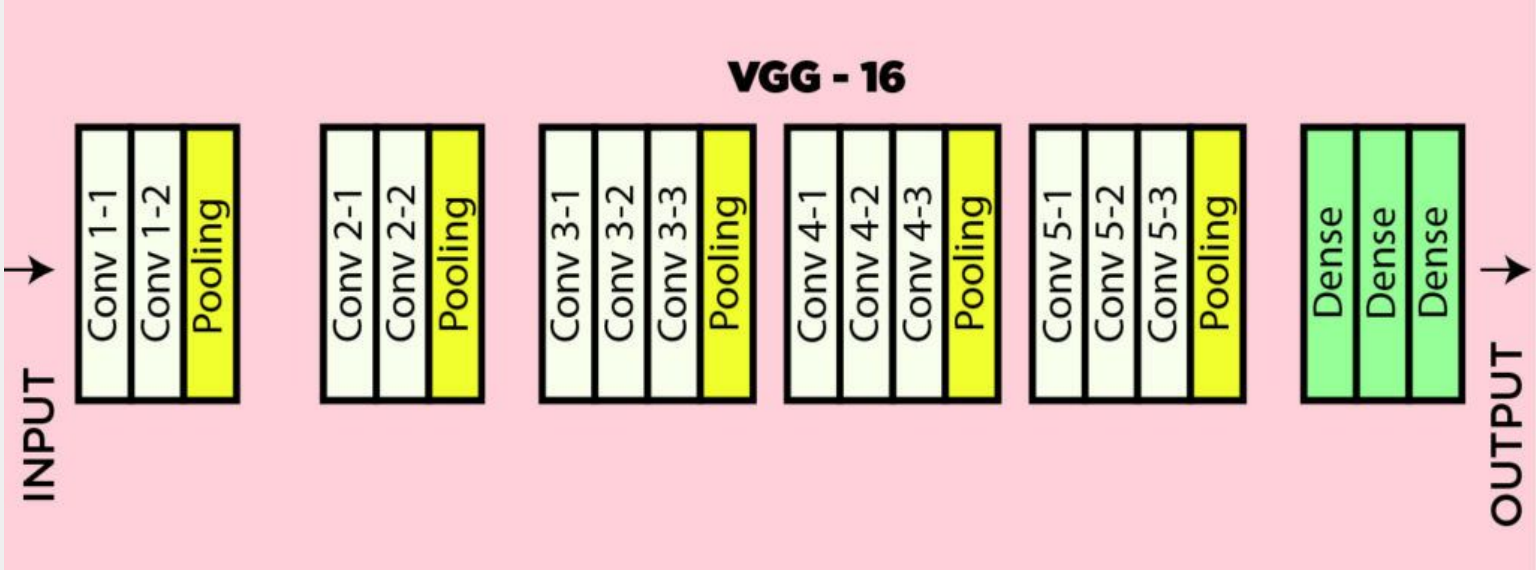
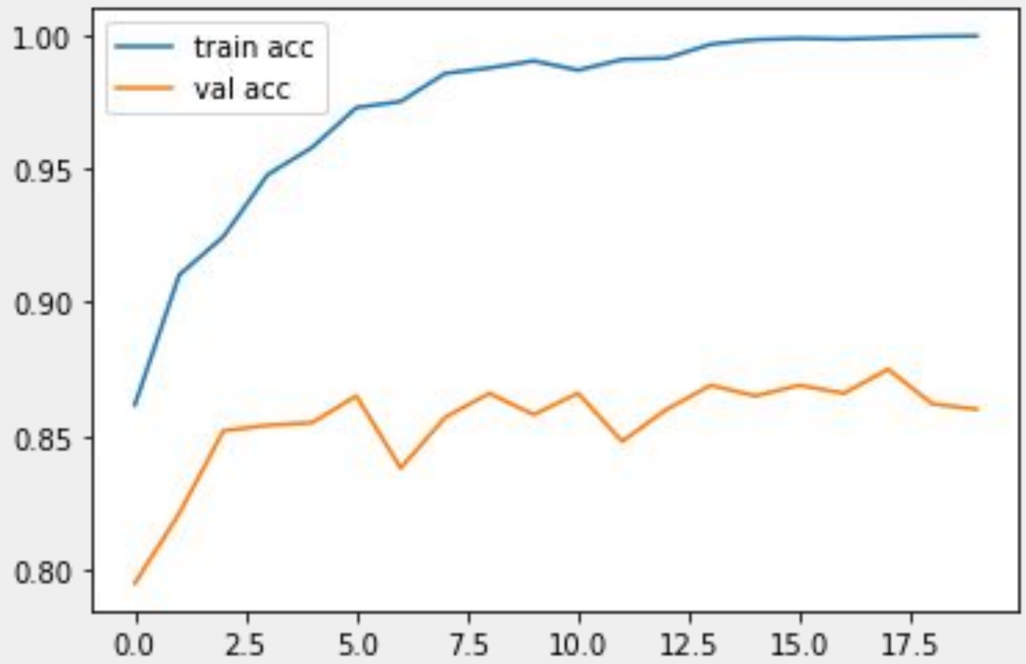
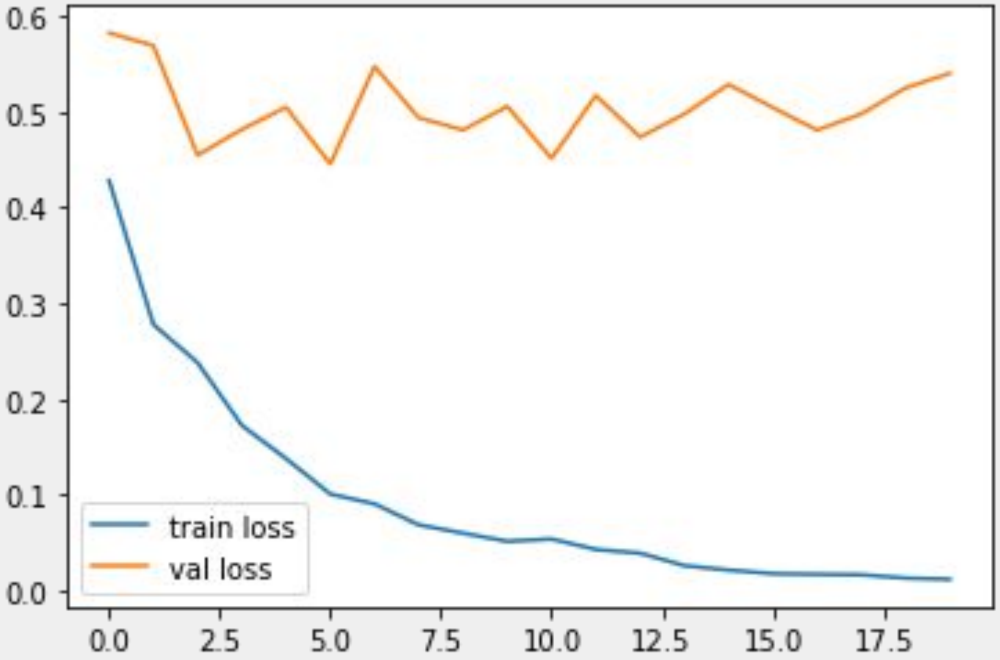


Image Credits: [9]

VGG16 RESULTS - TRAINING AND VALIDATION ACCURACY



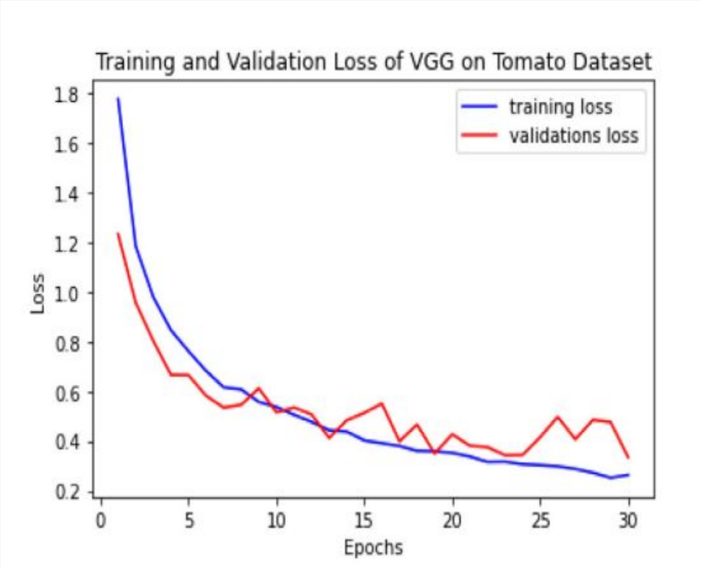
VGG16 RESULTS - TRAINING AND VALIDATION LOSS

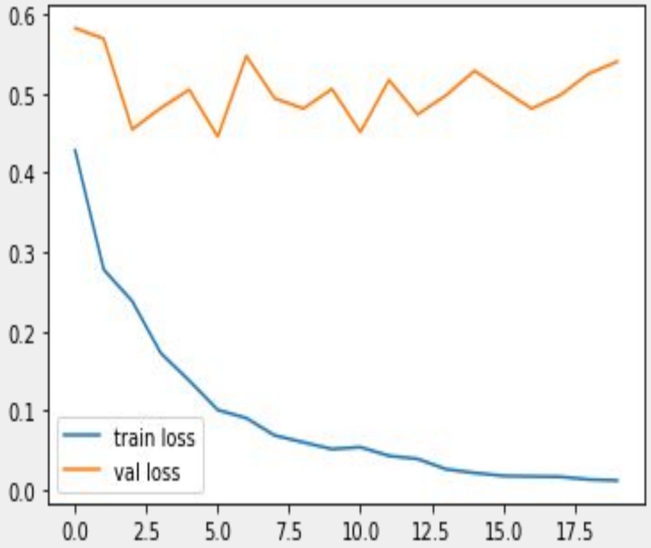


VGG16 RESULTS - CONFUSION MATRIX

COMPARISON OF MODELS

OUR VGG16 VS BASE PAPER-1 (LOSS)

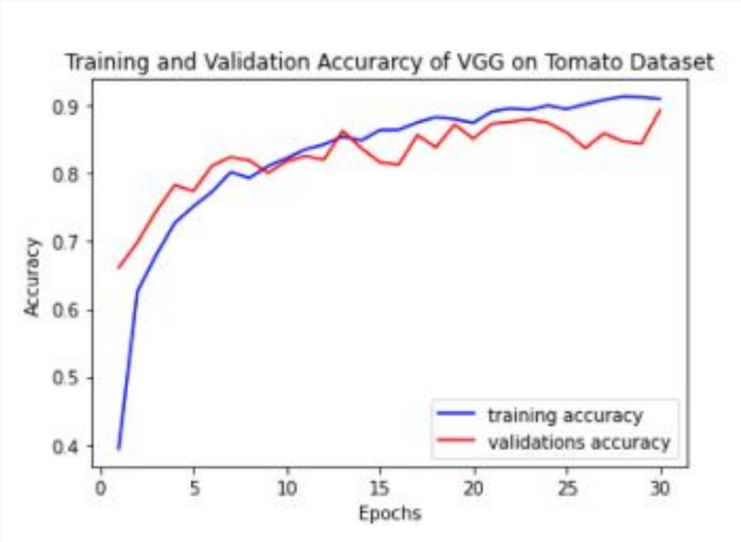


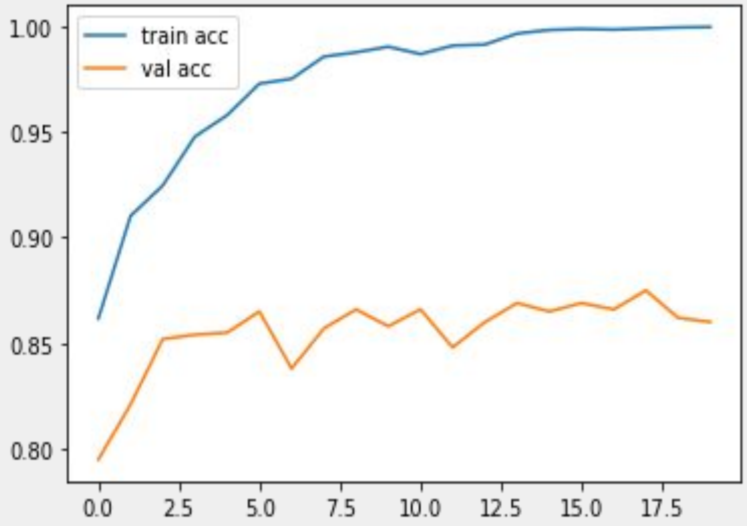


Base Paper 1 – VGG16
Validation Loss – 0.3042

Our Model – VGG16
Validation Loss – 0.540

OUR VGG16 VS BASE PAPER-1 (ACCURACY)





Base Paper 1 - VGG16
Validation Accuracy - 95.71%

Our VGG16
Validation Accuracy -86.00%

ALL RESULTS

Model	Dataset	Network	Architecture	Results
CNN1	kaggle	CNN	2 Conv Layers, 2 Max pooling, 1 Flatten Layer,1 Dense Layer, 1 Fully Connected Layer with batch default size	Validation accuracy - 85.60
CNN 2	kaggle	CNN	2 Conv Layers, 2 Max pooling, 1 Flatten Layer,1 Dense Layer, 1 Batch Normalization, 2 Fully Connected Layer with batch default size	Validation accuracy - 80.290
CNN 3	kaggle	CNN	2 Conv Layers, 2 Max pooling, 1 Flatten Layer,1 Dense Layer, 1 Fully Connected Layer with batch size 64	Validation accuracy - 81.599
INCEPTION-V3	kaggle	D-CNN	48 layered deep architecture	Validation accuracy - 79.799
VGG-16	kaggle	D-CNN	16 layered deep architecture	Validation Accuracy -86.00%

AVAILABLE DATASETS

- **Tomato Plant Dataset (Used) : Link**

There are 10000 images belonging to 10 classes for training and 1000 images belonging to 10 classes for testing.

- **Wheat Plant Dataset : Link**

There are 876 images to train the model on and 610 images in the test set for evaluation

- **Grape Plant Dataset : Link**

The dataset provide a collection of images of grapevine leaves, related to two classes: unhealthy leaves acquired from plants affected by Esca disease and healthy leaves.

AVAILABLE DATASETS

Additional (Future Work for Multi-class):

- **Plant Village Dataset: Link**

This includes 152 crop solutions, 38 crop classes, and 19 crop categories, for 54,303 crop leaves images. In the dataset, high quality JPEG image format with 5471 width and 3648 height pixels are available.

- **Multiple Crops, Disease wise Dataset : Link**

This dataset includes various types of crops each one with different no of disease classes.

ROAD MAP (TENTATIVE)

Phase 1. Data Gathering - Done
Phase 2. Data Pre- Processing - Done
Phase 3. Building our Initial Model -Done
Phase 4. Training and Detection - Done
Phase 5. Testing (2 weeks) - Yet to complete
Phase 6. Optimising (2 weeks) - Yet to complete
Phase 7. Multi-class Classification (4 weeks) - Yet to complete
Phase 6. Building an web application (2 weeks) - Yet to complete

REFERENCES

[1] Plant Disease and Plant Pathology | Britannica. Link

[2] Ministry of Agriculture & Farmers Welfare | PIB Delhi. Link

[3] Pantazi, X. E., Moshou, D., & Tamouridou, A. A. (2019). Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers. Computers and electronics in agriculture, 156, 96-104. Link

[4] Paymode, A. S., & Malode, V. B. (2022). Transfer learning for multi-crop leaf disease image classification using convolutional neural networks VGG. Artificial Intelligence in Agriculture. Link

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[5] Zhang, Y., Song, C., & Zhang, D. (2020). Deep learning-based object detection improvement for tomato disease. IEEE Access, 8, 56607-56614. Link

[6] Kulkarni, O. (2018, August). Crop disease detection using deep learning. In 2018 Fourth international conference on computing communication control and automation (ICCUBEA) (pp. 1-4). IEEE. Link

[7] Li, L., Zhang, S., & Wang, B. (2021). Plant disease detection and classification by deep learning—a review. IEEE Access, 9, 56683-56698. Link

[8] Nguyen, L. D., Lin, D., Lin, Z., & Cao, J. (2018, May). Deep CNNs for microscopic image classification by exploiting transfer learning and feature concatenation. In 2018 IEEE International Symposium on Circuits and Systems (ISCAS) (pp. 1-5). IEEE. Link

[9] VGG16 | CNN Model. Link

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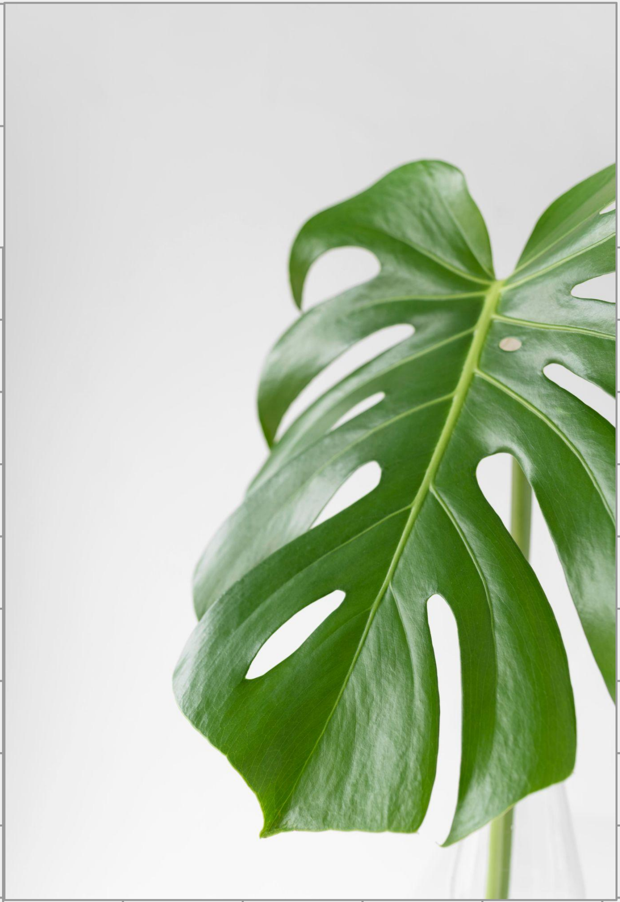

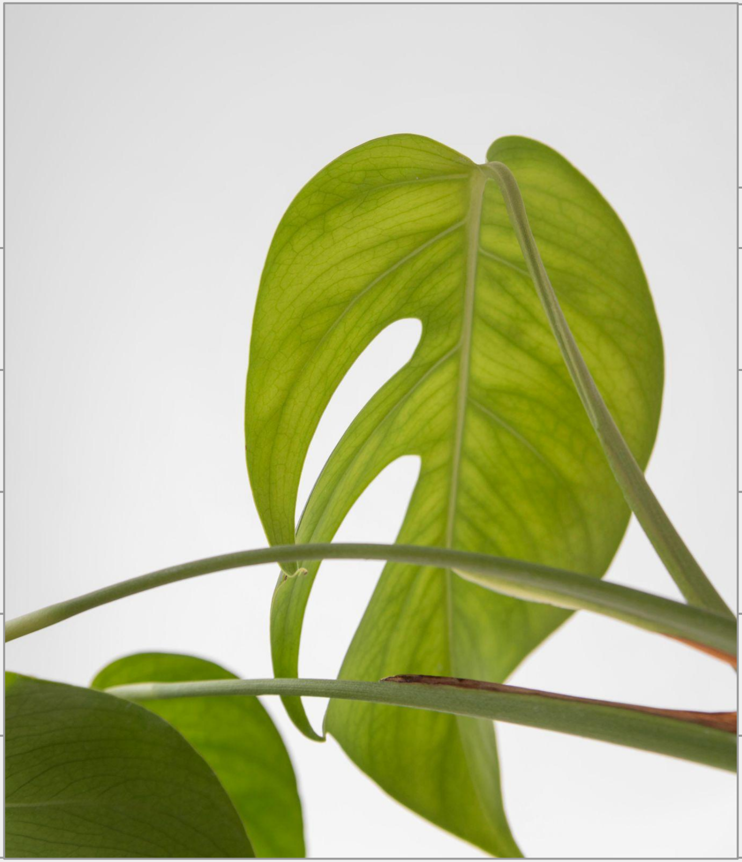

THANKS!

Do you have any questions?