Performance Analysis of Transfer Learning Model and Prediction of Corn Leaf Diseases

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Abstract: Agriculture is one in all the formost significant roles within growth and development of our nation economy. The identification of diseases is that the key of forestall the losses within the yield and quantity of the agriculture product. Diseases detection on the plant is incredibly critical for sustainable agriculture. It's challenging to watch the plant the plant manually especially people who are new to farming. It requires excessive time interval. Therefore a correct prediction and detection of disease will reduce the utilization of fertilizer within the field, which helps from soil impurities. In this present paper we have explained how we train our model with normal dataset and augmented dataset and achieved accuracy greater than 95%
Keywords: Prediction, Transfer Learning, Corn LeafDiseases, VGG-16, VGG-19.

I. INTRODUCTION

To contribute to the event of countries, knowledge of agriculture sectors is crucial. Agriculture could be a one- of- a- kind source of wealth that develops farmers. For a powerful country, the event of farming is a necessity and a requirement within the global market. The world's population is growing at an exponential rate, necessitating the massive food production within the next 50 years. Information about differing kinds of crops and diseases occurring at each level and its analysis at an early stage play a key and dynamic role within the agriculture sector. A farmer's main problem is that the occurrence of assorted diseases on their crops. The disease classification and analysis of illnesses may be a crucial concern for agriculture's optimum foodyield. Food safety is an huge issue due to lack of infrastructure and technology, so crop disease classification and identification are important to be considered within the coming days. classification and identification are important to be considered within the coming days. Detection and recognition of crops illnesses is a vital study topic because it may be capable of monitoring huge fields of crops and detecting disease symptoms as soon as they occur on plant leaves. As a result finding a fast, efficient, least inexpensive, and effective approach to work out crops diseases instances is kind of important.

Transfrer Learning:-The study of transfer learning is motivated by the very fact that individuals can intelligently apply knowledge learned previously to resolve new problems faster or with better solutions. transfer learning is an machine learning method where we reuse a pre-trained model because the start line for a model on a new task. To put it simply a model trained on one task is repurposed on a second, related task as an optimization that permits rapid progress when modeling the second task. By applying transfer learning to a new task, one can achieve significantly higher performance than training with only a little amount of data.

Maize belongs to the Poaceae monocot family and is that the third most significant cereal crop in the world. Though maize isn't eaten directly, it's use to make several products like corn starch, syrup and ethanol. Maize plant leaves suffer from a range of infections, and the three most prevalent maize leaf diseases are the northern corn blight disease, common rust disease & grey leaf spot disease.

II. BACKGROUND AND RELETATED WORK

The study of transfer learning is motivated by The fact that people can intelligently apply knowledge learned previously to solve new problem faster or with better solution.

1) Chen and Wang proposed a corn leaf disease recognition method based on image processing technology and probabilistic neural network (PNN), with a recognition accuracy of 90.4%.
2) The extensive use of convolutional neural networks in the field of image recognition provides new ideas for improving the accuracy of the detection of plant diseases and insect pests. In their work,they used deep learning to classify leaf diseases of 14 types of crops with an accuracy rate of 99.35%.

3) Weihui Zeng, Haidong Li, Gensheng Hu, Dong Liang, Identification of maize leaf diseases by using the SKPSNet-50 convolutional neural network model, where they got accuracy of 92%.

4) Zhang based on the improved deep learning model of GoogLeNet and Cifar10 network, applied to the identification of diseases and insect pests of corn leaves, whose highest accuracy rate reached 98.9%.

5) Weihui Zeng, Haidong Li, Gensheng Hu, Dong Liang, Lightweight dense-scale network (LDSNet) for corn leaf disease identification 2022, the got accuracy of 95.4%.

6) J. Arun Pandian, G. Geetharamani and B. Annette, "Data Augmentation on Plant Leaf Disease Image Dataset Using Image Manipulation and Deep Learning Techniques.

III.   METHODOLOGY

A. Dataset

We have four type of corn leaf as follow.

1) Northern Leaf Blight Disease

The fungus Exserohilium turcicum is chargeable for the northern corn blight disease. The primary striking symptom for this disease is that the large grey cigar-shaped lesions that on the leaf's surface. Moderate to chill temperatures, and a comparatively high humidity level act as a catalyst for this diseases.

Early Stage   Advance Stage

2) Common Rust

Common rust disease is one more maize disease favoured by high humidity levels and cold temperatures. During this disease, variety of small tan spots develop on both the surfaces of the leaf and as a result, the photosynthesis of the leaf reduces drastically. the identical has shown.
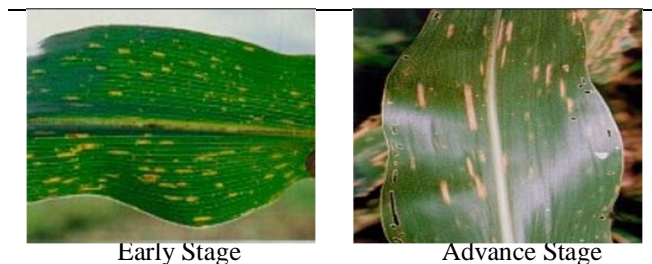

Early Stage   Advance Stage

3) Gray Leaf Spot

The Gray leaf spot caused by Cercospora zeae-maydis fungal pathogen, is one amongst the foremost significant yield-limiting foliar diseases found within the maize plant. Ever since being first reported in the 1970s, it's posed a heavy threat to maize production worldwide, with a big impact in large areas of Africa and also the U.S. Corn Belt. The symptoms of this disease characterized by linear (and rectangular) lesions on the lower surface of the leaf within the early stage, which later turns into rust spots.
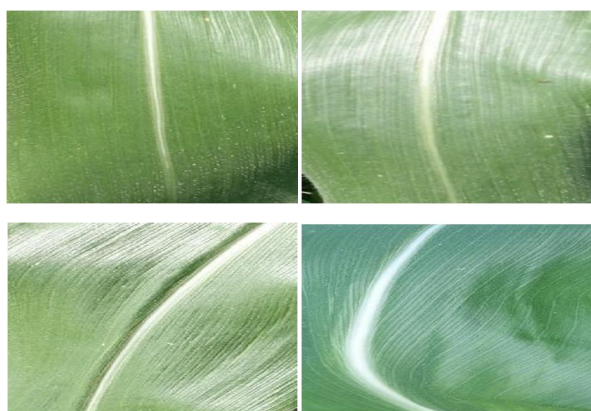
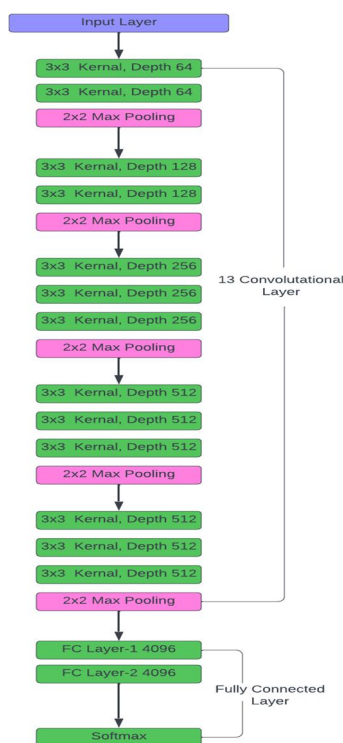Early Stage   Advance Stage

4) Healthy Leaf

Healthy maize leaves have been shown below. Four different samples have been picked for demonstration.

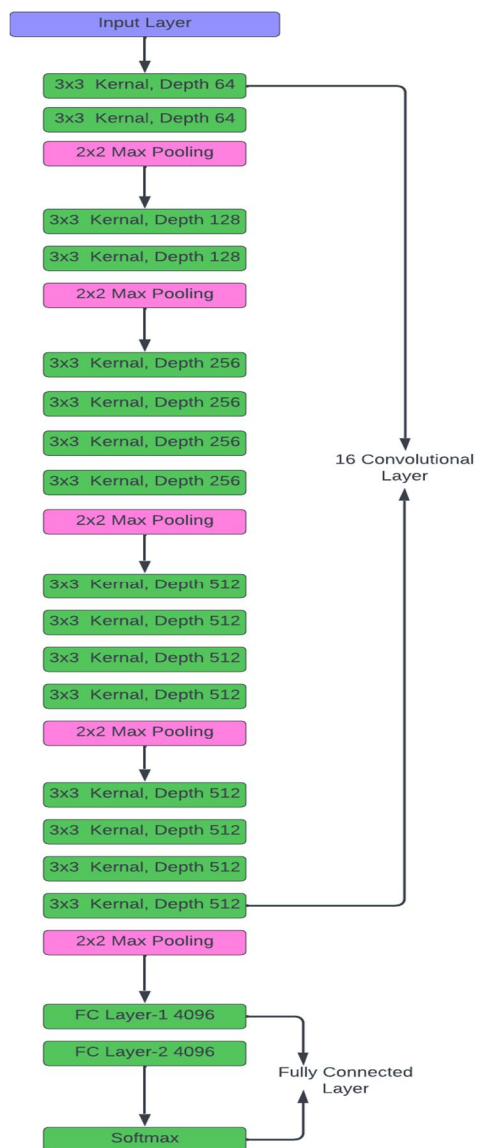### B. Transfer Learning Model

1) VGG-16

VGG-16 model architecture –   13 convolutional layers and 2 Fully connected layers and 1 Softmax   classifier VGG-16 - Karen Simonyan and Andrew Zisserman introduced VGG-16   architecture in 2014 in their paper Very Deep convolutation Network for Large Scale Image   Recognition. Karen and Andrew created a 16-layer network comprised of convolutional and fully connected layers. Using only 3×3 convolutional layers stacked on top of each other for simplicity.

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a) The first and second convolutional layers are comprised of 64 feature kernel filters and size of the filter is 3×3. As input image (RGB image with depth 3) passed into first and second convolutional   layer, dimensions changes to 224x224x64. Then the resulting output is passed to max pooling layer with astride of 2.

b) The third and fourth convolutional layers are of 128 feature kernel filters and size of filter is 3×3. These two layers are followed by a max pooling layer with stride 2 and the resulting output will be reduced to 56x56x128.

c) The fifth, sixth and seventh layers are convolutional layers with kernel size 3×3. All three use 256 feature maps. These layers are followed by a max pooling layer with stride 2.

d) Eighth to thirteen are two sets of convolutional layers with kernel size 3×3. All these sets of convolutional layers have 512 kernel filters. These layers are followed by max pooling layer with stride of 1.

e) Fourteen and fifteen layers are fully connected hidden layers of 4096 units followed by a softmax output layer (Sixteenth layer) of 1000 units.

2) VGG-19

VGG-19 model architecture – 16 convolutional layers and 2 Fully connected layers and 1 SoftMax classifier VGG-19 - Karen Simonyan and Andrew Zisserman introduced VGG-19 architecture in 2014 in their paper Very Deep Convolutional Network for Large Scale Image Recognition. Karen and Andrew created a 19-layer network comprised of convolutional and fullyconnected layers. Using only 3×3 convolutional layers stacked on top of each other for simplicity.

a) The first and second convolutional layers are comprised of 64 feature kernel filters and size of the filter is 3×3. As input image (RGBimage with depth 3) passed into first andsecond convolutional layer, dimensions changes to 224x224x64. Then the resultingoutput is passed to max pooling layer withastride of 2.

b) The third and fourth convolutional layers are of 128 feature kernel filters and size of filter is 3×3. These two layers are followed by a max pooling layer with stride 2 and the resulting output will be reduced to 56x56x128.

c) The fifth, sixth, seventh and eighth layers are convolutional layers with kernel size 3×3. All three use 256 feature maps. These layers are followed by a max pooling layer with stride 2.

d) Ninth to Sixteenth are two sets of convolutional layers with kernel size 3×3. All these sets of convolutional layers have 512 kernel filters. These layers are followed by max pooling layer with stride of 1.

e) Seventeenth and Eighteenth layers are fully connected hidden layers of 4096 units followed by a softmax output layer (Nineteenth layer) of 1000 units.

C. Transfer Learning With Leveraging Pretrained Models

ImageNet is a research project to develop a large database of images with annotations e.g. images and their labels. Pretrained models like InceptionV1, Inception V2, VGG-16 and VGG-19 are already trained on ImageNet which comprises of disparate categories of images. These models are built from scratch and trained by using high GPU's over millions of images consisting of thousands of image categories. As the model is trained on huge dataset, it has learned a good representation of low level features like spatial, edges, rotation, lighting, shapes and these features can be shared across to enable the knowledge transfer and act as a feature extractor for new images in different computer vision problems. These new images might be of completely different categories from the source dataset, but the pretrained model should still be able to extract relevant features from these images based on the principles of transfer learning. In this paper we will unleash the power of transfer learning by using pretrained model - VGG-16 and VGG-19 as an effective feature extractor to classify four type of corn leaf diseases even with fewer training images.

IV. ANALYSIS

As discussed earlier, first we will train our data without augmentation with VGG-16 and VGG-19. Later we will improve the accuracy using image augmentation technique. Finally, we will leverage the pretrained model VGG-16 and VGG-19 which is already trained on a huge dataset with diverse range of categories to extract features and classify images.

All the evalutation metrics will be compared in later stage.

*A. Pretrained Transfer Learning model as a feature extractor without Data Augmentation*
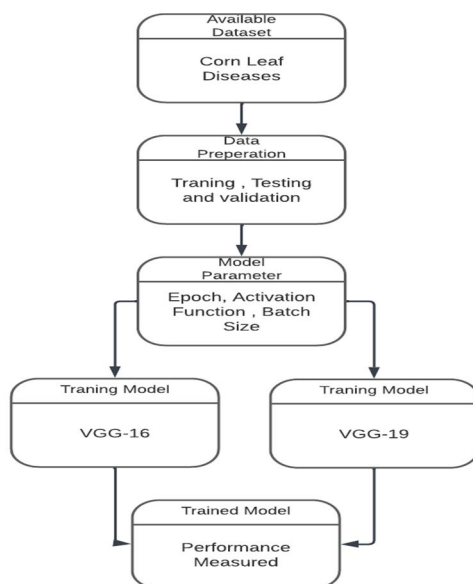
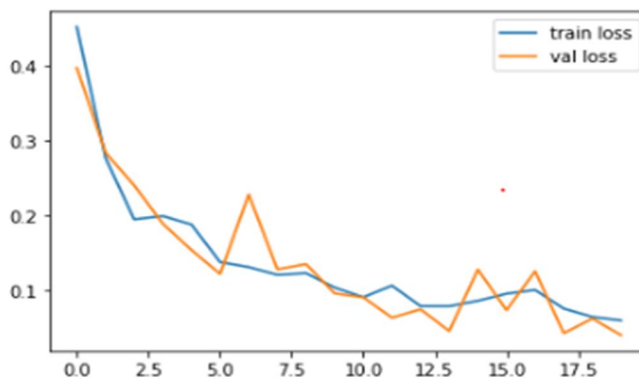*1)* *VGG-16 without data augmentation*

```
from keras.applications import VGG16
from keras.models import Model
import keras
vgg16 = VGG16(input_shape=IMAGE_SIZE + [3], weights='imagenet', include_top=False)
```

Above is the code to call VGG-16 pretrained model. We need to include weights = 'imagenet' to fetch VGG-16 model which is trained on the imagenet dataset. dataset. It is important to set include_top = False to avoid downloading the fully connected layers of the pretrained model.

Below are the model metrics for VGG-16 Model accuracy and loss after fine tuning the pretrained model without data augmentation.
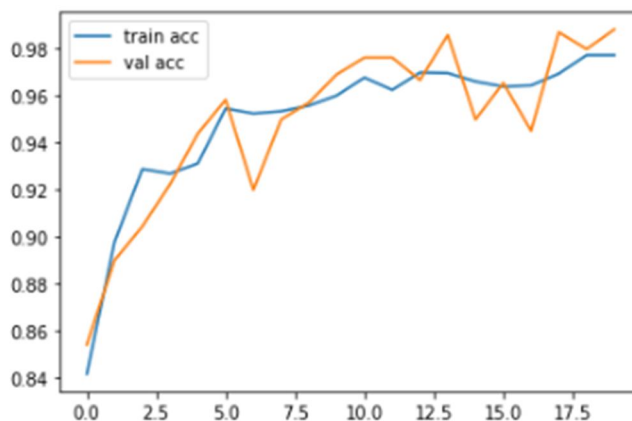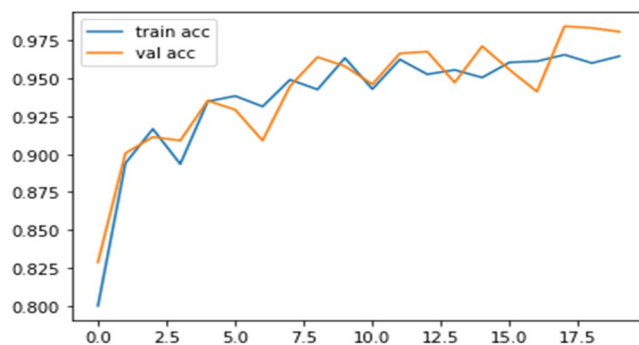

Traning and Validation accuracy plot.

Traning and Validation loss plot.

*2)* *VGG-19 Without Data Augmentation*

```
from keras.applications import VGG19
from keras.model import Model
import keras
vgg19 = VGG19(input_shape=IMAGE_SIZE + [3], weights='imagenet', include_top=False)
```

Above is the code to call VGG-19 pretrained model. We need to include weights = 'imagenet' to fetch VGG-16 model which is trained on the imagenet dataset. dataset. It is important to set include_top = False to avoid downloading the fully connected layers of the pretrained model.

Below are the model metrics for VGG-19 – Model accuracy and loss after fine tuning the pretrained model without data augmentation.

Traning and Validation accuracy plot.
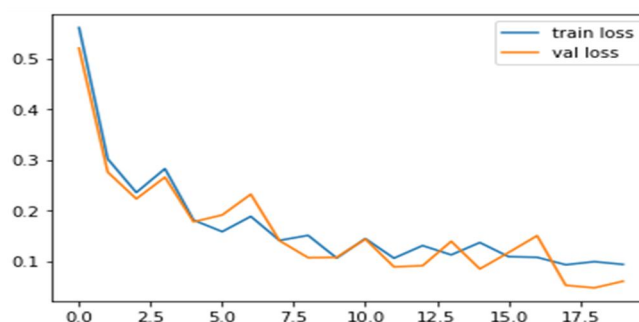
Traning and Validation loss plot.

B. Pretrained Transfer Learning Model As A Feature Extractor With Data Augmentation
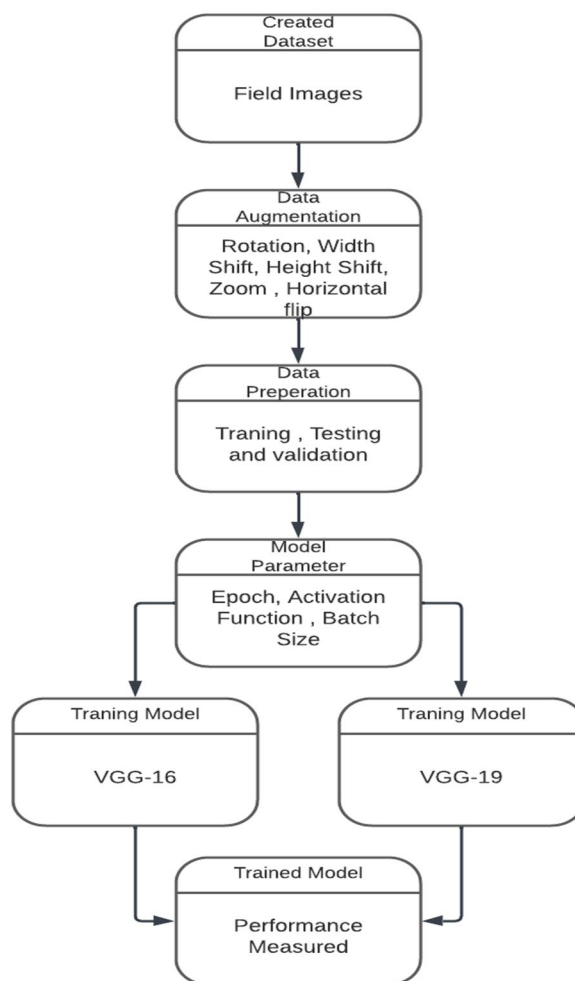
1) Data Augmentation

The performance of most ML models, and deep learning models in particular, depends on the quality, quantity and relevancy of training data. However, insufficient data is one of the most common challenges in implementing machine learning in the enterprise. This is because collecting such data can be costly and time-consuming in many cases.

Data augmentation is a process of artificially increasing the amount of data by generating new data points from existing data. This includes adding minor alterations to data or using machine learning models to generate new data points in the latent space of original data to amplify the dataset.

a) Rotating the image randomly by 50 degrees using the rotation_range parameter.
b) Translating the image randomly horizontally or vertically by a 0.2 factor of the image's width or height using the width_shift_range and the height_shift_range parameters.
c) Applying shear-based transformations randomly using the shear_range by 0.2 parameter and Zoom by 0.2

```python
from keras.preprocessing.image import ImageDataGenerator, array_to_img, img_to_array, load_img

datagen = ImageDataGenerator(
        rotation_range=50,
        width_shift_range=0.2,
        height_shift_range=0.2,
        shear_range=0.2,
        zoom_range=0.2,
        horizontal_flip=True,
        fill_mode='nearest')
```
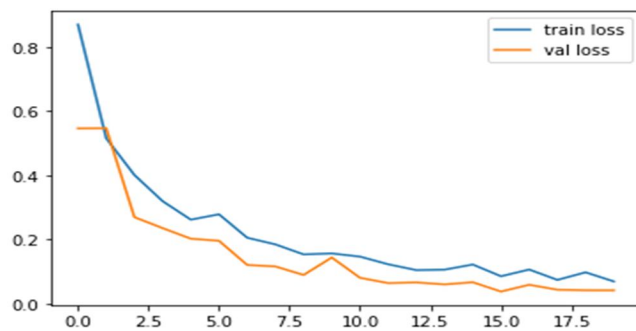
2) VGG-16 With Data Augmentation.

Below are the model metrics for VGG-16 Model accuracy and loss after fine tuning the pretrained model with data augmentation.
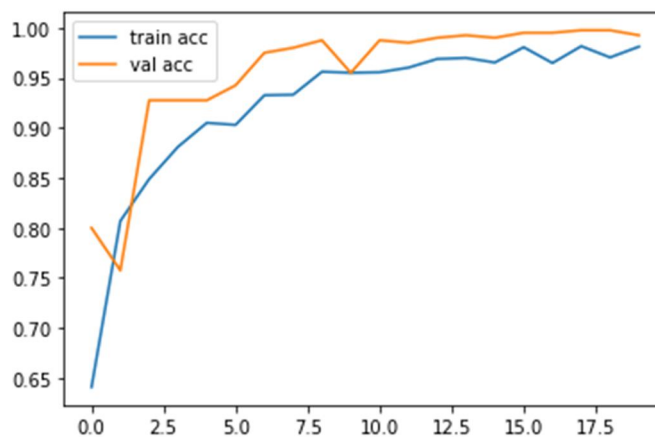
Traning and Validation accuracy plot.

Traning and Validation loss plot.

3) VGG-19 With Data Augmentation

Below are the model metrics for VGG-19 Model   accuracy and loss after fine tuning the pretrained model with data augmentation.
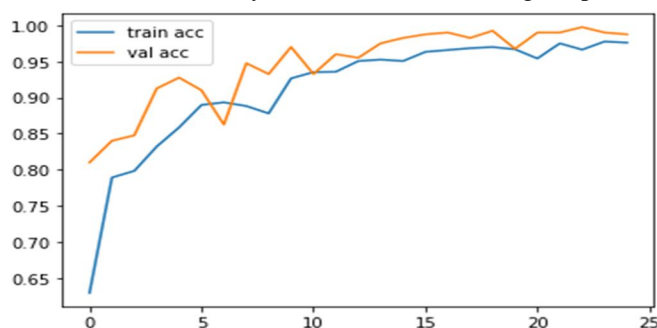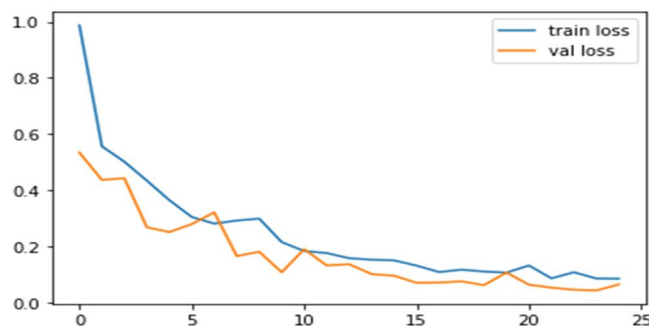

Traning and Validation accuracy plot.

Traning and Validation loss plot.

V.   COMPARATIVE RESULTS

	Training accuracy	Validation accuracy
VGG-16 without data augmenatation	97.10%	98%
VGG-19 without data augmenatation	96.47%	97.55%
VGG-16 with data augmenatation	98.20%	99.25%
VGG-19 with data augmenatation	97.60%	98.75%

Above table shows training and validation accuracy for two different model using with and without data augmentation.The first model VGG-16 without Data augmentation gives validation accuracy of 98%, but with data augmentation its validation accuracy is 99.25%. And the second model VGG-19 without Data augmentation gives the validation accuracy of 97.55%,but with Data augmentation its gives the validation acuuracy of 98.75%.

VI. CONCLUSION

The main goal of this research work is to train our model with and without data augmentation. So, we can say that by using the data augmentation with our model we can enlarge our data and introduce some new data point from the existing data for our model the get the better accuracy and predicition

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