

Covid-19 Detection

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Course: MTH 5320 Neural Networks (Project 1)

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Objective

The objective of this project is to determine whether a person is infected by Coronavirus or not. Chest Radiography is currently one of the crucial methods for the detection of COVID- 19 in patients. Chest radiography includes Chest CT- Scans and Chest X-Ray. The project should be able to detect Covid-19 from either Chest X-ray or Chest CT-Scan or both.

Introduction

COVID-19

Covid-19 is also termed as “Coronavirus(CoV).” It is a novel virus that was not identified in humans before 2020. Cov is the large family of SARS-Cov, and it is seen to be transmitted from animals to humans. This virus causes illnesses such as common cold, respiratory problems, etc. The outbreak of this virus has resulted in a pandemic; it has affected 37.1 million people and has caused 1.07 Million fatalities worldwide till date.

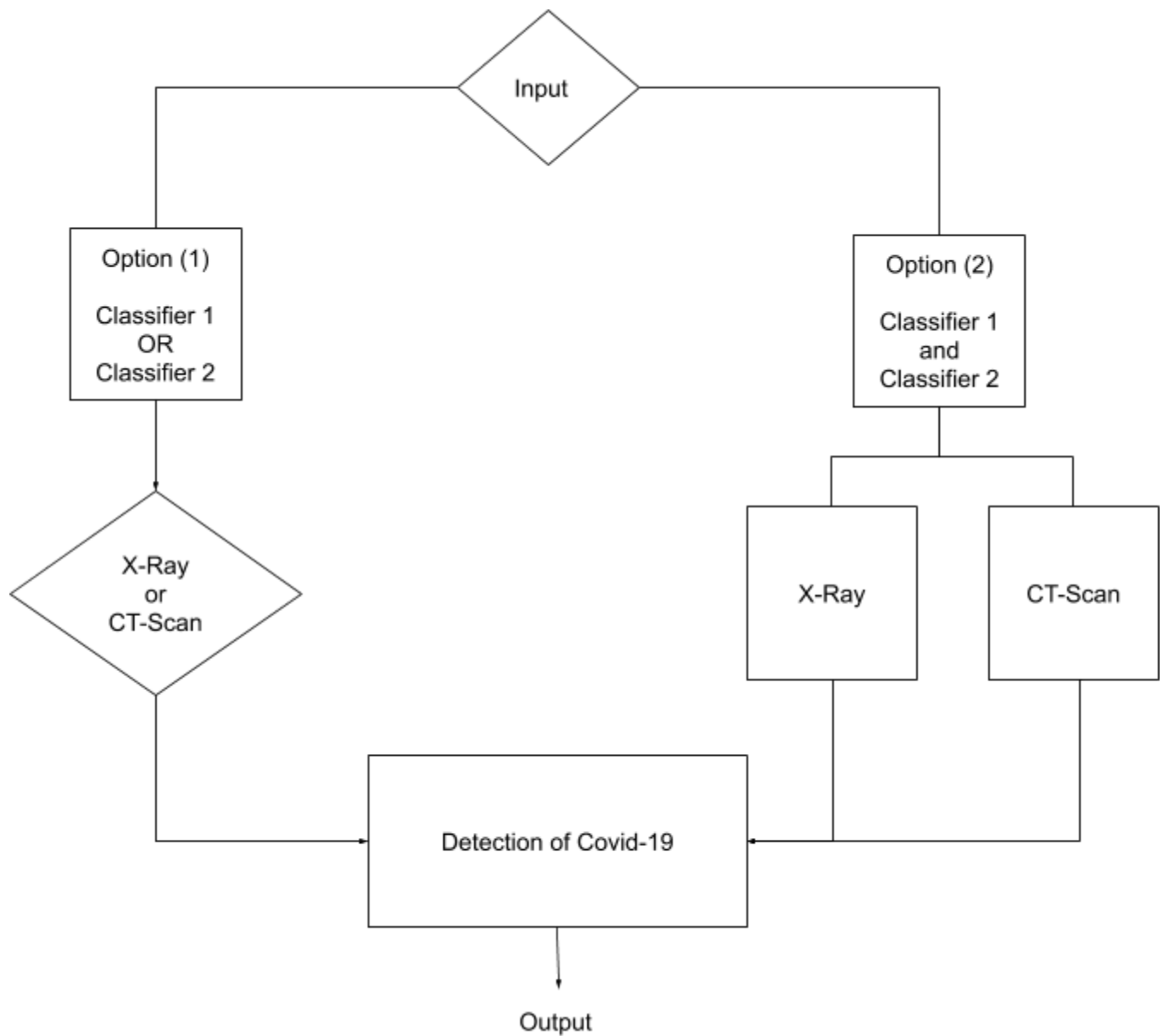
Why detection from Chest Radiography?

To provide Immediate results.

Currently, the Reverse transcription-polymerase chain reaction(RT PCR) test is taking 2-3 hours for the results.

Extend of spread can be detected from chest radiography.

Description



A Multi-Model Neural Network Classification
Classifier 1: Classification of Chest CT - Scan
Classifier 2: Classification of Chest X-Ray

Classifier 1 - Chest CT Scans

Dataset

Dataset Used: [CT Scans for COVID - 19](#)

Details :

Label 1 - NiCT - Images with no information (5705 Images)

Label 2 - niCT - Negative Covid-19 CT Scans (9979 Images)

Label 3 - piCT - Positive Covid-19 CT Scans (4001 Images)

This data set has some images of shape (512 x 512) and some of (1211 x 1211) pixels.

Data Pre-Processing

The Images from Label “NiCT” were removed as they had no information, which can help in classification.

1) Resizing

Original Image Size : 512 x 512 Pixels and 1211 x 1211 Pixels

Converted Image Size : 75 x 75 ,

Reason: Faster Execution, Reducing computational complexity, and time.

2) Normalization

Method 1 - Using `normalize()` function - It does standard normalization, $\mu=0$ and $\sigma=1$

Method 2 - Using `MinMax Scaler ()` - In this approach, the data is scaled to a fixed range, usually 0 to 1

Processed Dataset :

The dataset was processed into two new labels :

Label: ‘1’ → Negative COVID - 19 (9979 Images)

Label: ‘2’ → Positive COVID - 19 (4001 Images)

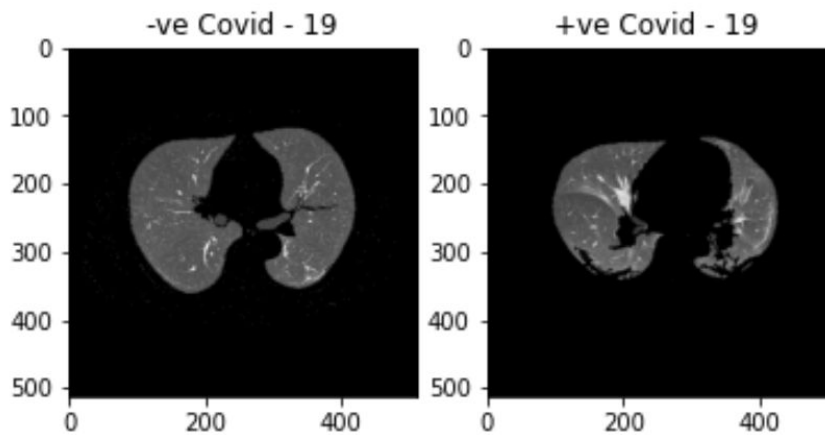
Images from both the labels are converted into shape (75,75,3)

3 represents the Channel.

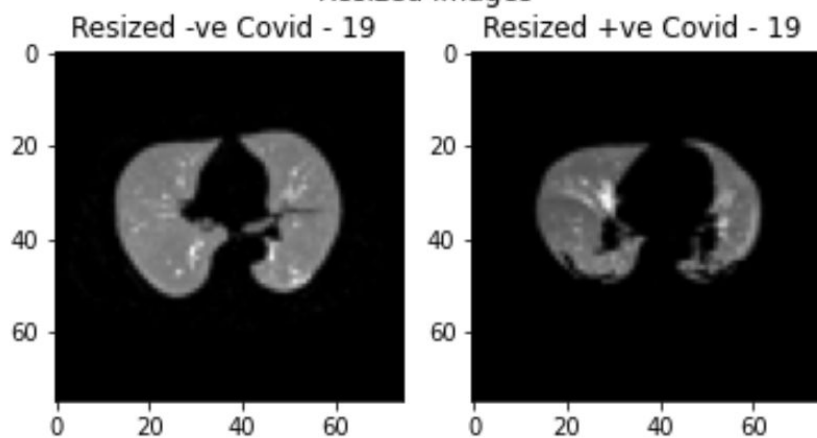
Data Visualization



Original Images



Resized Images



As shown in the image, there is no major data loss in the resized image.

Architectures, Tuning - Hyperparameters, Regularization.

Architecture: Input Layer → Hidden Layers → Output Layer

As the processed images are in the size of 75 X 75 pixels and 3 channels.

The input Layer has $(75 \times 75 \times 3)$ or (16875) Neurons.

We have 2 Labels so the Output layer will have (2) Neurons

Architecture: $[(75 \times 75 \times 3), \text{Hidden- layers}, 2]$

Network Architectures Tested :

$[(75 \times 75 \times 3), 16, 2]$

$[(75 \times 75 \times 3), 64, 16, 2]$

$[(75 \times 75 \times 3), 128, 16, 2]$

$[(75 \times 75 \times 3), 128, 64, 2]$

$[(75 \times 75 \times 3), 256, 128, 64, 2]$

$[(75 \times 75 \times 3), 512, 256, 128, 64, 2]$

Along with different Hidden layers, a total of 11 different architectures with different Combinations of Activation function, Loss function, Weight initialization methods were tested.

Parameters Tested :

Activation Function : Sigmoid , ReLU , ELU

Loss Function: cross-entropy and sum-of-square

Regularization : L1 regularization, L2 regularization, L1 & L2 regularization.

Weight Initialization Methods: Normal, Glorot, LeCun, He, Uniform

Results

Highest Accuracy

Architecture : [(75*75*3) , 512 , 256 , 128 , 64 , 2]

Activation Function : ReLU

Loss Function: Sum-of-Squares

Weight Initialization: Glorot

Momentum: 0

Learning Rate : 0.01

Regularization: L1 Regularization , L 1 = 0.01, L2 =0

Accuracy :

Training set accuracy

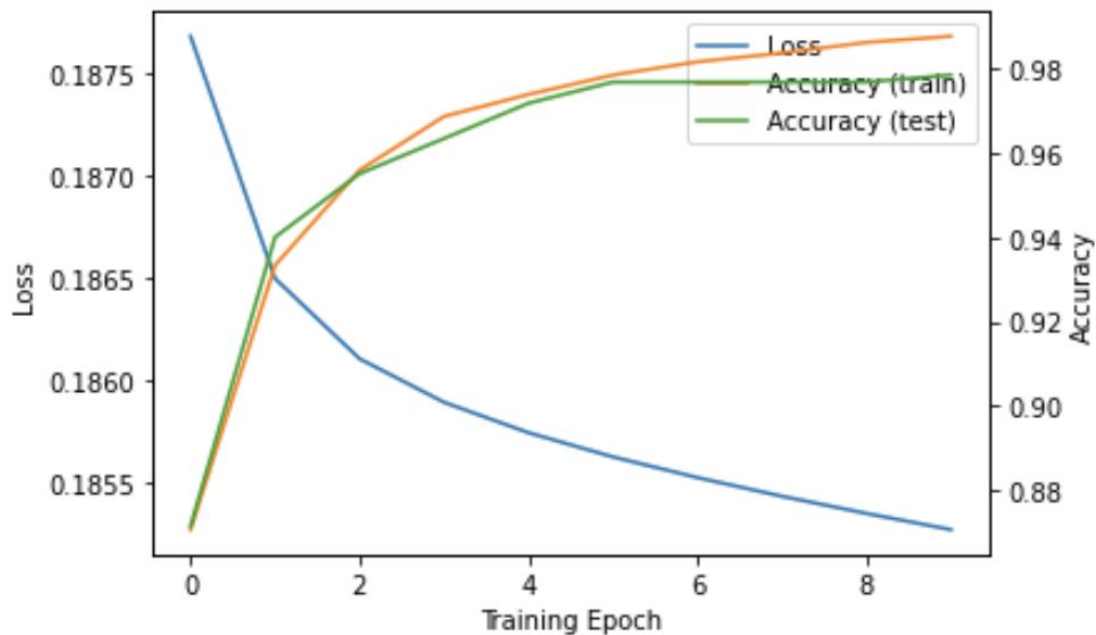
0.9875

Test set accuracy

0.9783333333333334

Val set accuracy

0.9833333333333333



Second Highest Accuracy :

Architecture : [(75*75*3) , 512 , 256 , 128 , 64 , 2]

Activation Function : ELU

Loss Function: Sum-of-Squares

Weight Initialization: Glorot

Momentum: 0

Learning Rate: 0.1

Regularization: L1 = 0 , L2 =0

Accuracy :

Training set accuracy

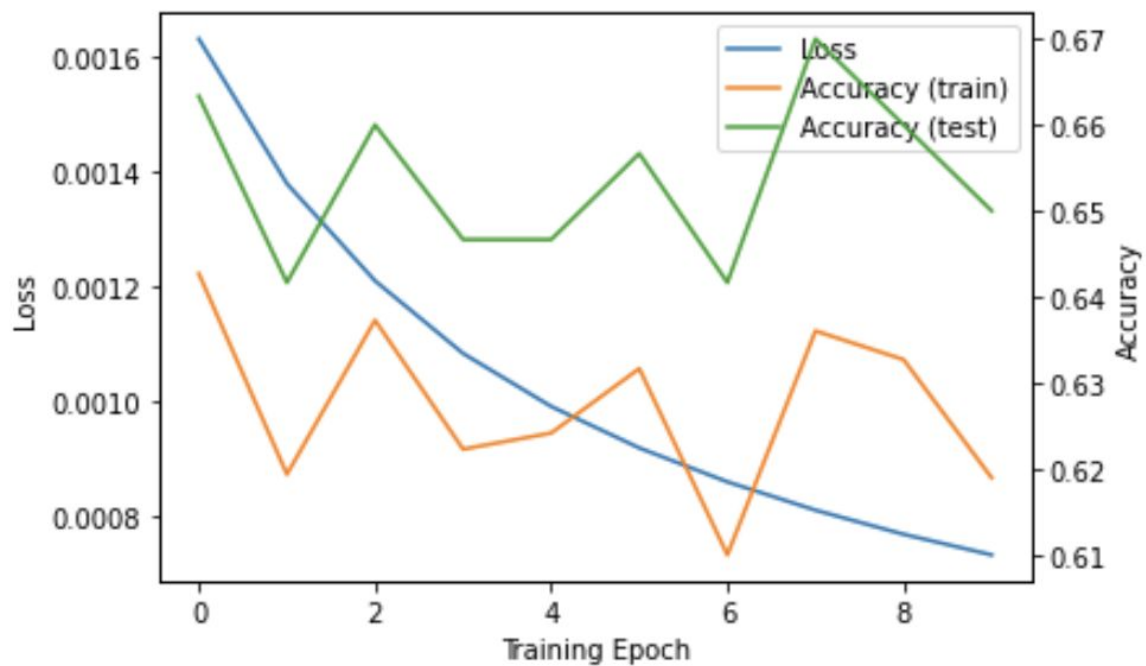
0.6189583333333334

Test set accuracy

0.65

Val set accuracy

0.65



Third Highest Accuracy :

Architecture : [(75*75*3) , 512 , 256 , 128 , 64 , 2]

Activation Function : ELU

Loss Function: Cross-Entropy

Weight Initialization: Uniform

Momentum: 0

Learning Rate : 0.01

Regularization: L1 = 0 , L2 = 0

Accuracy :

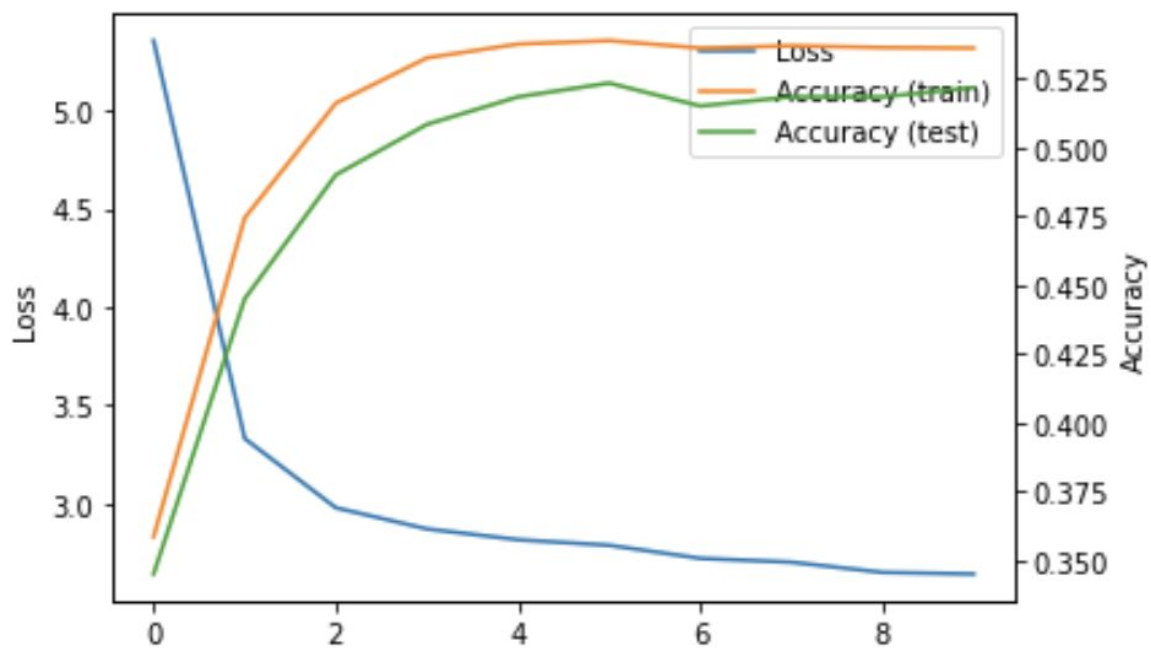
0.5360416666666666

Test set accuracy

0.5216666666666666

Val set accuracy

0.52



Classifier 2: Chest X-Ray

Dataset

Dataset Used

[Positive COVID-19 X-Rays](#)

[Negative COVID-19 X-Rays](#)

[Dropbox Link](#)

Details

Label: '1' is assigned for positive COVID-19, images were downloaded from the dataset.

Label: '2' is assigned for negative COVID-19, Images from folder "Normal" used.

There were only 224 Images combined together from both the labels, which is very low, so data augmentation is required.

Data Augmentation & Data Pre-Processing

Normalization

Images were normalized with a scale of $1/255$, to reduce the computational complexity and time.

Resizing

Original Image Size : 1165 x 1165 Pixels, Channel = 3

Converted Image Size : 75 x 75 pixels , Channel = 3

Data Augmentation is a technique to increase the number of Neural Network training images without changing its orientation.

Features used for Data Augmentation :

Horizontal Flip: Images are flipped Horizontally.

Shear Range: Images were slanted by nearly 20% (> 20% can change Image Orientation)

Zoom = Images were Zoomed by 20% (> 20% can change Image aspect ratio)

A total of :

Train - 4700 Images for Training, 700 Images for Testing, 700 Images for Validation were created by Augmentation.

Data Preprocessing was done along with the data augmentation.

ImageDataGenerator of Keras was used for DataAugmentation:

```
#As data is low, we will perform augmentation for Training Data
from keras.preprocessing.image import ImageDataGenerator, array_to_img, img_to_array, load_img
datagen = image.ImageDataGenerator(

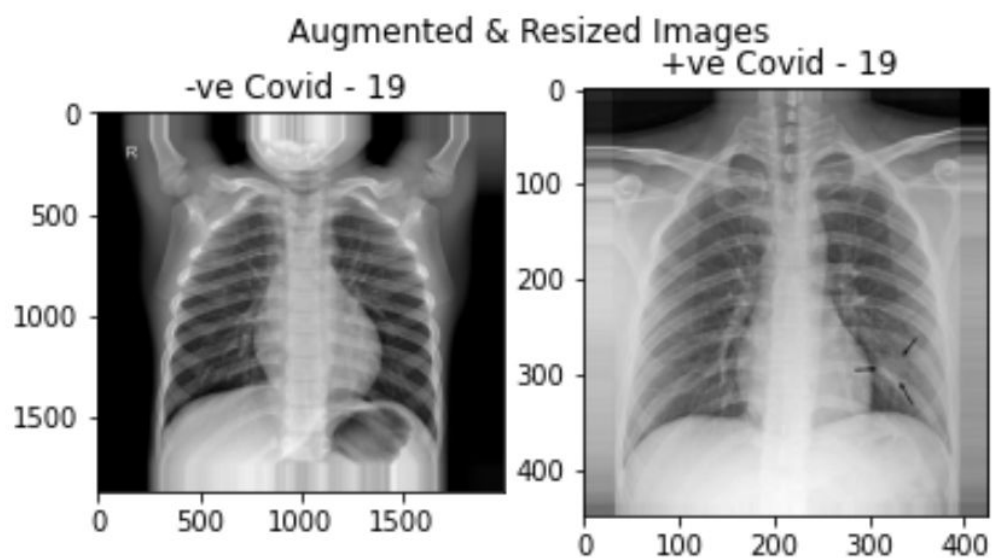
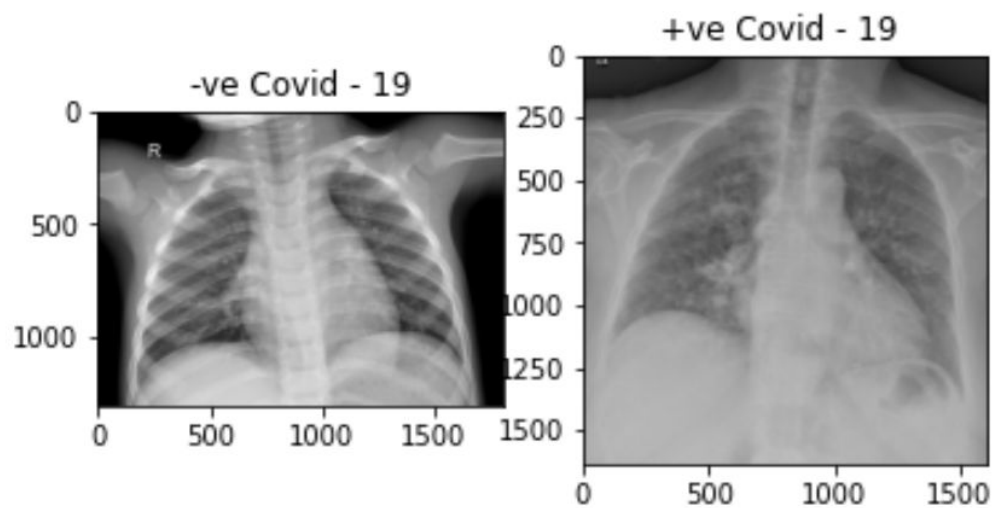
    #Parameters for Data Augmentation
    #Rescaling the images
    rescale = 1./255,
    #Flipping the image
    horizontal_flip = True,
    #Slanting the image
    shear_range = 0.2,
    #Zooming
    zoom_range = 0.2,

)
```

Data Visualization



Original Images



As seen in figure Augmented and Resized Images are having no major loss.

Architectures, Tuning - Hyperparameters, Regularization.

Architecture: Input Layer → Hidden Layers → Output Layer

As the processed images are in the size of 75 X 75 pixels and three channels.

The input Layer has $(75 \times 75 \times 3)$ or (16875) Neurons.

We have 2 Labels, so the Output layer will have (2) Neurons.

Architecture: $[(75 \times 75 \times 3), \text{Hidden- layers}, 2]$

Network Architecture Tested :

$[(75 \times 75 \times 3), 16, 2]$

$[(75 \times 75 \times 3), 64, 16, 2]$

$[(75 \times 75 \times 3), 128, 16, 2]$

$[(75 \times 75 \times 3), 128, 16, 2]$

$[(75 \times 75 \times 3), 256, 128, 16, 2]$

Along with different Hidden layers, 13 different architectures with different Combinations of Activation function, Loss function, Weight initialization methods were tested.

Parameters Tested :

Activation Function : Sigmoid , ReLU , ELU

Loss Function: cross-entropy and sum-of-square

Regularization : L1 regularization, L2 regularization, L1 & L2 regularization.

Weight Initialization Methods: Normal, Glorot, LeCun, He, Uniform

Results

Highest Accuracy

Architecture : [(75*75*3) , 128 , 16 , 2]

Activation Function : ELU

Loss Function: Sum-of-Squares

Weight Initialization: normal

Momentum: 0

Learning Rate : 0.01

Regularization: L1 & L2 Regularization , L1 = 0.001 , L2 = 0.001

Accuracy:

Training Time : 295.3686304092407 seconds

Training set accuracy

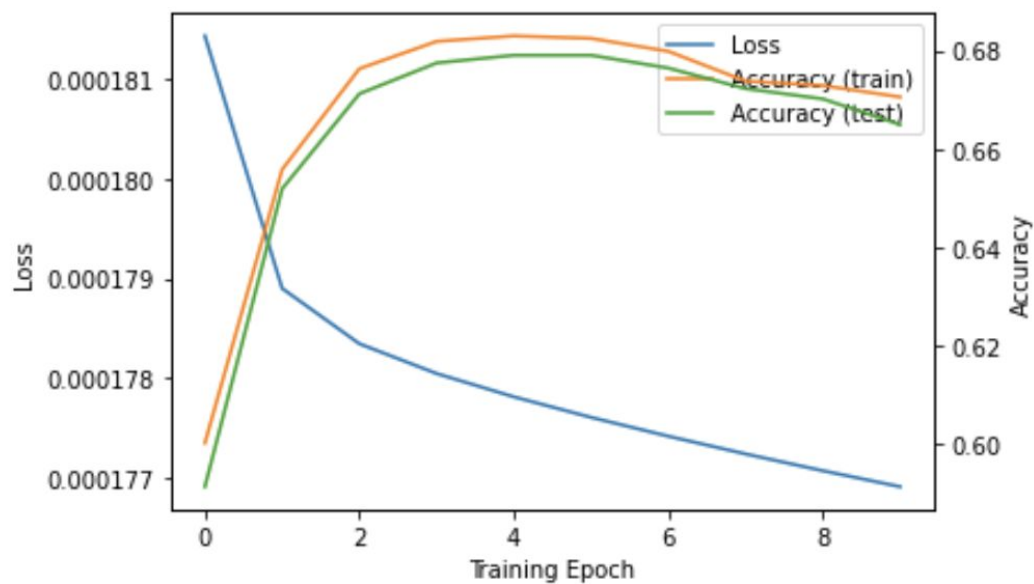
0.670534813319879

Test set accuracy

0.6649269311064718

Val set accuracy

0.6388744137571651



Second Highest Accuracy

Architecture : [(75*75*3) , 256, 128, 16, 2]

Activation Function : ReLU

Loss Function: Sum-of-Squares

Weight Initialization: normal

Momentum: 0

Learning Rate : 0.01

Regularization: L1 & L2 Regularization , L1 = 0.001 , L2 = 0.001

Accuracy:

Training set accuracy

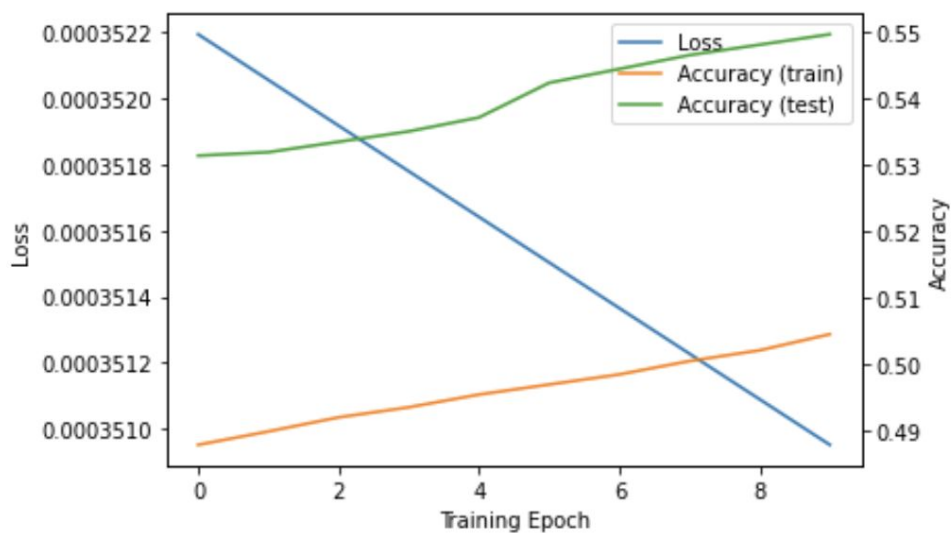
0.5044399596367306

Test set accuracy

0.5495824634655533

Val set accuracy

0.5471599791558103



Third Highest Accuracy

Architecture : [(75*75*3) , 128 , 16 , 2]

Activation Function : ELU

Loss Function: Sum-of-Squares

Weight Initialization: Normal

Momentum: 0

Learning Rate : 0.01

Regularization: L1 = 0 , L2 = 0

Accuracy:

Training set accuracy

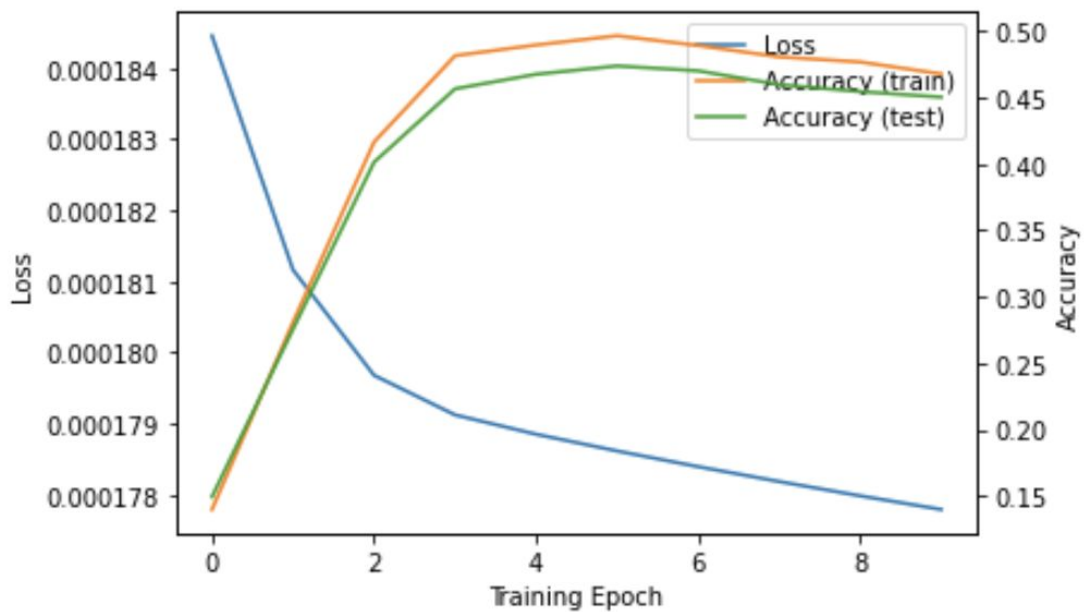
0.4679112008072654

Test set accuracy

0.45041753653444677

Val set accuracy

0.4585721730067744



Conclusion

It is seen that Learning rate , Weight Initialization and Loss Function had the major impact on accuracy.

Future Work

More Detailed Feature Extraction using higher end models like CNN can provide better accuracy.

Images will be augmented in more numbers and to be tested on CNN Model.