Prediction of Covid-19 Using Hyperparameter Optimized Convolutional Neural Network

S Mohana Saranya[a], R R Rajalaxmi[b], S.Mohanapriya[c], S.Prasida[d], P.Nithyalaxmi[e] and J.Revathi[f]

[a] Assistant Professor, Department of CSE, Kongu Engineering College, India
[b]Professor, Department of CSE, Kongu Engineering College, India.
[c]Assistant Professor, Department of CSE, Kongu Engineering College, India.
[d,e,f] UG Student, Department of CSE, Kongu Engineering College, India.

Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 20 April 2021

Abstract: All over the world, there are heavy cases of COVID-19 patients those exhibiting the symptoms. In a very short period of time, this pandemic virus has become drastic across the country. A fast detection of corona spread is necessary for both the infected and uninfected person for the further spreading. The preexisting techniques used methods like Linear Regression, Support Vector Machine (SVM) and Naive Bayes are not producing better results. Our aim is to bring out better outcomes and to produce good accuracy. Instead of machine learning we opt for deep learning approaches in our work. Image preprocessing will be done by Histogram Equalization algorithm and further the image classification is done by Convolution Neural Network (CNN) architectures such as VGG-16 and ResNet-50 by using 350 images of X-ray datasets. From the comparison, VGG-16 produce better train and test accuracy of 92% and 98.4% .Hence the accuracy of VGG-16 was further tuned using Hyper Parameter Optimization using Tensor Board which produces better outcomes.

Keywords: Deep learning, CNN, VGG-16, ResNet-50, Hyper Parameter Optimization.

1. Introduction

The pandemic novel corona virus (COVID-19) has resulted in economical contingency and healthcare issues. The whole world suffered from this virus, not only in one specific country. It was initially identified from Wuhan, in China in December 2019. At the month of January the WHO has announced a statement the spreading of COVID-19 to be a part of International solicit from public health emergency control[1]. In several countries many scientists are doing research but they didn't discover any vaccines. The fast detection of spread is necessary for both the infected and uninfected person for the further spread. It is transmitted from one person to another person who contacts an infected person like a chain process. In the diagnosis of these epidemic doctors, nurses and hospital staffs play a vital role while there is severe situation. Rise in temperature, High Fever, cold, Sore throat, Head ache, Loss of smell , Fatigue, Dry cough, Tiredness are the symptoms for the deadly spreading corona virus[2]. Initially the people get affected by throat infection as the symptoms for the novel corona virus disease, and suddenly people face difficulty in breathing. These will take 5-6 days to show that the person gets infected with corona virus. People with mild symptoms will recover soon by taking home remedies. It will be severe for the person who is affected with diabetes, heart problems, lung cancer, asthma etc... This makes high risks of mortality in patients.

COVID-19 can medically be diagnosed on the basis of symptoms. In addition to laboratory testing, the swabs taken from the nose and throat then chest Computed tomography images are useful in diagnosing COVID-19 in individuals with high clinical infections. In order to diagnose the disease effectively, researchers and medical analyst have developed many approaches like Machine learning techniques. The existing work is applicable for particular region, and gives less accuracy in forecasting the upcoming cases[3]. In our work, to enhance accuracy in prediction, Deep Learning method is preferred. As DL gives a hopeful result in wide scenarios, recently it has also entered into the domain of medicine for achieving better accuracy. CNN, one of the famous DL model emerged being the best in image classification and gave surprising progress. Multiple outperforming pre trained models such as Alex Net, VGG16, Google Net, ResNet50, Squeeze Net and many more available to gain the hopeful result[4].

The significance of this paper is to collect the COVID-19 dataset and to improvise the image appearance, using histogram equalization, in turn to classify the covid affected person X-ray and non covid persons X-ray images with far above the ground accuracy, with the help of hyper parameter optimization using tensor board. The remaining part of this paper is planned as Chap 2 present the related work carried out in the existing paper. Chap 3 explains the brief discussion about the proposed work done for the classification of covid-19 patients Chap 4 discuss about the works mentioned where the results achieved and conclusion of the whole paper was in Chap 5.

2. Related Work

A Squeeze Net data based light CNN model is preferred in this work. The work classifies the covid and non covid x-ray images using a dataset of 2758 images. Where 60% was used for training, 20% was used for test and 20% was used for validation. The resultant method brings accuracy of 85.03%[5].VGG-16 have compared with different CNN models like ResNet18, ResNet50 and Squeeze net. The dataset contains 2905 images with three class labels like covid, non covid and pneumonia. The dataset was divided in the fashion of 80:20 train and test ratio. The proposed architecture exceeds the current prediction accuracy and gave the highest accuracy of 92.7%[6].Multi Objective Differential Evolution (MODE) based CNN model was compared with popular architecture likes CNN, ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS).Where their proposed design achieves an accuracy of 95.8%. 5000 CT scan images with 60:40 test train ratio which belongs to two different classes labels[7].

Among various deep learning model, Xception is differentiated with Inception V3, ResNeXt by using 6432 chest x-ray images. Three class labels like covid, non covid and pneumonia were classified using Xception has emerged an accuracy of 97.2%[8].The categorization of covid and non-covid patients using DenseNet-16,VGG-19 and ResNet-50 architectures with the dataset of around 1000 CT scan images was experimented. Among them VGG-19 achieves better accuracy of 94.5%[9].

ResNet-50,GoogleNet and ResNet-18 architectures are used for categorization of covid, non covid and pneumonia patients using X-Ray dataset containing 3850 images in the ratio of 50:30:20.Among them ResNet-18 achieves better accuracy of 97.5%[10]. InceptionV3, ResNet-80, DenseNet-121and few more models are used for the categorization of covid and non-covid patients using ensemble of transfer learning. X-ray image dataset was used in the ratio of 60:25:15 for train test and validate. The result shows that ensemble transfer learning provides a better accuracy than normal transfer learning strategies[11]. In this paper ResNet-18,ResNet-80 and DenseNet-121 are used along with Genetic DCNN for around 5000 X-ray image dataset in the labeling of covid and non-covid patients. GDCNN achieves outperforming accuracy of 95%[12].

AlexNet,VGGNet-16,VGGNet-19,ResNet-50 and GoogleNet algorithms was used to identify the categorization of covid and non covid patients using Ct radiography digital images dataset containing 850 images .Among them ResNet-50 achieves better accuracy of 85.5%[13]. In this paper a lightweight CNN architecture was proposed and compared with ResNet-50 along with augmentation techniques like DC-GAN for the labeling of covid and non-covid patients using nearly 3900 X-ray images dataset and the proposed model achieved better accuracy of 96%[14]. Deep CNN model, CVDNet is used in this work for recognize COVID-19 patients as normal & pneumonia affected persons using chest x-ray images .They used 1341 normal images, 219 covid images, 1345 pneumonia chest x-ray images. Residual neural network model was used. It was mainly constructed to capture global and local features of input images by using various Kernel sizes. The accuracy acquire was 96.69%[15].

Hyper Parameter Tuning Inception (HPTI-V4) model used for classification and detection of Diabetic Retinopathy from fungus images. The histogram and Inception v4 are the feature extraction process involved in segmentation process. The Bayesian Optimization technique is used for Hyper Parameter tuning in Inception v4. The HPTI-V4 acquires best accuracy of 99.49%[16]. DETL method was used to screen covid images. The 305 x-ray images were used; it is acquiring from four open source database. Class labels are normal, pneumonia, covid, other disease. The Grad-CAM is used for detection transparency to get more attention in classification. It results with best accuracy of 90.13%[17].

3. Proposed Model and Algorithm

3.1 Dataset Collection

For our work the dataset used was taken from kaggle. The compiled data set used is an open source which recently comprised of 350 X- Ray images of patients. We classify X-ray images into two parameters as NORMAL and COVID. For testing purpose we have transformed the images in the ratio containing of 70% of training data and 30% of testing data.

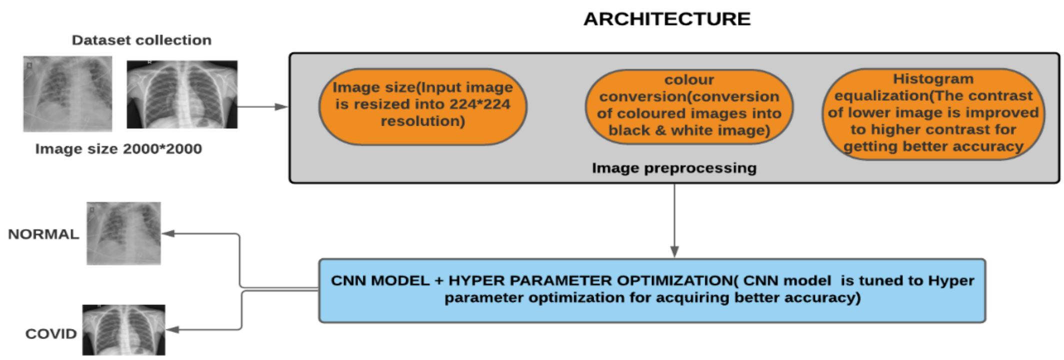

Figure: 3.2.1 Proposed Architecture

3.2 Dataset Preprocessing

For converting the data into uniform size pre-processing concept is used therefore, we have resized the original images into the similar size of 224*224.The finalized input for the model is to be proposed as 224 ×224 ×3 image. Further those images are preprocessed using histogram equalization algorithm.

3.3 Histogram Equalization

Histogram Equalization is an image processing technique which was used to improve the contrast in images. This will gain a high contrast image from the areas of lower contrast images. A color of an image represents the number of pixels in each type of a color component for given images.

Figure: 3.3.1before Histogram Equalization

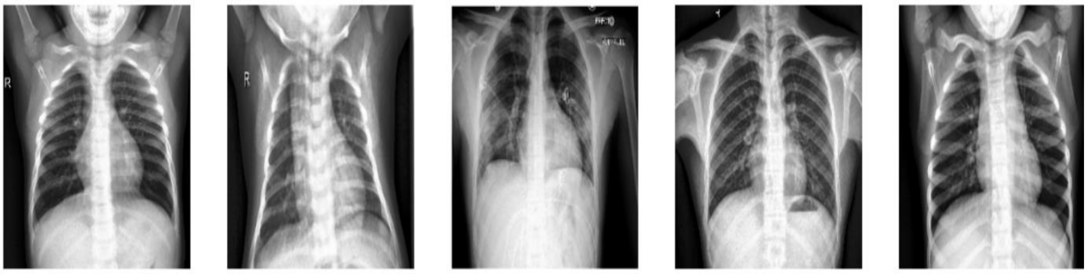

Figure: 3.3.2after applying Histogram Equalization

From the above figures 3.3.1 and 3.3.2, it clearly shows the contrast of the images are gained higher after applying Histogram Equalization algorithm, this higher contrast images tends to classify the images much better than with the lower contrast images.

3.4 Architecture

There are many variants of DL architectures are developed such as AlexNet, VGG16, GoogLeNet, ResNet50, SqueezeNet and many more to produce an outstanding performance. Here in our study we used VGG-16 and RESNET50 to find the x-ray images as COVID or NORMAL.

3.4.1 VGG-16

The Visual Geometry Group(VGG), a Convolutional Neural Network model developed by K.Simonyan and A. Zisserman. In VGG-16, a number 16 represents total layers of 16 which have the same weights.

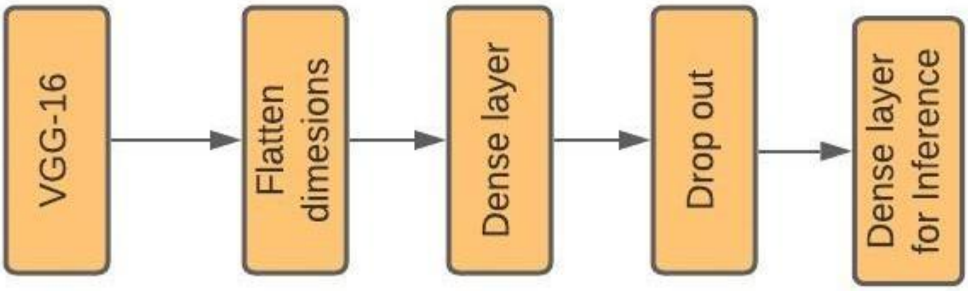

Figure: 3.1.1abstract form of VGG – 16 architecture

It contains Convolution and pooling layers. It is utilized to prepare on more pictures.VGG-16 was acquainted with diminishing the parameters in the convolution layers and enhanced preparing time.The complexity of the network regulated by VGG-16.

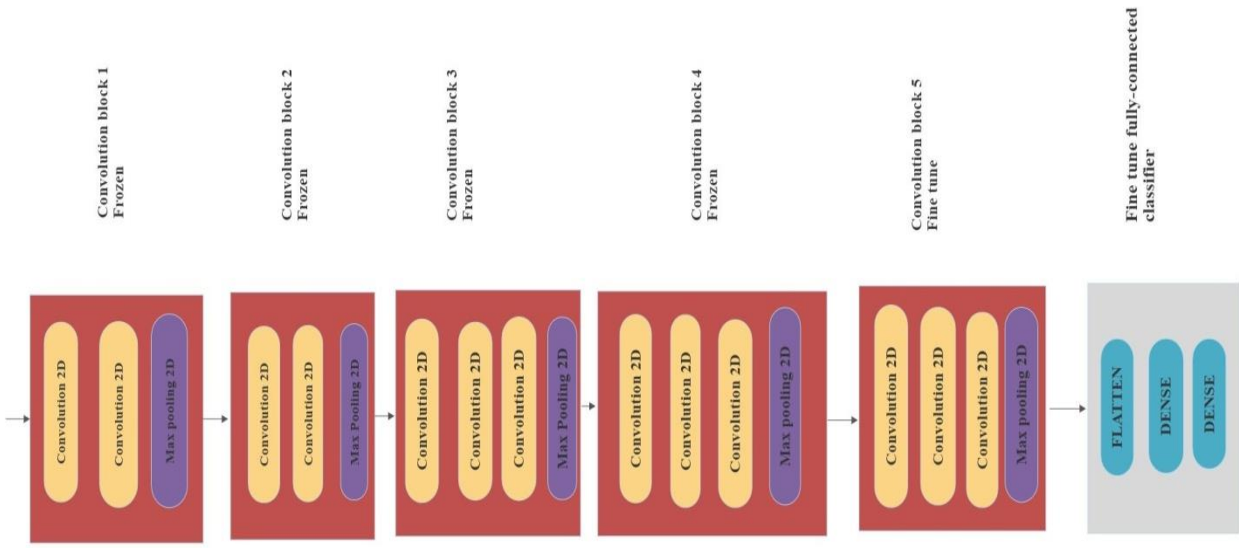

Figure: 3.1.2 Architecture of VGG-16

In the above figure, the blue layer indicates max-pooling layers along with the activation function i.e., ReLU. Each and every red rectangle column indicate the convolution layers. The layers of VGG-16 were sorted in the order of image pre-processing; the input image size was changed to 224x224 pixels. The network was trained with varied batch size and with 10 epochs. At the output, the input images were re-sized to number of pixels along with accuracy.

3.4.2 ResNet-50

ResNet-50,a CNN with 50 deep layers. It is used as a deep transfer model for future extraction. From the loaded pre-trained Image Net database which have been trained for million images. The network has an image input size of 224x224.

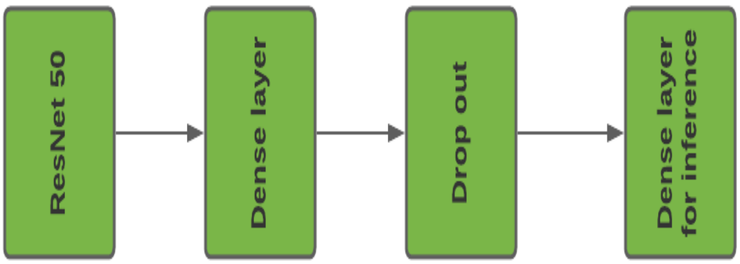

Figure: 3.2.1abstract form of ResNet-50 architecture

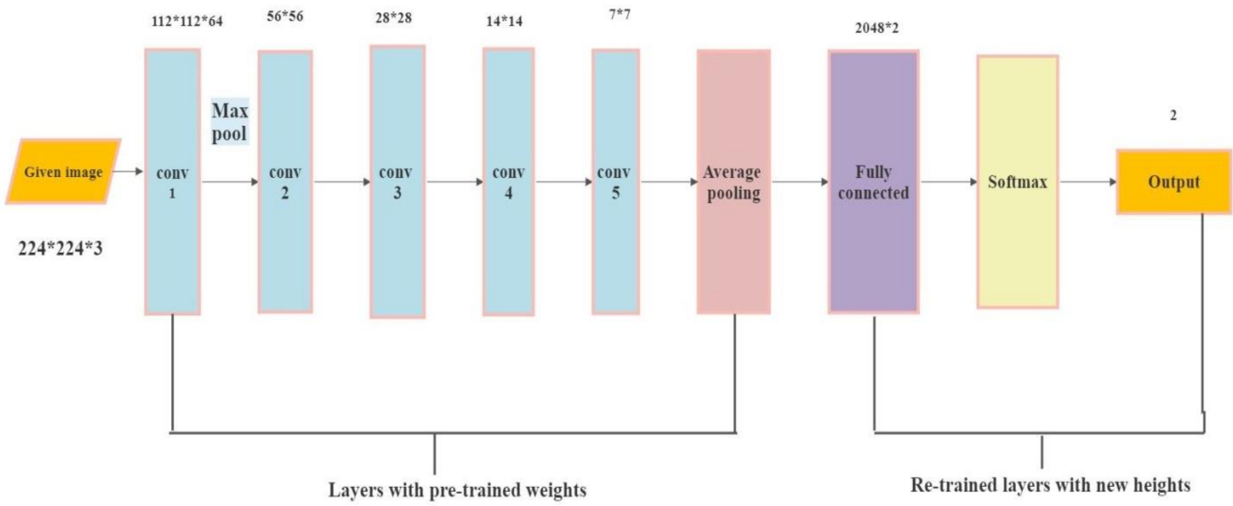

Figure: 3.2.2 Architecture of ResNet-50

A residual neural network is a subgroup of residual networks used to train million images. ResNet-50 will be useful for image classification in predicting the COVID-19 patients. It used skip connection to pass information over layers to layers allowing researchers to build deeper networks. Skip connection helps the network to understand global features. The ResNet-50 composed of 5 stages with each block having convolution and identity. Each convolution and identity blocks has each of 3 convolution layers. This architecture is used to enhance the model performance and to bring down the training time. At the output, the input images are re-sized to pixels.

3.5 Hyper Parameter Optimization

The parameters which are set by the user before the training starts are known as Hyper Parameter. Using various Hyper Parameter techniques such as learning rate or drop out, optimizer, weight size for building various deep learning models. It aims to find the right combination of various parameters and to find either minimum or maximum accuracy of a function. The accuracy of the pre-trained model is increased using this Hyper Parameter Optimization technique.

In Tensor Board, the HParams Dashboard helps in identifying the best experiment sets of hyper parameters. The steps to be followed are:

1) Summarize the experimental setup and HParams.
2) To log hyper parameters and metrics apply Tensor Flow runs.
3) Starting and logging the runs all under the one parent directory.
4) In Tensor Board's HParams dashboard the results will be visualized.

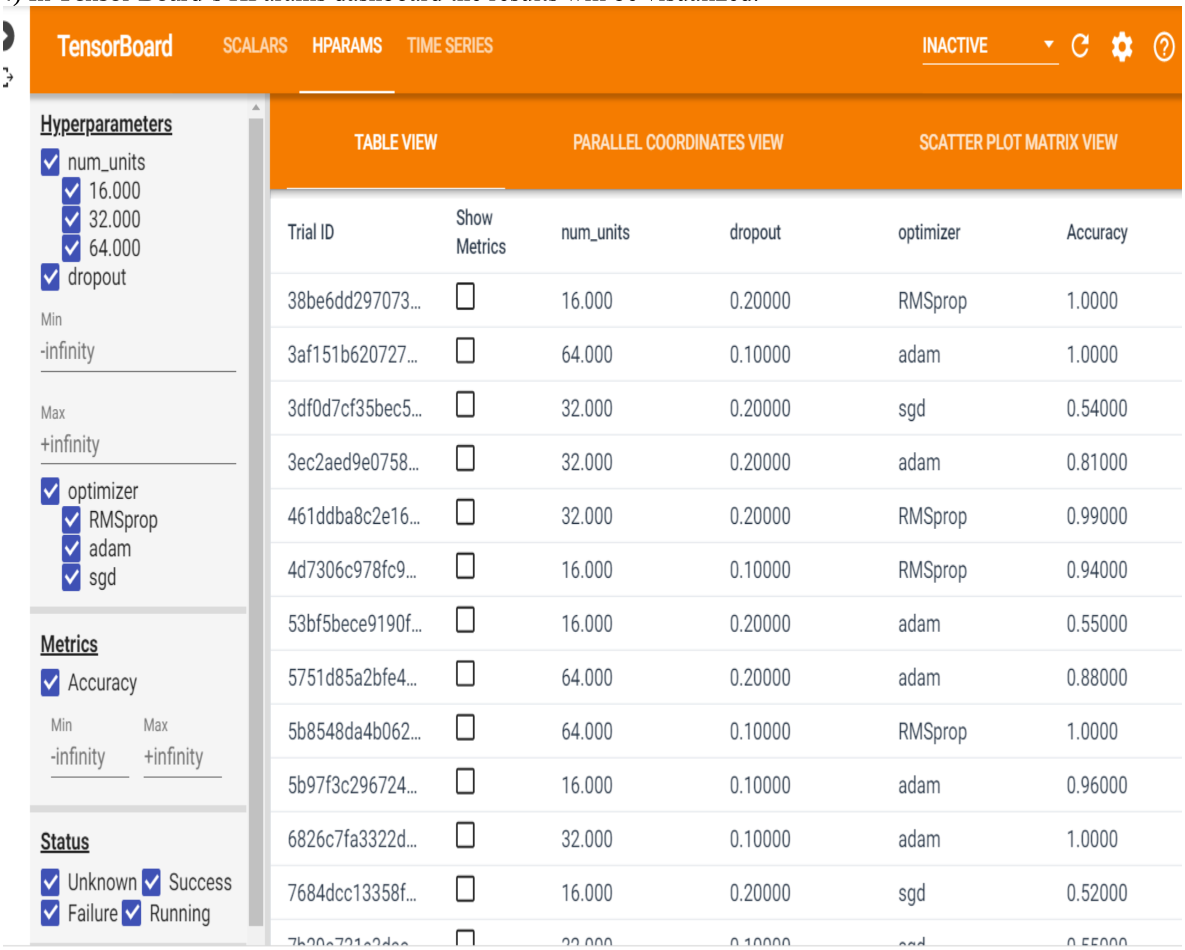

Figure: 3.4.1 Tensor board's HParams Dashboard

4. Result & Discussion

We have applied a dataset of 350 X-ray images which are taken from Kaggle with 2 class labels. The below table with graph clearly shows that the training and test accuracy using VGG-16 and ResNet-50 architecture before and after applying a Histogram Equalization algorithm.

Table 1. Accuracy without Histogram equalization

Architecture	Train	Test
VGG-16	95	87.86
ResNet-50	49	83.81

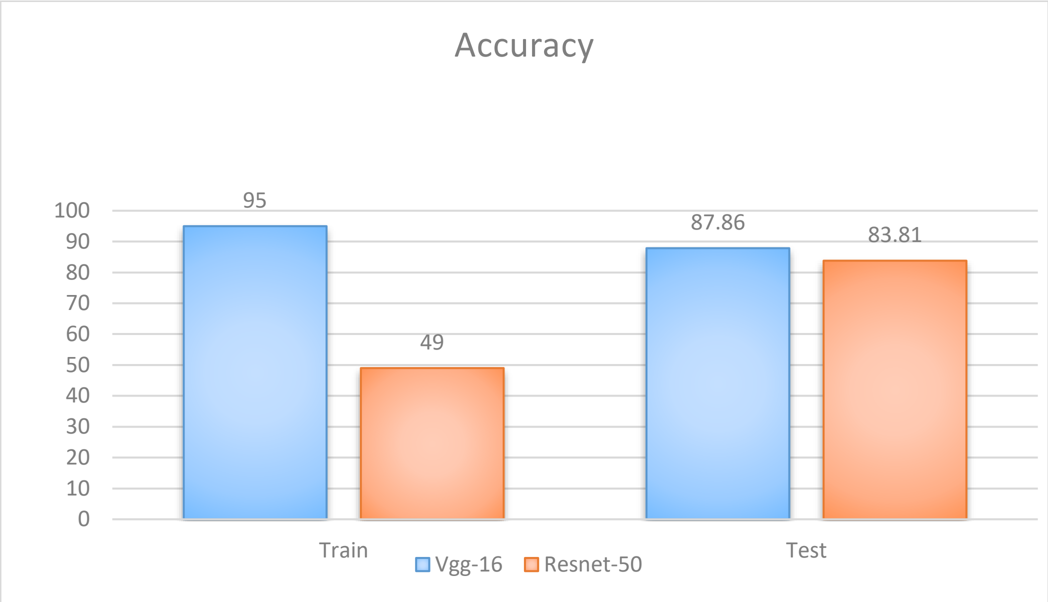

Figure: 4.1 Graph Representation for without Histogram equalization

Table 2. Accuracy with Histogram equalization

Architecture	Train	Test
VGG-16	92	98.4
ResNet-50	46	73.68

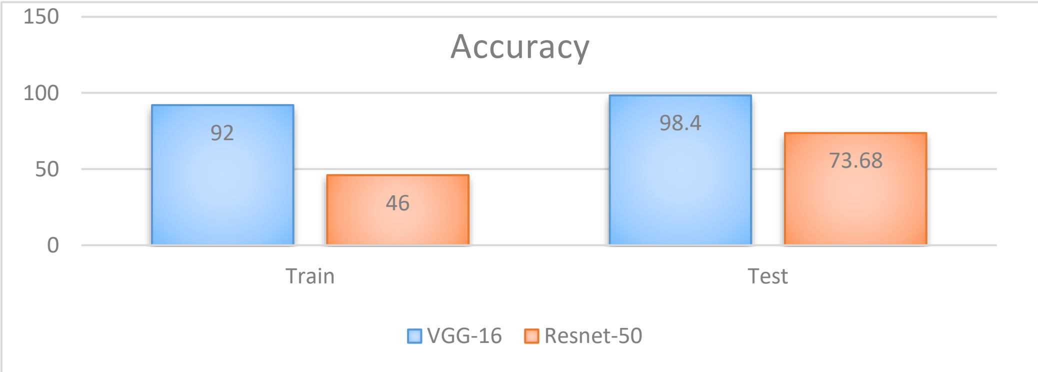

Figure: 4.2 Graph Representation for with Histogram equalization

With the comparison between two architectures, VGG-16 provides the best accuracy. Further the VGG-16 architecture was tuned using the HyperParameter Optimization using TensorBoard and which gave a promising performance increase.

num units= 16			**num units = 32**			**num units = 64**		
Dropout	**Optimizer**	**Accuracy**	**Dropout**	**Optimizer**	**Accuracy**	**Dropout**	**Optimizer**	**Accuracy**
0.1	RMS Prop	0.94	0.1	RMS Prop	0.98	0.1	RMS Prop	1.00
0.1	Adam	0.96	0.1	Adam	1.00	0.1	Adam	1.00
0.1	Sgd	0.55	0.1	Sgd	0.55	0.1	Sgd	0.47

0.2	RMS Prop	1.00	0.2	RMS Prop	0.99	0.2	RMS Prop	0.70
0.2	Adam	0.55	0.2	Adam	0.81	0.2	Adam	0.88
0.2	Sgd	0.55	0.2	Sgd	0.54	0.2	Sgd	0.47

Table 3.VGG-16 with Histogram Equalization

num units = 16			**num units = 32**			**num units = 64**		
Dropout	**Optimizer**	**Accuracy**	**Dropout**	**Optimizer**	**Accuracy**	**Dropout**	**Optimizer**	**Accuracy**
0.1	RMS Prop	0.98	0.1	RMS Prop	0.97	0.1	RMS Prop	0.95
0.1	Adam	0.96	0.1	Adam	0.85	0.1	Adam	0.99
0.1	Sgd	0.49	0.1	Sgd	0.89	0.1	Sgd	0.47
0.2	RMS Prop	0.98	0.2	RMS Prop	0.51	0.2	RMS Prop	1.00
0.2	Adam	0.55	0.2	Adam	0.99	0.2	Adam	0.98
0.2	Sgd	0.47	0.2	Sgd	0.49	0.2	Sgd	0.66

Table 4.VGG-16 without Histogram Equalization

Table 3 and Table 4 shows the comparison between the hyperparameters like batch size, optimizer and dropout and clearly shows which gaves better accuracy at which situation in VGG architecture. It also compared the VGG models trained using original dataset as well as histogram equalized dataset.

5. Conclusion And Future Work

The various architectures like VGG-16 and ResNet-50 are compared and showed VGG-16 gains a higher accuracy of 87.86% without preprocessing algorithm and 98.4% with histogram equalization algorithm. For further improvement in classification accuracy Hyper Parameter Optimization was done with the help of hyper parameters like number of units, optimizers and dropout. This further increased the final accuracy to a notable value. This work can be extended further with an increase in the dataset size using techniques like data augmentation and Generative Adversarial Network to achieve good results. Even this can also be extended with considering few other hyper parameters for optimization along with other data preprocessing methods.

References

1. "Archived: WHO Timeline - COVID-19." https://www.who.int/news/item/27-04-2020-who-timeline---covid-19 (accessed Mar. 31, 2021).
2. H. Panwar, P. K. Gupta, M. K. Siddiqui, R. Morales-Menendez, and V. Singh, "Application of deep learning for fast detection of COVID-19 in X-Rays using nCOVnet," *Chaos, Solitons and Fractals,* vol. 138, p. 109944, 2020, doi: 10.1016/j.chaos.2020.109944.
3. C. Shorten, T. M. Khoshgoftaar, and B. Furht, "Deep Learning applications for COVID-19," *J. Big Data*, vol. 8, no. 1, 2021, doi: 10.1186/s40537-020-00392-9.
4. S. Mohana Saranya, R. R. Rajalaxmi, R. Prabavathi, T. Suganya, S. Mohanapriya, and T. Tamilselvi, "Deep Learning Techniques in Tomato Plant - A Review," *J. Phys. Conf. Ser.*, vol. 1767, no. 1, 2021, doi: 10.1088/1742-6596/1767/1/012010.
5. M. Polsinelli, L. Cinque, and G. Placidi, "A light CNN for detecting COVID-19 from CT scans of the chest," *Pattern Recognit. Lett.*, vol. 140, pp. 95–100, 2020, doi: 10.1016/j.patrec.2020.10.001.
6. S. Pathan, P. C. Siddalingaswamy, and T. Ali, "Automated Detection of Covid-19 from Chest X-ray scans using an optimized CNN architecture.," *Appl. Soft Comput.*, vol. 104, p. 107238, 2021, doi: 10.1016/j.asoc.2021.107238.
7. D. Singh, V. Kumar, Vaishali, and M. Kaur, "Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks," *Eur. J. Clin. Microbiol. Infect. Dis.*, vol. 39, no. 7, pp. 1379–1389, 2020, doi: 10.1007/s10096-020-03901-z.
8. R. Jain, M. Gupta, S. Taneja, and D. J. Hemanth, "Deep learning based detection and analysis of COVID-19 on chest X-ray images," *Appl. Intell.*, 2020, doi: 10.1007/s10489-020-01902-1.
9. V. Shah, R. Keniya, A. Shridharani, M. Punjabi, J. Shah, and N. Mehendale, "Diagnosis of COVID-19 using CT scan images and deep learning techniques," *Emerg. Radiol.*, 2021, doi: 10.1007/s10140-020-01886-y.

10. T. Ozcan, "A Deep Learning Framework for Coronavirus Disease (COVID-19) Detection in X-Ray Images," vol. 90, no. 352, 2020, doi: 10.21203/rs.3.rs-26500/v1.
11. P. gifani, A. Shalbaf, and M. Vafaeezadeh, "Automated detection of COVID-19 using ensemble of transfer learning with deep convolutional neural network based on CT scans," *Int. J. Comput. Assist. Radiol. Surg.*, vol. 16, no. 1, pp. 115–123, 2021, doi: 10.1007/s11548-020-02286-w.
12. R. G. Babukarthik, V. Ananth Krishna Adiga, G. Sambasivam, D. Chandramohan, and A. J. Amudhavel, "Prediction of covid-19 using genetic deep learning convolutional neural network (GDCNN)," *IEEE Access*, vol. 8, pp. 177647–177666, 2020, doi: 10.1109/ACCESS.2020.3025164.
13. M. Loey, G. Manogaran, and N. E. M. Khalifa, "A deep transfer learning model with classical data augmentation and CGAN to detect COVID-19 from chest CT radiography digital images," *Neural Comput. Appl.*, vol. 0123456789, 2020, doi: 10.1007/s00521-020-05437-x.
14. M. A. Zulkifley, S. R. Abdani, and N. H. Zulkifley, "COVID-19 screening using a lightweight convolutional neural network with generative adversarial network data augmentation," *Symmetry (Basel).*, vol. 12, no. 9, pp. 1–17, 2020, doi: 10.3390/SYM12091530.
15. C. Ouchicha, O. Ammor, and M. Meknassi, "CVDNet: A novel deep learning architecture for detection of coronavirus (Covid-19) from chest x-ray images," *Chaos, Solitons and Fractals*, vol. 140, 2020, doi: 10.1016/j.chaos.2020.110245.
16. K. Shankar, Y. Zhang, Y. Liu, L. Wu, and C. H. Chen, "Hyperparameter Tuning Deep Learning for Diabetic Retinopathy Fundus Image Classification," *IEEE Access*, vol. 8, pp. 118164–118173, 2020, doi: 10.1109/ACCESS.2020.3005152.
17. S. Basu, S. Mitra, and N. Saha, "Deep Learning for Screening COVID-19 using Chest X-Ray Images," *2020 IEEE Symp. Ser. Comput. Intell. SSCI 2020*, no. Ml, pp. 2521–2527, 2020, doi: 10.1109/SSCI47803.2020.9308571.