1570762468-An Improved Classification of Chest X-ray Images Using Adaptive Activation Function

5th International Conference on Electronics, Materials Engineering and Nano-Technology.
(IEMENTech 2021)

Authors : **Tribikram Dhar**, Gourab Adhikari and Sheli Sinha Chaudhuri

Contents

Introduction

- Coronavirus disease 2019 (COVID-19) is a contagious disease caused by severe acute respiratory syndrome coronavirus.
- One of the major symptom is acute respiratory problem which led to higher ICU admissions and mortality rates.
- It is imperative to shift our focus from conventional lab based testing to X-ray based testing process as the latter is much more cost-effective, robust, portable and at the same time reduces the risk of infection.

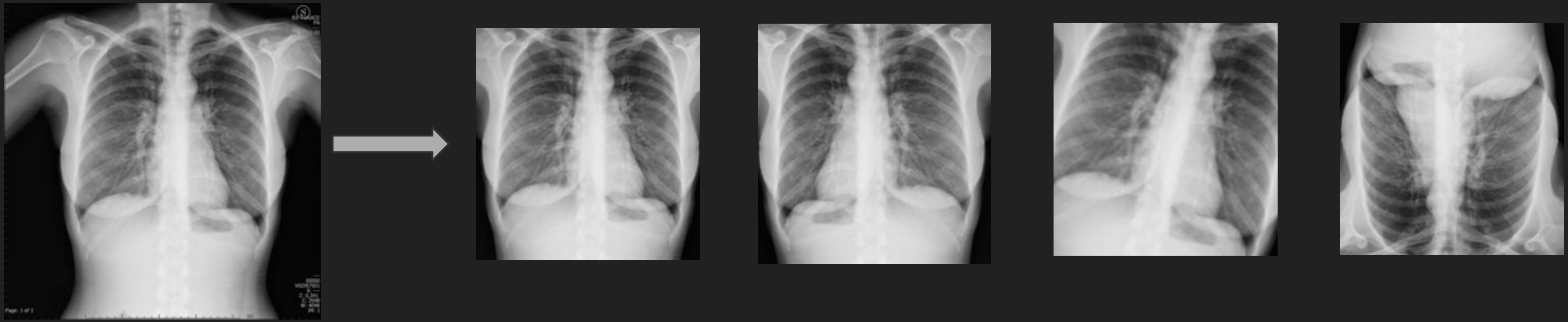
CXR of Covid-19 subject

CXR of healthy subject

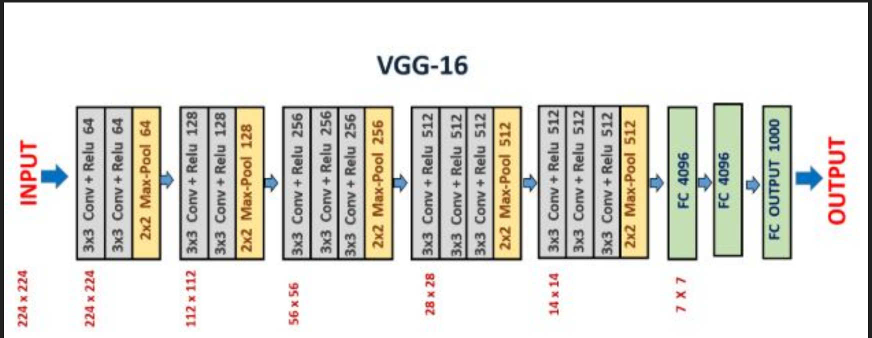
CXR of viral pneumonia subject

Description of the Dataset

- The dataset comprised of CXR scans of Covid-19 patients, viral Pneumonia patients and healthy individuals in .png format and of size 299x299.
- The scans had prints and watermarks of patient IDs in the edges which are artifacts to the training architectures. In order to avoid these unwanted noise, the images were center cropped to a size of 224x224 and a majority of ROI was kept over lungs.
- The CIR before and after augmentation for class viral pneumonia was 2.24 and 1.49.
- The data was split into training, validation and testing sets in the ratio of 8:1:1.
- The images were normalised using min- max scalar method to scale the values within 0-1.
- The study was divided into two categories:
    - Study-I : a binary classification problem i.e. covid-19 scans and healthy scans
    - Study-II : classification of three classes i.e. covid-19 , viral pneumonia and healthy scans

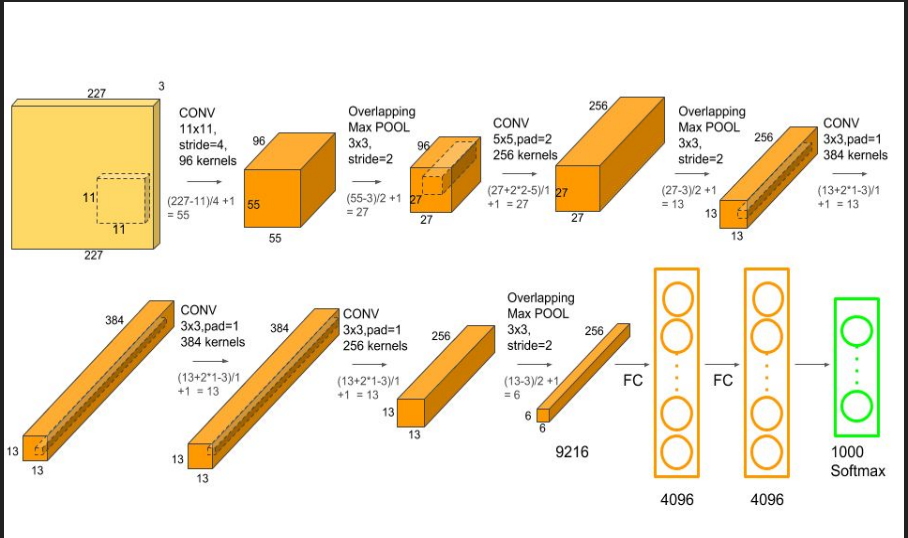


Some Well-known CNN Architectures



Architecture of VGG-16

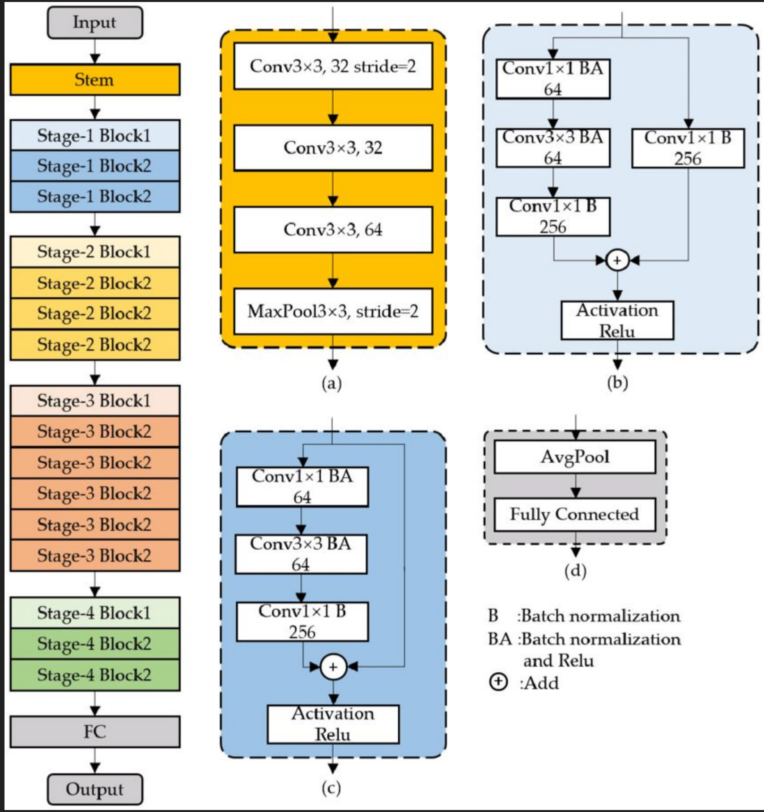
- Number of parameters (in million): 134.2
- Total memory consumed (in MB): 731.1
- Activation used: Relu
- Loss function : Negative Log Likelihood
- Optimizer : Adam optimizer. Lr = 0.001
- Training time (in mins): 168



Architecture of Alexnet

- Number of parameters (in million): 56.9
- Total memory consumed (in MB): 226.0
- Activation used: Relu
- Loss function : Negative Log Likelihood
- Optimizer : Adam optimizer. Lr = 0.001
- Training time (in mins): 67

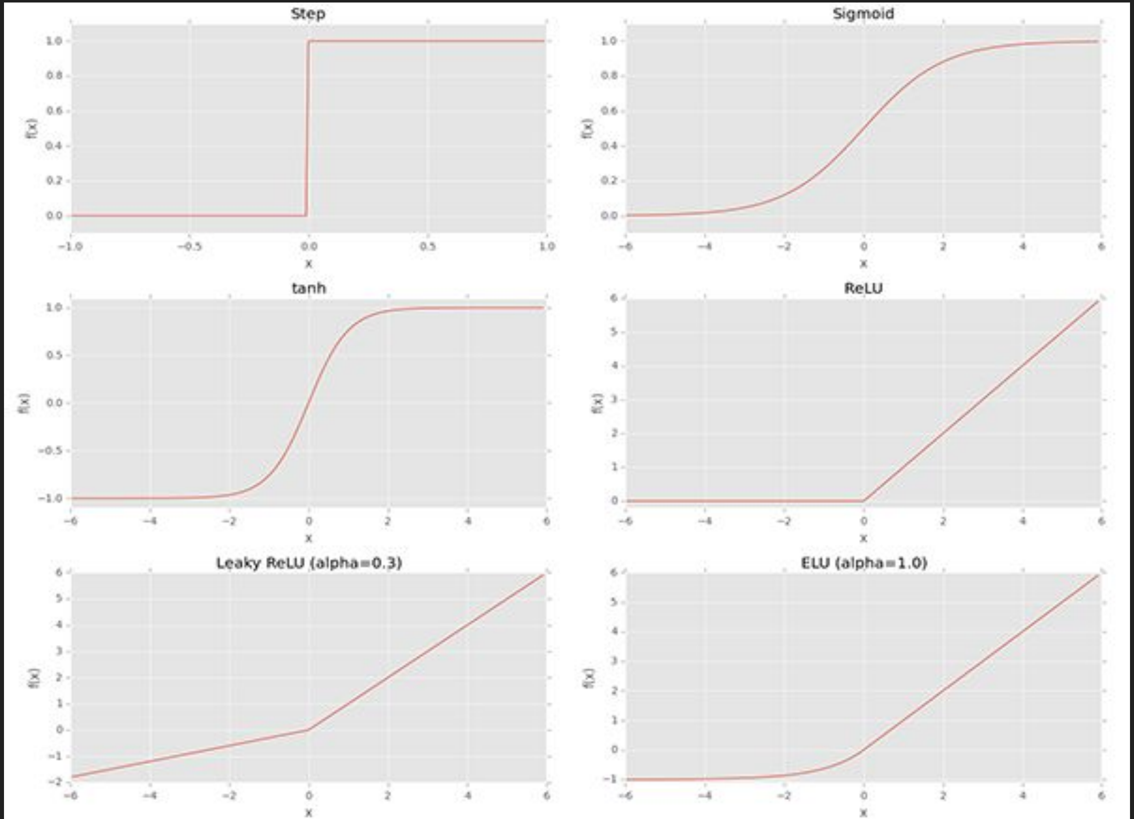
Some well-known Architectures(*contd..*)



Architecture of Resnet-50

- Number of parameters (in million): 23.5
- Total memory consumed (in MB): 376.4
- Activation used: Relu
- Loss function : Negative Log Likelihood
- Optimizer : Adam optimizer. Lr = 0.001
- Training Time (in mins): 121

Activation Functions

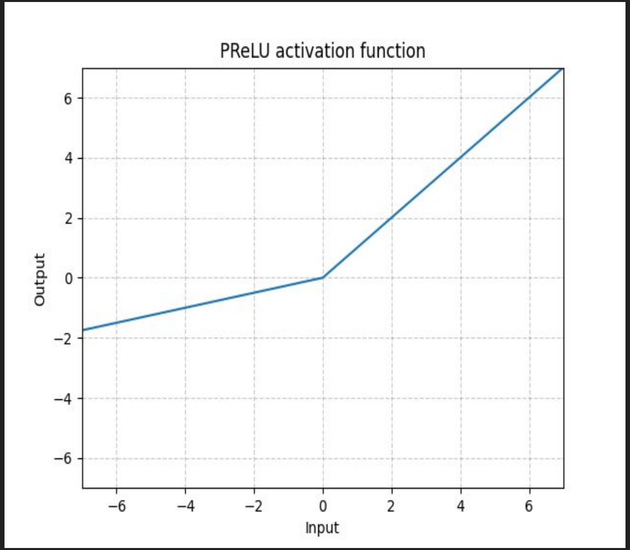


PReLU

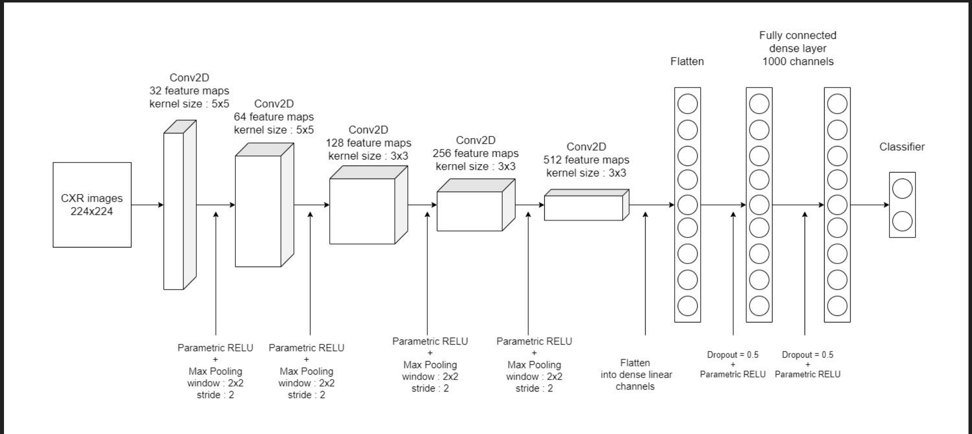
f(x) = max(0,x)+ a*min(0,x)

For ReLU ; a=0

For Leaky ReLU ; a= predefined by user



Experimental Results



The proposed architecture with PRelu activation function

- Number of parameters (in million): 12
- Total memory consumed (in MB): 87.8
- Training time (in mins): 114

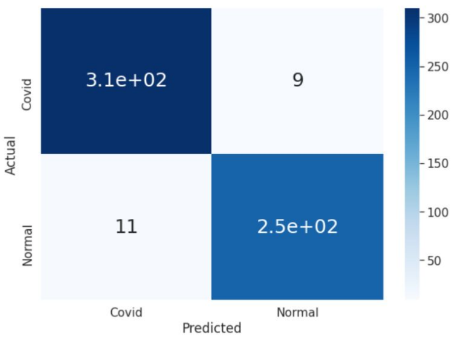
Formulated metric scores for study I

	Accuracy	F1 score	Precision	Sensitivity	Training time
AlexNet	96.54	96.13	96.51	95.76	1 hr 7 min
ResNet-50	91.19	90.46	97.58	85.32	2 hr 11 min
VGG-16	94.47	94.66	93.42	95.94	2hr 58 min
Proposed architecture	96.89	96.77	95.74	97.82	1hr 54 min

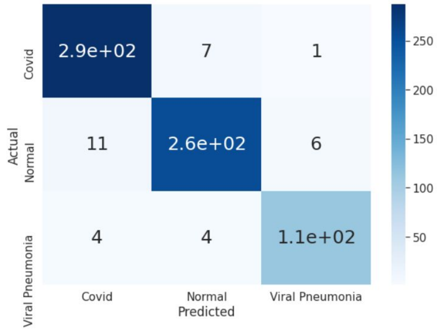
Formulated metric scores for study II

	Accuracy	F1 score	Precision	Sensitivity	Training time
AlexNet	96.15	96.13	95.19	95.19	1 hr 16 min
ResNet-50	91.00	91.00	90.75	90.75	2 hr 30 min
VGG-16	94.13	94.13	93.15	93.15	3hr 22 min
Proposed architecture	96.75	96.74	96.74	96.74	2hr 5 min

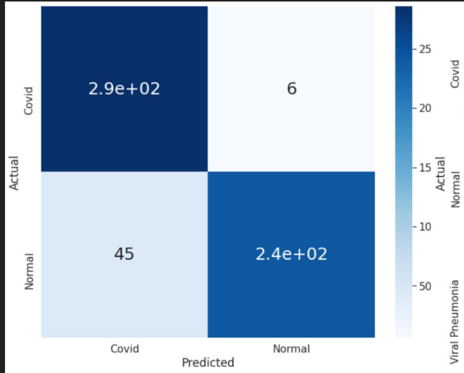
Experimental Results(*contd..*)



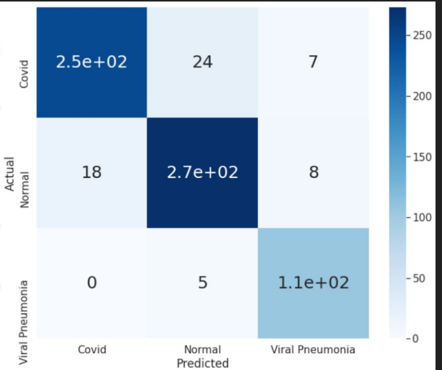
Confusion matrix after evaluation on AlexNet for study (i)



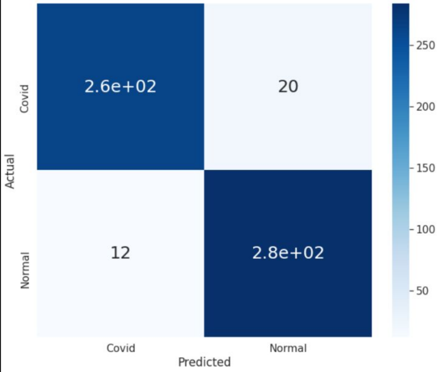
Confusion matrix after evaluation on AlexNet for study (ii)



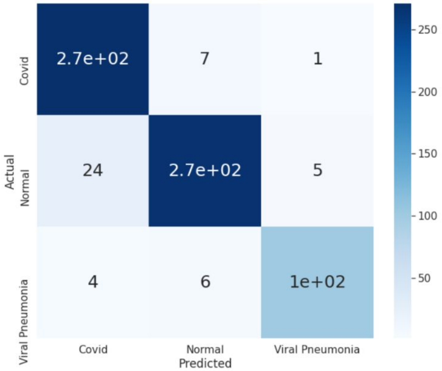
Confusion matrix after evaluation on ResNet 50 for study (i)



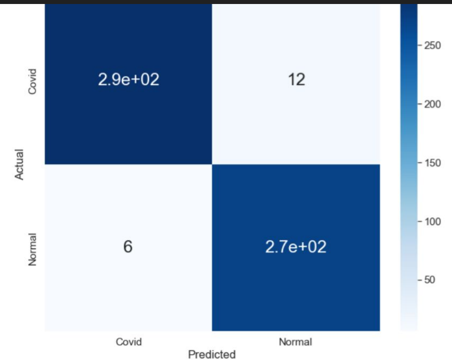
Confusion matrix after evaluation on ResNet 50 for study (ii)



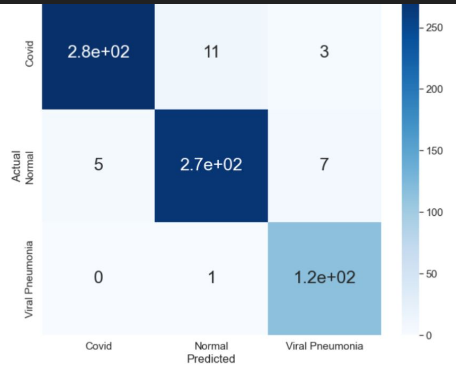
Confusion matrix after evaluation on VGG 16 for study (i)



Confusion matrix after evaluation on VGG 16 for study (ii)



Confusion matrix after evaluation on proposed architecture for study (i)

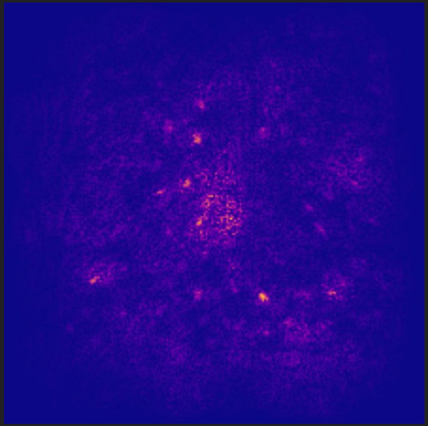
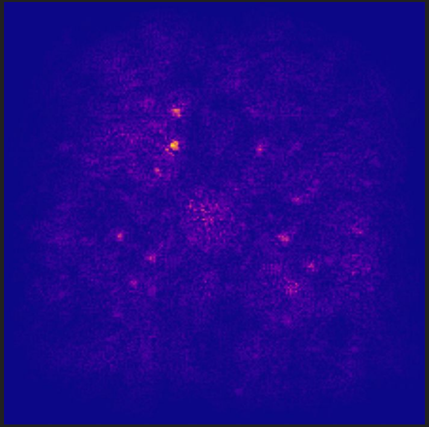
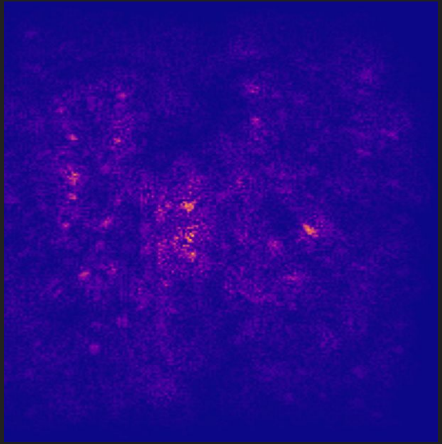


Confusion matrix after evaluation on proposed architecture for study (ii)

Conclusion and Future works

- The experiments in both the studies conducted have shown that using an adaptive activation function gives the CNN a much better accuracy in classification and detection of COVID-19 infection.
- The proposed architecture powered with a PReLU performs better than the same architecture powered with ReLU with an increased accuracy of 2%.
- These methods could help in proper tracking of infected individuals when they are being diagnosed in a pathological centre and the automatic method for detecting Sars Cov-2 infection using CNNs could play a vital role in monitoring the spread of this disease.
- The final frontier of our future efforts could be finding a way to monitor viral growth in lungs through time series CXR image data of COVID patients generating heatmaps from feature maps.

Below are three saliency maps of COVID-19, normal individuals and Viral Pneumonia patients respectively.

References

1. Deep Learning by Ian Goodfellow, Yoshua Bengio and Aaron Courville . MIT Press
2. Batch Normalisation : Accelerating Deep Network Training by Reducing Internal Covariate Shift, Ioffe et al. (2015)
3. Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification, Kaiming He et al. (2015)
4. Negative Log Likelihood Ratio Loss for Deep Neural Network Classification, Yao et al. (2018)

Thank You