COVID AND PNEUMONIA CLASSIFICATION USING DEEP LEARNING APPROACH

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Abstract

Recent studies indicate that detecting radiographic patters on X-rays and scans can yield high sensitivity and specificity for COVID 19 identification. Especially, during pandemic crisis, there is need to scan patients a quickly and accurately. Deep learning approaches are widely used in the medical community. However, they require large datasets. In this work, we have experimental setup which uses various deep learning techniques including convolution neural networks, transfer learning and few shot learning. A novel method of few-shot learning using Siamese networks for chest X-rays has been implemented and various paradigm of transfer learning metrics are observed. The results show that transfer learning and few-shot learning can be used to train and test different models accurately with less amount of data.

1. Introduction

The novel corona virus 2019-nCoV now SARS-Cov2 commonly called as COVID-19 has significantly caused significantly caused short term and long term social and economic impacts. Medical imaging like X-rays and CT scans are promising and efficient alternative tool for the detection of COVID-19. Though RT-PCR tests are primarily used for the detection of COVID-19, scans are very important in knowing the intensity of the lungs being affected.

Patients with COVID-19 can develop symptoms that belong to common flu, pneumonia, and other respiratory diseases in the first 4 to 10 days. X-ray images are widely used because they are not expensive as CT scans. Moreover, radiological features can be observed in patients such as consolidations or GCO, both unilateral and bilateral. Two examples are shown below,

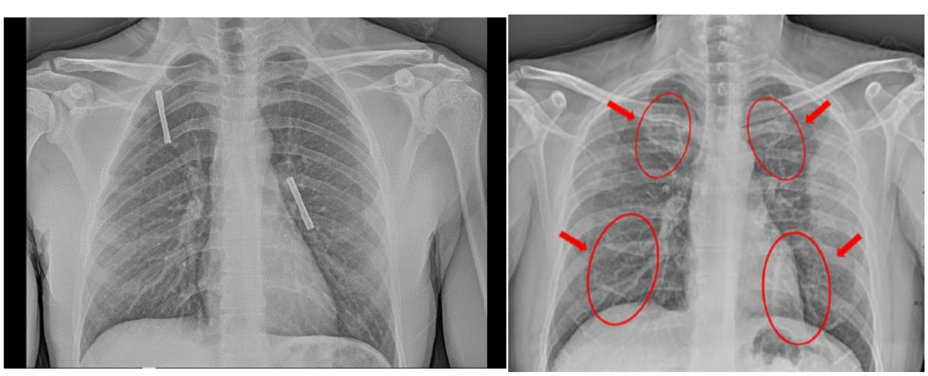

Figure 1. (a) X-ray image showing a healthy person (b) X-ray image showing the COVID-19 affected person

On the other hand, pneumonia is an infectious disease that also affects lungs and according to WHO, it is considered a leading cause of death in children. Pneumonia can be caused by fungus, bacteria or virus attack. In the same way, pneumonia possess radiological features such as consolidation by fluid accumulations. Two examples are shown below,

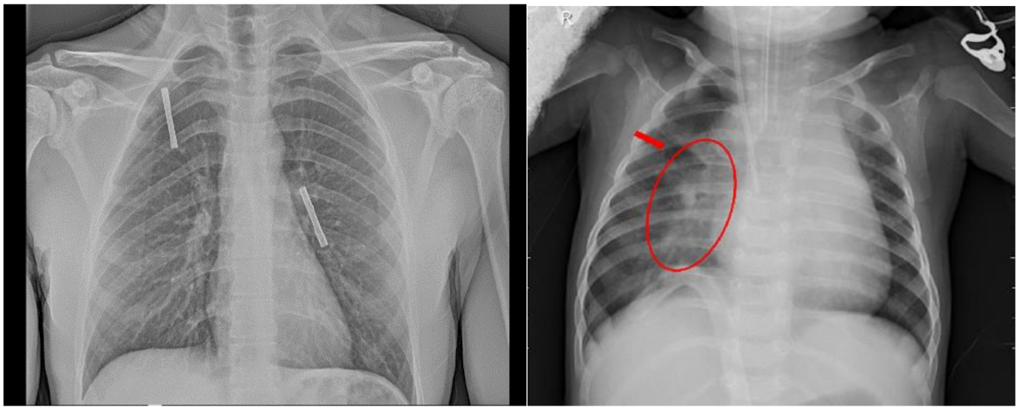

Figure 2. (a) X-ray image showing a healthy person (b) X-ray image showing the penumonia infected person with fluid and consolidations found in the right lung.

In this work, several deep learning techniques have been implemented including CNNs, transfer learning using VGG-16 and ResNet50 by tuning parameters and few shot learning using Siamese networks. To validate the effectiveness and compare the performance of models, we have performed extensive set of experiments and showcased results. The project code has been made available for validation and replication of these experiments.

2. Related Work

Athanasios Voulomimos, et. al [1], proposed a method to learn the COVID-19 infected area using Few-shot U-Net Deep Learning Model using CT Images. To overcome the difficulties of Few-shot learning, this paper introduced a method for network model training using very small number of samples using U-net architecture. The results obtained using the architecture performed better than the traditional model. Using 4-fold cross validation results, the proposed method observed an improvement of 5.388 ± 3.046 % for all test data regarding the IoU metric and similar increment of 5.394 ± 3.015 for the F-1 score.

Shruthi Jadon implemented a metric-based method [2], to compare the results of logistic regression, CNNs, Transfer learning and Few-shot learning using Siamese networks. Due to scarcity in the data, a low data regime method was used. The paper focuses on a multi-class classification problem of COVID-19, Normal and Viral Pneumonia. A conceptive investigation of overfitting and regularization of the model was studied. This paper solely focuses on the supervised and unsupervised method to address the problem of COVID Detection. There is an increase in the accuracy of the Few-shot model with 96.4% accuracy compared to the baseline accuracy 83%.
Though the paper is based on multi-class approach, there is not a clear evidence and indication of the approach carried out throughout the experiment.

3. Dataset

In this section, we describe the datasets we have used to carry out these research experiments.

- Covid-19 Radiography database is a collaborative effort by various universities in Asia. It consists of 1200 COVID-19 images, 1341 normal images and 1345 viral pneumonia images.

- Covid-19 dataset with the help of University of Montreal. This dataset consists of 317 labelled images into three categories: Viral Pneumonia, Normal and Covid.

4. Methodology

From this research, Convolution Neural Networks have been chosen as the baseline model to compare the results of Transfer Learning and Few-shot learning.

4.1 Convolution Neural Networks

Convolution layer Neural Networks plays a major role in image classification problems. Most of the models built using CNNs are helpful in transforming various manufacturing industries, food industries and medical industries. CNNs extract specific form of features from images to analyze the object in the image. They are called as feature extractor because of the range of images extracted within layer. In this work, a five-layered convolution neural network model, a four-layered convolution neural network model and a three-layered convolution neural network model are chosen as baselines.

Like any CNN model, the neural network models are built with CNN layers to extract the various features from input images. Followed by a pooling layer, to decrease the size of the convolved feature map to reduce computational costs and a fully connected layer consisting of weights and biases along with neurons. To prevent overfitting of training dataset, drop out layers can be used. Activation functions are finally used to learn and approximate any kind of continuous and complex relationship between variables of the network.

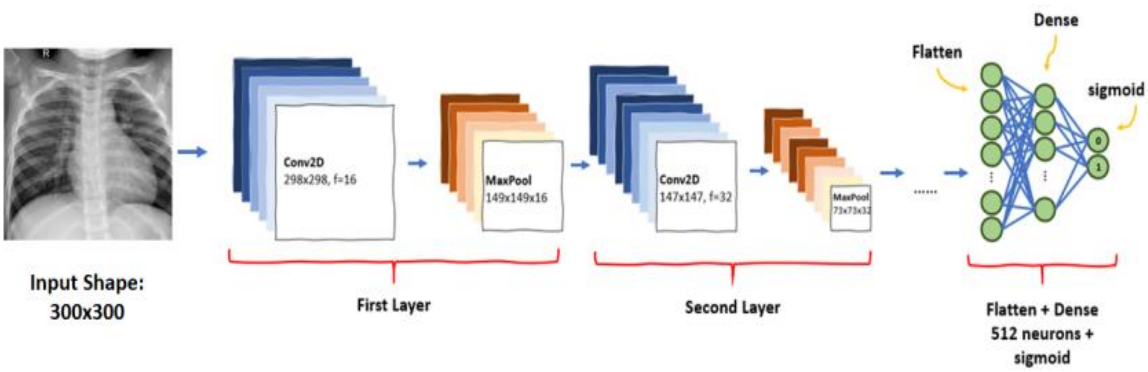

Figure 3. Simple convolution Neural Network

4.2 Transfer Learning

Transfer learning refers to a scenario where an architecture has been optimized on a similar domain dataset. One of main advantages of using transfer learning is that it uses one trained neural network for generalization and then uses the current dataset to improve those parameters. Transfer learning became popular and has helped resolve scarce data situations in many cases, but we generally do not get similar domain data with medical images. In this approach, two transfer learning models are experimented – VGG16 and ResNet50.

4.2.1 VGG16 Transfer Model

Transfer learning model is implemented with pre-trained datasets. On top of VGG16 Model, a number of dense layers for the number of classes are added and images are flattened. Then, dropout functions are added finally. As part of optimization of transfer learning model, a call back function is added to allow Early Stopping which in entails that the model will stop in case of val_loss. The model is trained with 100 epochs and 200 epochs respectively. Finally, a total of 22 epochs is used in the final model after optimization.

4.2.2 ResNet50 Transfer Model

ResNet50 transfer model is like VGG16 model, with same number of classes for dense layers and flattened images.

4.3 Few-shot learning using Siamese Networks

4.3.1 Siamese Networks

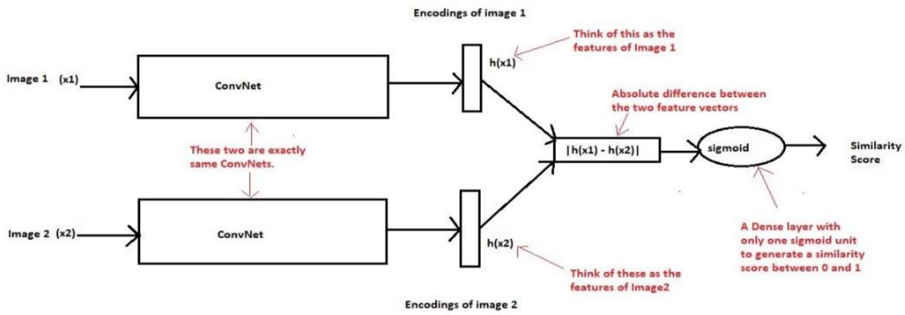

Figure 4. Siamese Network

Data Pre-processing – Two pairs are created. i.e., 1st pair – similar→ y=0, 2nd pair – dissimilar → y=1

Contrastive Loss Function: As we know, contrastive loss function consists of two parts,

1. For similar points: (1-y) *(distance function) ^2
2. For dissimilar points: y*(max (0, (m - distance function))

The distance function is considered as Euclidian function, also known as root mean square

Siamese Network Architecture

1. In the ***forward once***, pass through all layers and return the output embeddings
2. In forward, call ***forward once*** 2 times for the input pair given and return the embeddings obtained.

Train the model for 9 epochs and plot the loss function and test embeddings.

4.3.2 Few-shot learning

Few shot learning is a sub-field of machine learning which aims to develop models that can be trained with less amount of dataset. There are three types of few-shot learning approaches: Metrics based, Models based, and Optimization based. Metrics based approaches focus on learning better embeddings whereas models based, and optimization-based approaches focus on improving the architectural components and optimization algorithms respectively.
A few shot learning with Siamese networks is implemented in this project. For image type data, these architectures are generally chosen to be of Convolution Neural Networks followed by a contrastive loss function. For training a Siamese network, we pass the input in set of pairs. For instance, 2 input images are taken (x1, x2) and labelled as similar or not, then these images (x1 and x2) are passed through the ConvNet to generate fixed length feature vector for each (h(x1) and h(x2)).

Assuming that, the model is trained properly, the following hypothesis can be made,

1. If the two images belong to a same character, then their feature vectors must also be similar.
2. If the two images belong to a different character, then their feature vectors will also be different.

This idea of extracting embeddings on basis of similarity and dissimilarity helps model to train will a smaller number of examples.

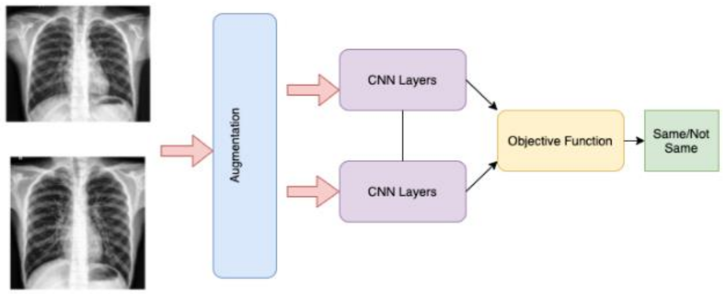

Figure 5. Few-shot learning using Siamese Networks

5. Performance Evaluation

5.1. Precision

Precision quantifies the number of positive class predictions that belong to the positive class. In other words, it is the ratio of the True Positives to all the observed Positives predictions.

$$\text{Precision}=\frac{TP}{TP+FP}$$

5.2 Recall

Recall quantifies the number of positive class predictions made out of all positive examples in the dataset.

$$\text{Recall}=\frac{TP}{TP+FN}$$

5.3 F-1 Score

F1-score considers both precision and recall metrics. So, it is a good indicator of how the model performs. In fact, The F1 score can be interpreted as a harmonic mean of the precision and recall metrics, where an F1 score reaches its best value at 1 and worst score at 0. The relative contribution of precision and recall to the F1 score are equal.

$$\text{F1-Score}=\frac{2*Precision*Recall}{Precision+Recall}$$

5.4 Accuracy

Accuracy is the fraction of predictions that the model got right since it is calculated as the ratio of all true predictions to all the possible predictions.

$$\text{Accuracy}=\frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}=\frac{TP+TN}{TP+TN+FP+FN}$$

6. Results

6.1. Baseline Models

As mentioned above, the baseline models with 3 different implementations of convolution neural networks are mentioned,
The CNN layers were simplified in the process to obtain better accuracy from 5 to 3.

CNN Models	Train Accuracy	Train Loss	Test Accuracy	Test Loss
Model 1 – Layers 5	0.58	4.65	0.629	4.17
Model 2 – Layers 4	0.59	3.5	0.619	2.59
Model 3 – Layers 3	0.759	0.894	0.688	0.947

Table 1. Performance of CNN

The train accuracy and test loss are obtained for each model of CNN.

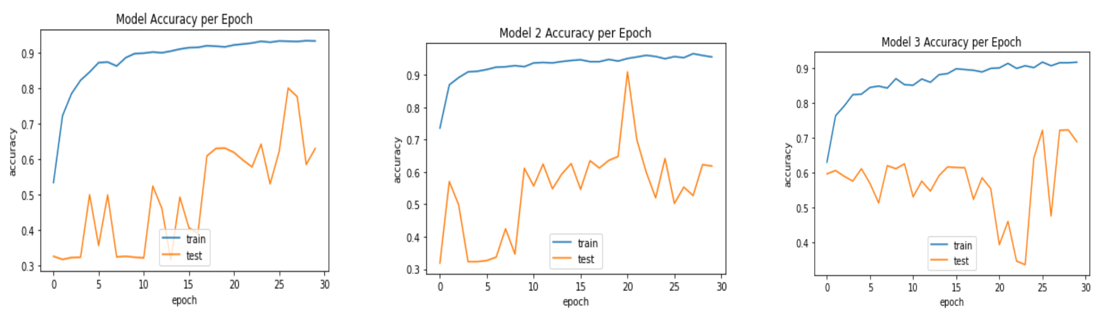

Figure 6. Model Accuracy (a) CNN with 5 layers, (b) CNN with 4 layers, (c) CNN with 3 layers

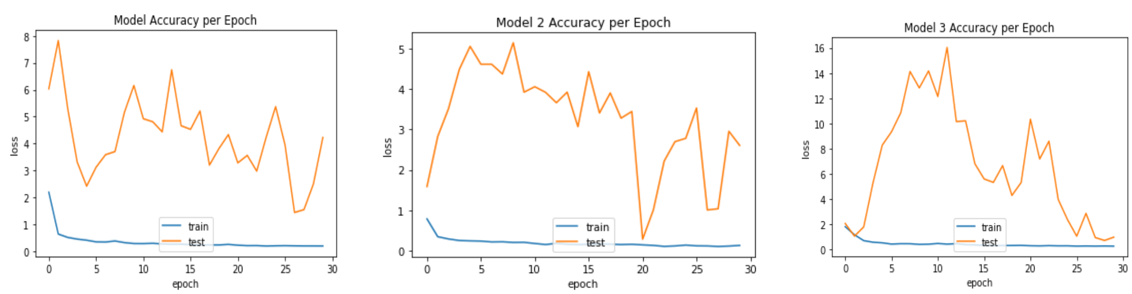

Figure 7. Model Loss (a) CNN with 5 layers, (b) CNN with 4 layers, (c) CNN with 3 layers

6.2 Transfer Learning

Three different transfer learning models are listed below,

Models	Train Accuracy	Train Loss	Test Accuracy	Test Loss
VGG16 (with 100 epochs)	0.92	0.205	0.859	0.359
VGG16 (200 epochs)	0.944	0.173	0.86	0.36
VGG16 (with Call Back 22 epoch)	**0.935**	**0.202**	**0.873**	**0.318**

Table 2. Performance of Transfer Learning

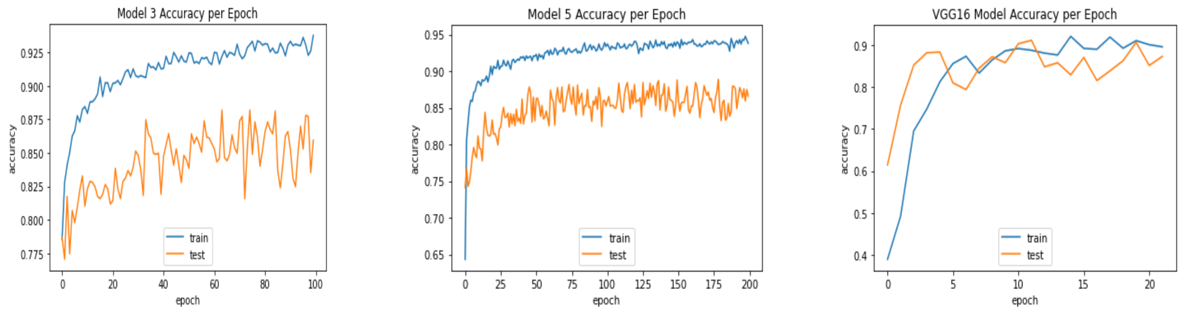

Figure 8. Model Accuracy (a) VGG16 with 100 epochs (b) VGG16 with 200 epochs, (c) VGG16 (Call back)

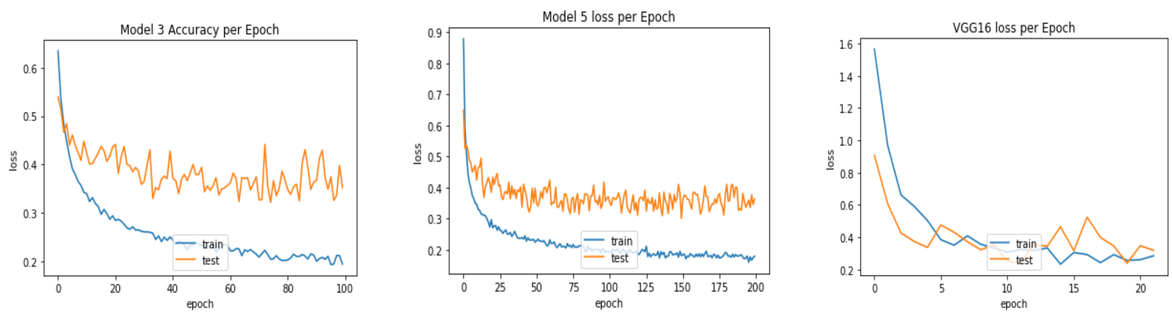

Figure 9. Model Loss (a) VGG16 with 100 epochs (b) VGG16 with 200 epochs, (c) VGG16 (Call back)

6.3 Few-shot learning with Siamese network

After carefully performing few-shot learning using Siamese network embeddings, a training loss of 1.10 and validation loss of 1.10 are obtained. A test accuracy of 36.25% and F1-score 28% is obtained for 200 epochs.

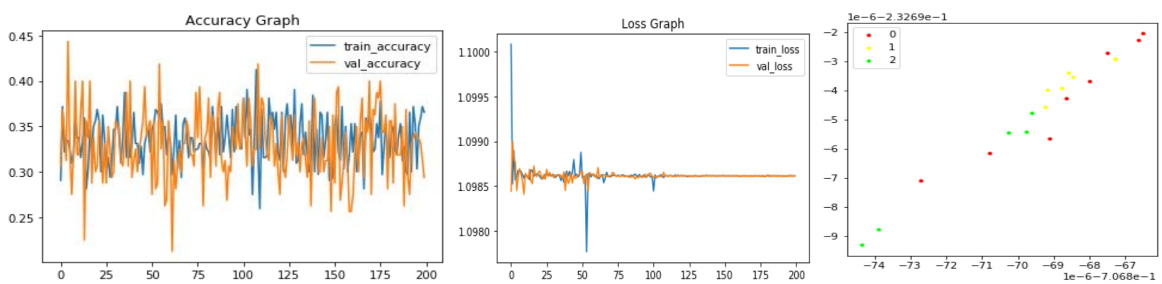

Figure 10. Few-shot learning with Siamese Network (a) Accuracy Graph, (b) Loss graph, (c) Test Embeddings

7. Observation

After carefully performing experiments and analyzing the outcomes, the following observations can be made,

- The change in the distribution of data can lead to low accuracy score. For instance, when data is scare it is tough to determine the real distribution of data, even if we segregate data into test, train and validation set. The performance will differ in real data distribution.
- The class imbalance of data distribution – Covid, Pneumonia and Healthy patients. With the less amount of research work, there are only few examples available for each class of data and it is very tricky to arrive at conclusive evidence with respect to imbalance in data.

8. Conclusion and Future Work

Though the models performed better with baseline models for CNN and Transfer Learning, the model with few-shot learning using Siamese networks did not perform well. With 200 epochs and lesser dataset, the results were not as satisfying as reported. The work could be an extension to obtain more data and increase the area to improve the test and train accuracy.

Parameter optimization could be done using Bayesian optimization framework. Some of the parameters that can optimized are learning rate, layer-wise momentum, layer-wise L2 regularization penalty, convolution filter sizes, number of filters in each layer and fully connected layers.

References

[1] Shruti Jadon. (2021). A Few-Shot U-Net Deep Learning Model for COVID-19 Infected Area Segmentation in CT Images.

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