<u>MINI PROJECT-1</u>

Project Report

Detection of COVID-19 on X-Ray image datasets using Deep Learning

Priyanshu-IIT2019196

Palen Pushkar-IIT2017042

Chaudhari Yogiraj Prakash-IIT2020254

Mohd Wasif-IIT2020227

Rahul-IIT2020244

Under the supervision of:- Dr Anupam Agrawal

Table of Contents

1. Introduction

The COVID-19 pandemic is very lamentable and has spread across the world. India is one of the most affected countries in the second wave of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The virus spreads very fast and can be contracted at all ages, which can lead to serious illness. As a highly contagious viral disease caused by SARS-CoV-2, COVID-19 has wreaked havoc on the world's demography, killing over 2.9 million people globally, making it the most significant global health epidemic since the 1918 influenza pandemic. Patients older than 60 years, as well as those with medical problems, should be considered at a higher risk of being infected by SARS-CoV-2. When this virus attacks the human body, there may be two scenarios: mild and severe. At the onset of the coronavirus infection, one issue is certain: the virus has a negative effect on lung health. As a result, doctors advise patients to keep track of their oxygen levels with an oxygen meter so that any abnormalities can be detected and treated early. The virus normally attacks the lungs in the human body and causes pneumonia in severe cases. Subsequently, it decreases the oxygen level instantly. Because this virus has no cure thus far, the only solution before a vaccine is to prevent the spread of the virus. Therefore, tests and trace is the only solution thus far. Normally, the polymerase chain reaction (PCR) test is widely used in medical science for testing. However, because the number of cases is increasing rapidly, it has become nearly impossible to perform enough tests through PCR, as it is time-consuming and costly. Therefore, an alternative testing is required so that infected people can be identified quickly and quarantined or isolated. To date, some deep learning approaches have been used to identify viruses. However, the results of these deep learning techniques are not sufficient to deal with a medical-related diagnosis system.

COVID-Net, a deep CNN architecture built from chest X-ray (CXR) images for the detection of COVID-19, was introduced in previous research. Research was also conducted to classify CXR images into three groups: a transfer learning-based CNN model was used for COVID-19, non-COVID-19, and regular pneumonia.

This project too is a deep learning approach for identifying SARS-CoV-2-infected patients. In the classification, feature extraction in the CNN model can be achieved with high performance. Filter-based feature extraction is used in the CNN model, which can be effective for classification. CNNs can classify images with complex identities. A large number of weight parameters can be reduced using the CNN architecture. CXR images will be used as a sample dataset because X-ray equipment is low cost and time-efficient, as well as small and available in almost every clinic. Therefore, fewer developing countries can benefit from this research. This will help detect coronavirus from CXR images within the shortest possible time. This will reduce the pressure on PCR testing, which is costly and time- consuming. False negatives were a common issue in PCR tests results, which is not helpful for the current situation. If we can develop a model with very high accuracy, false result problems can be resolved.

2. Literature Survey

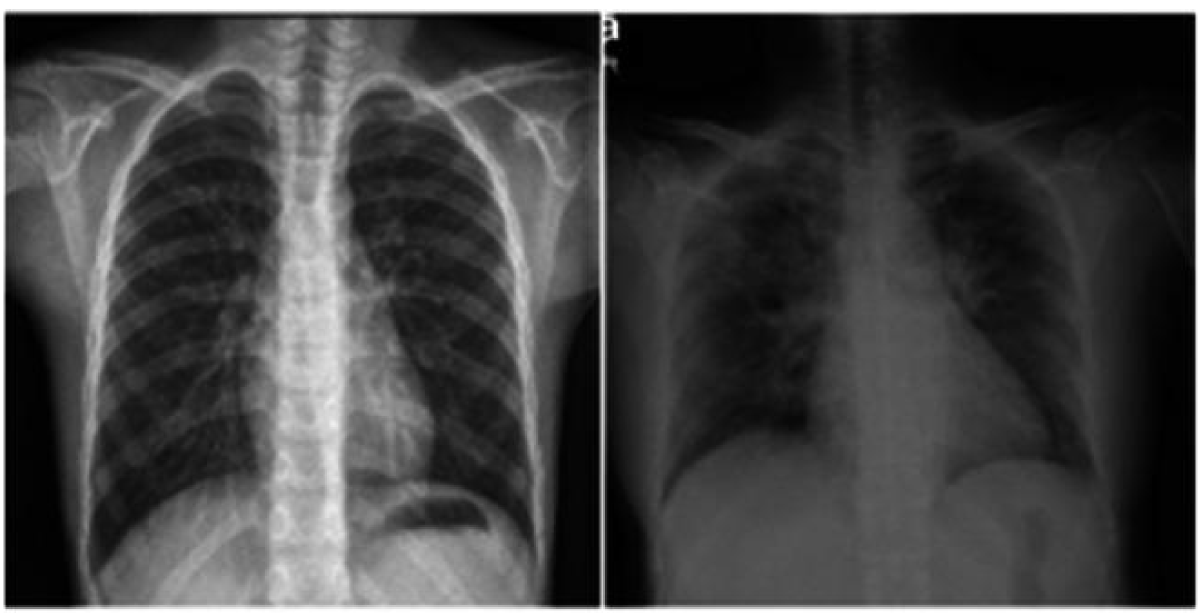
We referred to the following research papers/journals for our project:-

Study	**Method Used**	**Accuracy**	**Advantages**	**Drawbacks**
Wang and Wong et al	Covid-Net	92.40 %	Accuracy is fine. Easy to implement	Use of an unbalanced dataset High computational complexity due to training of deep neural network
Sethy et al	Res-Net50 + SVM	95.38 %	Accuracy is High	Use of a dataset with a limited number of samples

Ioannis et al.	VGG-19	93.48 %	Accuracy is fine Use of high number of samples in dataset Balanced dataset	High computational complexity due to training of deep neural network
Sarra et al	VGG-16+Transfer learning	96.77%	Works well with a small dataset	High chances of false negatives in case of imbalance data.
Somenath et al	ResNet50+ Lung Contour	97.33%	Lack of validation, i.e., use of the program in a different setting or context.	Accuracy, sensitivity, specificity, and F1 scores of the model were high.
Talo et al	DarkCovidNet	98.08%	The model classified chest X-ray images without using a feature extraction technique.	Use of a limited number of COVID-19 X-ray images.
Anabia et al	STM-RENet	99%	Highest accuracy	Model training is computationally intensive.

3. Problem Statement

The primary objective of the project is to predict and detect Covid-19 on Chest X-Ray images using some deep learning approaches. This is a two-class classification problem where the input will be an X-Ray image and the output could be either Normal or COVID positive. The scarcity of medical data or datasets is one of the greatest challenges for researchers in medical-related research, and data is one of the most crucial components of deep learning approaches. Data analysis and labeling are both costly and time consuming. Transfer learning provides the advantage of avoiding the requirement for large datasets. The calculations become lower and less costly. Transfer learning is a method in which the pretrained model, which is trained on a large dataset, is transferred to the new model that needs to be trained, including new data that are relatively smaller than required. The CXR images were of two classes. One is normal, and the other is a SARS-CoV-2-infected patient.



(A) (B)

4. Methodology

We start by implementing a Transfer Learning based approach. Due to the insufficient number of free COVID-19 radiography images, it is not possible to develop a CNN model from scratch to automatically identify COVID-19 from X-ray images. In order to control this problem, we adopt a famous method called “transfer learning” and fine-tune three well-known pre-trained models on the prepared data set. Most deep learning applications use a transfer learning method, which requires fine-tuning of the pre-trained framework. We start with an existing network and enter new data containing previously unknown classes. After making some modifications to the network, we can immediately perform a new task. There exist two major fashions to use pre-trained models for multiple tasks. The first method is to use the already pre-trained model as a feature extractor, in other words, the weights of the pre-trained model are not suitable for new tasks, since the extracted features are then run through a new classifier, which is trained from scratch. This process will use the convolutional basis of the previously trained network, run new data through it, and train a new classifier on the output. In the second method, the network is fine-tuned for new tasks. Thus, the weight of the pre-trained model is regarded as the first value of the new task and is updated while training the network. In our case, due to the limited resources used to obtain COVID-19 images, we only fine-tune the last layer of the CNN and use the pre-trained model as the feature extractor.

Using this approach, we got an accuracy of around 96.77% on a data size of about 600 images. A major disadvantage of using the Transfer Learning approach is that there are high chances of False Negatives and low data sizes cause overfitting over higher parameters. So we then implement another model which is based on ResNet50 using Lung Contours and GRAD-CAM. This method too could only achieve an accuracy of 97.33%. This too wasn’t enough. Then we implemented a modification of the popular DarkNet model called DarkCovidNet. It is a YOLO based multi-class classification approach and we could achieve an accuracy of about 98.08%. We needed further improvement in detecting False Negatives and thus for our final implementation, we approached a channel boosting method on the existing STM-RENet method. Using this method, we achieved an accuracy of around 99%. This way, we were able to approach the challenge of COVID detection with high accuracy.

5. Languages/tools used

Some details about our proposed languages/tools to be used in the project implementation are given below:-

Language to be used : Python, MATLAB
Environment : PyCharm and Anaconda, Jupyter Notebook, MATLAB

Libraries to be Used :

- Pandas - Data Pre-processing
- Numpy - Mathematical tools
- Matplotlib - Plotting Maps
- Keras - Deep Learning Models
- SkLearn - Machine Learning Algorithms
- Itertools - Data Structures
- cv2 - Image Processing
- Fastai
- PyTorch

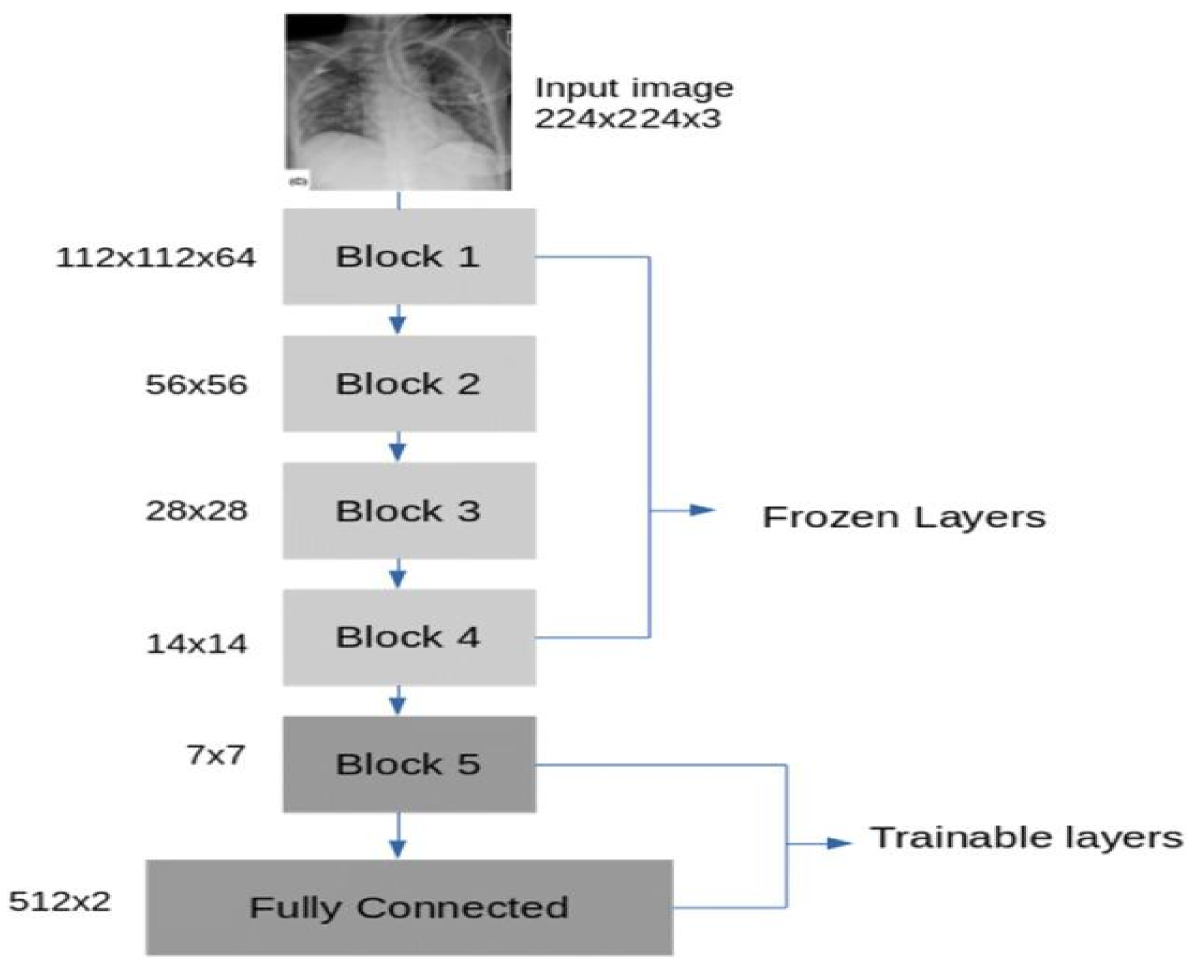
6. Implementation

(i) Implementation using Transfer Learning

Here we are going to use Transfer Learning with advanced and popular architectures like VGG-16, InceptionV2, ResNet with pre-trained weights on our image dataset. Then adapt it to our dataset. So, it will be our base Model.

The dataset will be obtained from the different sources some of which are live active medical datasets on various repositories while some are from Kaggle. For testing, we will use a publicly available Kaggle dataset called ChestX-ray8 which consists of a total of 625 images of chest X-Rays, out of which 125 are X-Ray images of chest containing Covid-19 virus and other 500 images with no traces of Covid-19 virus.

In this transfer learning approach, we will use the parameters from an existing ImageNet model and freeze all layers except the last layers. We also performed data augmentation on our dataset and fine tuning of the last layer. It can be represented as follows:-

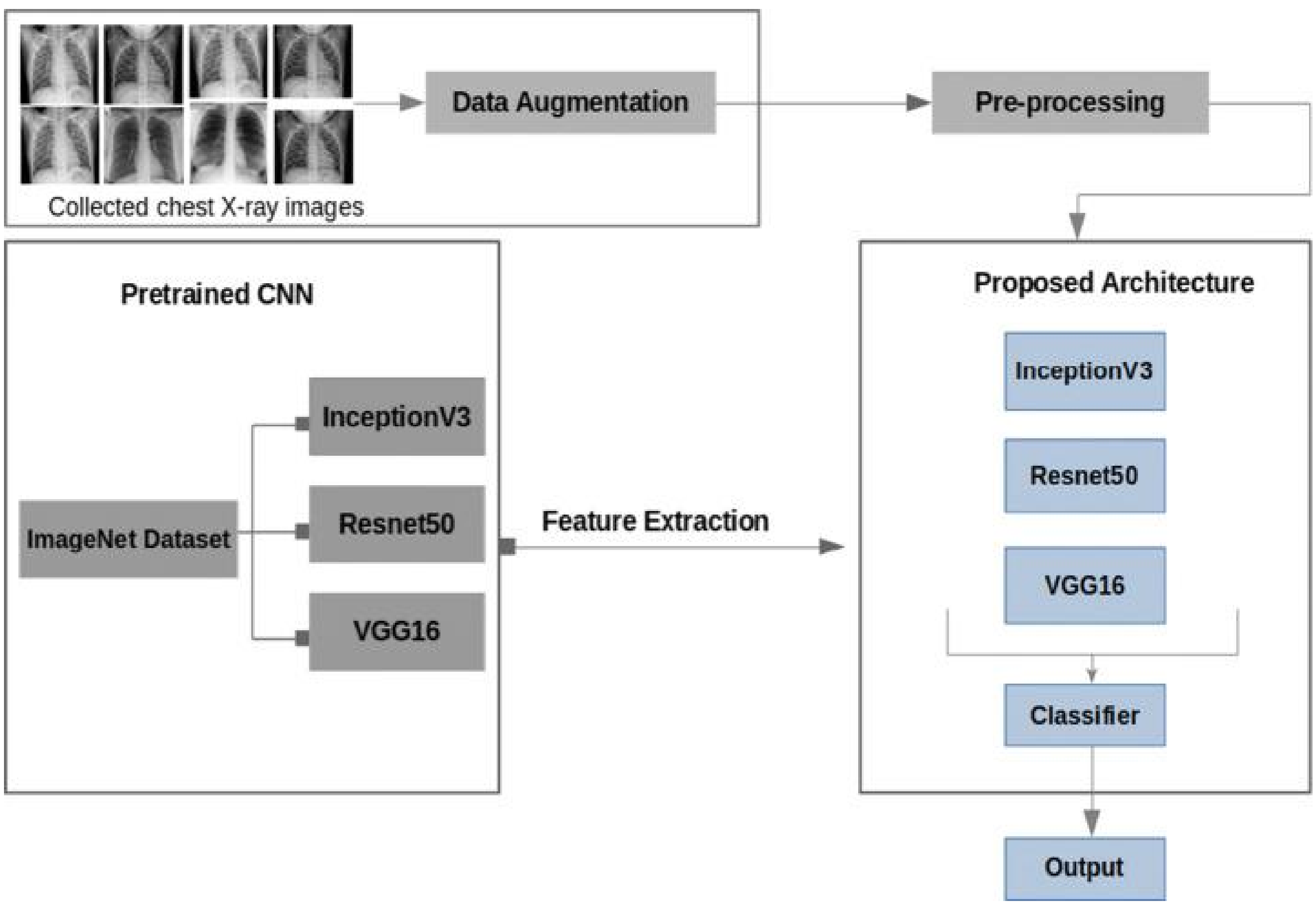


We will be using a sequential method as we are creating a sequential model. Sequential model means that all the layers of the model will be arranged in sequence, then we will add:

AveragePooling2 layer of 4x4 pool size

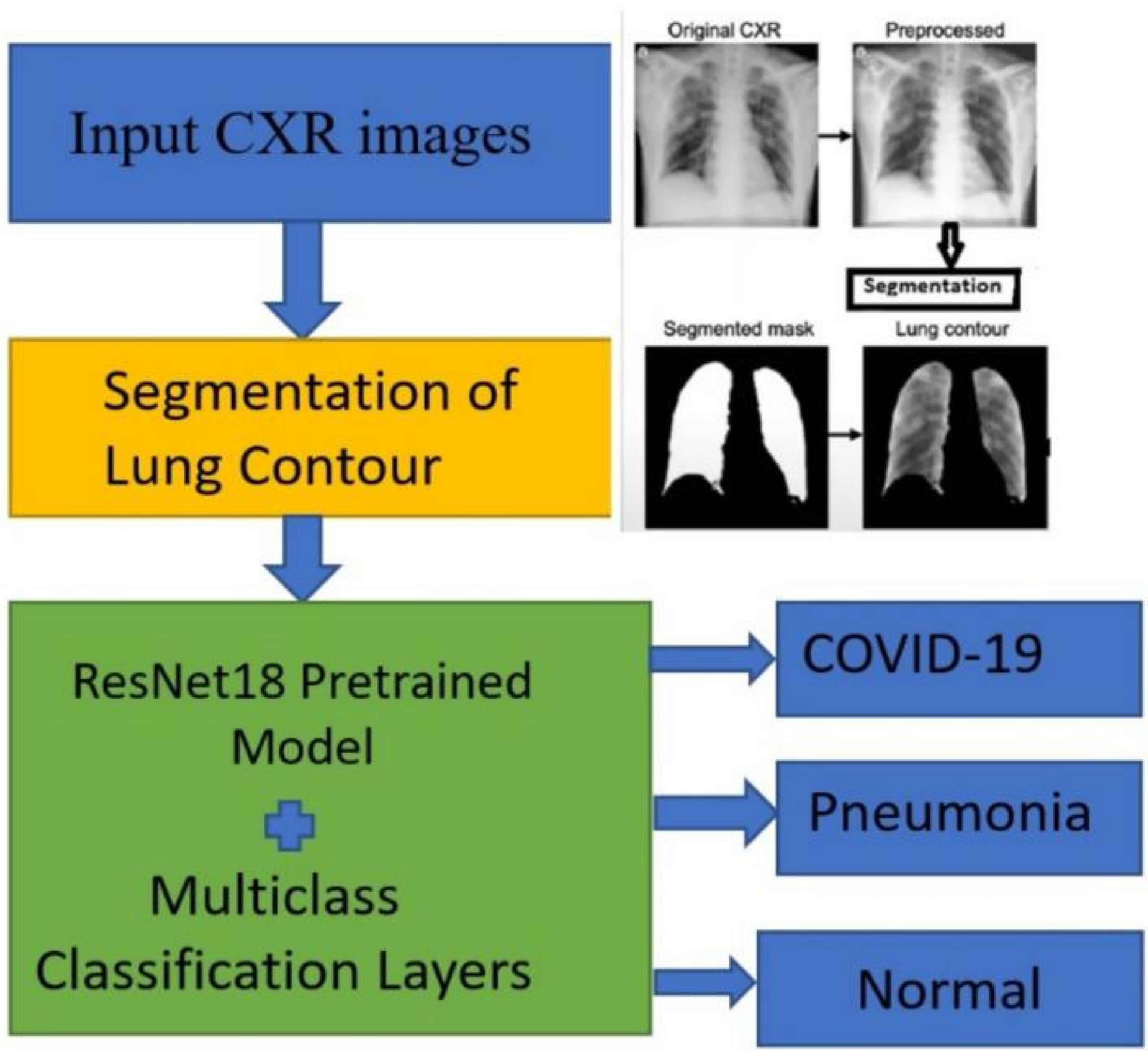
Fully Connected :

- 1 x Flatten :
- 1 x Dense of 64 units
- 1 x Dropout set at 50%
- 1 x Dense of Softmax layer of 2 units



(ii) Implementation using Residual Networks

In this method, we used a ResNet to detect COVID-19 using chest X-ray (CXR) images. Radiographic images are readily available and can be used effectively for COVID-19 detection compared to other expensive and time-consuming pathological tests. We used a dataset of 10,040 samples, of which 2143 had COVID-19, 3674 had pneumonia (but not COVID-19), and 4223 were normal (not COVID-19 or pneumonia).



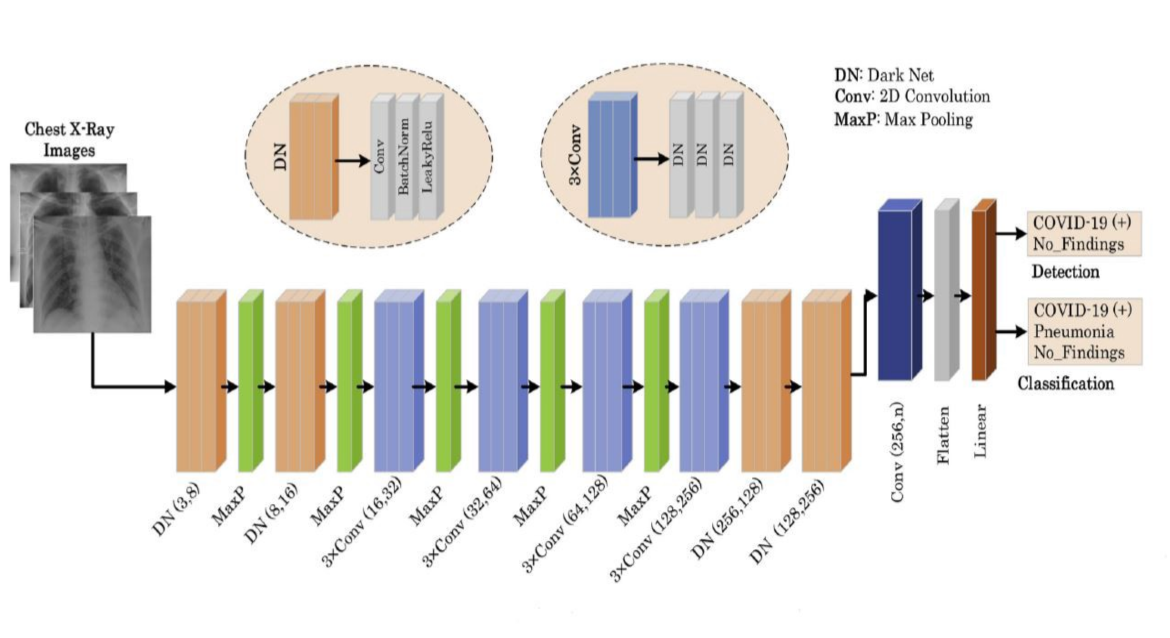
Our proposed model used a large dataset of 10,040 samples, of which 2143 had COVID-19, 3674 had pneumonia, and 4223 were normal (not COVID-19 or pneumonia). Due to augmentation, there are horizontal, vertical, and rotational flip; in these processes the image sample was increased by 65%.

(iii) Implementation using DarkCovidNet

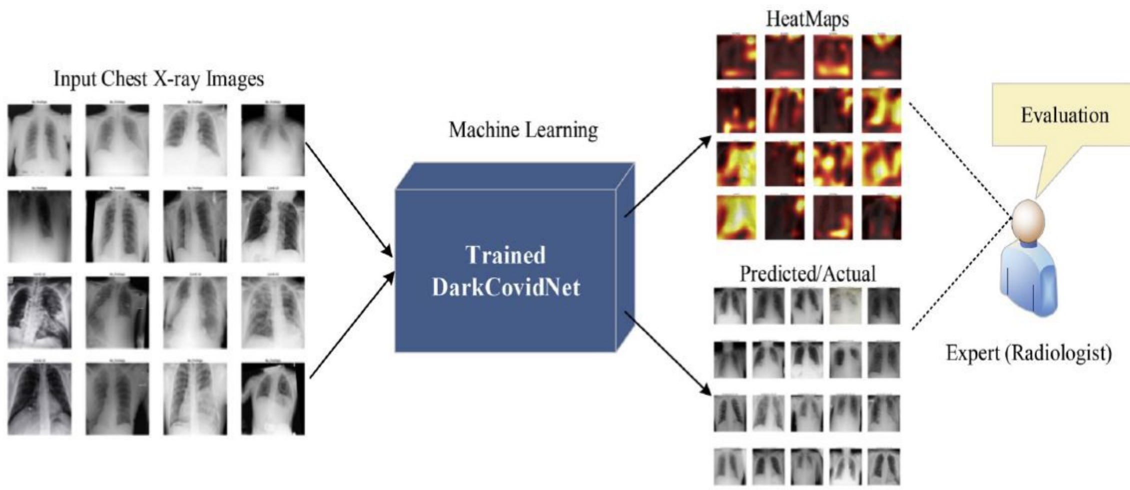
We have used the Darknet-19 model as the base model of this implementation. Darknet-19 is the classifier model that forms the basis of a real-time object detection system named YOLO (You only look once).

The Darknet-19 model has proven to be the state-of-the-art model in object detection technique. The proposed architecture consists of 17 convolutional layers. The architecture diagram is given below.

Each DN (DarkNet) layer has one convolution layer followed by BatchNorm and LeakyReLU operations. The 3 x Conv layer has the same setup three times in successive form.

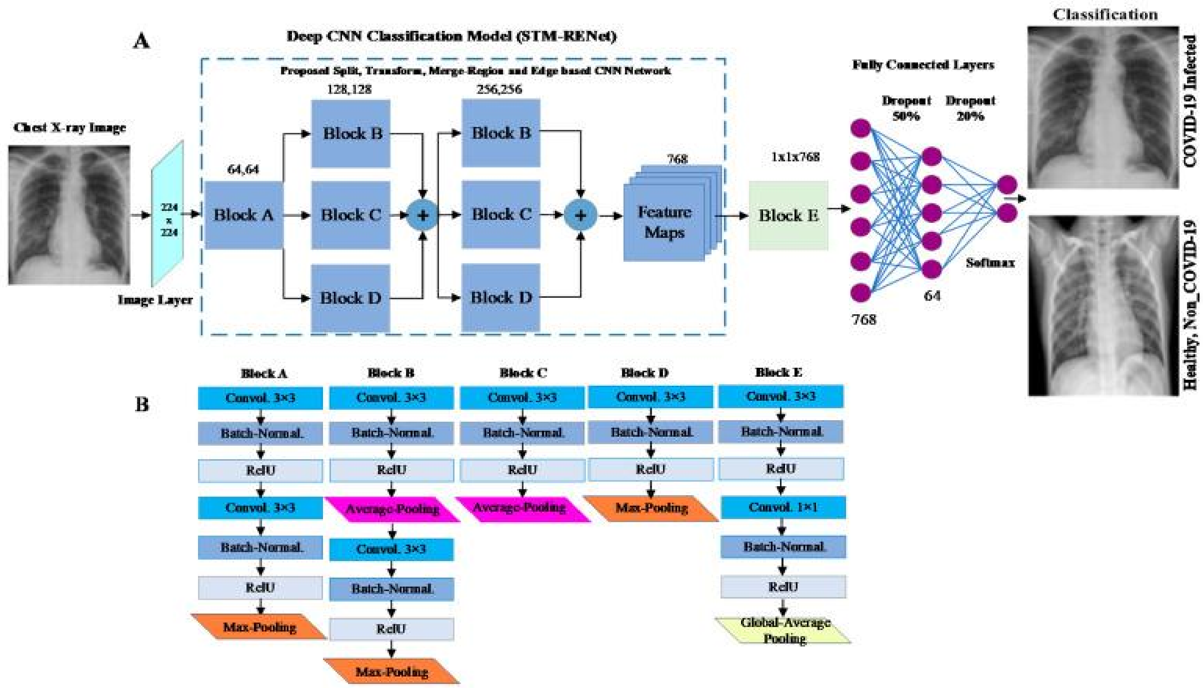


The DarkCovidNet deep learning model consists of 1,164,434 parameters. We have used Adam optimizer for weight updates, cross-entropy loss function, and selected the learning rate as 3e-3



(iv) Implementation using CB-STM-RENet

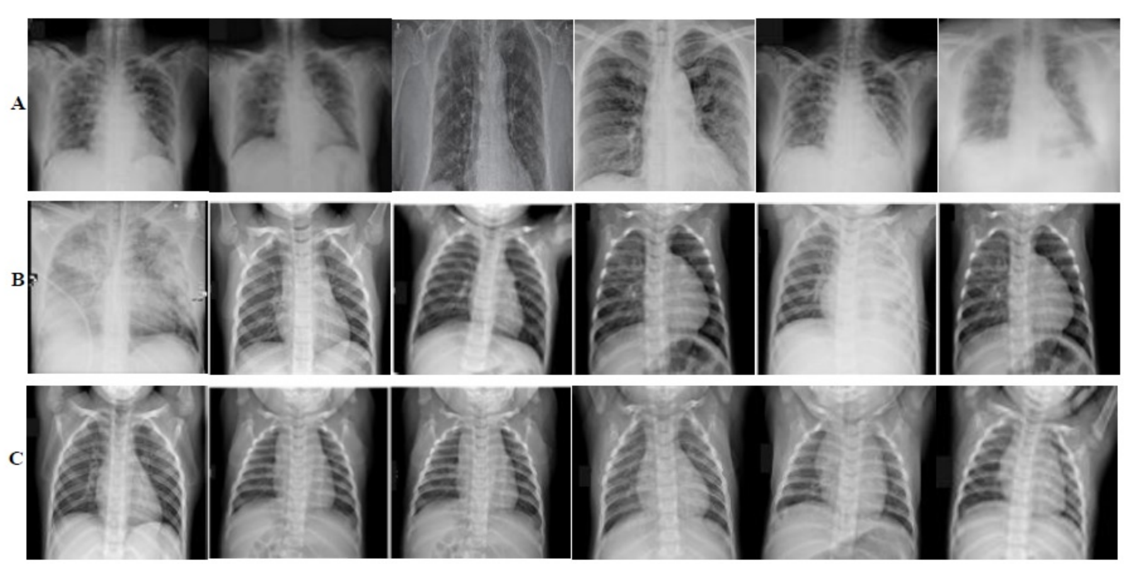
This implementation was a new technique based on CB CNN for automated detection of COVID-19 from chest X-Ray images. The technique targets the discrimination of COVID-19 infected from both non-COVID-19 infected and Healthy individual. In this regard, a new CNN classifier based on novel split-transform-merge (STM) block was developed that systematically implements RE-based operations for the learning of COVID-19 specific patterns and termed as “STM-RENet”. The learning capacity of the proposed CNN is enhanced using Channel Boosting to improve the detection rate while maintaining high precision. The CB CNN is termed as “CB-STM-RENet”. The performance of the proposed technique is compared with several existing CNNs by implementing them from scratch as well as by adapting them using TL on X-Ray dataset for COVID-19 detection. The overall workflow is shown below:



Three different Chest X-Ray images datasets were used.

- CoV-Healthy-6k
- CoV-NonCoV-10k
- CoV-NonCoV-15k

Panel (A), (B), and (C) show COVID-19 infected, Non-COVID-19 infected, and Healthy images, respectively.

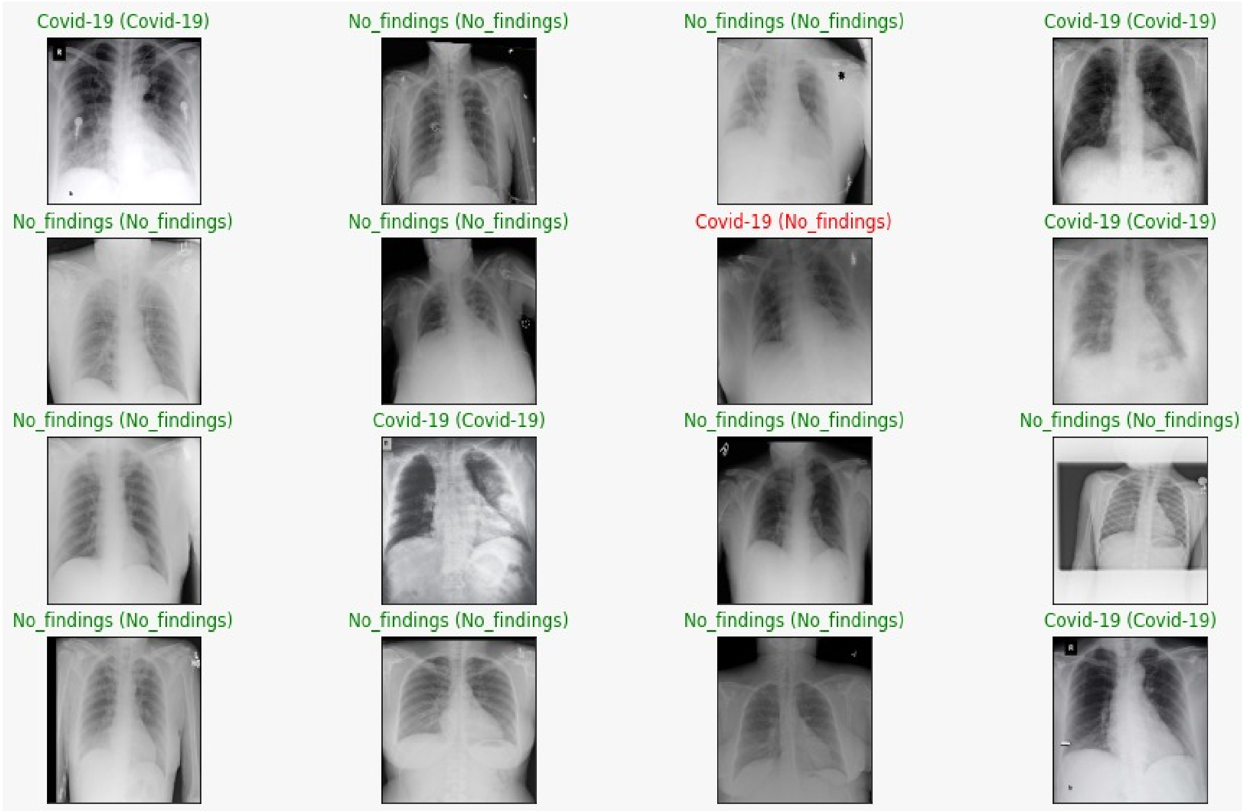


7. Results and Comparison

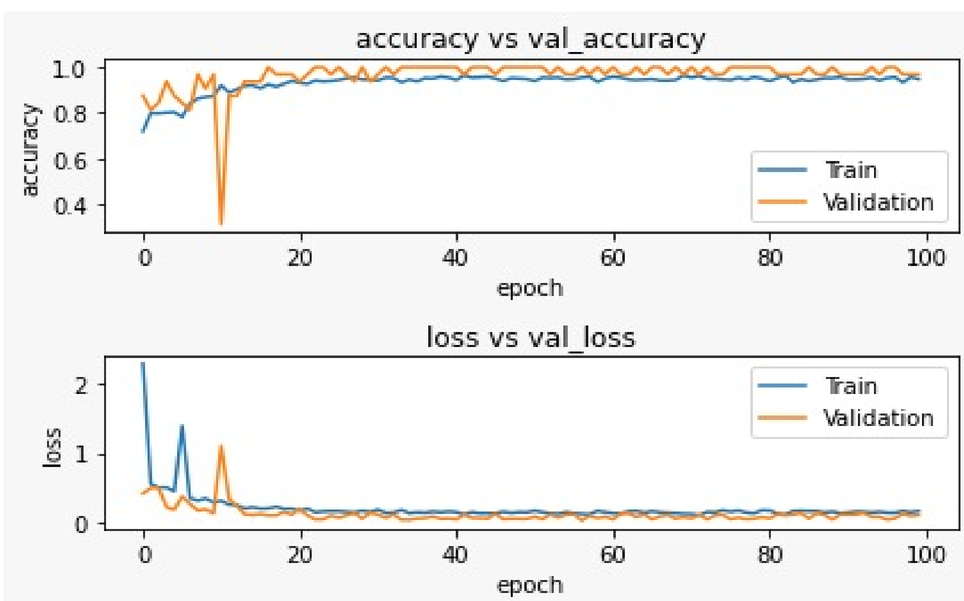
In the **transfer learning** approach for VGG-16, we train the fine tuned model for 100 epochs.

```
Epoch 00095: ReduceLROnPlateau reducing learning rate to 1.8626452377018543e-12.
15/15 [==============================] - 2s 127ms/step - loss: 0.1489 - accuracy: 0.9423 - val_loss: 0.0763 - val_accuracy: 0.9688
Epoch 96/100
15/15 [==============================] - ETA: 0s - loss: 0.1342 - accuracy: 0.9530
Epoch 00096: val_loss did not improve from 0.02241
15/15 [==============================] - 2s 125ms/step - loss: 0.1342 - accuracy: 0.9530 - val_loss: 0.0348 - val_accuracy: 1.0000
Epoch 97/100
15/15 [==============================] - ETA: 0s - loss: 0.1335 - accuracy: 0.9573
Epoch 00097: val_loss did not improve from 0.02241
15/15 [==============================] - 2s 126ms/step - loss: 0.1335 - accuracy: 0.9573 - val_loss: 0.0551 - val_accuracy: 1.0000
Epoch 98/100
15/15 [==============================] - ETA: 0s - loss: 0.1585 - accuracy: 0.9338
Epoch 00098: val_loss did not improve from 0.02241

Epoch 00098: ReduceLROnPlateau reducing learning rate to 9.313226188509272e-13.
15/15 [==============================] - 2s 124ms/step - loss: 0.1585 - accuracy: 0.9338 - val_loss: 0.1167 - val_accuracy: 0.9688
Epoch 99/100
15/15 [==============================] - ETA: 0s - loss: 0.1416 - accuracy: 0.9573
Epoch 00099: val_loss did not improve from 0.02241
15/15 [==============================] - 2s 129ms/step - loss: 0.1416 - accuracy: 0.9573 - val_loss: 0.0888 - val_accuracy: 0.9688
Epoch 100/100
15/15 [==============================] - ETA: 0s - loss: 0.1582 - accuracy: 0.9487
Epoch 00100: val_loss did not improve from 0.02241
15/15 [==============================] - 2s 130ms/step - loss: 0.1582 - accuracy: 0.9487 - val_loss: 0.1017 - val_accuracy: 0.9688

 This Model took 231.49 seconds (3.9 minutes) to train for 100 epochs
```

While testing, 16 images in a batch and we get the following output:-

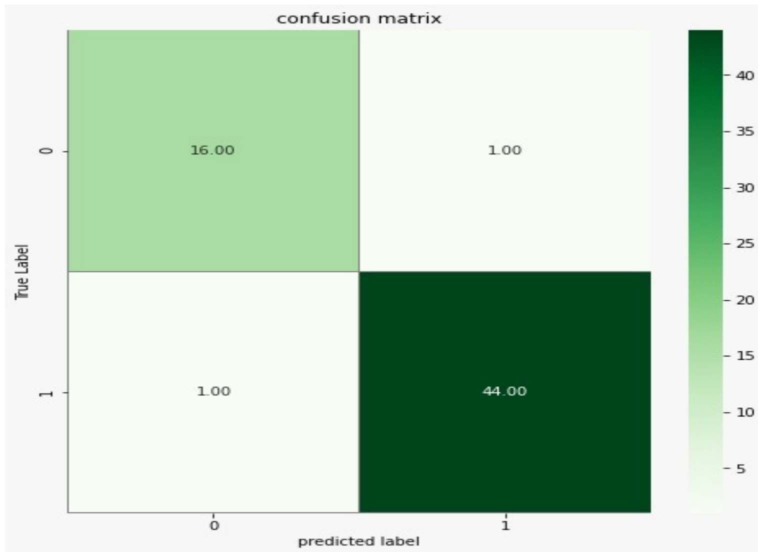


This result shows one falsely predicted result out of 16 generated results. Most of the results were correctly predicted by our model. The following graphs were obtained for the loss and accuracy by our model:-



From the Training and Validation accuracy graph above, our model does not seem to be overfitted, which is great. Our Training and Validation Loss graph above also indicates a good learning rate, which is amazing.

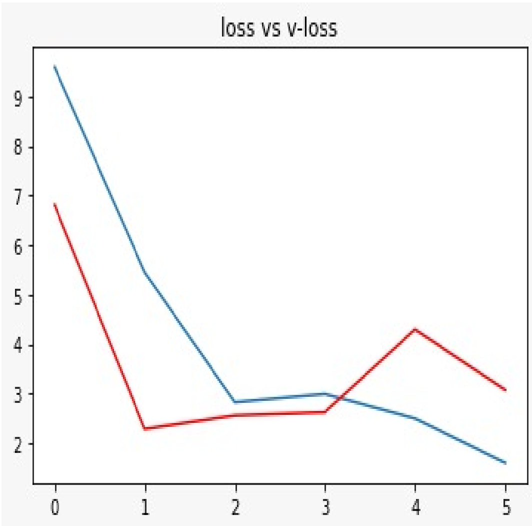
The following confusion matrix was obtained by our model:-

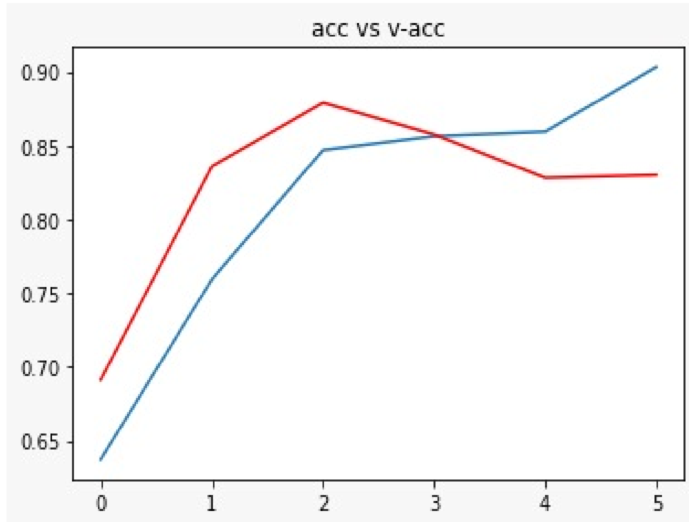


It is clear that the model can sometimes deceive in stating that a person is not infected but it could be. Anyways, we need the expertise to explain this kind of stuff, especially when it comes to medicine. We must not forget that we do not have enough images for Covid-19. Our confusion matrix indicates that there are disturbing errors.

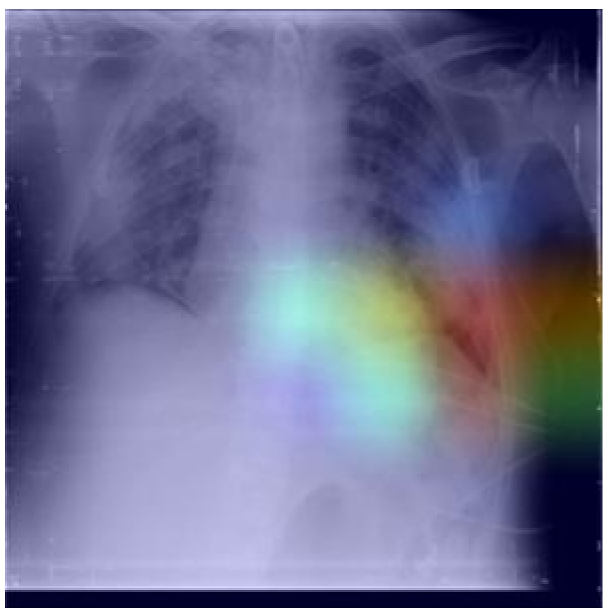
In the **ResNet50** approach, we ran the model for around 30 epochs and obtained the following graphs for accuracy and loss:-

```
Epoch 1/30
10/10 [==============================] - 42s 700ms/step - loss: 10.3360 - accuracy: 0.5762 - val_loss: 6.8106 - val_accuracy: 0.6914

Epoch 00001: val_accuracy improved from -inf to 0.69141, saving model to bestmodel.h5
Epoch 2/30
10/10 [==============================] - 6s 603ms/step - loss: 7.0514 - accuracy: 0.7239 - val_loss: 2.2904 - val_accuracy: 0.8359

Epoch 00002: val_accuracy improved from 0.69141 to 0.83594, saving model to bestmodel.h5
Epoch 3/30
10/10 [==============================] - 6s 601ms/step - loss: 2.3962 - accuracy: 0.8527 - val_loss: 2.5626 - val_accuracy: 0.8789

Epoch 00003: val_accuracy improved from 0.83594 to 0.87891, saving model to bestmodel.h5
Epoch 4/30
10/10 [==============================] - 6s 600ms/step - loss: 2.9127 - accuracy: 0.8555 - val_loss: 2.6281 - val_accuracy: 0.8574

Epoch 00004: val_accuracy did not improve from 0.87891
Epoch 5/30
10/10 [==============================] - 6s 593ms/step - loss: 2.4209 - accuracy: 0.8661 - val_loss: 4.2963 - val_accuracy: 0.8281

Epoch 00005: val_accuracy did not improve from 0.87891
Epoch 6/30
10/10 [==============================] - 6s 603ms/step - loss: 1.3532 - accuracy: 0.9124 - val_loss: 3.0766 - val_accuracy: 0.8301
```





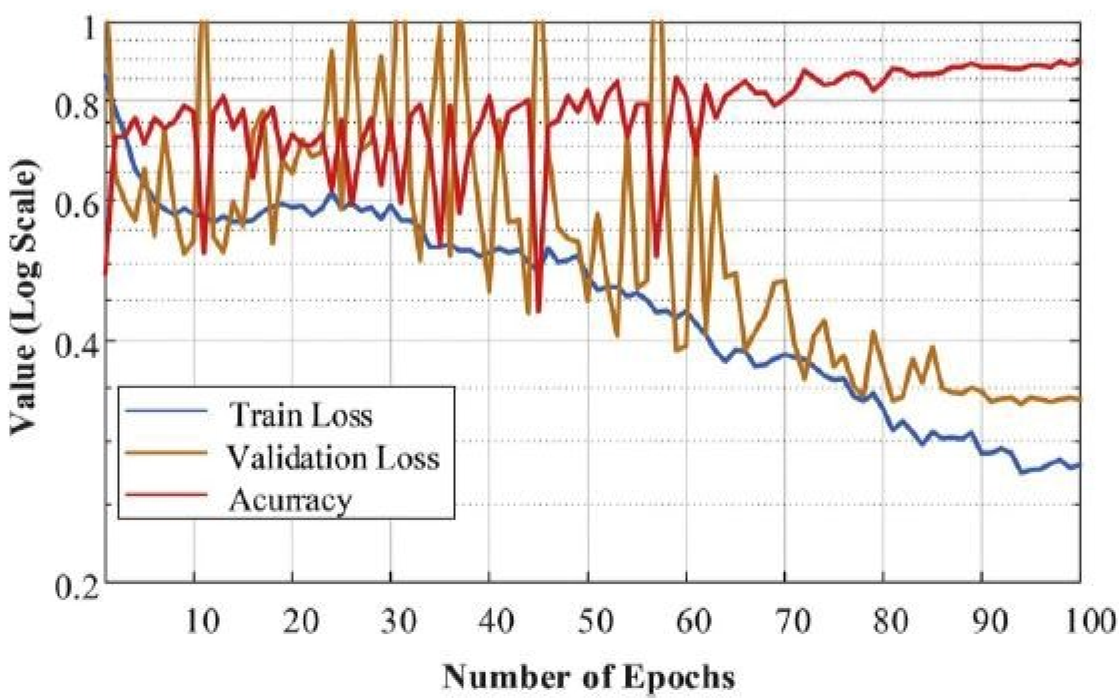
This implementation also included a GRADCAM. This grad-cam function returns the heat map, which later is mapped on the input X-Ray, with this we can determine which area in the chest has COVID-19.



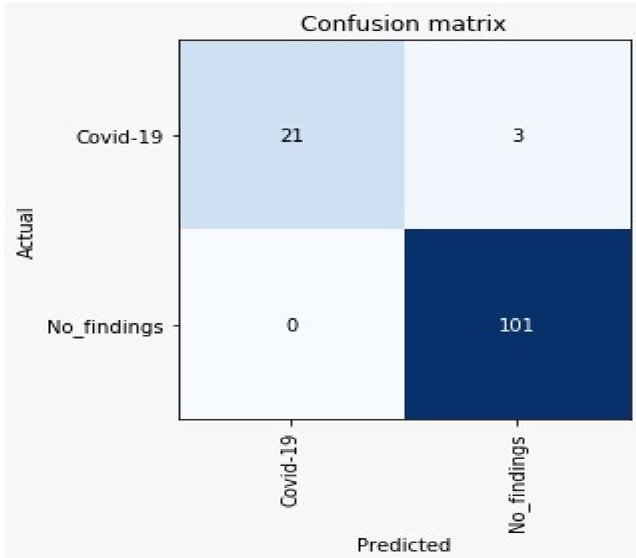
For the implementation of **DarkCovidNet**, we ran the model up to 100 epochs.

epoch	train_loss	valid_loss	accuracy	time
0	0.342396	0.790685	0.192000	00:13
1	0.261838	0.538252	0.880000	00:13
2	0.218703	0.141111	0.968000	00:13
3	0.190542	0.084161	0.976000	00:12
4	0.169056	0.091254	0.968000	00:13
5	0.162072	0.142616	0.952000	00:13
6	0.153581	0.101810	0.968000	00:14
7	0.170246	0.152644	0.960000	00:13
8	0.176809	0.166867	0.936000	00:13
9	0.159235	0.102111	0.968000	00:12
10	0.150246	0.113522	0.976000	00:13
11	0.153357	0.401838	0.848000	00:13
12	0.153655	0.131616	0.952000	00:13
13	0.156841	0.374867	0.872000	00:12
14	0.162700	0.084386	0.984000	00:13

After training we obtain the following variations for accuracy and loss with the number of epochs:



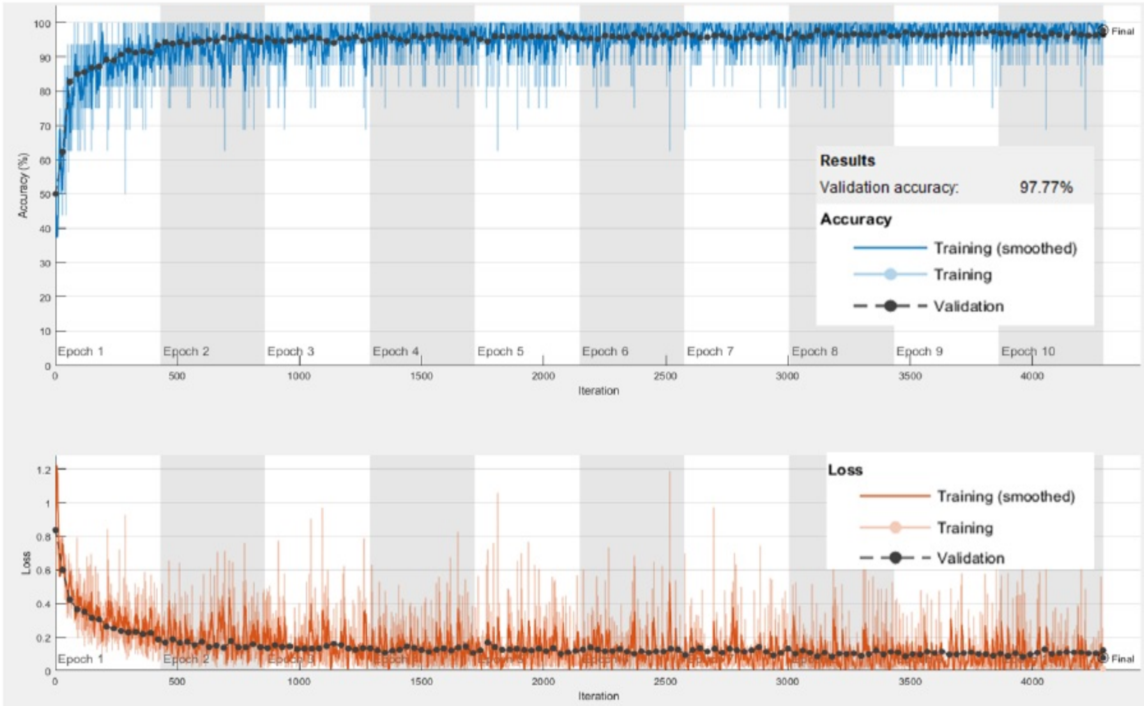
The following confusion matrix was obtained as a result:



For the channel boosted **STM-RENet** we obtained the highest accuracy of around 99%. The other evaluation parameters are summarized in tabular form below:

Techniques	Accuracy %	MCC	F-Score	Precision	Specificity
STM_RE_CB Net	98.53%	0.97	0.98	0.98	0.98
STM_RENet	97.58%	0.96	0.98	0.99	0.99

The accuracy and loss plots against the number of epochs were also plotted. This curve shows that the model achieves optimal accuracy in just a few epochs and then stays constant pretty much.



A comparison analysis of the various methods we implemented is given below:-

Techniques	Accuracy%	MCC	F-Score	Precision	Specificity
STM_RE_CBNet	98.53%	0.97	0.98	0.98	0.98
STM_RENet	97.58%	0.96	0.98	0.99	0.99

This graph shows the comparison between performances of Channel boosted STM and non Channel Boosted STM with two different datasets.

Techniques	Accuracy%	MCC	F-Score	Precision	Specificity
STM_RE_CBNet	97.48%	0.95	0.98	0.98	0.96
STM_RENet	97.58%	0.84	0.92	0.88	0.86

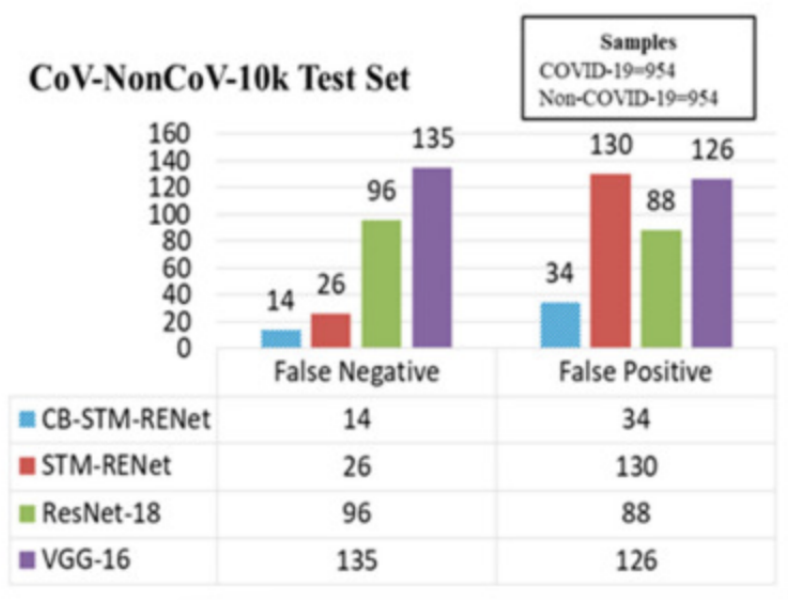
The following tables show a comparison between ResNet50 and VGG-16 (transfer learning) when tested on the Cov-NonCoV10k dataset:

Techniques	Accuracy %	MCC	F-Score	Precision	Specificity
Resnet50	96.59%	0.93	0.96	0.95	0.95
VGG-16	95.74%	0.91	0.95	0.95	0.95

Techniques	Accuracy %	MCC	F-Score	Precision	Specificity
Resnet50	90.36%	0.81	0.90	0.90	0.91
VGG-16	86.32%	0.73	0.86	0.86	0.87

Comparison between all models:

The following graph shows the comparison of false positives and false negatives of all the models we implemented. This shows that while VGG-16 with transfer learning gave the lowest performance, the channel boosted STM-RENet gave the highest performance and hence the lowest number of false positives and false negatives.

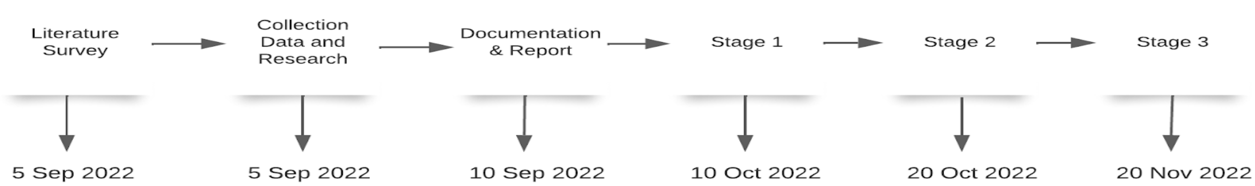


8. Conclusion

Early diagnosis of the novel coronavirus is extremely important to avoid further spread of the virus to others. Along this work, we designed various methods based on deep learning that uses chest X-ray images related to patients affected with COVID-19 and patients without COVID-19 to automatically detect the disease. According to our research results, due to its high overall performance, we believe it is of nature to help doctors and health experts make clinical decisions. COVID-19 presents a threat to the world's healthcare community and kills millions of people. Due to the large number of patients seen outdoors or in emergencies, doctors have limited time, and computer-aided analysis could rescue lives through early screening as well as appropriate care. This is very helpful in a pandemic, especially when the available health resources do not match the burden of disease as well as the need for preventive measures to be taken. Research in deep learning always strives to build better representations of reality and to create models capable of learning these representations from unlabeled data on a large scale. As a future perspective work, we are in the point of thinking to combine the four proposed models in this work and to train all the layers as a new approach to provide a better result.

9. Activity Time Chart

We followed the following timeline to complete various aspects of the project work:



10. References

[1] A. Uddin, B. Talukder, M. Monirujjaman Khan, and A. Zaguia, "Study on convolutional neural network to detect COVID-19 from chest X-rays," Math. Probl. Eng., vol. 2021, pp. 1–11, 2021.

[2] R. Sethi, M. Mehrotra, and D. Sethi, "Deep Learning based Diagnosis Recommendation for COVID-19 using Chest X-Rays Images," in 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA), 2020.

[3] L. Wang and A. Wong, "COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images," arXiv [eess.IV], 2020.

[4] I. D. Apostolopoulos and T. A. Mpesiana, "Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks," Phys Eng Sci Med, vol. 43, no. 2, pp. 635–640, 2020.

[5] S. Guefrechi, M. B. Jabra, A. Ammar, A. Koubaa, and H. Hamam, "Deep learning based detection of COVID-19 from chest X-ray images," Multimed. Tools Appl., vol. 80, no. 21–23, pp. 31803–31820, 2021.

[6] S. Chakraborty, B. Murali, and A. K. Mitra, "An efficient deep learning model to detect COVID-19 using chest X-ray images," Int. J. Environ. Res. Public Health, vol. 19, no. 4, p. 2013, 2022.

[7] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. Rajendra Acharya, "Automated detection of COVID-19 cases using deep neural networks with X-ray images," Comput. Biol. Med., vol. 121, no. 103792, p. 103792, 2020.

[8] S. H. Khan, A. Sohail, A. Khan, and Y.-S. Lee, "COVID-19 detection in chest X-ray images using a new channel boosted CNN," Diagnostics (Basel), vol. 12, no. 2, p. 267, 2022.