CSE4009 CAPSTONE Project

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

CXRcovNet:COVID-19 detection from CXR images using transfer learning approaches.

AHMED SHMELS-18BCE2427

ROZA KEFELEGN-18BCE2431

KEMAL MUDIE -18BCE2433

Under the guidance of

Dr. Rajkumar S

Associate Professor Grade 1

School of Computer Science & Engineering

03/06/2022

TABLE OF CONTENTS

Introduction

RT-PCR is the most extensively utilized COVID-19 detection technology.

- ✓ PCR kits, are expensive and require 6-9 hours to confirm infection in the patient.
- ✓ It produces low sensitivity,
- ✓ It produces false-negative findings.

To tackle the limitation of PCR imaging tools such as chest X-rays and (CT) scan are utilized to identify and diagnose COVID-19. In our project Chest X-rays are preferred over CT scans.

- ✓ CXR machines are accessible in most hospitals.
- ✓ CXR machines are less expensive than CT scan devices.
- ✓ CXR emit less ionizing radiation than CT scans.
- ✓ COVID-19 reveals various radiological signatures that easily identified by using chest CXR .

DL-based techniques to automatic analysis of chest X-rays can be used, which may shorten the analysis time.

Hence, our motive is to develop an automated DL-based approach for the detection of COVID-19 in chest X-rays.

Problem statement

- Our aim in this project is to create an image classification model that can predict Chest X-Ray scans with a reasonably high accuracy.
- The goal is to identify whether a patient can potentially be diagnosed with COVID-19.

Objective

In approach 1: Fine tune 3 pretrained CNN model and Identify the most suitable DL model for identify covid-19

In approach 2: design and train our own new custom-designed CNN model (CXRcovNet) to detect Covid-19 and conduct a comparative performance analysis of our proposed methodology with other state-of-the-art approaches

Application

- Used in hospitals to detect covid-19.
- it will substitute over PCR test, because X-ray machines are accessible in the majority of hospitals
- automate the examination of covid, shorten the analysis time and reduce Radiologist's work that helps to tackle covid spread.
- And the research finding will be addional input of knowledge in computer vision and image classification area.

Literature survey

Related work	modularity	Class	Data used	Evaluation method	model	Performance	Research gap
(Jain et al., 2021)	CXR	3	576, 4,273, 1,583	Train: Test = 5467: 965	Inception V3, Xception, ResNeXt	95.3% (+ / - 2.1%)	Comparison of existing state-of-the-art CNN models; Demonstrates high accuracy, sensitivity and very high specificity
(Apostolopoulos & Mpesiana, 2020)	CXR	3	224, 700, 504	5-fold cross validation	VGG 19, Mobile Net v2, Inception, Xception, Inception Resnet v	90.5% (± 6.97%)	Comparison of existing state-of-the-art CNN models; High on accuracy and very high specfcity. There seems to be some issues mentioned in the reported sensitivity data
(Hussain et al., 2021)	CXR	4,3,2	500, 400, 400, 800	5-fold cross validation	novel CNN model called CoroDet	91.2% /94.2%/ 99.1%	the model is not either under-fit or over-fit for 3,4 class
(Khan et al., 2020)	CXR	4,32	284, 327, 330, 310	Train test split	CoroNet (Xception) CoroNet uses Xception	89.6%/95 %/99 %	The model has been trained and tested on a small dataset of few hundred images

Literature survey

Related work	Modularity	Class	data used	Evaluation method	Classification model used	Performance	Research gap
(Ozturk et al., 2020)	CXR	3	625,125,500	5-fold cross validation	New method - DarkCovidNet	98.08	New method - DarkNet proposed. Demonstrates very high accuracy, sensitivity and specificity. However, number of images used is quite low
(Wang et al., 2020)	CXR	3	1300,538, 8066	Train: test	New method - COVIDNet	93.30	New method - COV- IDNet proposed. Demonstrates high accuracy, sensitivity and specfcity
(Das et al., 2021)	CXR		1,006,538, 468	5-fold cross validation	New ensemble method combining InceptionV3, Resnet50V2 and Densenet201	91.62	Unique ensemble-based technique proposed. Demonstrates high accuracy, sensitivity and specfcity
(Mahmud et al., 2020)	CXR	4	610 ,305,305	5-fold cross validation	tacked Multi-Resolution CovXNet	90.2%	New method - CovXNet proposed. Demonstrates very high accuracy, sensitivity and specfcity. However, number of images used is quite low

Literature survey

Related work	modularity	class	data used	Evaluation method	model	Performance	the research gap summary
(Chowdhury et al., 2020)	CXR	3	423 COVID-19, 1485 viral pneumonia, and 1579 normal chest X-ray images.	Train test split	VGG-19 CheXNet ResNet-18	96 96.4 96.44	The author tests for 2,3,4 with image augmentation and without augmentation The model archived highest accuracy with augmented data
(Saha et al., 2021)	CXR	3,2		70% training set, 10% validation set, and 20% test set	COV-VGX extracts distinct features	98.91% 99.37%	The model active high accuracy for covid class And the author balanced the dataset for all class
(Li et al., 2020)	CXR	3	Coronavirus = 1197 Normal = 10,192 Pneumonia = 7399		COVID-GATNet	94.30%	COVID-GATNet is created by combining DenseNet with Graph Attention Network (GAT). It employs the attention mechanism to optimize model parameters and classification performance.
(Toraman et al., 2020)	CXR	3,2	231/1050/1050 COVID-19 images were increased from 231 to 1050 by data augmentation method	10-fold cross validation	Convolutional CapsNet	84.22, 97.24	propose a new network model with five conv layers. processing time slow

Data sets

- Importing the from Kaggle [publication ,public repository, Kaggle , GitHub]
- Importing Libraries
- Preparing Training and Test Sets
- Creating Custom Dataset
- Image Transformations
- Prepare Data Loader
- Data Visualization
- Creating the Model
- Training the Model
- Show the Predictions
- Saving the Model
- Inference on a Single Image

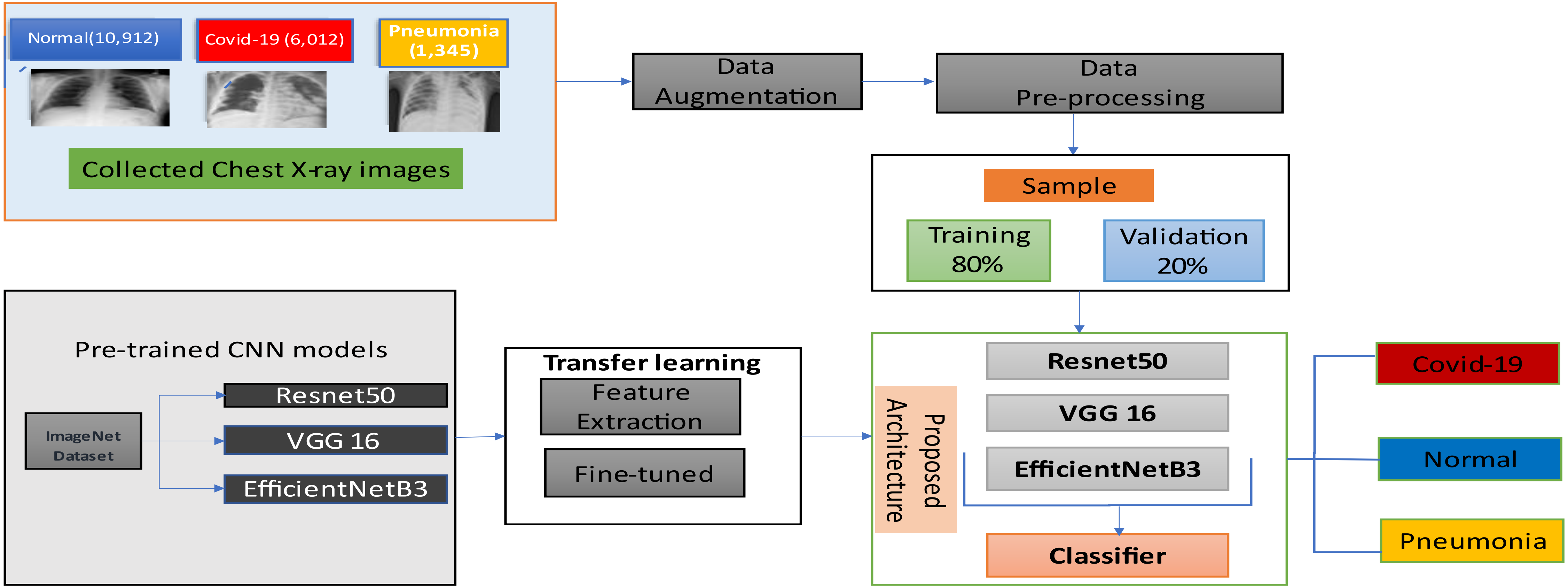
Techniques	Range
Rescale Factor	1/255
Shear range	0 to 0.1 Rad counterclockwise
Zoom range	0.9 to 1.1
Channel shift range	150
RandomHorizontalFlip	True
RandomVerticalFlip	True
Height shift range	10%
Rotation range	-90 to 90
Train-test split ratio	80%:20%
Width shift range	10%
Normalize	Mean = 0.485, 0.456, 0.406, STd= 0.229, 0.224, 0.225
Shuffle	True

Hyperparameters and data set used

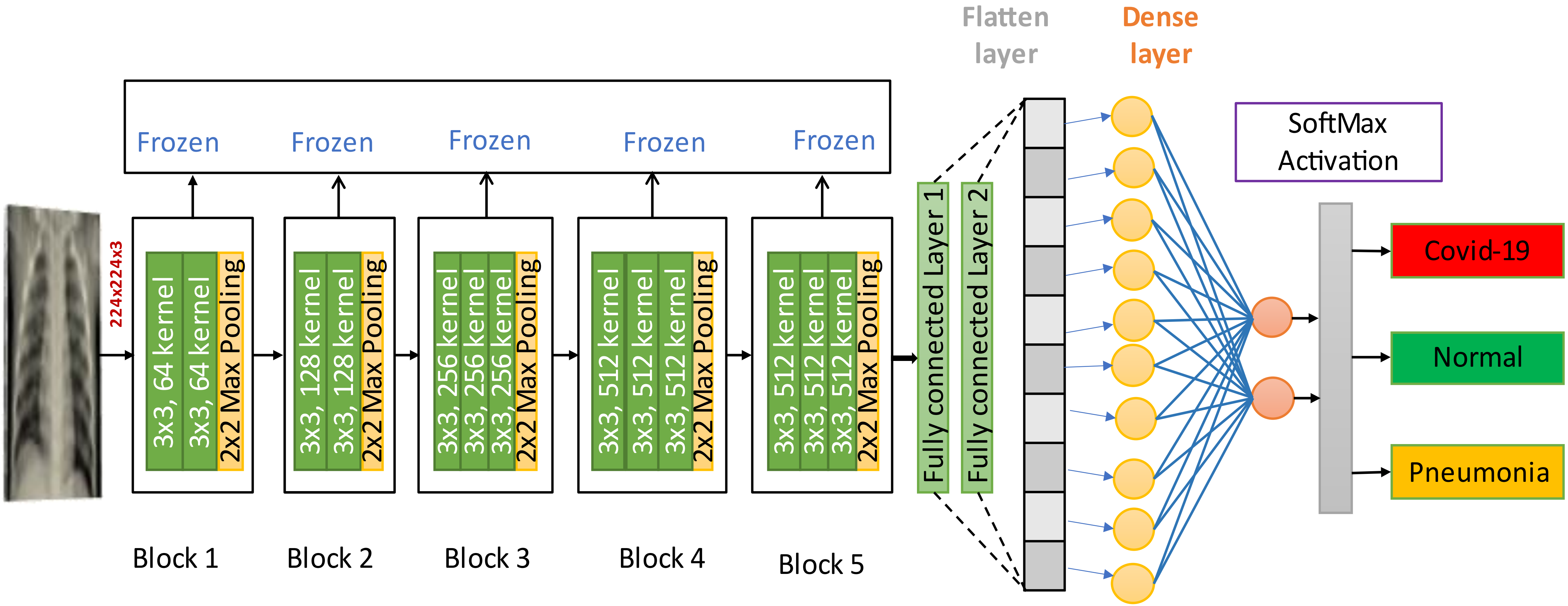
Data source	Name of class	Total data collected	Testing	Modality
(Rahman et al., 2021b) (Chowdhury et al., 2020)	Infected - covid	3616	240	X-Ray images
	health	10192	240	
	Infected Pneumonia	1335	240	

List of hyperparameters	Setup
Input image Re size	224x224x3
Batch size	32
Number of Epoch	22
activation function	Relu
Optimizer used	Adam
Model	Sequential
Learning rate (LR)	0.003
Loss function used	Categorical cross entropy
dropout probability	0.5

Proposed methodology 1



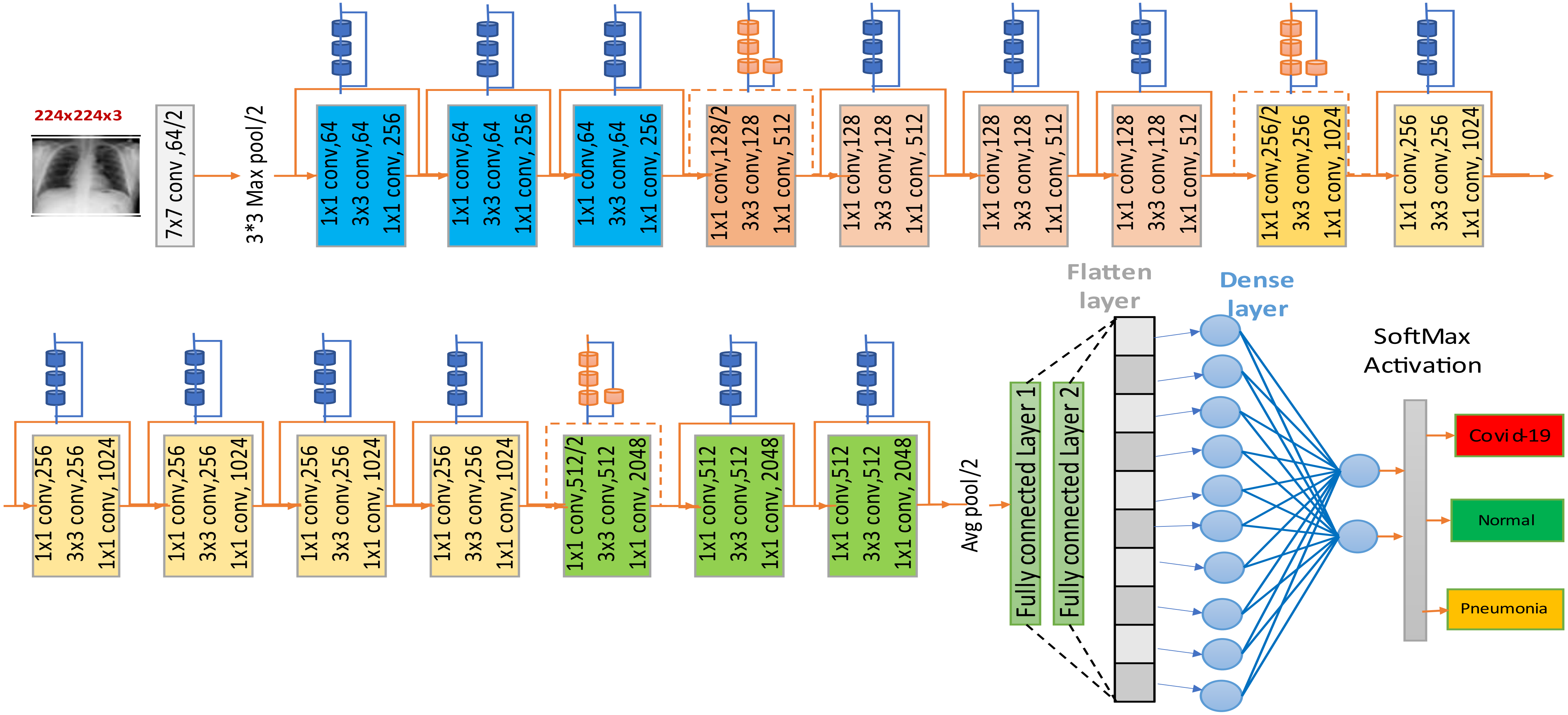
Proposed VGG-16 architecture



Proposed VGG-16 model summary

Layer type	Output shape	#Parma
input_1 (InputLayer)	224 × 224 × 3	0
block1_conv1 (Conv2D)	224 × 224 × 64	1792
block1_conv2 (Conv2D)	224 × 224 × 64	36928
block1_pool (MaxPooling2D)	112 × 112 × 64	0
block2_conv1 (Conv2D)	112 × 112 × 128	73856
block2_conv2 (Conv2D)	112 × 112 × 128	147584
block2_pool (MaxPooling2D)	56 × 56 × 128	0
block3_conv1 (Conv2D)	56 × 56 × 256	295168
block3_conv2 (Conv2D)	56 × 56 × 256	590080
block3_conv3 (Conv2D)	56 × 56 × 256	590080
block3_pool (MaxPooling2D)	28 × 28 × 256	0
block4_conv1 (Conv2D)	28 × 28 × 512	1180160
block4_conv2 (Conv2D)	28 × 28 × 512	2359808
block4_conv3 (Conv2D)	28 × 28 × 512	2359808
block4_pool (MaxPooling2D)	14 × 14 × 512	0
block5_conv1 (Conv2D)	14 × 14 × 512	2359808
block5_conv2 (Conv2D)	14 × 14 × 512	2359808
block5_conv3 (Conv2D)	14 × 14 × 512	2359808
block5_pool (MaxPooling2D)	7 × 7× 512	0
flatten (Flatten)	25088	0
dense (Dense)	64	1605696
dropout (Dropout)	64	0
dense_1 (Dense)	3	195
Total params: 16,320,579 Trainable params: 1,605,891 Non-trainable params: 14,714,688		

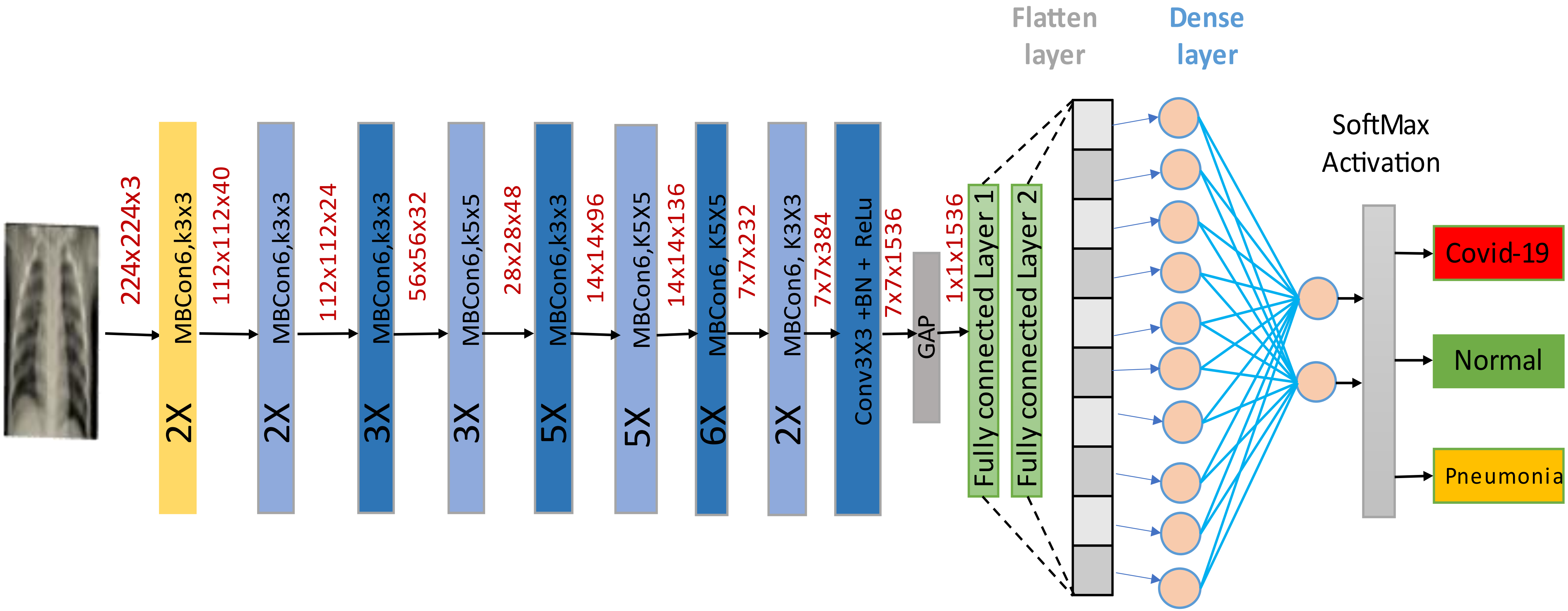
Proposed ResNet-50 architecture



Proposed ResNet-50 model summary

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
resnet50 (Functional)        (None, 2048)              23587712
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 6147
=================================================================
Total params: 23,593,859
Trainable params: 23,540,739
Non-trainable params: 53,120
_________________________________________________________________
```

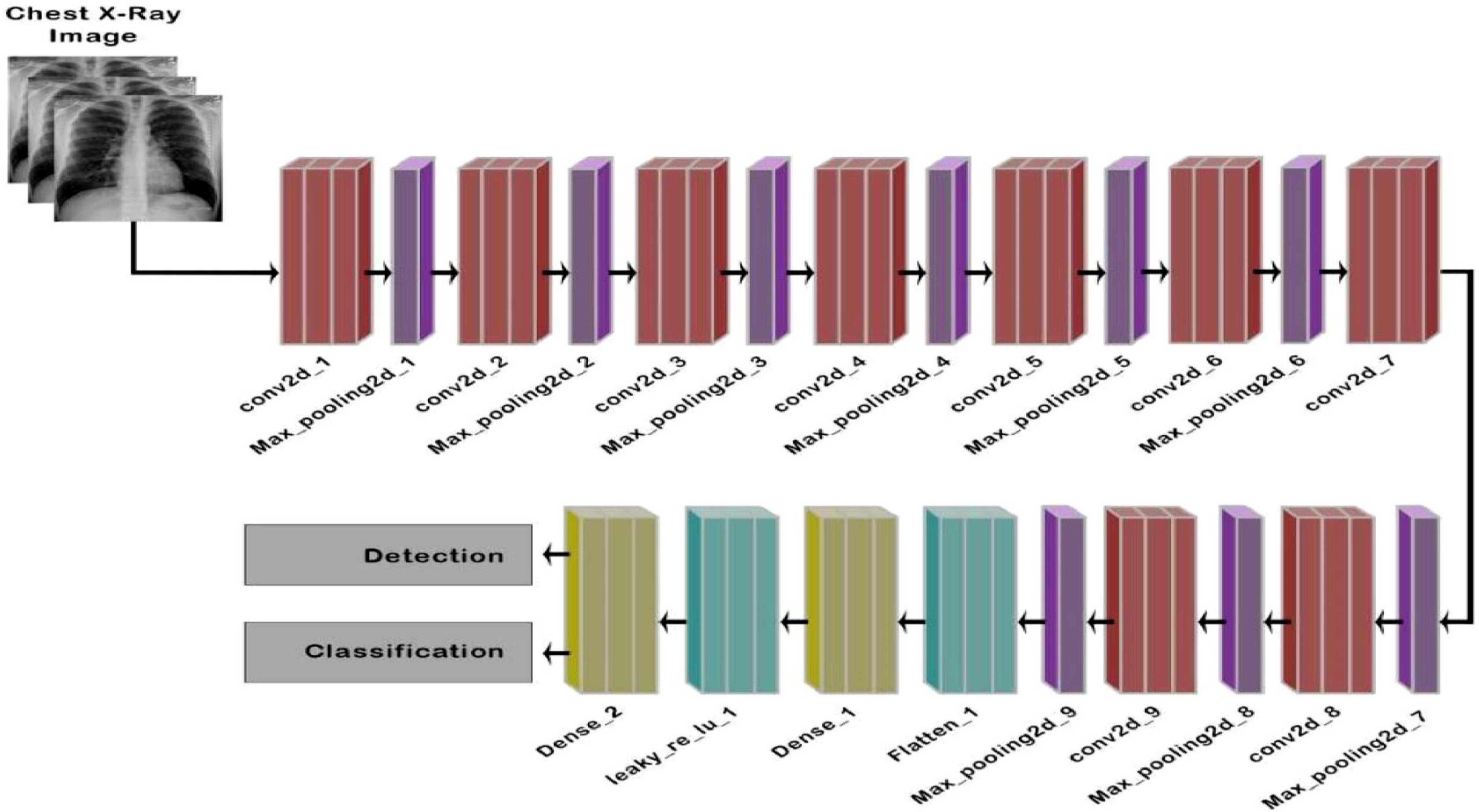
Proposed Efficient Net –B3 architecture



Proposed Efficient Net –B3 model summary

```
block7b_se_reshape (Reshape)     (None, 1, 1, 2304)   0          block7b_se_squeeze[0][0]
block7b_se_reduce (Conv2D)       (None, 1, 1, 96)     221280     block7b_se_reshape[0][0]
block7b_se_expand (Conv2D)       (None, 1, 1, 2304)   223488     block7b_se_reduce[0][0]
block7b_se_excite (Multiply)     (None, 7, 7, 2304)   0          block7b_activation[0][0]
                                                                 block7b_se_expand[0][0]
block7b_project_conv (Conv2D)    (None, 7, 7, 384)    884736     block7b_se_excite[0][0]
block7b_project_bn (BatchNormal  (None, 7, 7, 384)    1536       block7b_project_conv[0][0]
block7b_drop (Dropout)           (None, 7, 7, 384)    0          block7b_project_bn[0][0]
block7b_add (Add)                (None, 7, 7, 384)    0          block7b_drop[0][0]
                                                                 block7a_project_bn[0][0]
top_conv (Conv2D)                (None, 7, 7, 1536)   589824     block7b_add[0][0]
top_bn (BatchNormalization)      (None, 7, 7, 1536)   6144       top_conv[0][0]
top_activation (Activation)      (None, 7, 7, 1536)   0          top_bn[0][0]
max_pool (GlobalMaxPooling2D)    (None, 1536)         0          top_activation[0][0]
batch_normalization_3 (BatchNor  (None, 1536)         6144       max_pool[0][0]
dense_6 (Dense)                  (None, 256)          393472     batch_normalization_3[0][0]
dropout_3 (Dropout)              (None, 256)          0          dense_6[0][0]
dense_7 (Dense)                  (None, 3)            771        dropout_3[0][0]
==================================================================================================
Total params: 11,183,922
Trainable params: 11,093,547
Non-trainable params: 90,375
```

Proposed methodology 2



CXRcovNet model summary

Layer (type)	Output Shape	Param #
batch_normalization_6 (BN)	224, 224, 1	4
conv2d_18 (Conv2D)	224, 224, 64	640
max_pooling2d_18 (MaxPooling)	112, 112, 64	0
conv2d_19 (Conv2D)	112, 112, 64	36928
max_pooling2d_19 (MaxPooling)	56, 56, 64	0
dropout_18 (Dropout)	56, 56, 64	0
conv2d_20 (Conv2D)	54, 54, 32	18464
max_pooling2d_20 (MaxPooling)	27, 27, 32	0
dropout_19 (Dropout)	27, 27, 32	0
flatten_6 (Flatten)	23328	0
dense_12 (Dense)	128	2986112
dropout_20 (Dropout)	128	0
dense_13 (Dense)	3	387
Total params: 3,042,535 Trainable params: 3,042,533 Non-trainable params: 2		

Performance matrix

1. Confusion metrics (CM)

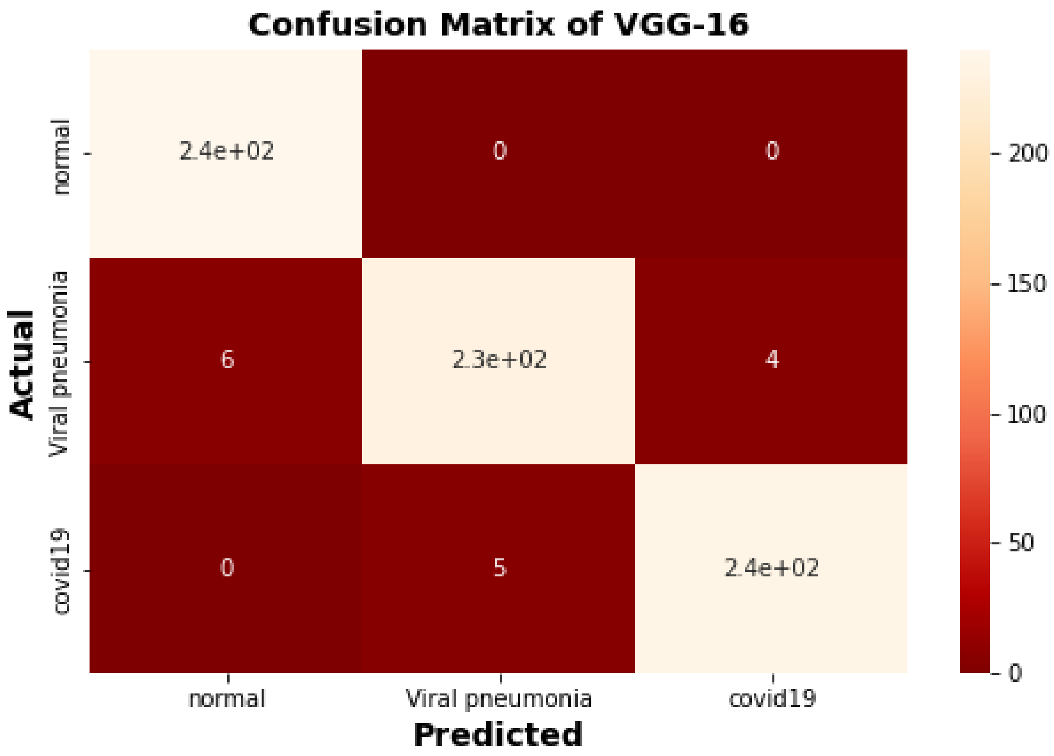
Matric	Formula	Interpretation
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Overall performance of a model
Precision	$\frac{TP}{TP+FP}$	How accurate the positive predictions are
Recall Sensitivity	$\frac{TP}{TP+FN}$	Coverage of the actual positive sample
Specificity	$\frac{TN}{TN+FP}$	Coverage of the actual negative sample
F1 score	$\frac{2TP}{2TP+FP+FN}$	Hybrid matric useful for unbalanced classes

2. Receiver operating characteristics (ROC) and AUC

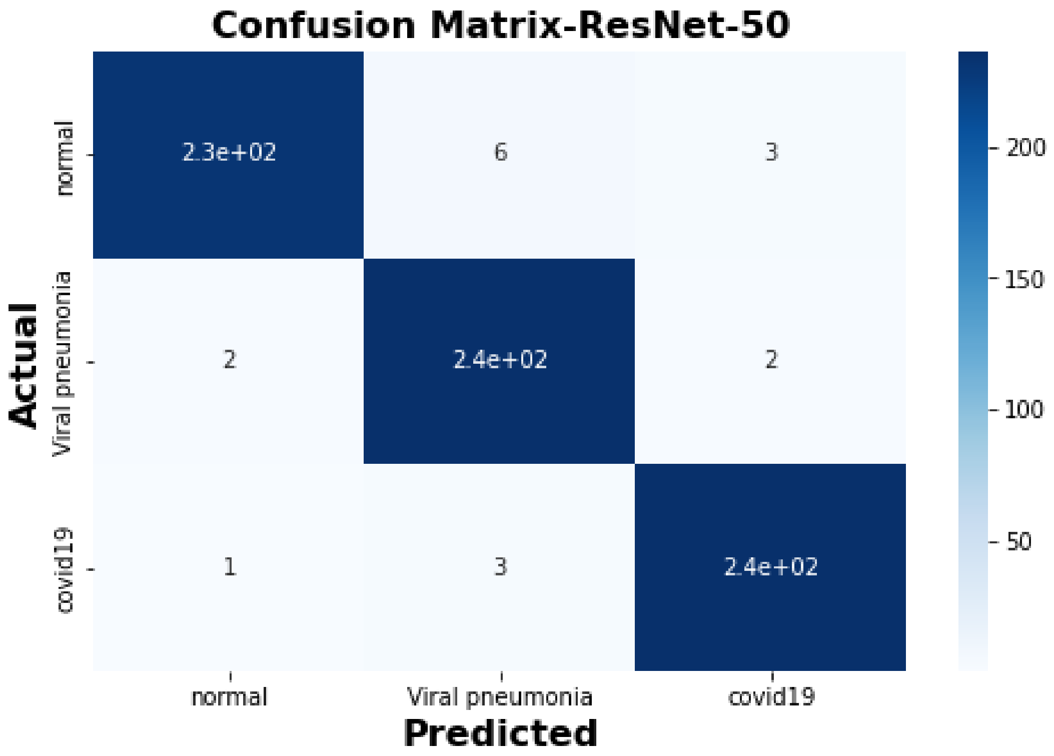
Matric	Formula	Equivalent
True positive rate TPR	$\frac{TP}{TP+FN}$	Recall, sensitivity
False positive rate FPR	$\frac{FP}{TN+FP}$	1- Specificity

Confusion matrix

VGG-16: Confusion Matrix for 3 classes

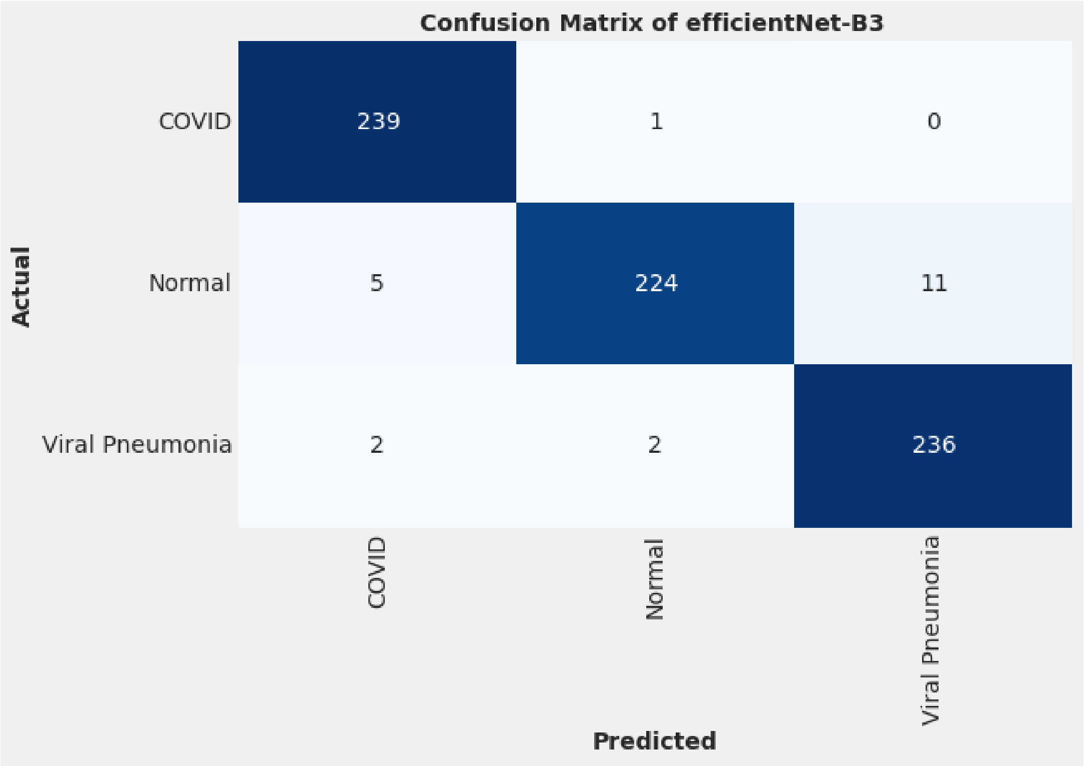


ResNet-50: Confusion Matrix for 3 classes

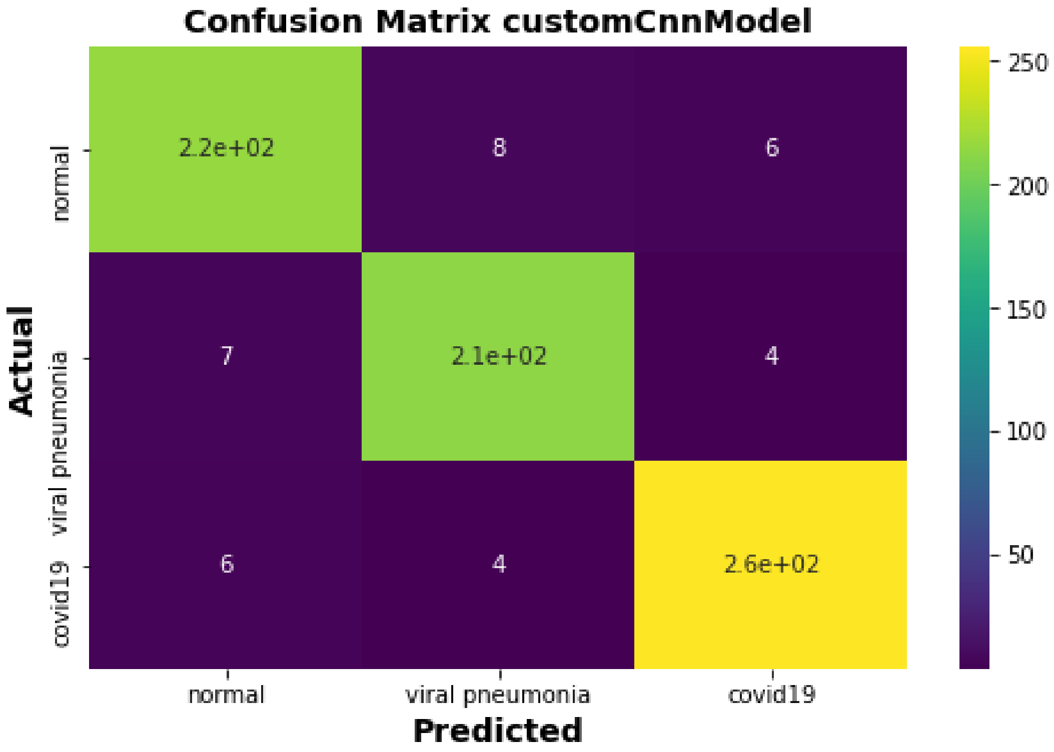


Confusion matrix

EffcientNet-B3: Confusion Matrix for 3 classes

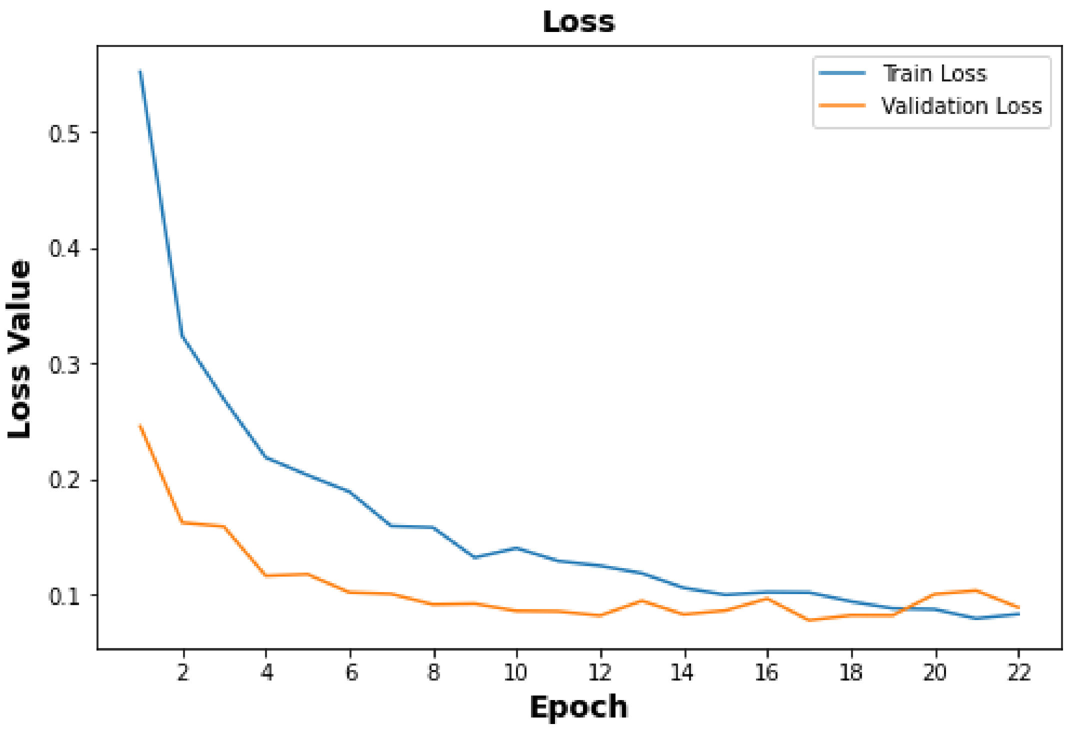


CXRcovNet: Confusion Matrix for 3 classes

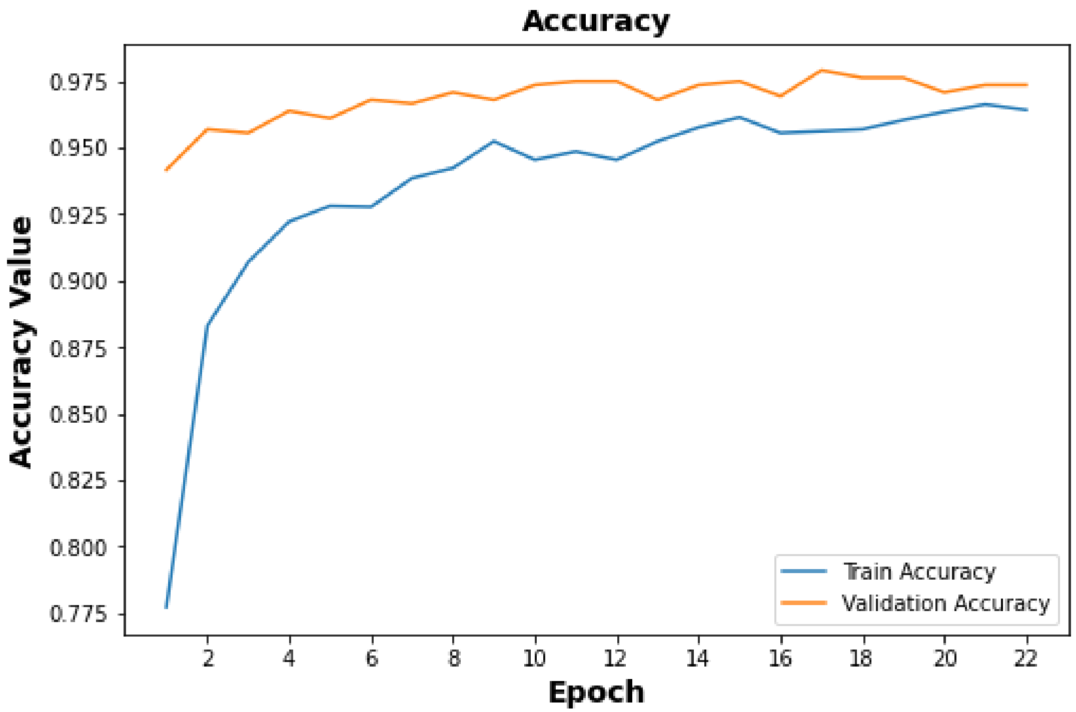


Model evaluation

VGG-16:Train loss vs validation loss

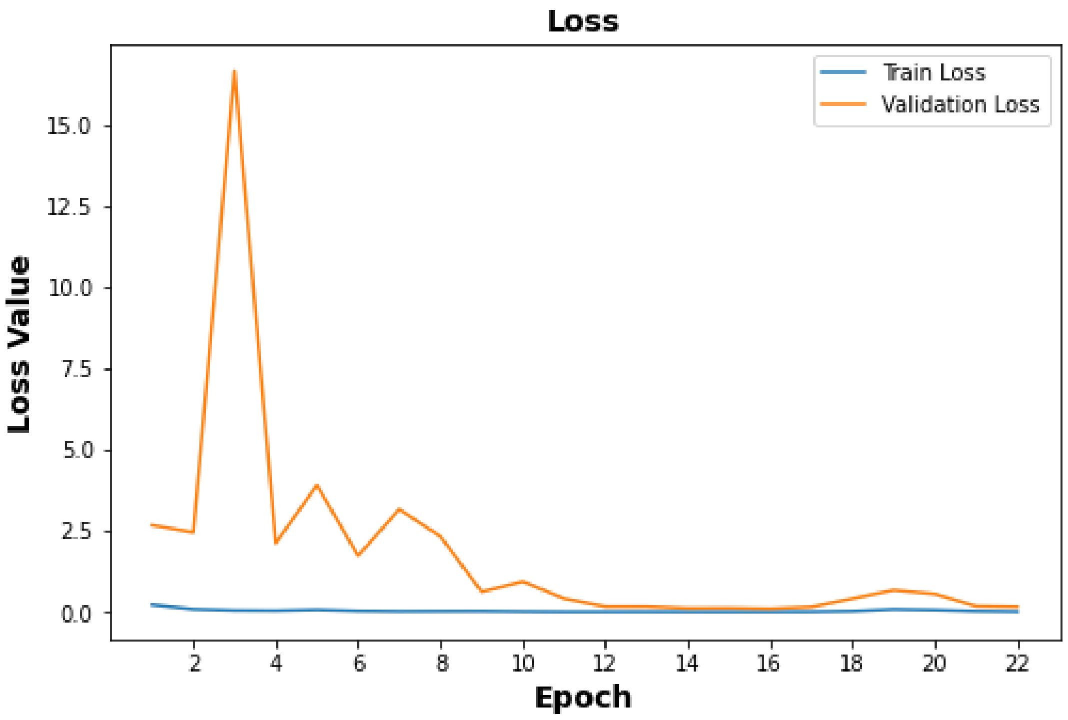


VGG-16: Tarin Acc vs Val accuracy

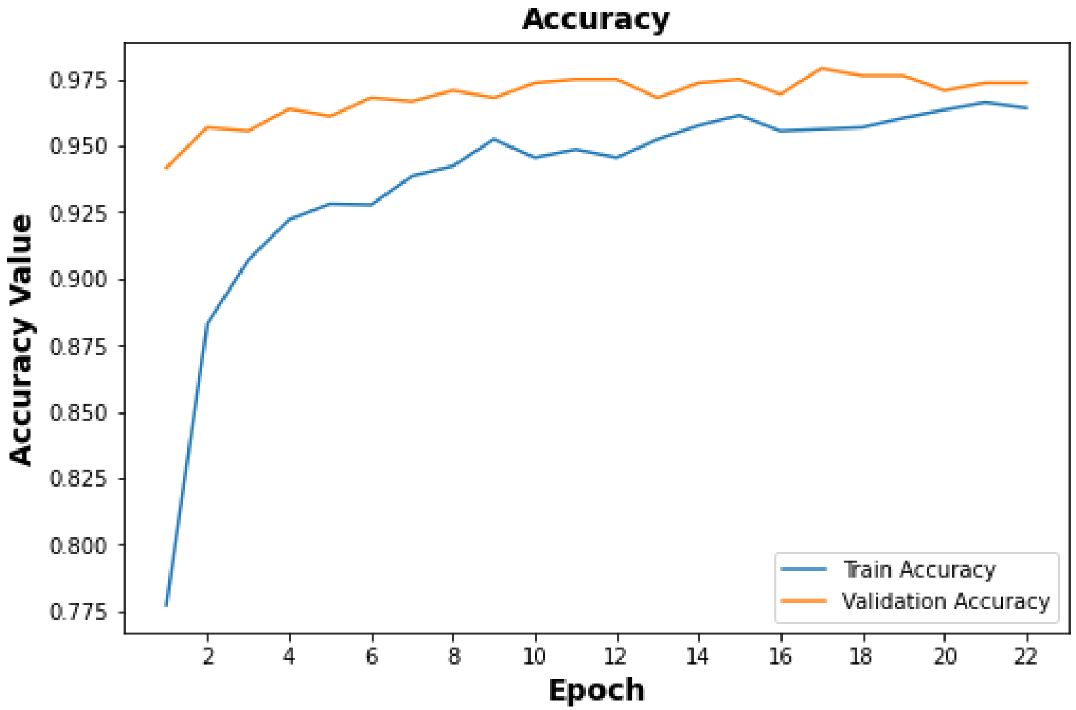


Model evaluation

ResNet-50:Train loss vs validation loss

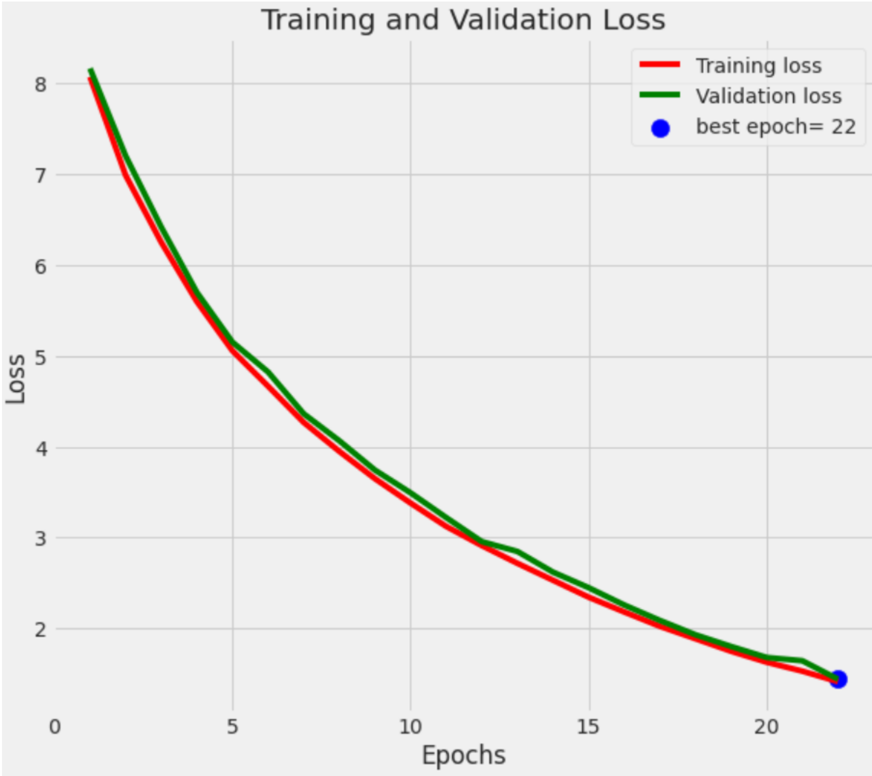


ResNET-50: Tarin Acc vs Val accuracy

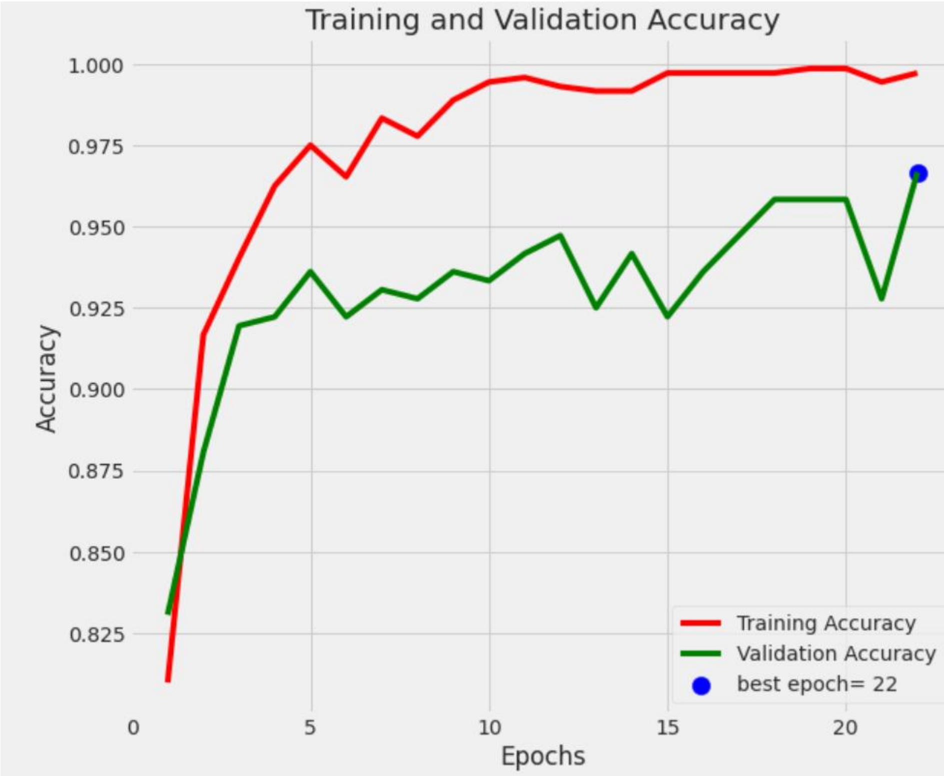


Model evaluation

EffcientNet-B3 :Train loss vs validation loss

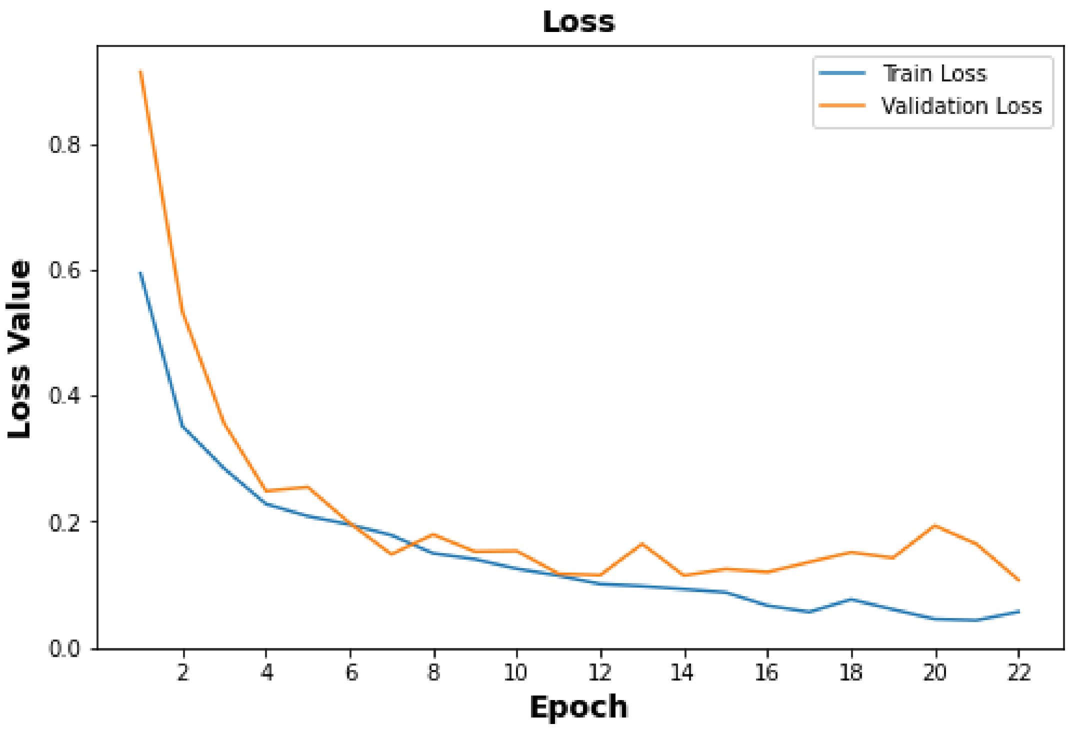


EffcientNet-B3 : Tarin Acc vs Val accuracy

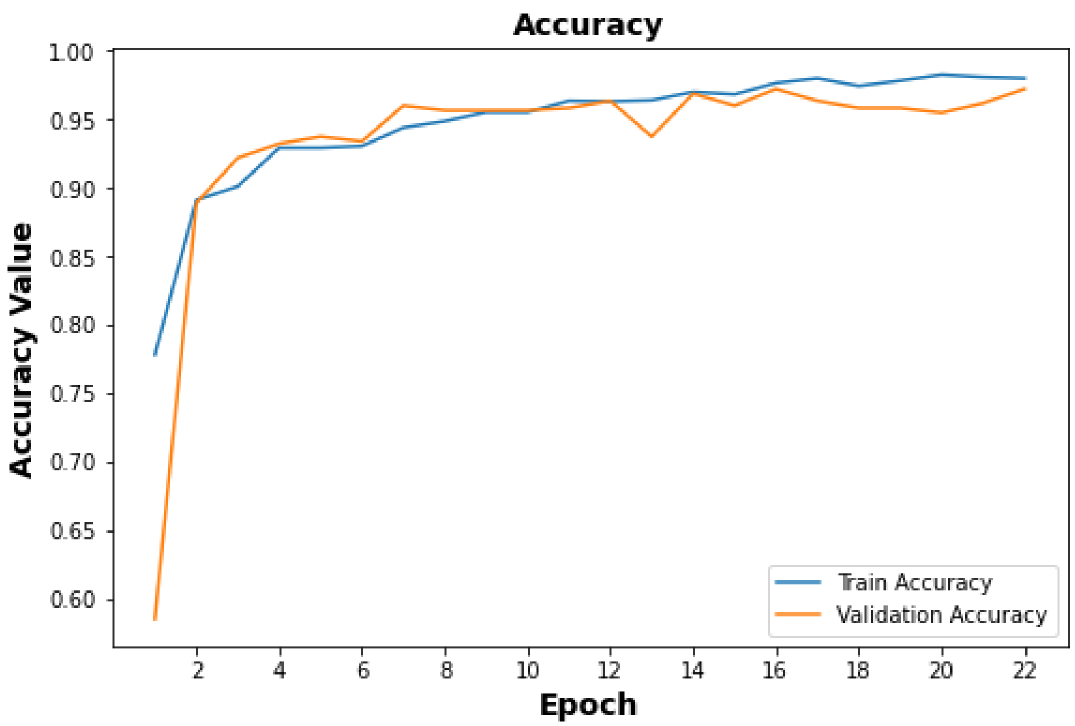


Model evaluation

CXRcovNet :Train loss vs validation loss

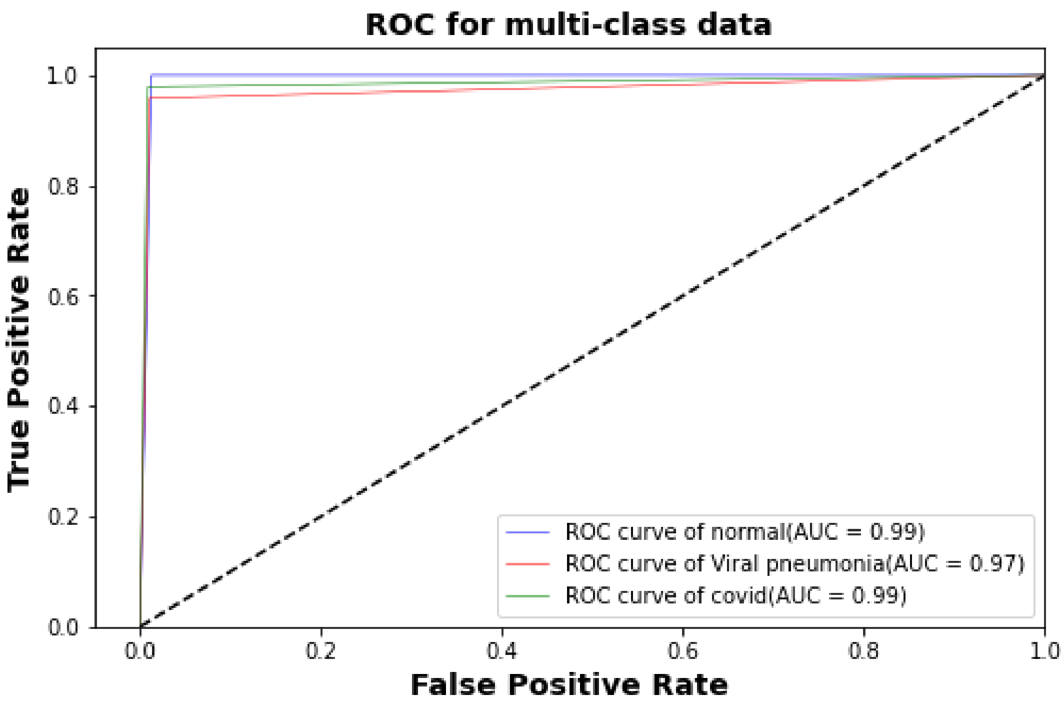


CXRcovNet : Tarin Acc vs Val accuracy

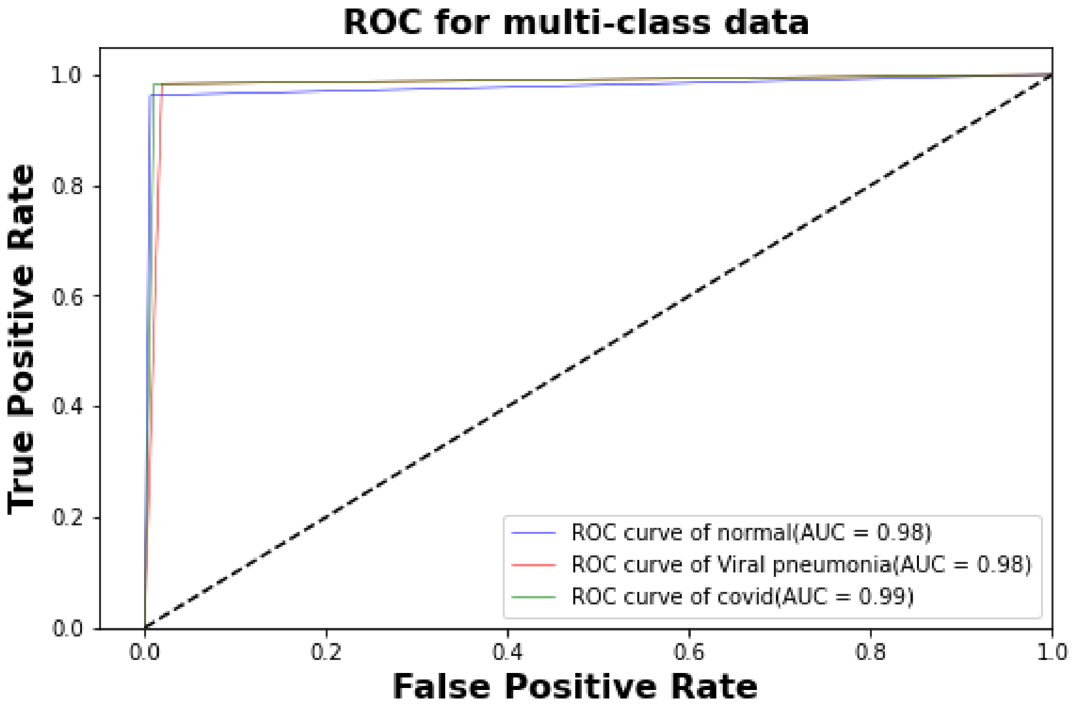


ROC evaluation

VGG-16:AUC

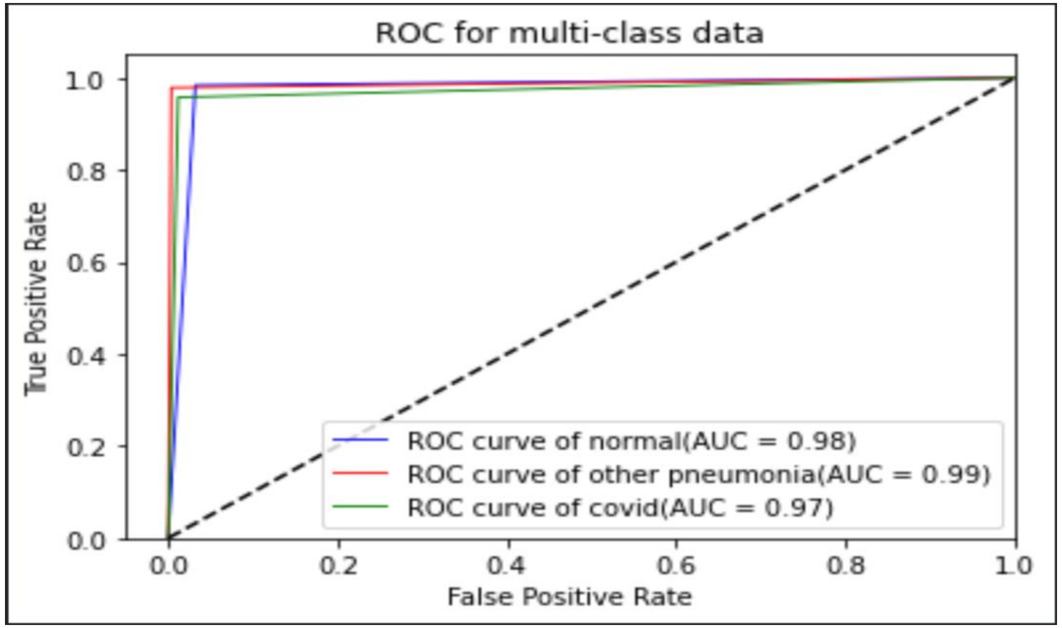


ResNet-50 :AUC

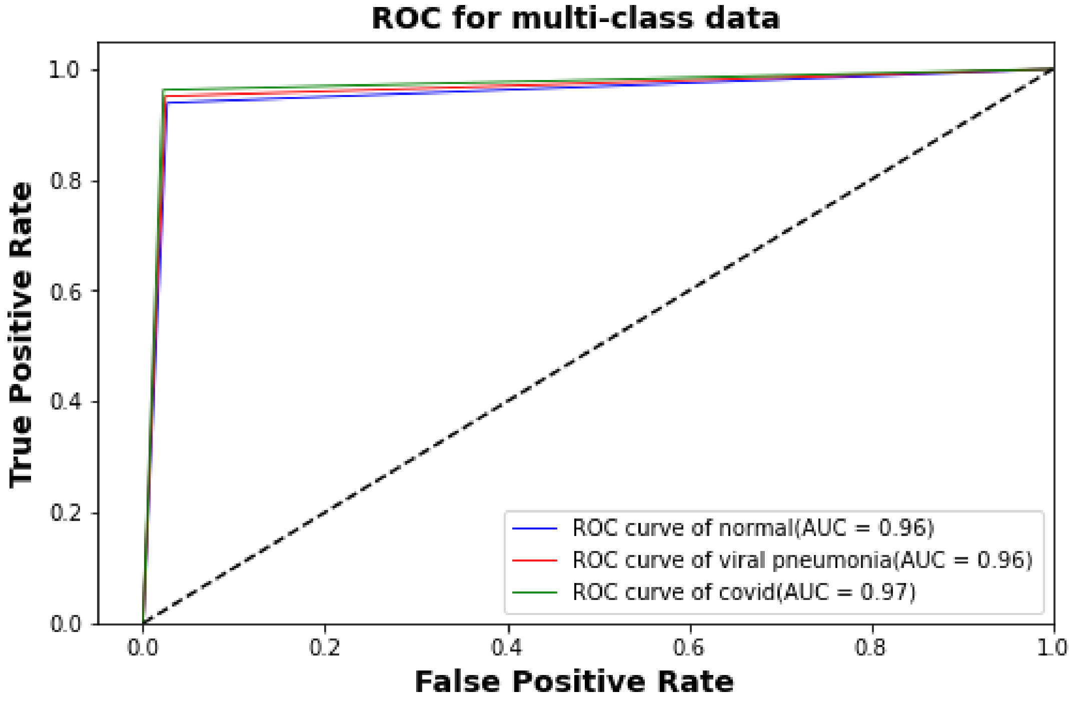


ROC evaluation

Efficient Net-B3 :AUC

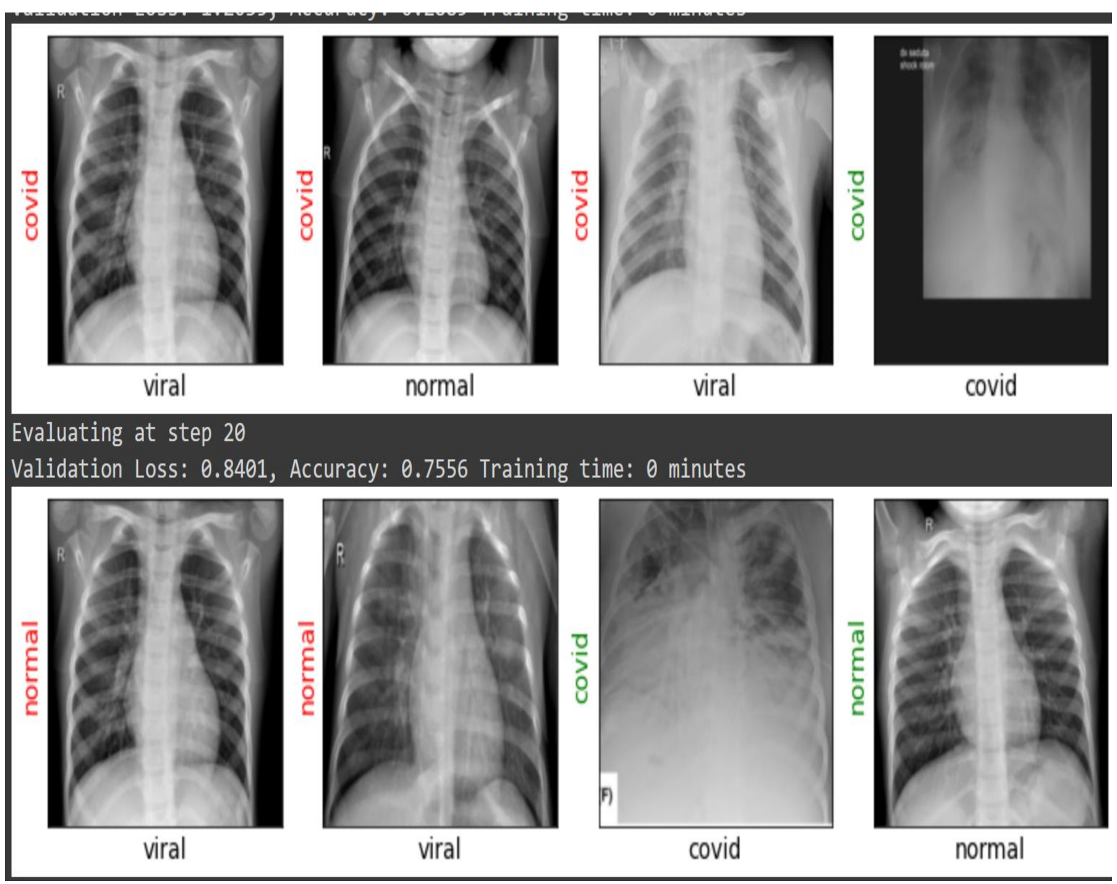


CXRcovNet :AUC

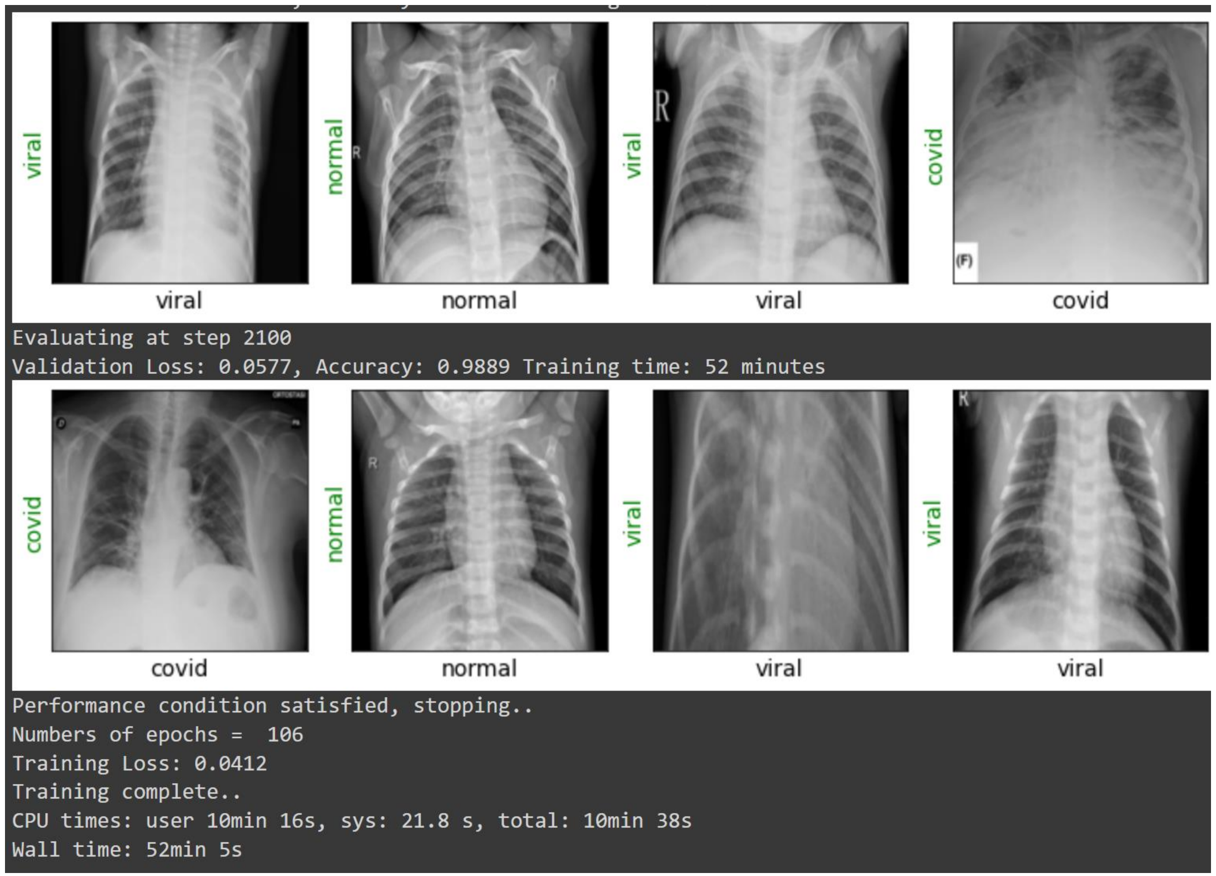


Predication/output

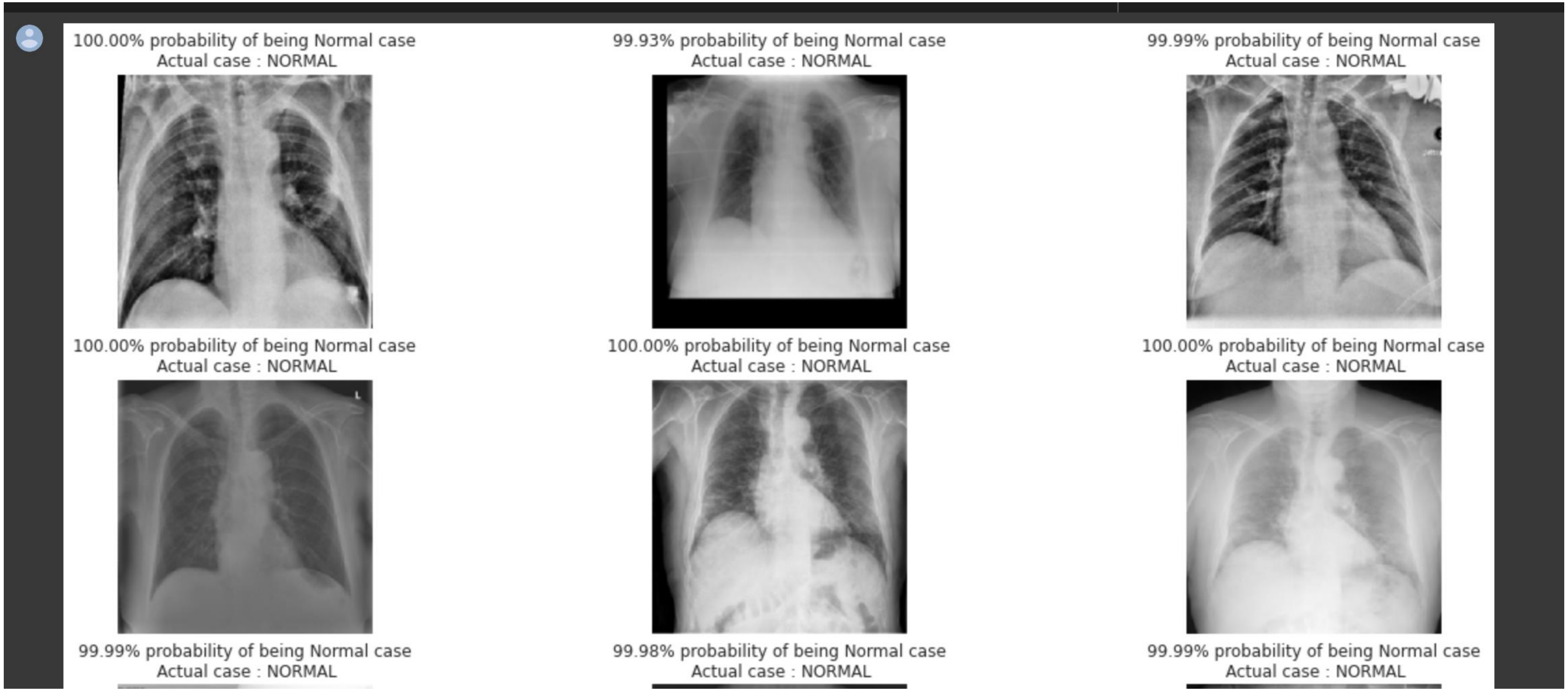
During training



After training



Inference on a Single Image and its Predication/ out put



Classification report summary

Classification model	Class	Precision %	Recall %	F1-score %	AUC %	Accuracy %
EfficientNet-B3	Covid-19	97	100	98	98	97
	Normal	99	93	96	99	
	Pneumonia	96	98	97	97	
VGG-16	Covid-19	97.5	100	98.7	99	97.9
	Normal	97.8	95.8	96.8	99	
	Pneumonia	98.3	97.9	98.1	97	
ResNet-50	Covid-19	98.7	96	97	99	97.6
	Normal	96	98	97	98	
	Pneumonia	98.7	98	98	98	
CXRcovNet	Covid-19	96.2	96.2	94.8	97	95
	Normal	94.3	93.9	94.1	96	
	Pneumonia	94.6	95.0	94.8	96	

Model	Best Epoch	BS	TrainLoss	TrainAcc	ValLoss	ValAcc
VGG-16	22	32	0.083	0.964	0.089	0.973
ResNet-50	22	32	0.005	0.99	0.157	0.969
EfficientNet-B3	22	32	1.413	0.997	1.440	0.966
CXRcovNet	22	32	0.045	0.984	0.106	0.972

Model Comparison

Related work	Evaluation method	Performance
(Ozturk et al., 2020)	New method -DarkCovidNet	98.08
(Wang et al., 2020)	New method - COVIDNet	93.30
(Das et al., 2021)	New ensemble method combining InceptionV3, Resnet50V2 and Densenet201	91.62
(Mahmud et al., 2020)	tacked Multi-Resolution CovXNet	90.2%
(Jain et al., 2021)	Inception V3, Xception, ResNeXt	95.3% (+ / - 2.1%)
(Apostolopoulos & Mpesiana, 2020)	VGG 19, Mobile Net v2, Inception, Xception, Inception Resnet v	90.5% (± 6.97%)
(Hussain et al., 2021)	Novel CNN model called CoroDet	94.2%
(Khan et al., 2020)	CoroNet (Xception)	95 %
(Chowdhury et al., 2020)	VGG-19 ,CheXNet , ResNet-18	96 ,96.4 ,96.44
(Saha et al., 2021)	COV-VGX extracts distinct features	98.91%
(Li et al., 2020)	COVID-GATNet	94.30%
(Toraman et al., 2020)	Convolutional CapsNet	84.22
In this study	**A. VGG-16** **B. ResNet-50** **C. Efficient Net-B3** **D. CXRcovNet**	**97.9 (VGG-16)** **97.6 (ResNet-50)** **97 (Efficient Net-B3)** **95 (CXRcovNet)**

Conclusion

- Our proposed pretrained (Efficient Net $-\mathrm{B3}$,ResNet-50 and VGG-16) and CXRcovNet achieved promising results on a small prepared dataset which indicates that given more data, the proposed model can achieve better results with minimum pre-processing of data.
- Overall, the proposed model substantially advances the current radiology-based methodology and during COVID-19 pandemic, it can be very helpful tool for clinical practitioners and radiologists to aid them in diagnosis, quantification and follow-up of COVID-19 cases.

Reference I:

1. Apostolopoulos, I. D., & Mpesiana, T. A. (2020). Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. *Physical and Engineering Sciences in Medicine*, *43*(2), 635–640. https://doi.org/10.1007/s13246-020-00865-4

2. Chowdhury, M. E. H., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M. A., Mahbub, Z. Bin, Islam, K. R., Khan, M. S., Iqbal, A., Emadi, N. Al, Reaz, M. B. I., & Islam, M. T. (2020). Can AI Help in Screening Viral and COVID-19 Pneumonia? *IEEE Access*, *8*, 132665–132676. https://doi.org/10.1109/ACCESS.2020.3010287

3. Das, A. K., Ghosh, S., Thunder, S., Dutta, R., Agarwal, S., & Chakrabarti, A. (2021). Automatic COVID-19 detection from X-ray images using ensemble learning with convolutional neural network. *Pattern Analysis and Applications*, *24*(3), 1111–1124. https://doi.org/10.1007/s10044-021-00970-4

4. Hussain, E., Hasan, M., Rahman, M. A., Lee, I., Tamanna, T., & Parvez, M. Z. (2021). CoroDet: A deep learning based classification for COVID-19 detection using chest X-ray images. *Chaos, Solitons and Fractals*, *142*. https://doi.org/10.1016/j.chaos.2020.110495

5. Jain, R., Gupta, M., Taneja, S., & Hemanth, D. J. (2021). Deep learning based detection and analysis of COVID-19 on chest X-ray images. *Applied Intelligence (Dordrecht, Netherlands)*, *51*(3), 1690–1700. https://doi.org/10.1007/s10489-020-01902-1

6. Khan, A. I., Shah, J. L., & Bhat, M. M. (2020). CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. *Computer Methods and Programs in Biomedicine*, *196*, 105581. https://doi.org/10.1016/J.CMPB.2020.105581

Reference II:

7. **Li, J., Zhang, D., Liu, Q., Bu, R., & Wei, Q. (2020). COVID-GATNet: A Deep Learning Framework for Screening of COVID-19 from Chest X-Ray Images. *2020 IEEE 6th International Conference on Computer and Communications (ICCC)*, 1897–1902. https://doi.org/10.1109/ICCC51575.2020.9345005**

8. **Mahmud, T., Rahman, M. A., & Fattah, S. A. (2020). CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization. *Computers in Biology and Medicine*, *122*. https://doi.org/10.1016/j.compbiomed.2020.103869**

9. **Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Rajendra Acharya, U. (2020). Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Computers in Biology and Medicine*, *121*(April), 103792. https://doi.org/10.1016/j.compbiomed.2020.103792**

10. **Saha, P., Sadi, M. S., Aranya, O. F. M. R. R., Jahan, S., & Islam, F.-A. (2021). COV-VGX: An automated COVID-19 detection system using X-ray images and transfer learning. *Informatics in Medicine Unlocked*, *26*, 100741. https://doi.org/10.1016/j.imu.2021.100741**

11. **Toraman, S., Alakus, T. B., & Turkoglu, I. (2020). Convolutional capsnet: A novel artificial neural network approach to detect COVID-19 disease from X-ray images using capsule networks. *Chaos, Solitons and Fractals*, *140*. https://doi.org/10.1016/j.chaos.2020.110122**

12. **Wang, L., Lin, Z. Q., & Wong, A. (2020). *COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images*. https://doi.org/10.1038/s41598-020-76550-z**

- Thank you