An automated approach for the classification of Covid-19 and pneumonia patients from chest X ray images using LSTM based models.

Project & Thesis-II : CSE 4250

Presented by Group 3913

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Introduction

- COVID-19 pandemic
- Assist doctors to ease out their burdensome task

Motivation & Objectives

- Slow and Inaccurate Results
- High cost and unavailability of medical kits
- Too much workload
- Absence of trained staff
- Human Prone Errors and Risk Factors

Literature Review

Summary of Related Works

Paper Author & Reference	Dataset	Methodology	Result
M. Z. Islam et al. [3]	NIH dataset & images from different websites	CNN- LSTM, CNN	Accuracy : 99.4%, Specificity : 99.2%, Sensitivity : 99.3% F1-score : 98.9%
B. Sekeroglu et al. [16]	Covid-19 X-ray image collection, images from Cohen & Kermany.	APPN & ReLU approach , ConvNet, Transfer learning	Accuracy : 98.50% Specificity : 99.18% Sensitivity :93.84%, AOC scores : 96.51%.
A. K. Das et al. [18]	CheXpert, Chest-X Ray, pneumonia, Covid-19 image data collection, Covid-Chest X-ray dataset	DenseNet201, Resnet50v2 and Inceptionv3	Accuracy: 95.7% Sensitivity : 98%.
K. F. Haque et al. [9]	Chest X-ray Images (pneumonia), different chest X-ray images	CNN	Accuracy : 97.56% , Precision : 95.34% , ROC curve area : 97.6% , F1-score : 97.61%.
A. Abbas et al. [14]	Lung Segmentation in CXR, Automatic Tuberculosis screening, covid-chestxray dataset	DeTraC Architecture, CNN, ResNet18	Accuracy : 95.12%, Sensitivity : 97.91%, Specificity : 91.87%, Precision : 93.36%.

Paper Author & Reference	Dataset	Methodology	Result
S. Hussain Khan et al. [10]	CoV-Healthy-6k, CoV-NonConV-10k, CoV-NonConV-15k	Deep CNN, Channel Boosted STM-RENet	Accuracy : 96.53%, F-score : 95%, MCC : 93%, AUC : 98%
T. Gao et al. [11]	The new England Journal of Medicine, Kaggle	CNN, Bonferroni correction, VGG-19	Precision : 95%, Recall : 98%, F1-score : 95%
R. Kumar et al. [26]	Chest X-ray Images (pneumonia), COVID-19 public dataset from Italy	SMOTE, ResNet 152	Accuracy : 97% Logistic Regression : 96.6%, Nearest Neighbors : 94.7%, Decision Tree : 93.1%, Random Forest : 97.3%, AdaBoost Classifier : 92.1%, Naive Bayes : 88.9%, XGB Classifier : 97.7%.
P. K. Sethy et al. [12]	Covid-chext-xray dataset, conVid19-X-rays	CNN, ResNet50, SVM	Accuracy : 98.66% Sensitivity : 95.33% F1 Score : 95.34% FPR : 2.33%
T. Ozturk et al. [28]	X-ray image dataset, Chest Xray8 database	DarkCovidNet	Accuracy : 98.08%, Specificity : 95.3%, Sensitivity : 95.13%, Precision : 98.03%, F1-Score : 96.51%.

Paper Author & Reference	Dataset	Methodology	Result
A. Narin, et al. [24]	Chest X-ray 8 database, Chest X-Ray Images (Pneumonia)	InceptionV3, ResNet50, ResNet101, ResNet152, Inception-ResNetV2	Accuracy for : Dataset-1 : 96.1% , Dataset-2 : 99.5% , Dataset-3 : 99.7% .
L. Wang et al. [15]	COVIDx, Chest CXR images, COVID-Net github respiratory	VGG-19, ResNet-50, CNN	Accuracy : 93.3%, PPV : 98.9% .
Ç. Polat et al. [19]	ChestX-ray14, COVID-19 imagedata collection, Chest X-ray collection from Indiana University.	ResNet, DenseNet, VGG architectures , nCoV-NET , Grad-CAM	Accuracy: 97.10%
A. Makris et al. [13]	Dr. Joseph Cohen's Github repository, chest-xray-pneumonia	VGG16, VGG19, MobileNet V2, Inception V3, Xception, InceptionResNetV2, DenseNet201, ResNet152 V2 and NASNetLarge.	VGG-16 ; VGG-19 Accuracy : 95.88% ; 95.03%, Specificity : 98% ; 100%, Sensitivity : 96% ; 92%, Precision : 96% ; 100%, F1-Score : 96% ; 96%;
S. Ahmed et al. [25]	X-ray images (chest), SIRM COVID-19 Database, nCOVID-19 Dataset, Chest X-Ray Images (Pneumonia).	ResNet-50	Accuracy : 96.9%, Specificity : 100%, Sensitivity : 100%, Precision : 100%, F1-score : 100%.

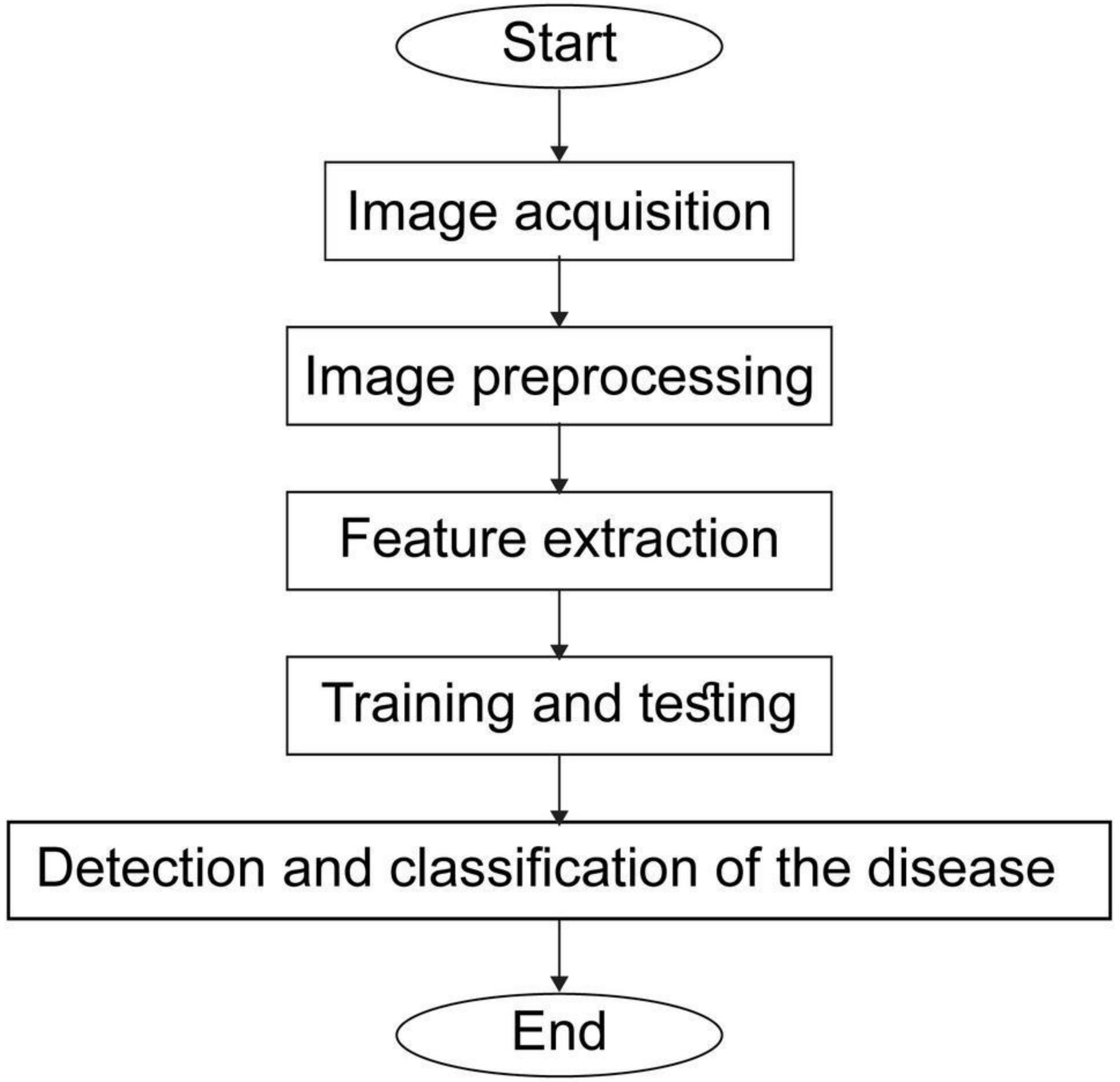
Summary of Related Works

Paper Author & Reference	Dataset	Methodology	Result
X. P. Burgos Artizzu et al. [17]	COVID chest x ray dataset , COVIDEEP, ChestX-ray 8 database,	DNN, SqueezeNet, Inception-V3, VGG16, MobileNet, Xception, VGG19+MobileNet	Accuracy : 90%, Precision : 100%
F. A. Saiz et al. [7]	(RSNA),Radiopaedia, and (SIRM)	HRnet	Accuracy : 99.26%, Sensitivity : 98.53%, Specificity : 98.82% .
S. Sakib et al. [20]	U.S. National Library of Medicine Tuberculosis Datasets, TB_portals	CNN	Accuracy : 98.6% , AU : 90%
K. Akyol et al. [6]	COVID-19 Image Data Collection, Chest X-ray 8	DNN, Bi-LSTM, VGG-16, ResNet-50, DenseNet-121	Accuracy : 97.6% , Specificity : 97.6% , Sensitivity : 91.2%, Precision : 96.86%
S. D. Deb et al. [29]	COVID-19 Image Data Collection	Hybrid architecture : NASNet, MobileNet, DenseNet	Accuracy for : NASNet : 84.23% MobileNetV2 : 86.78% DenseNet201 : 87.6 Ensemble : 91.39%
T. B. Chandra et al. [30]	COVID-Chestxray set by Cohen , Montgomery set, NIH ChestX-ray 14 set	KNN, ANN, DT, NB, SVM(Linear Kernel, Poly Kernel, RBF Kernel), Majority voting	Accuracy : 91.329%, Specificity : 86.207%, Precision : 87.368%, F1-score : 91.713%, Recall : 96.512%
Z. Mousavi et al. [4]	Mooney P. Chest X-Ray Images (pneumonia) , Covid-19 X-rays , Covid-19 Radiography database, Covid Chest X-ray dataset	DNN, CNN-LSTM, InceptionV3, Xception, ResNet50, VGG19	Accuracy : 99.4%, Specificity : 99.4%, Sensitivity : 99.4%
M. S. Al-Rakhami et al. [21]	COVID-19 Image Data Collection, COVID-19 chest X-ray, COVID-19 X-ray Cases, COVID-19 DATABASE,COVID-19 Chest X-Ray Image Repository, Chest X-Ray Images (Pneumonia, NIH Chest X-rays TB_portals	VGG19-RNN, VGG-19, DenseNet121, InceptionV3, Inception-ResnetV2, VGG19-RNN	Accuracy : 99.86%, Precision : 99.78%, F1-score : 99.78%, Recall : 99.78%
H. Naeem et al. [5]	SARS-CoV-2 CT scan dataset, Covid-19 database	CNN-LSTM, LSTM, GRU, RNN, DNN, CNN-RNN, CNN-GRU	Accuracy : 98.94% Precision : 99%, F1-score : 99%, Recall : 99%. Loss: 0.02%
S. Akter et al. [22]	COVID-19 radiography database	CNN, Mobilenetv2, modified MobileNetV2, VGG-19, ResNet101, InceptionV3, NFNET, GoogLeNet, DenseNet121, EfficientNetB7, AlexNet, VGG16, ResNet50	Accuracy : 98 Specificity : 97%, Precision : 97%, F1-score : 97%, Recall : 98%
A. Bhatt acharyya, et al. [8]	chest radiographs (SCR) dataset X-ray images, COVID-19 chest X-ray images , chest X-ray images (Pneumonia)	VGG-19, BRISK, SIFT, Conditional GAN	Accuracy : 96.60% Specificity : 97.4%, Sensitivity : 95%
W. Kusa kunniran et al. [23]	Chestx-ray8	CNN, ResNet-101	Accuracy : 98% Specificity : 98%, Sensitivity : 97%
D. Singh et al. [27]	chest radiographs (SCR) dataset X-ray images	CNN	Accuracy:94.48%, Specificity : 94.53%, Kappa stat : 94.18%, F1-score : 93.89%, Sensitivity : 93.83%

Methodology

Methodology

Work Flow of our system



Methodology

Datasets Collection

- Dataset 1 (Primary Dataset) :

  COVID19_Pneumonia_Normal_Chest_Xray_PA_Dataset

	Total	Covid + images	Pneumonia images	Normal
Training Set	5551	1850	1851	1850
Testing Set	1388	463	462	463

TOTAL: 6939

- Dataset 2 (Secondary Dataset) :

  COVID19_Pneumonia_Normal_Chest_Xray_Images

	Total	Covid images	Normal images	Pneumonia images
Training Set	4182	1301	1441	1440
Testing Set	1046	325	361	360

TOTAL: 5228

- Training : 80%

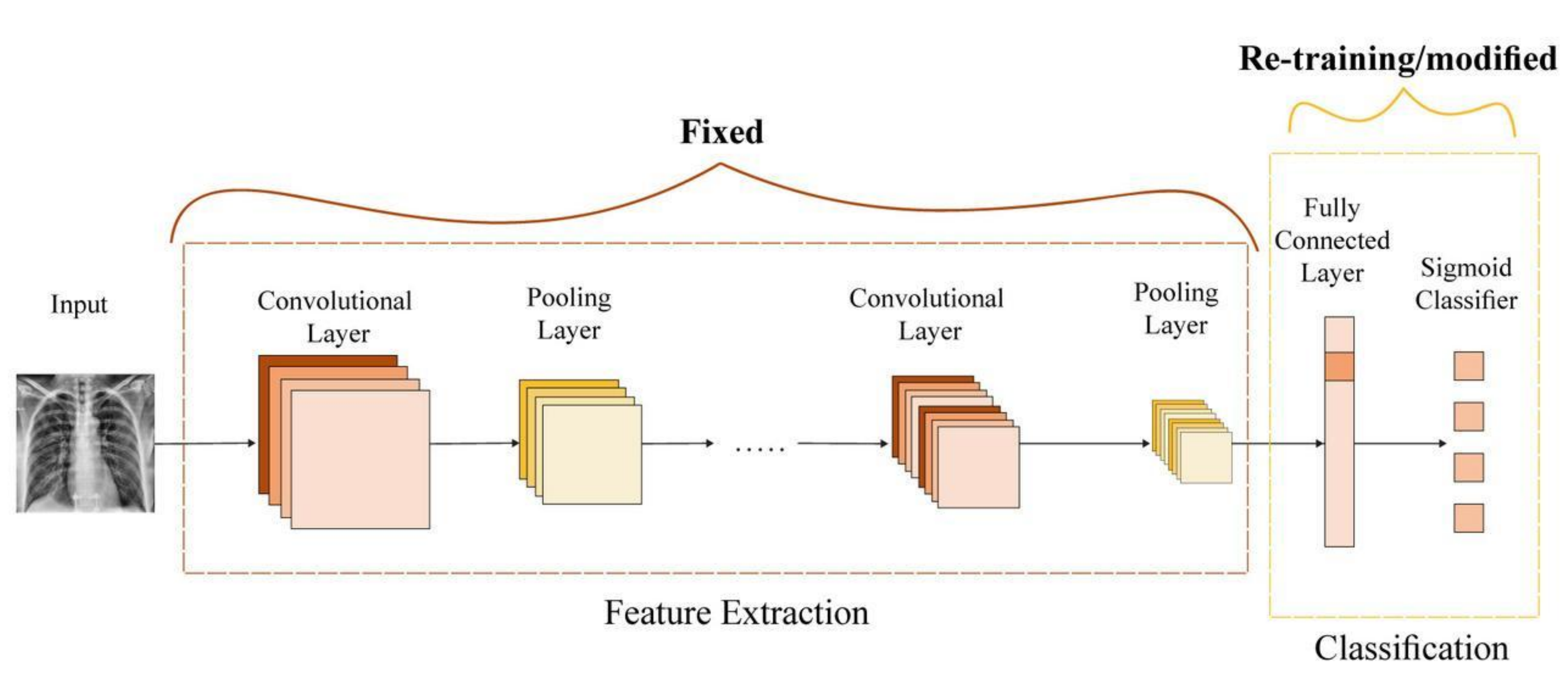
  Validating : 20%

- Testing : 20%

Methodology

Tools Used

- Image Preprocessing and Augmentation
- Convolutional Neural Network (CNN)

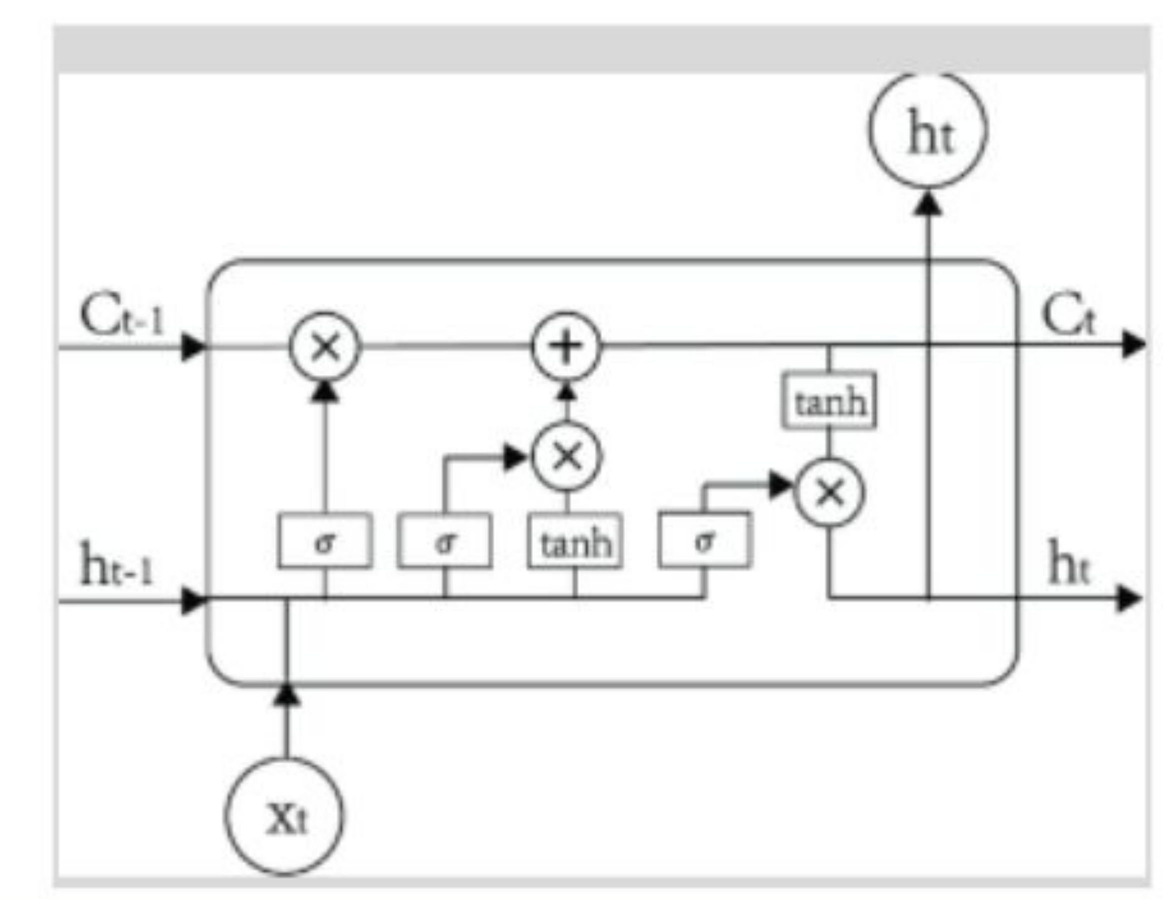


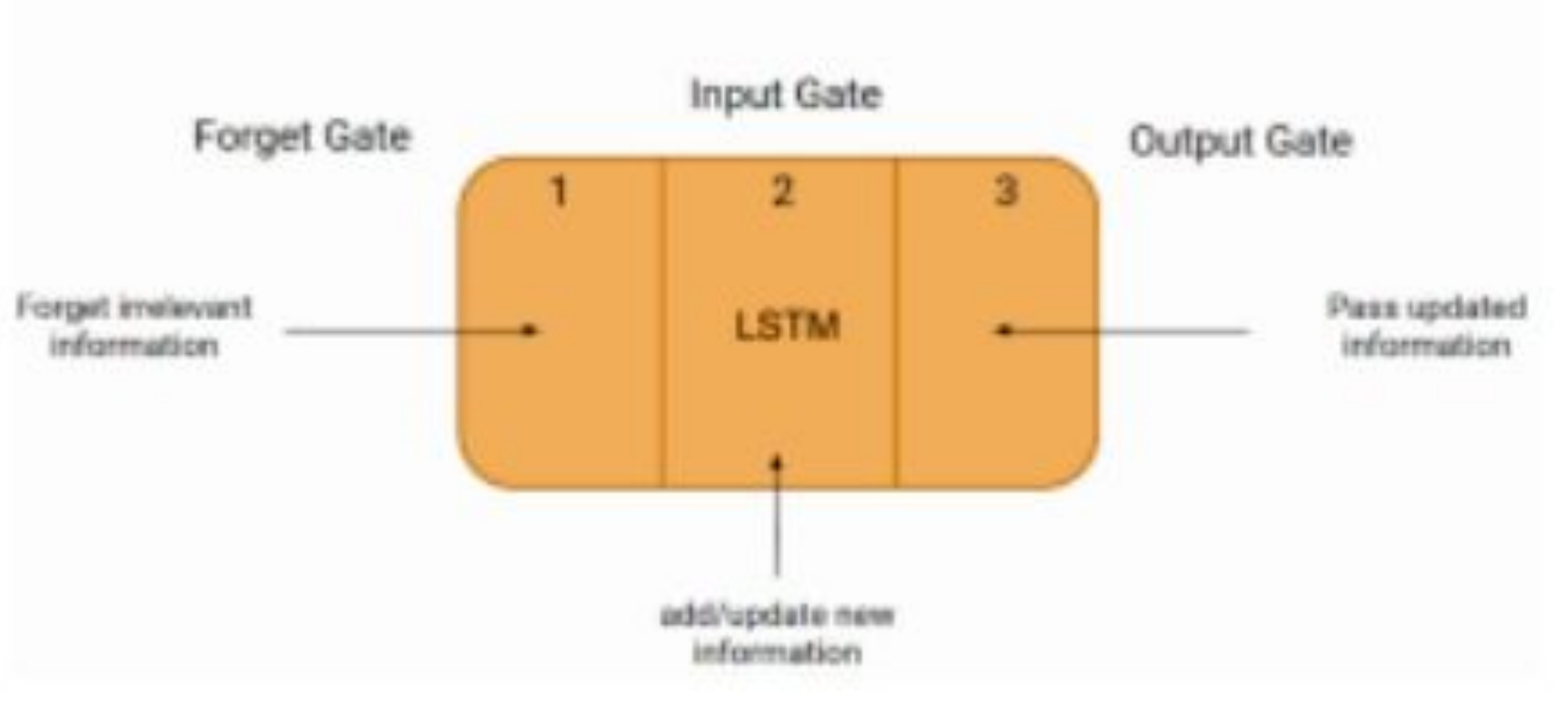
- Transfer Learning

Methodology

- Reference Models of Experiment 1

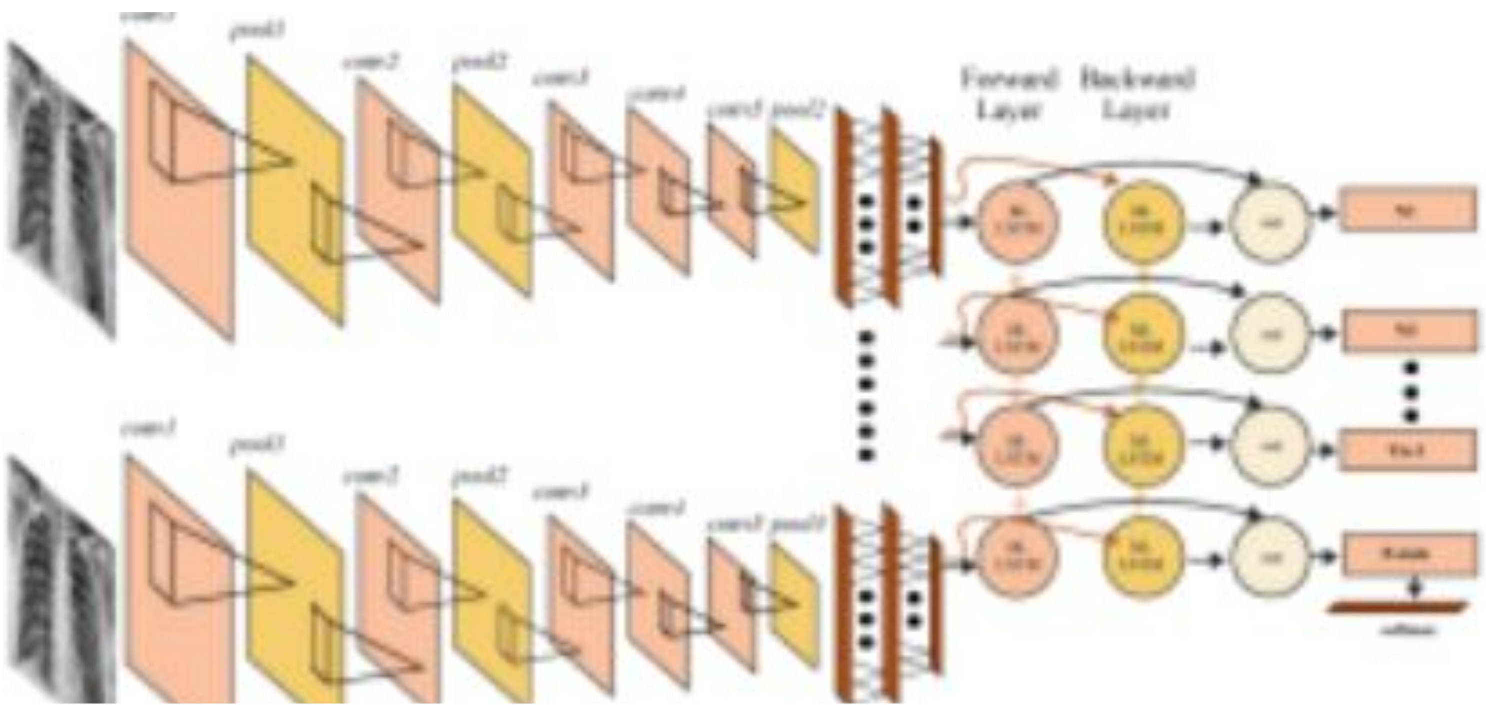
01 CNN-LSTM



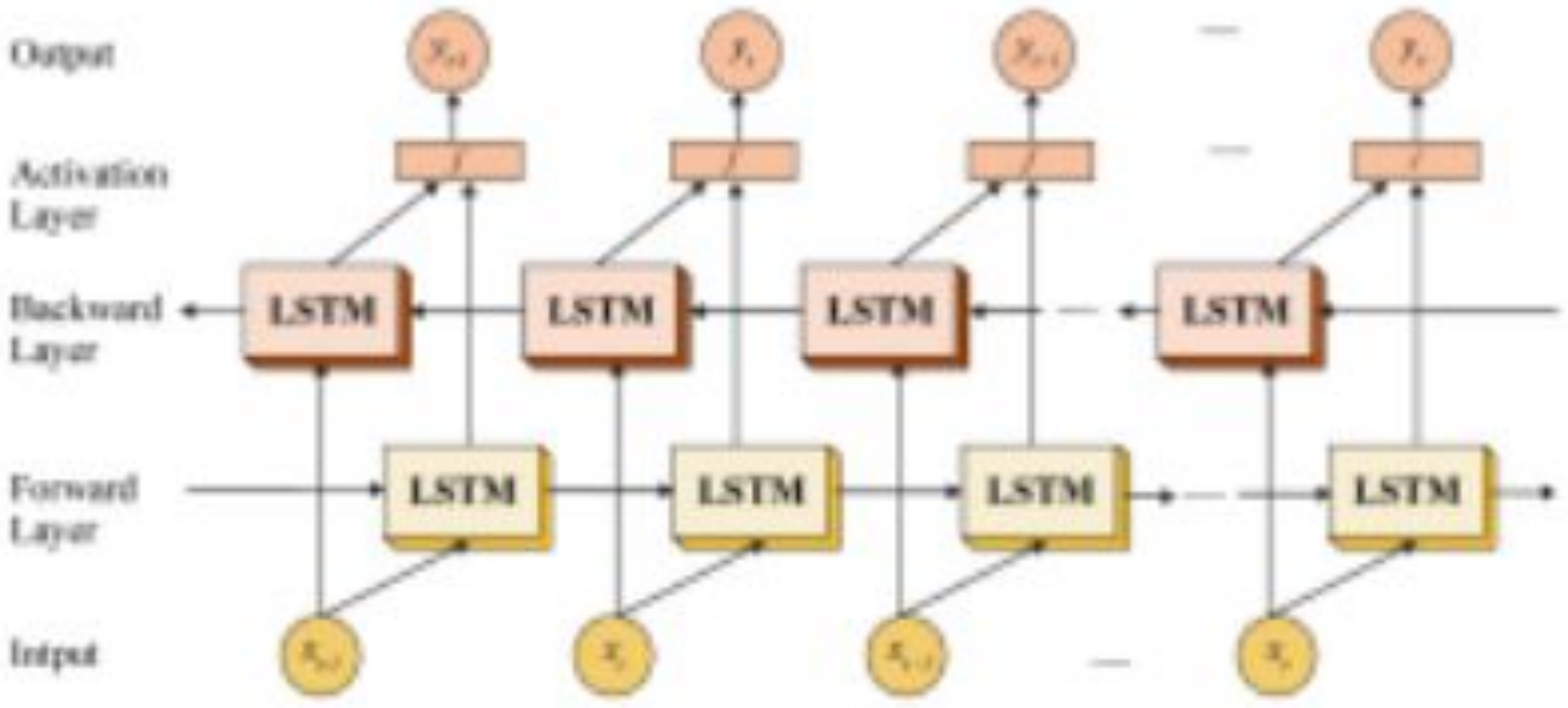


Methodology

- Reference Model of Experimment 1



02 CNN-BiLSTM



Methodology

- Reference models of Experiment 2

03 VGG19-LSTM

04 VGG16-LSTM

05 VGG16-BiLSTM

06 InceptionResNetV2

Tools Used

- Google Colab platform - used for training and testing
- GPU - Tesla K80
- Keras library of TensorFlow version 2.2.0 and python 3.8 - for model formation

Methodology

Hyperparameter settings for the models

	Model Name					
Parameters	**CNN-LSTM**	**CNN-BiLSTM**	**VGG19-LSTM**	**VGG16-LSTM**	**VGG16-BiLSTM**	**InceptionR- snetV2**
Learning Rate	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Number of epochs	32	32	20	40	40	10
Training batch size	16	16	32	32	16	16
Validation batch size	16	16	32	32	16	16
Total number of parameters	25M	58M	25M	25M	25M	25M
Optimizer	Adam	Adam	Adam	Adam	Adam	Adam

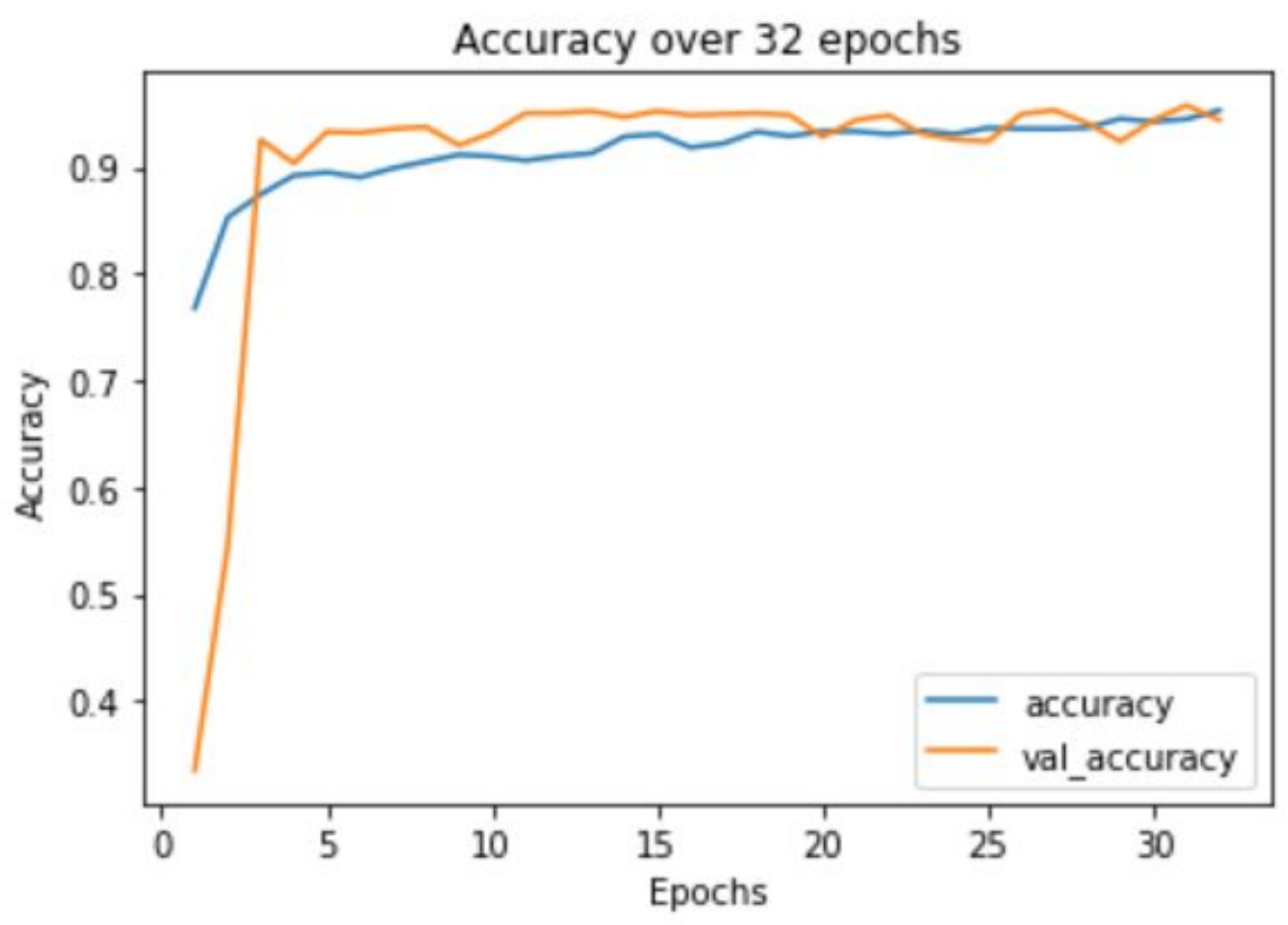
Result Analysis

Result Analysis

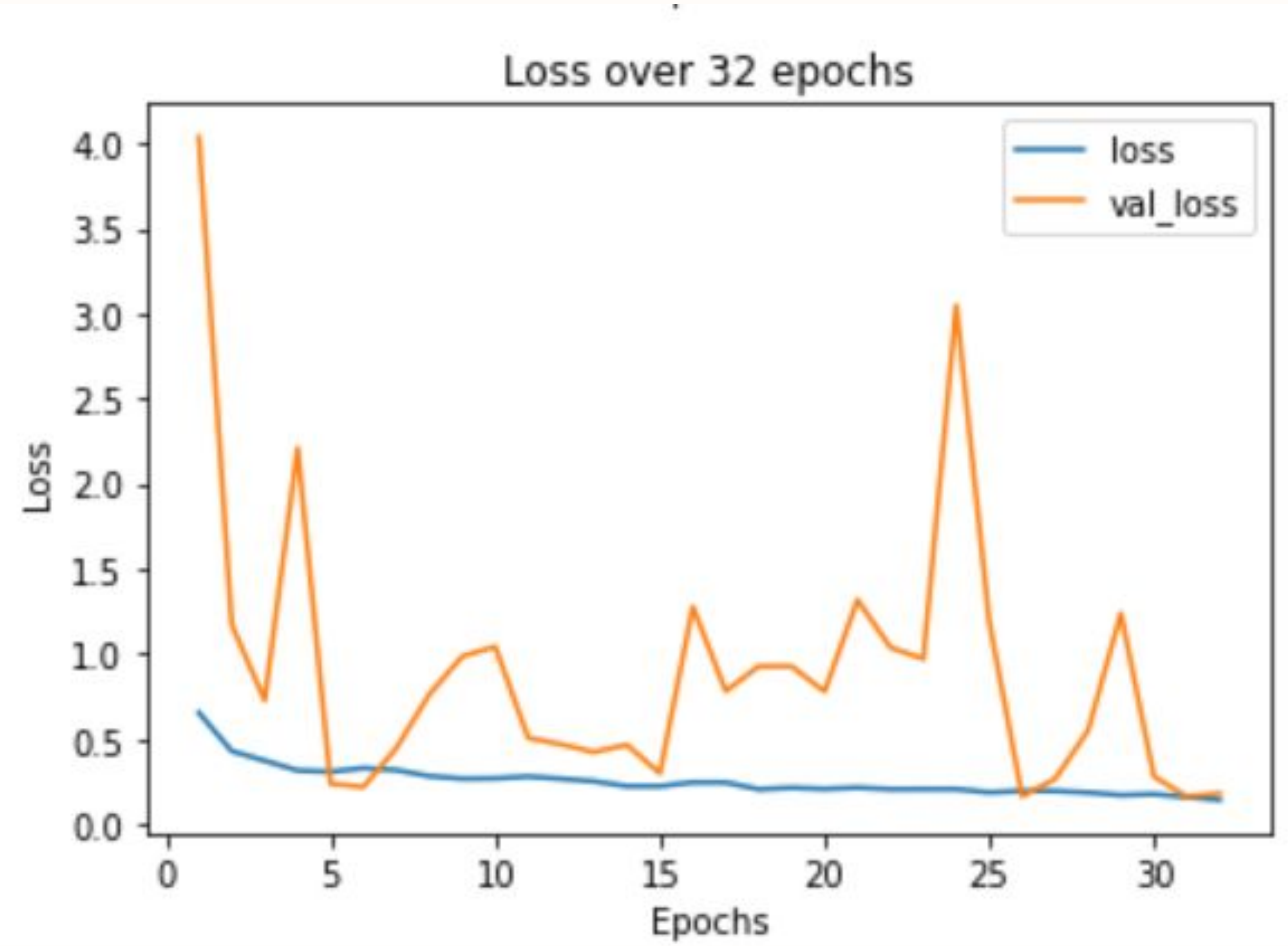
CNN-LSTM : Dataset 1

- x = number of epochs
  y_{left} = accuracy
  y_{right} = loss

- Training and validation accuracy



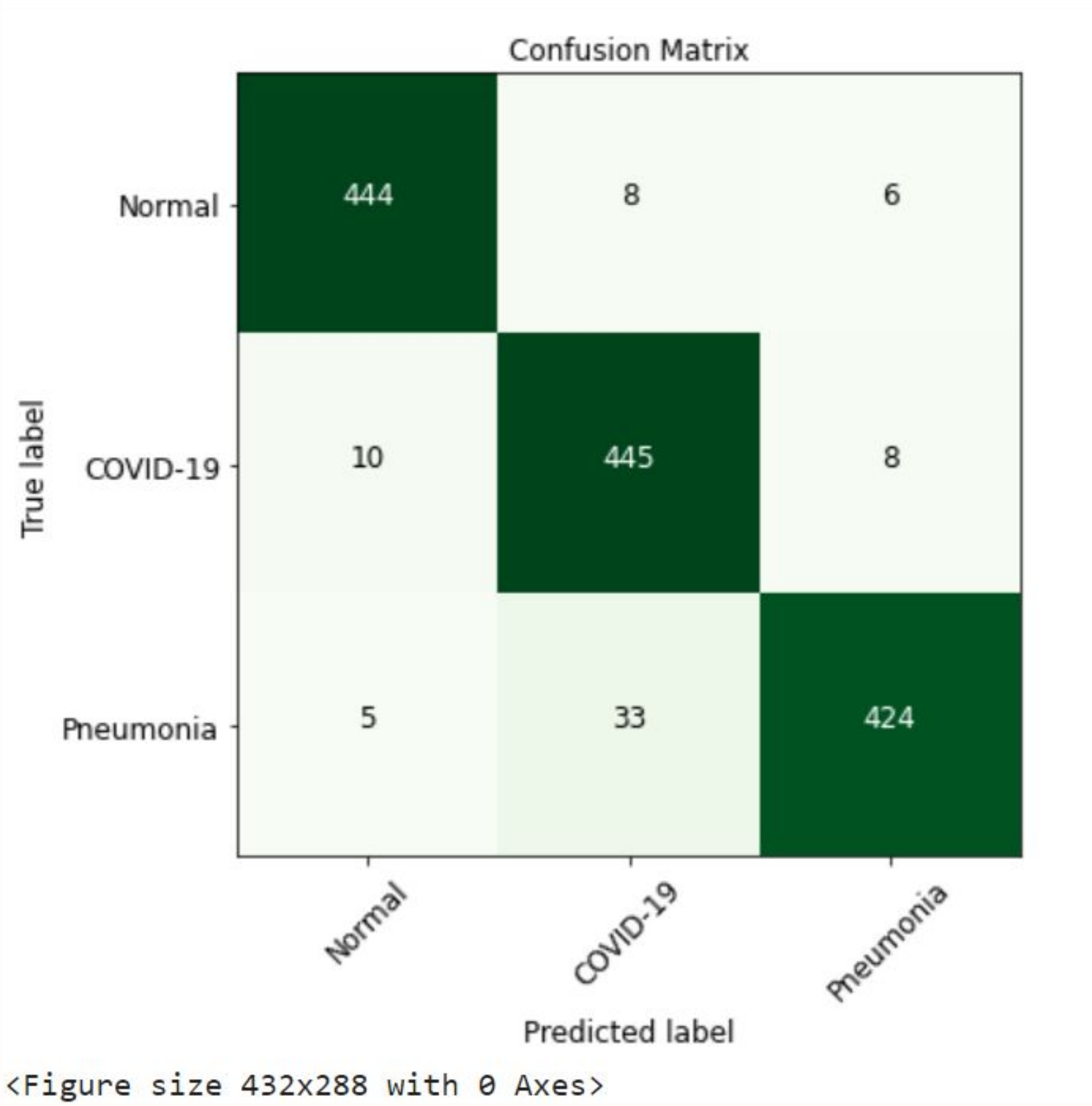
- Training and validation loss



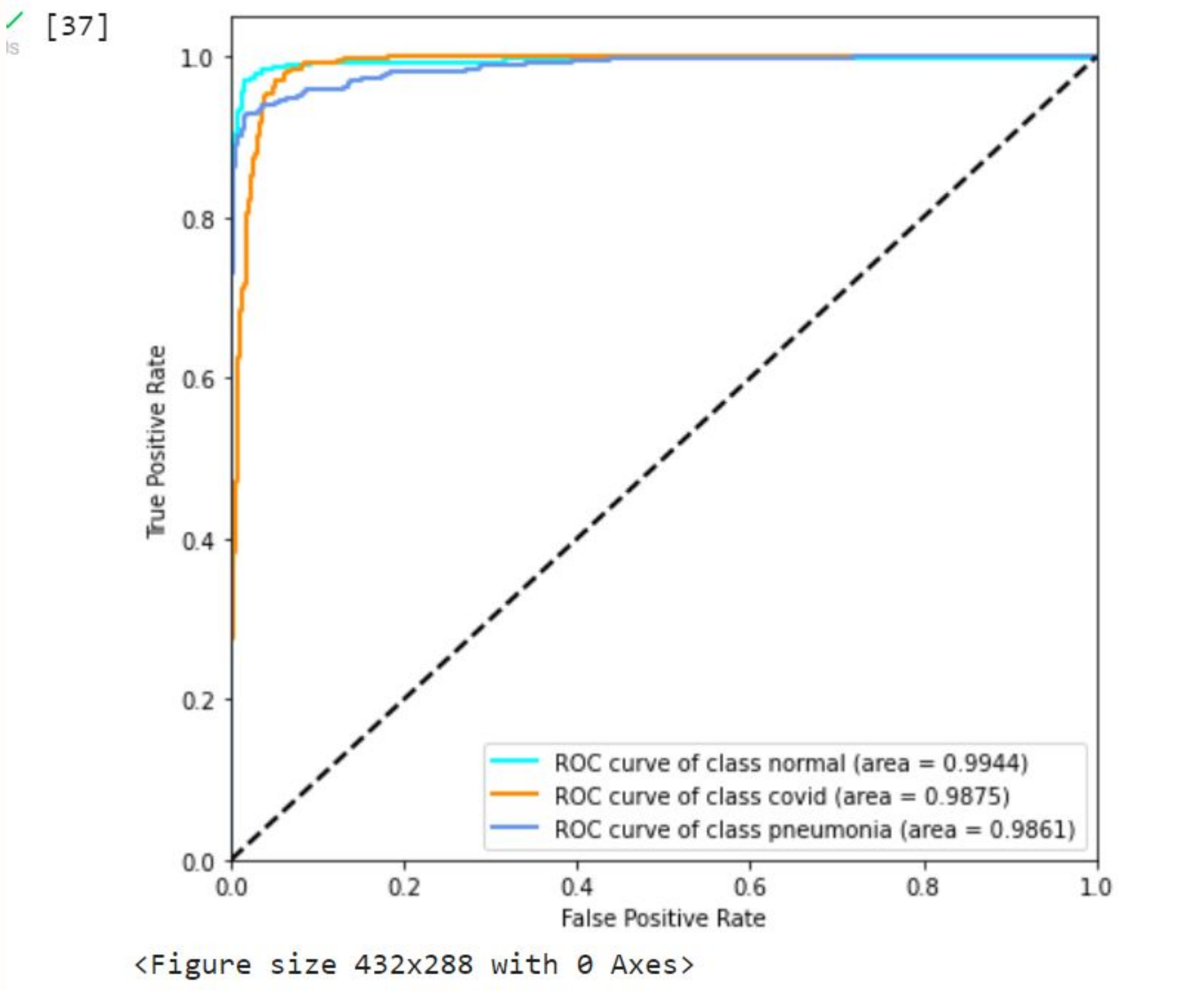
Result Analysis

CNN-LSTM : Dataset 1

- Confusion Matrix



- ROC curve



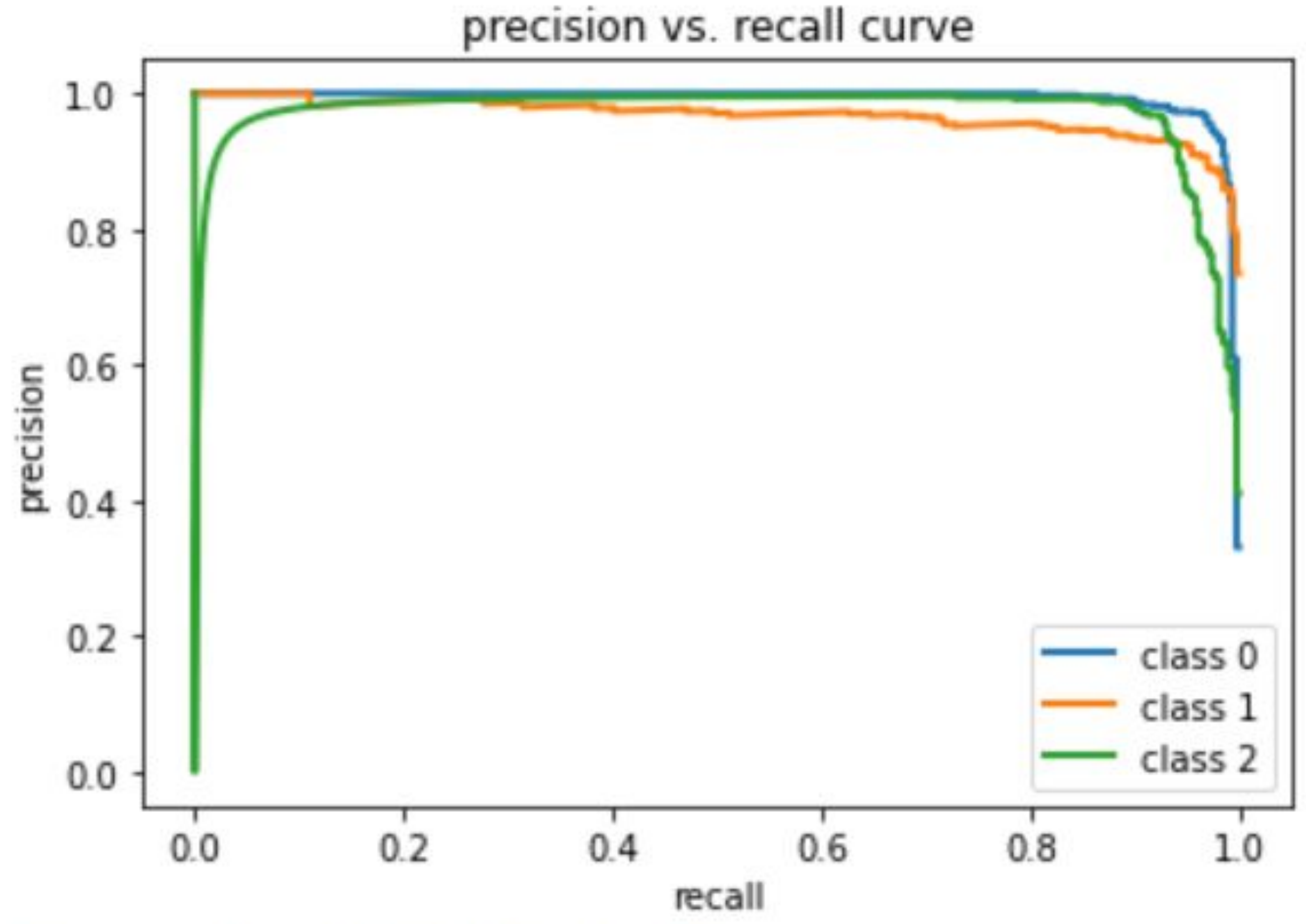
Result Analysis

CNN-LSTM : Dataset 1

- Classification report

	precision	recall	f1-score	support
normal	0.97	0.97	0.97	458
covid	0.92	0.96	0.94	463
pneumonia	0.97	0.92	0.94	462
accuracy			0.95	1383
macro avg	0.95	0.95	0.95	1383
weighted avg	0.95	0.95	0.95	1383

- Precision vs Recall Curve



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Result Analysis

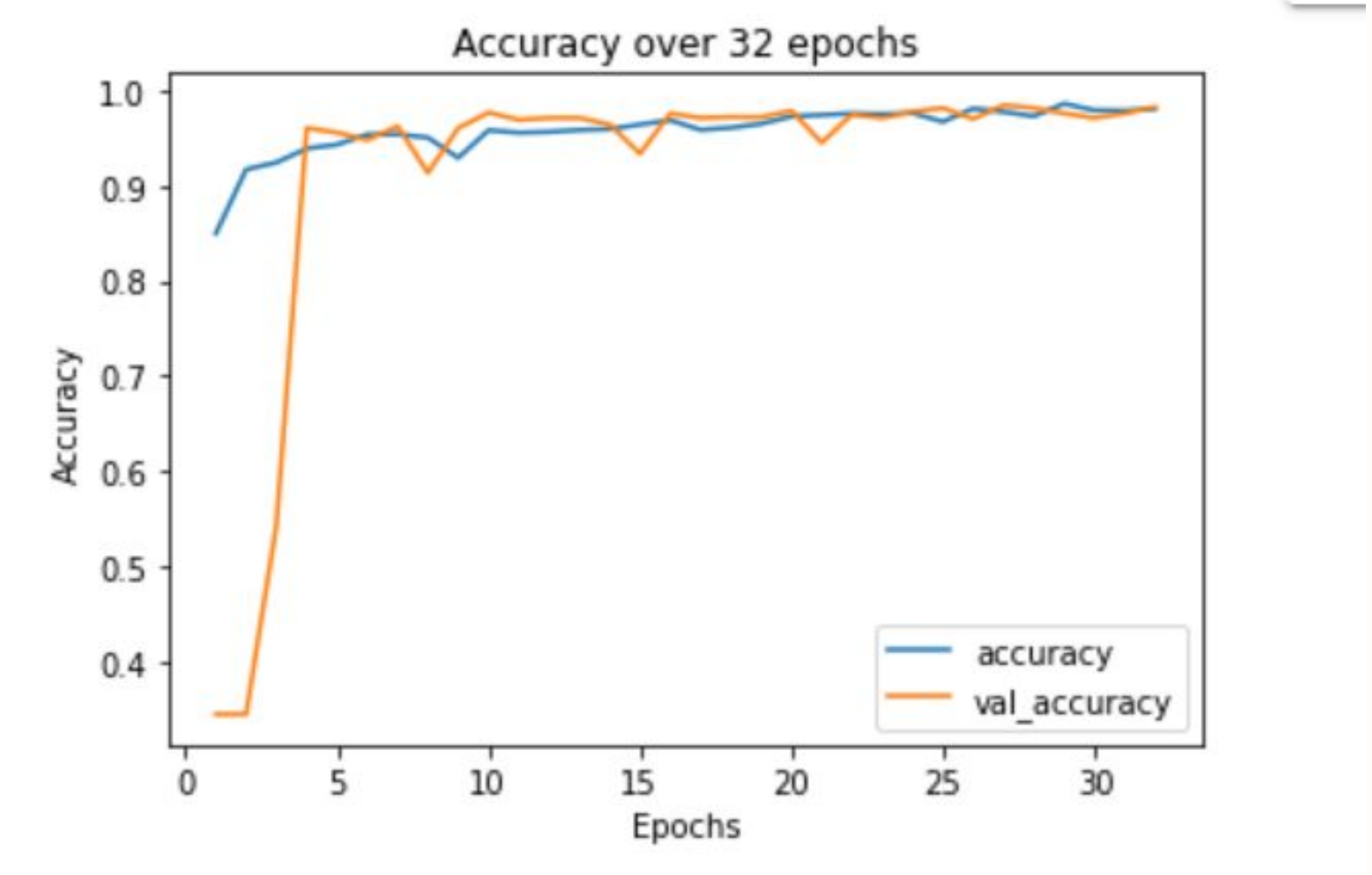
CNN-LSTM : Dataset 2

x = number of epochs

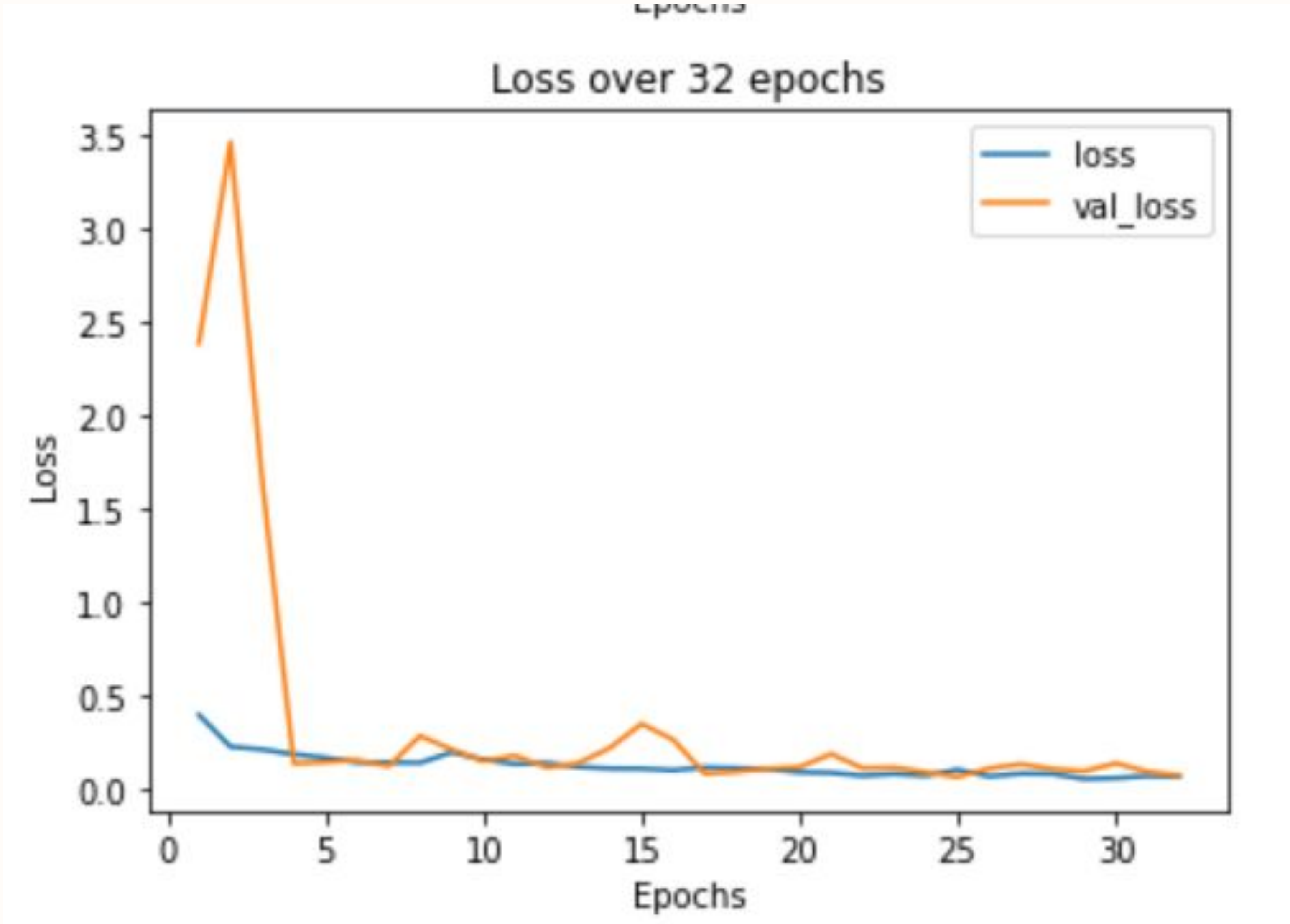
y_{left} = accuracy

y_{right}= loss

- Training and Validation accuracy



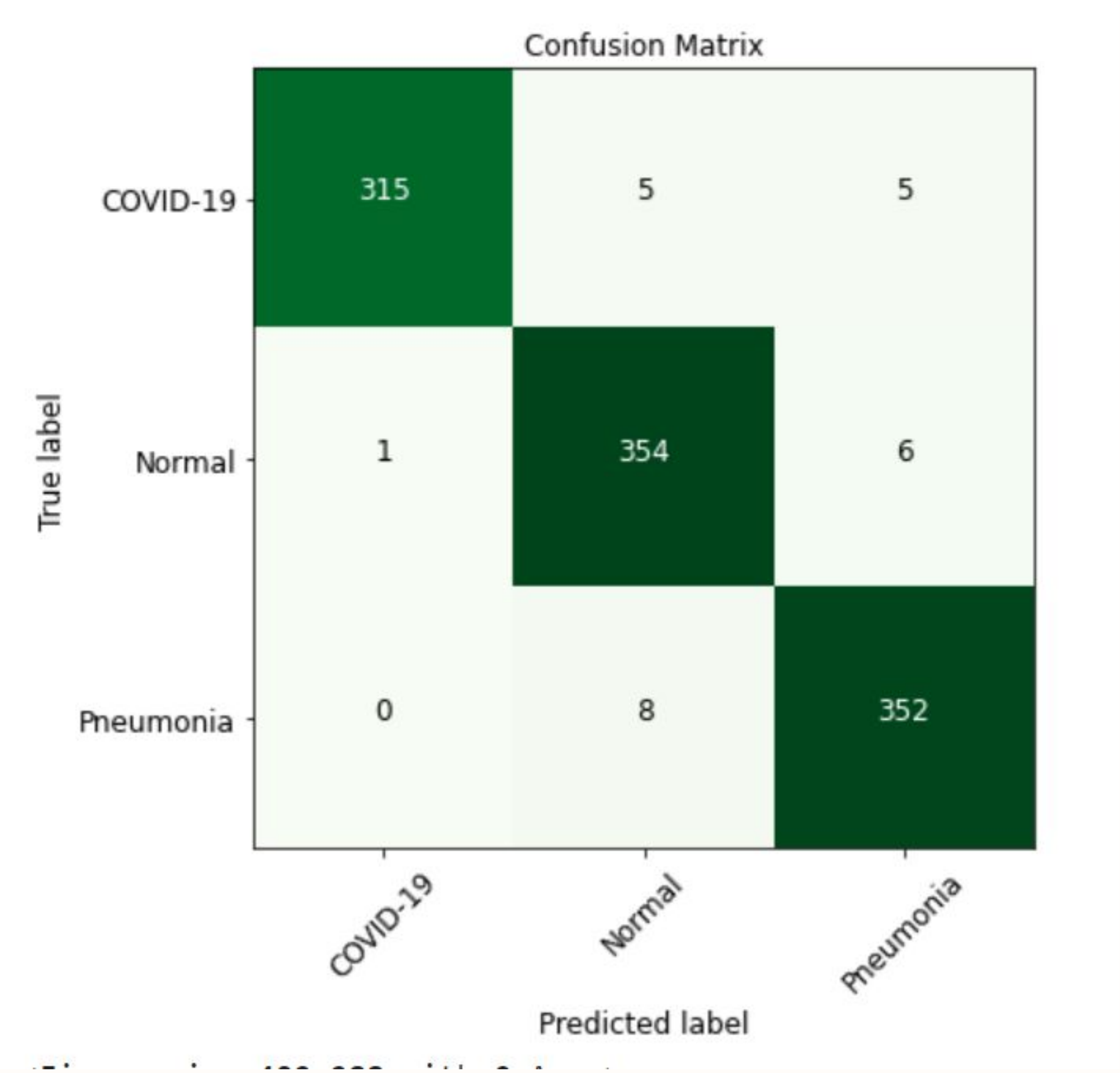
- Training and validation loss



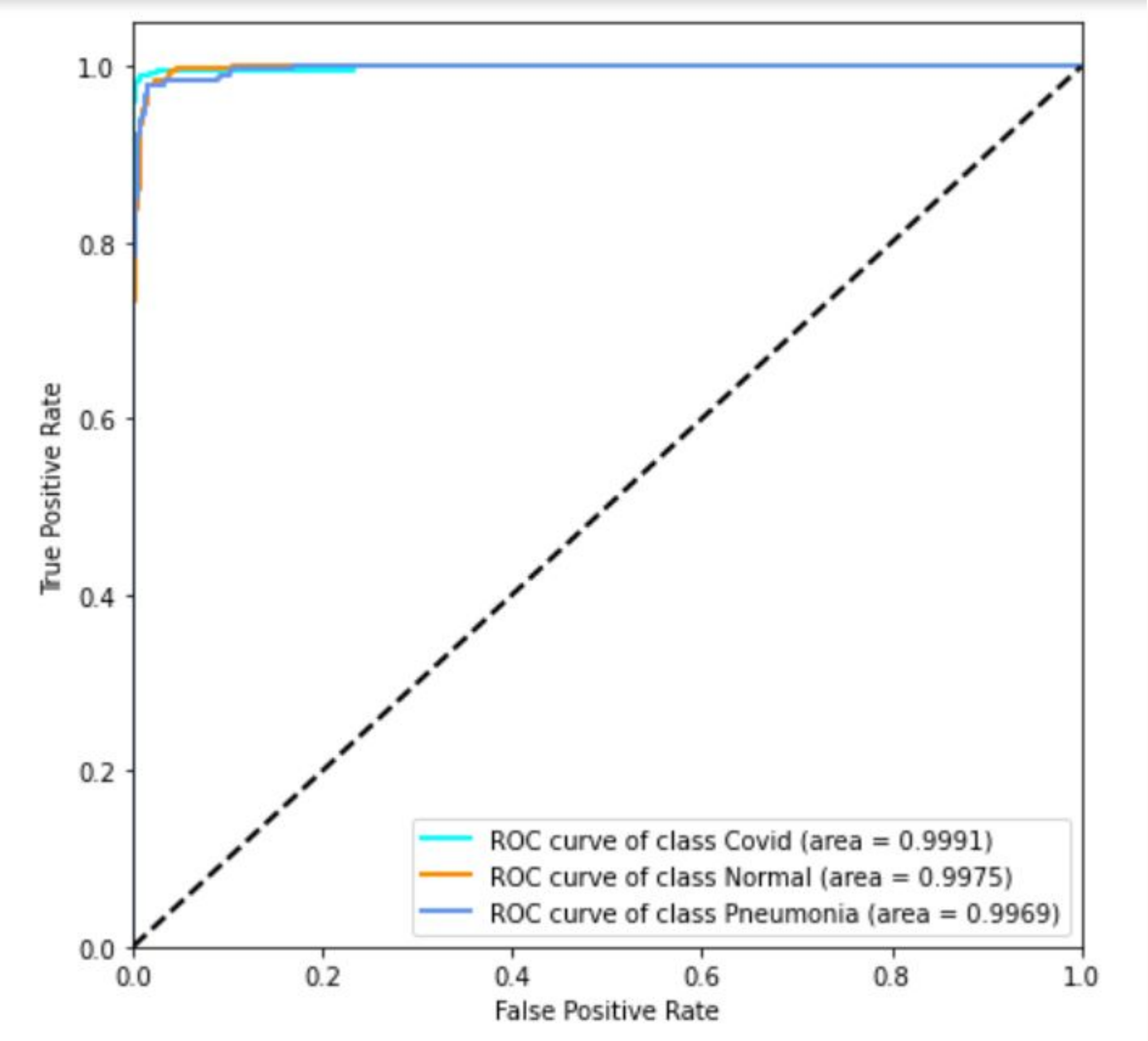
Result Analysis

CNN-LSTM : Dataset 2

- Confusion Matrix



- ROC curve



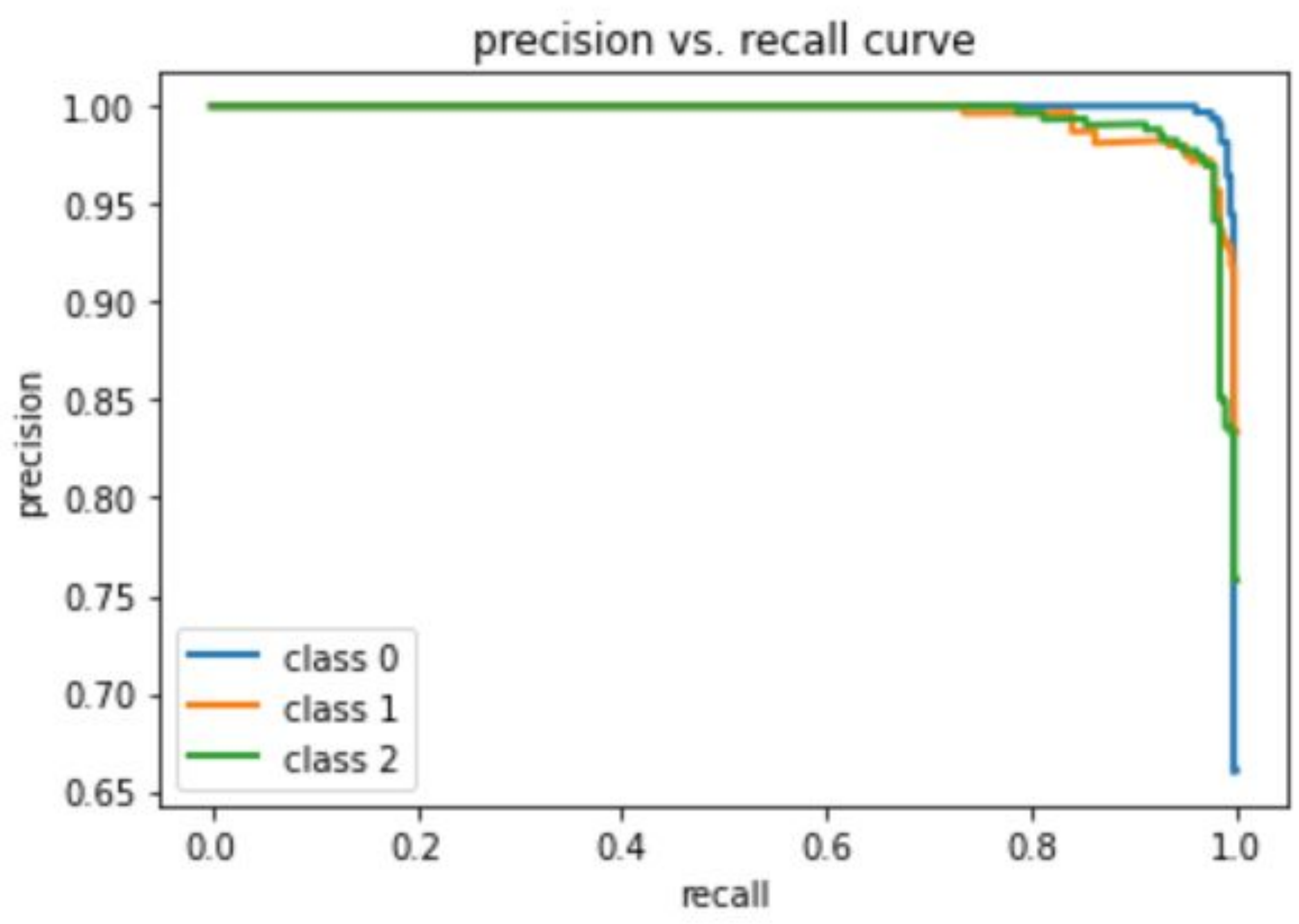
Result Analysis

CNN-LSTM : Dataset 2

- Classification report

	precision	recall	f1-score	support
Covid	1.00	0.97	0.98	325
Normal	0.96	0.98	0.97	361
Pneumonia	0.97	0.98	0.97	360
accuracy			0.98	1046
macro avg	0.98	0.98	0.98	1046
weighted avg	0.98	0.98	0.98	1046

- Precision vs Recall Curve



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Result Analysis

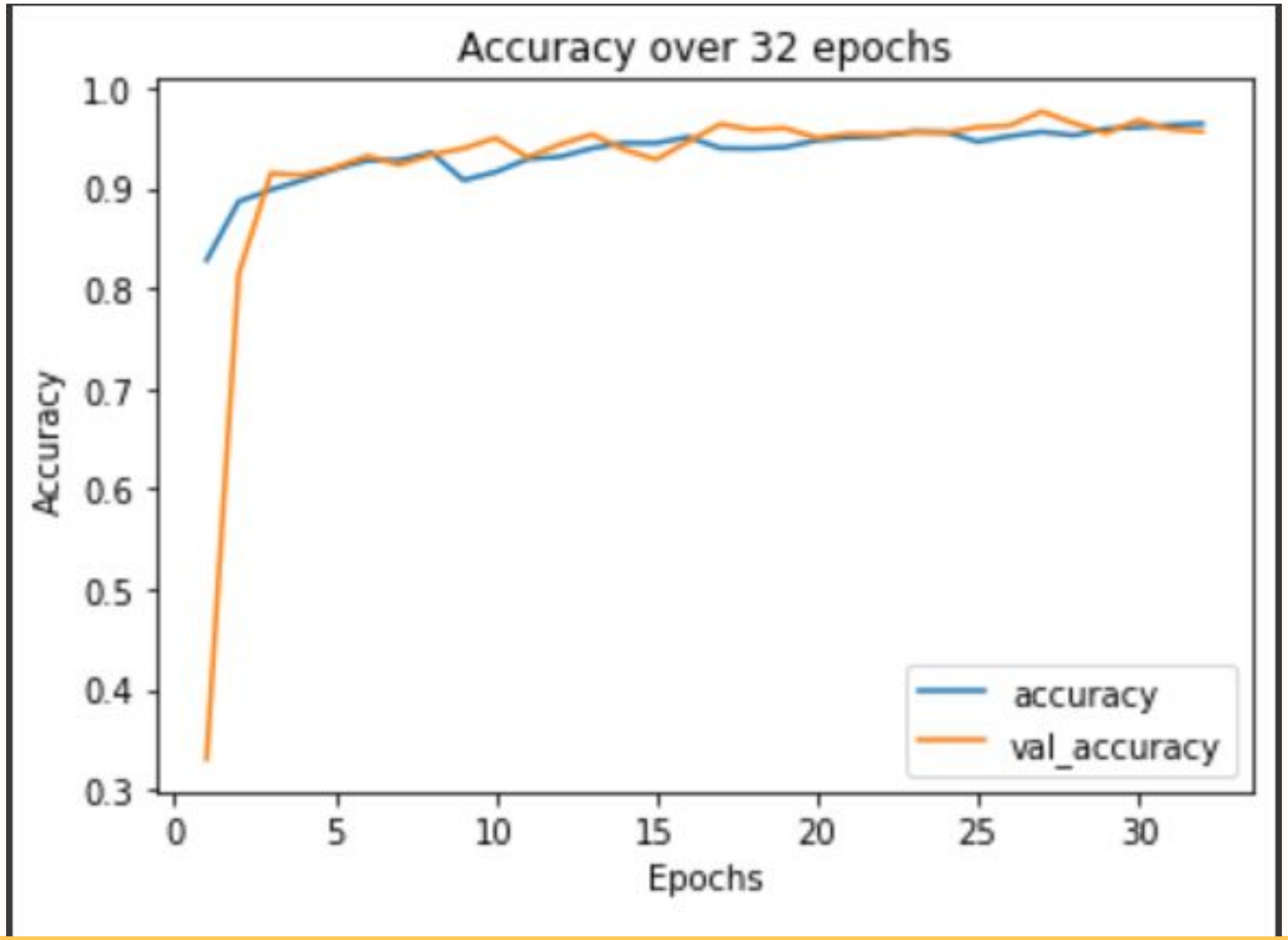
CNN-BiLSTM : Dataset 1

x = number of epochs

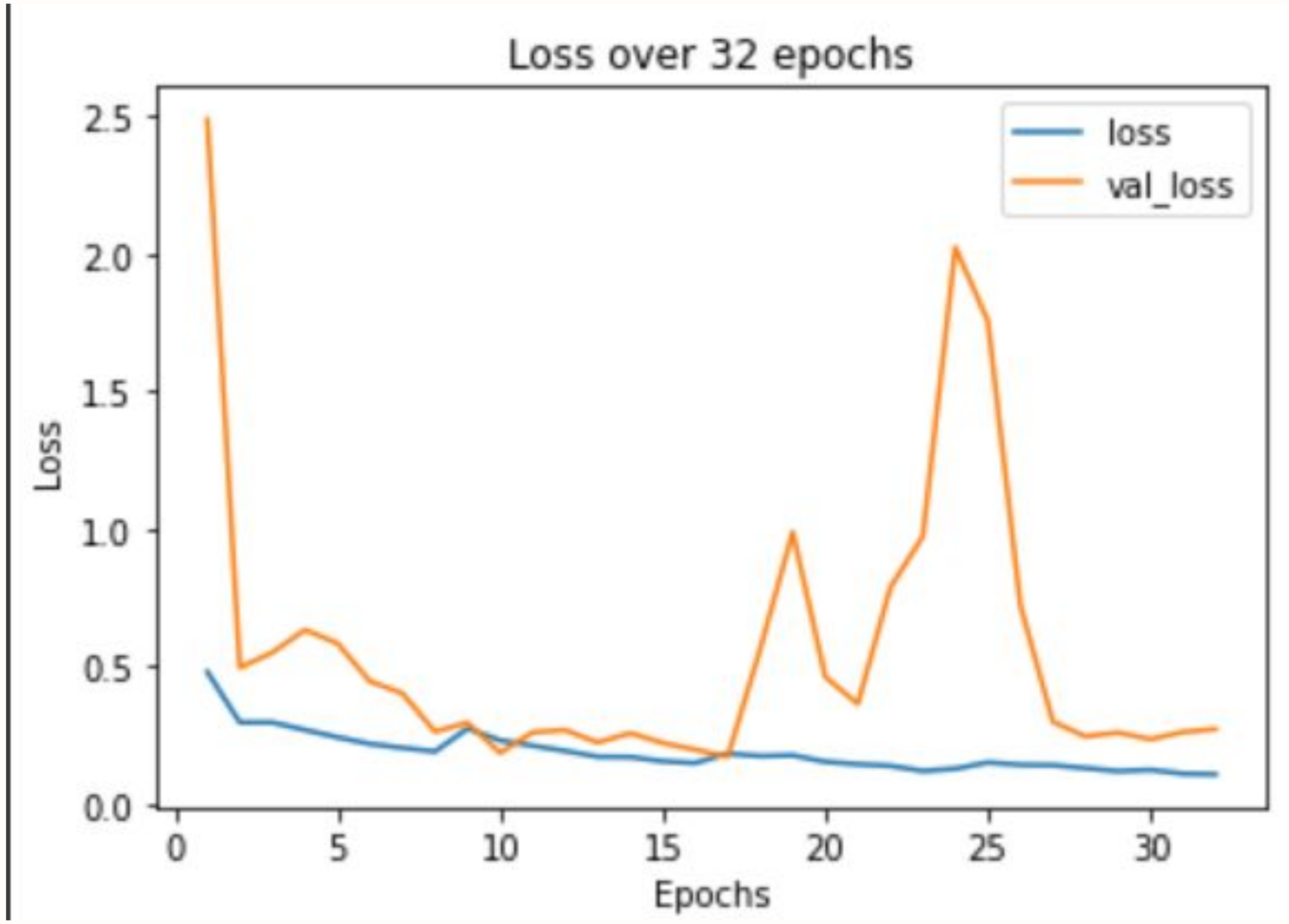
y_{left} = accuracy

y_{right} = loss

- Training and Validation accuracy



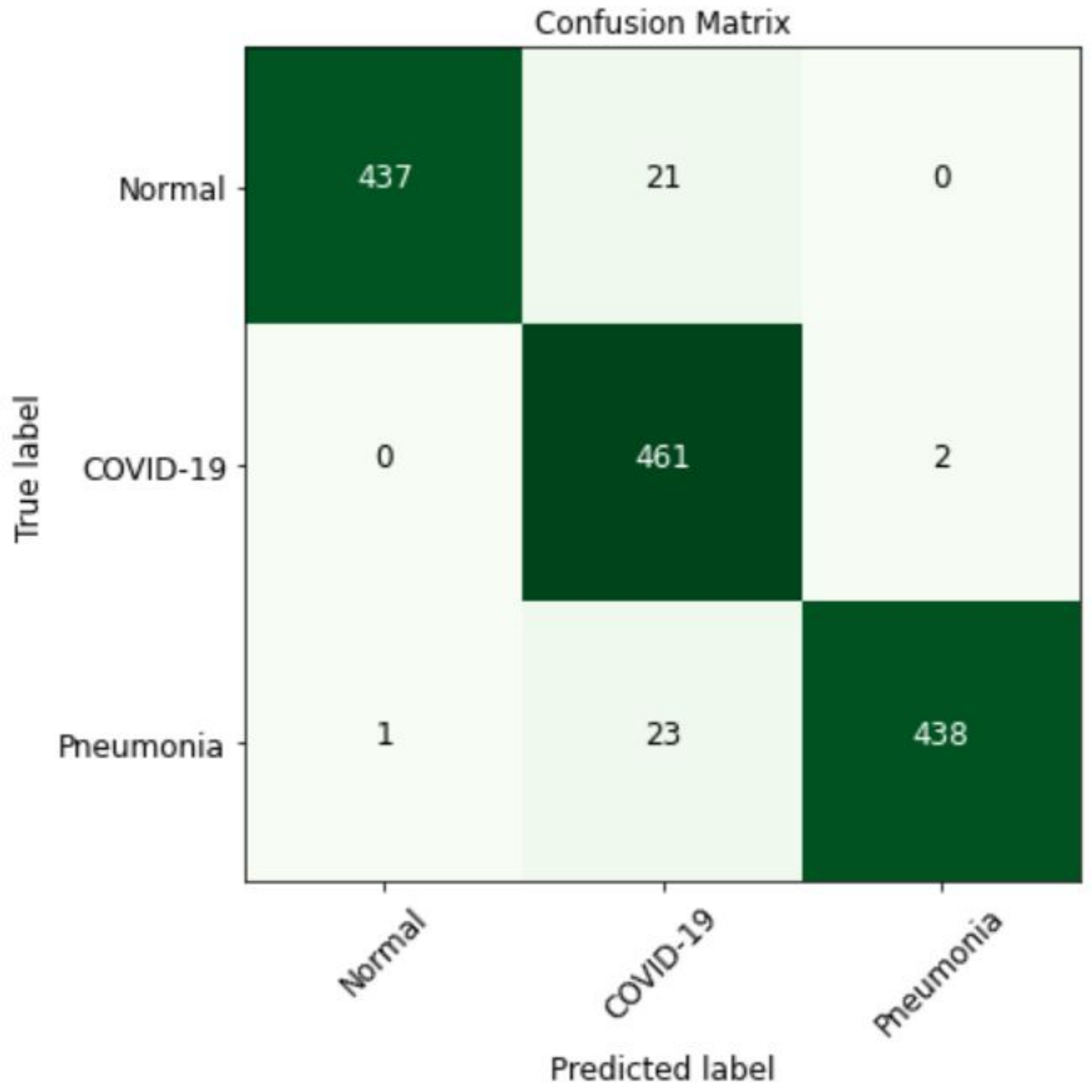
- Training and validation loss



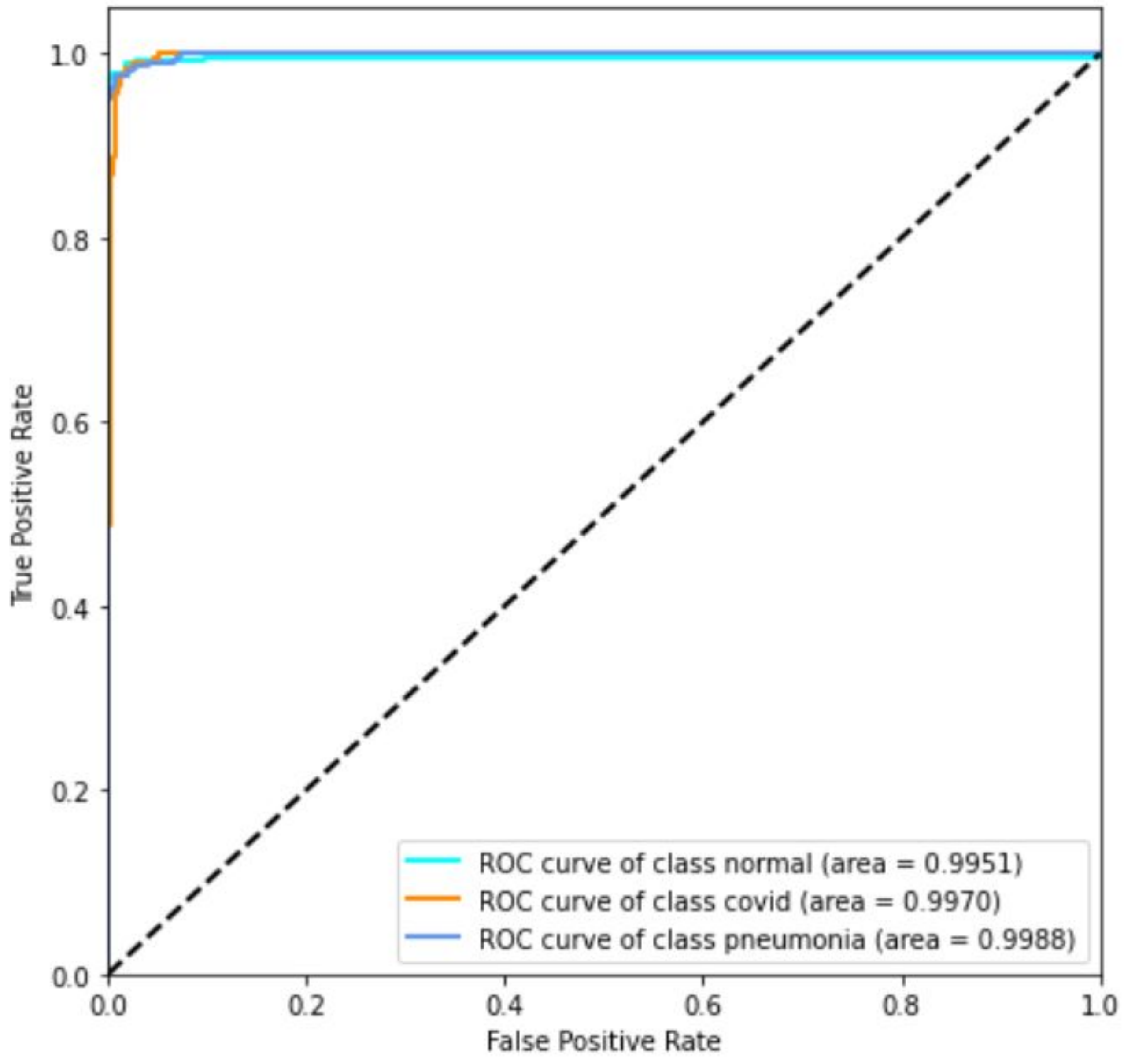
Result Analysis

CNN-BiLSTM : Dataset 1

- Confusion Matrix



- ROC curve



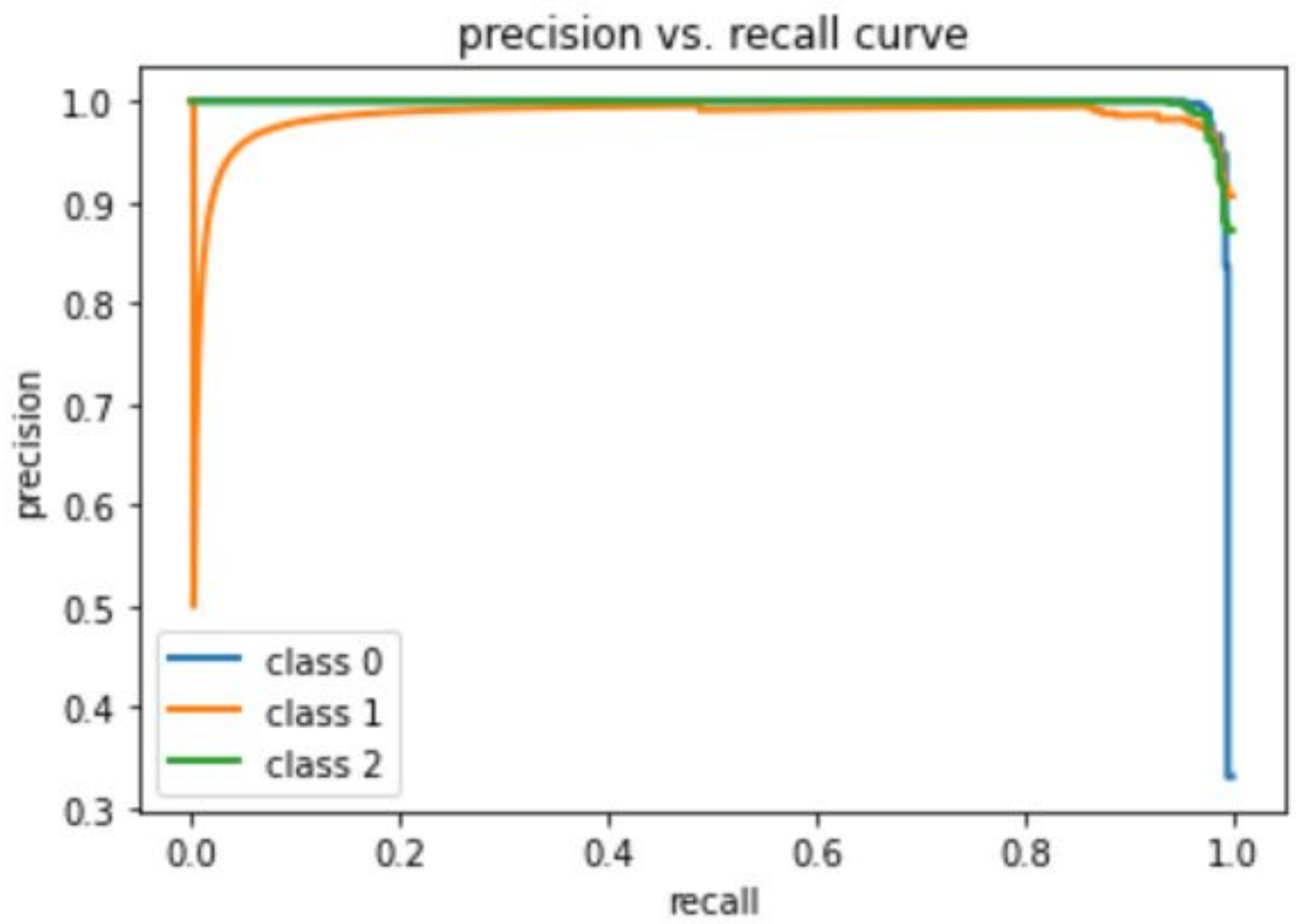
Result Analysis

CNN-BiLSTM : Dataset 1

- Classification report

	precision	recall	f1-score	support
normal	0.9977	0.9541	0.9754	458
covid	0.9129	0.9957	0.9525	463
pneumonia	0.9955	0.9481	0.9712	462
accuracy			0.9660	1383
macro avg	0.9687	0.9660	0.9664	1383
weighted avg	0.9686	0.9660	0.9663	1383

- Precision vs Recall Curve



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Result Analysis

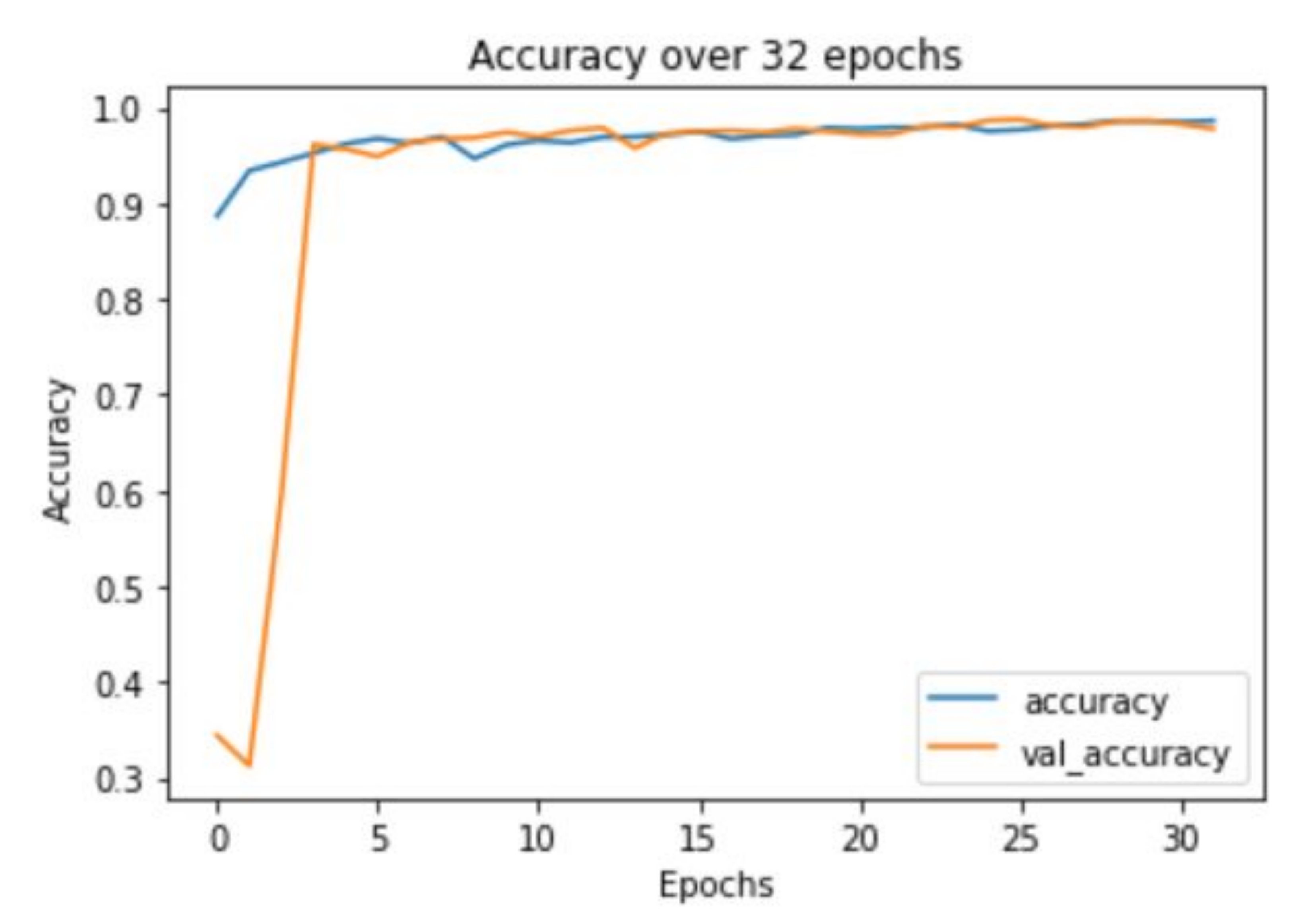
CNN-BiLSTM : Dataset 2

- x = number of epochs

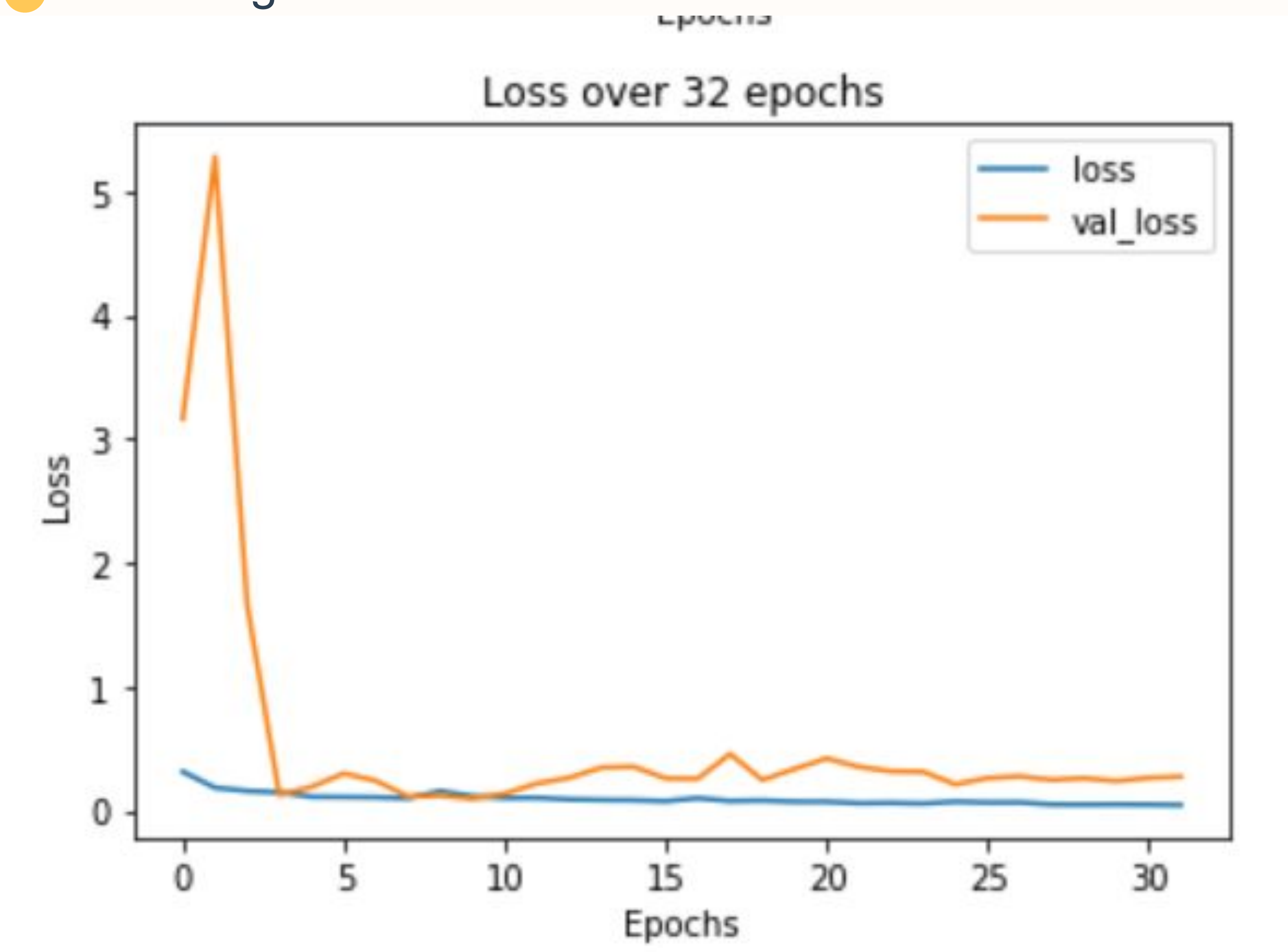
  y_{left} = accuracy

  y_{right} = loss

- Training and validation accuracy



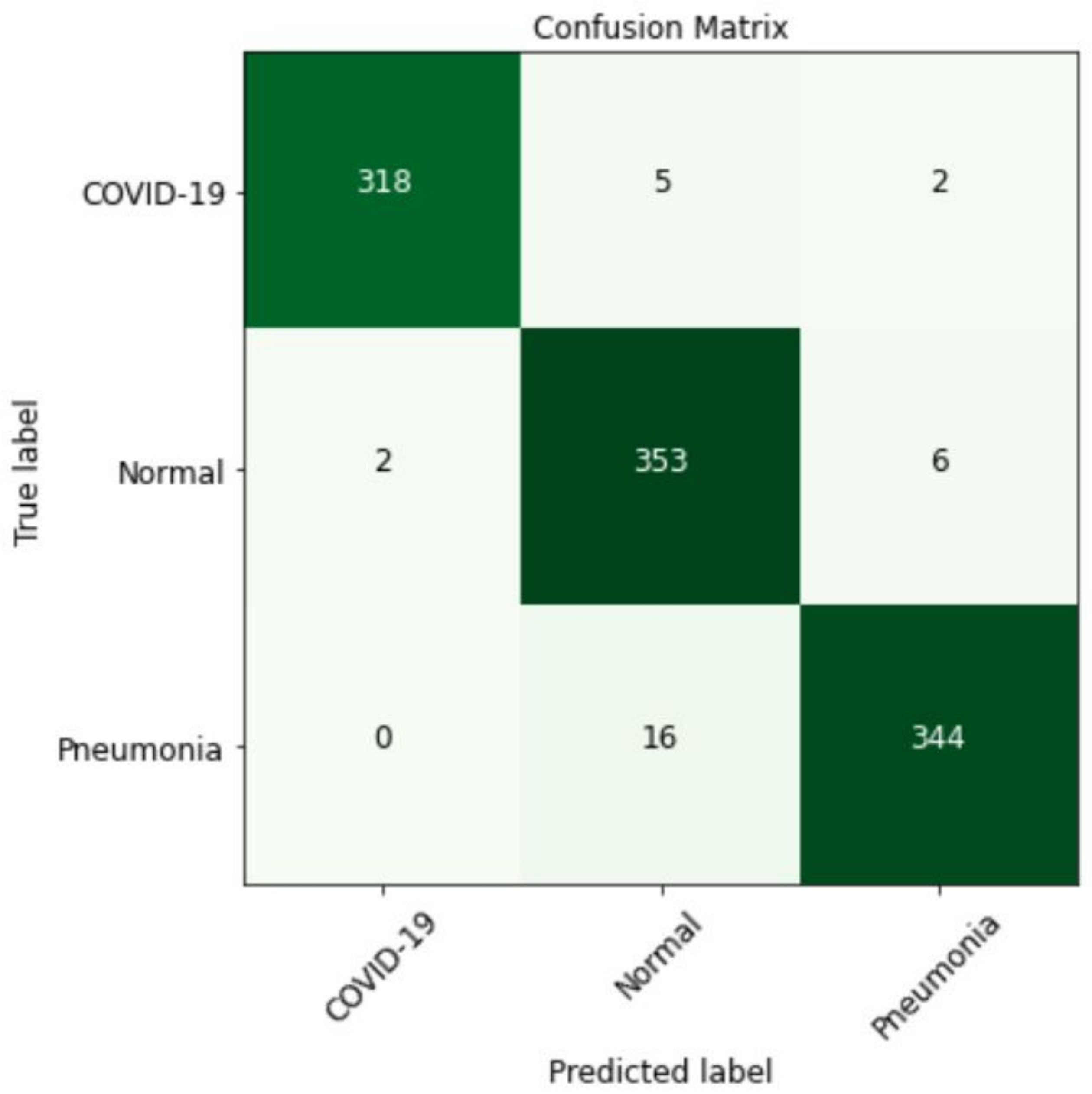
- Training and validation loss



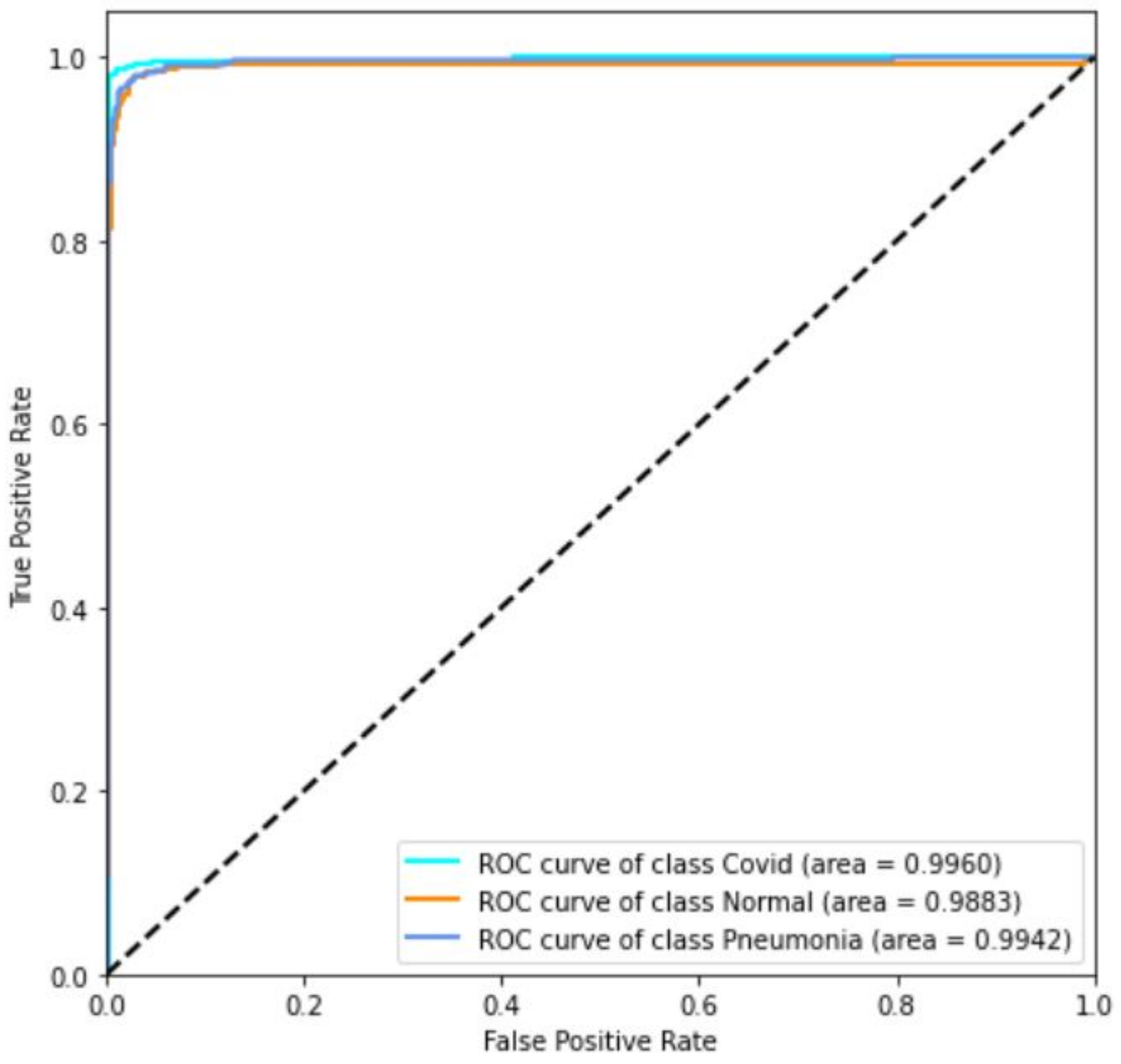
Result Analysis

CNN-BiLSTM : Dataset 2

- Confusion Matrix



- ROC curve



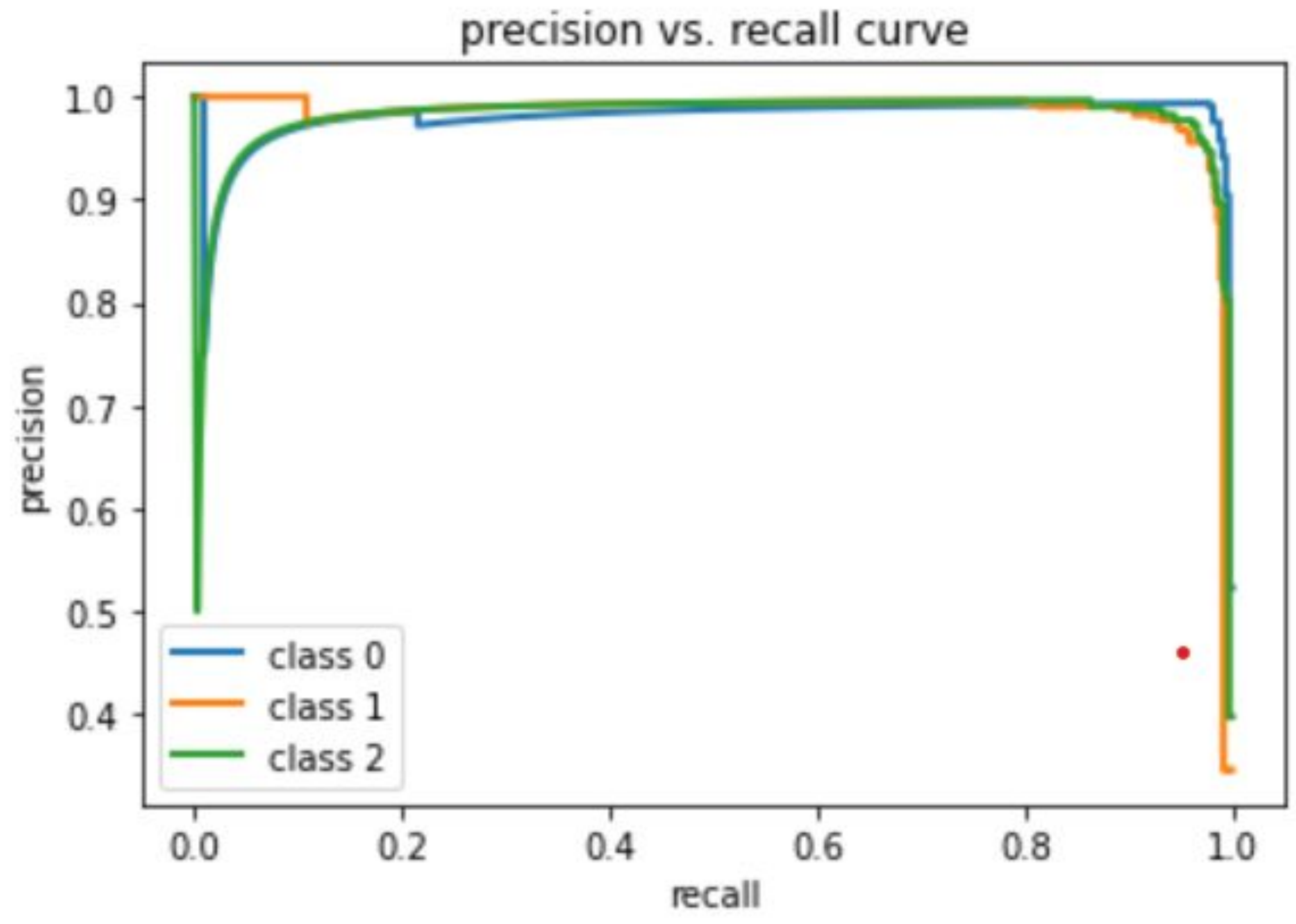
Result Analysis

CNN-BiLSTM : Dataset 2

- Classification report

	precision	recall	f1-score	support
Covid	0.99	0.98	0.99	325
Normal	0.94	0.98	0.96	361
Pneumonia	0.98	0.96	0.97	360
accuracy			0.97	1046
macro avg	0.97	0.97	0.97	1046
weighted avg	0.97	0.97	0.97	1046

- Precision vs Recall Curve

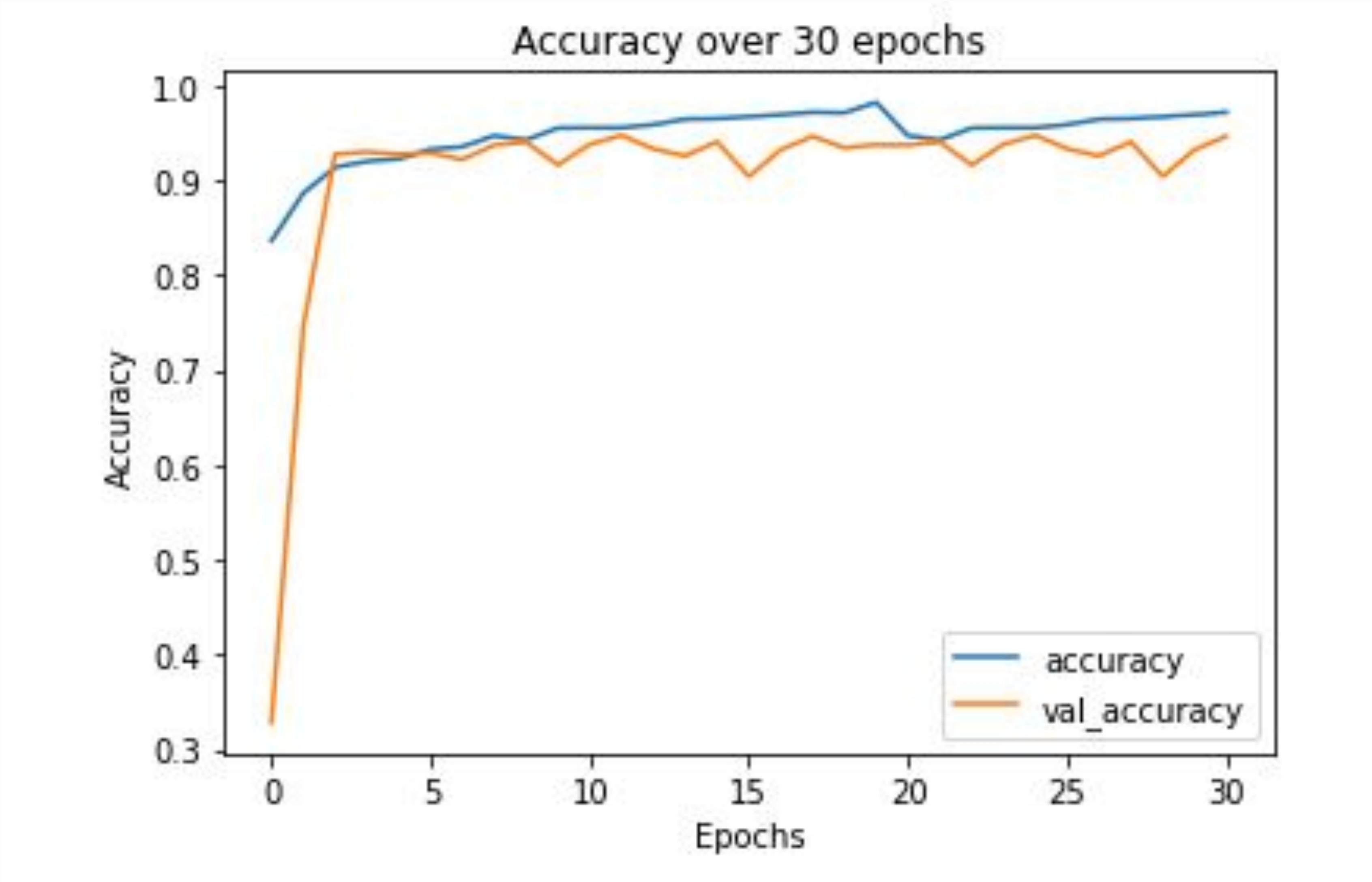


Result Analysis

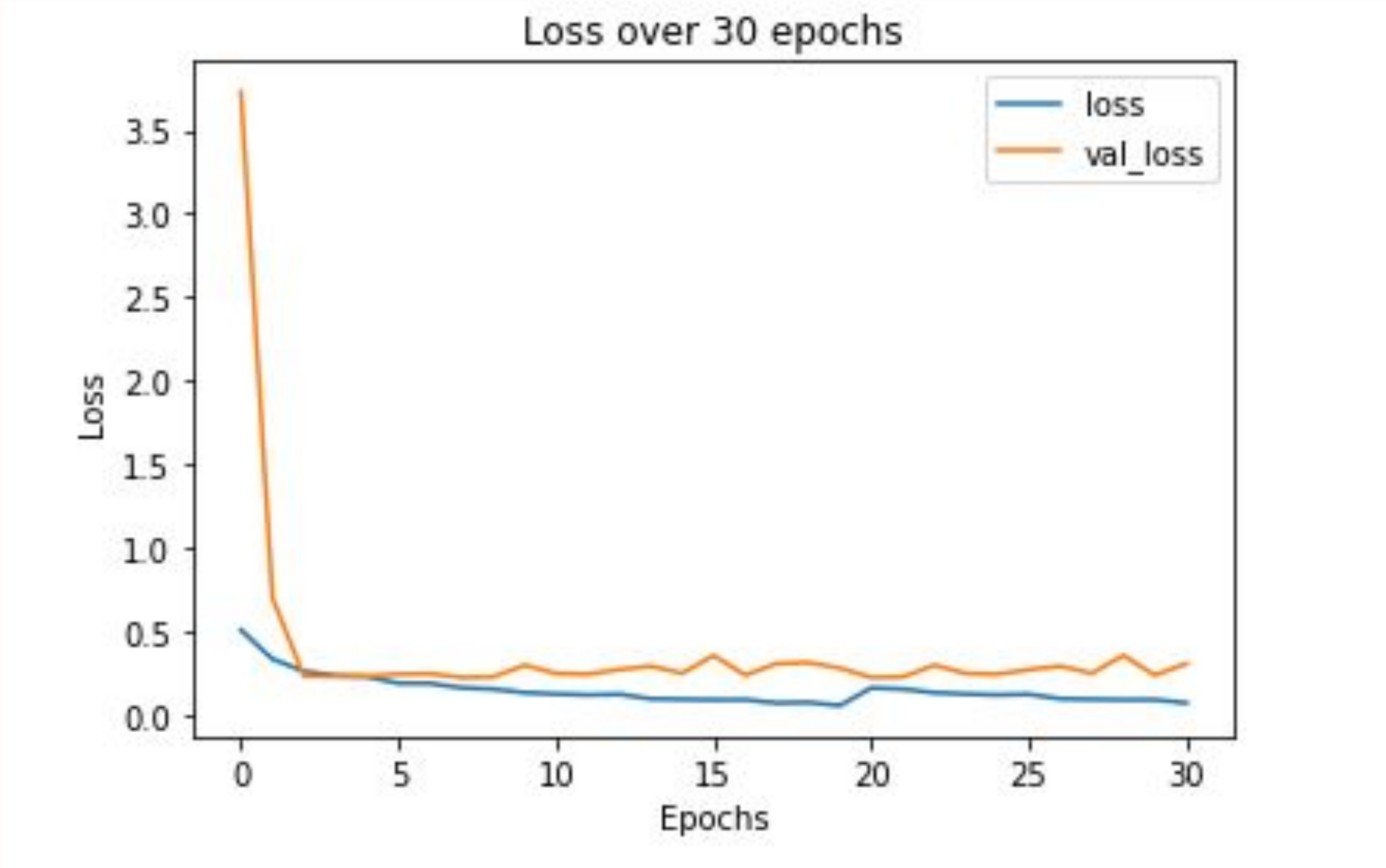
VGG19-LSTM (Dataset 1)

- x = number of epochs
  y_{left} = accuracy
  y_{right} = loss

- Training and validation accuracy



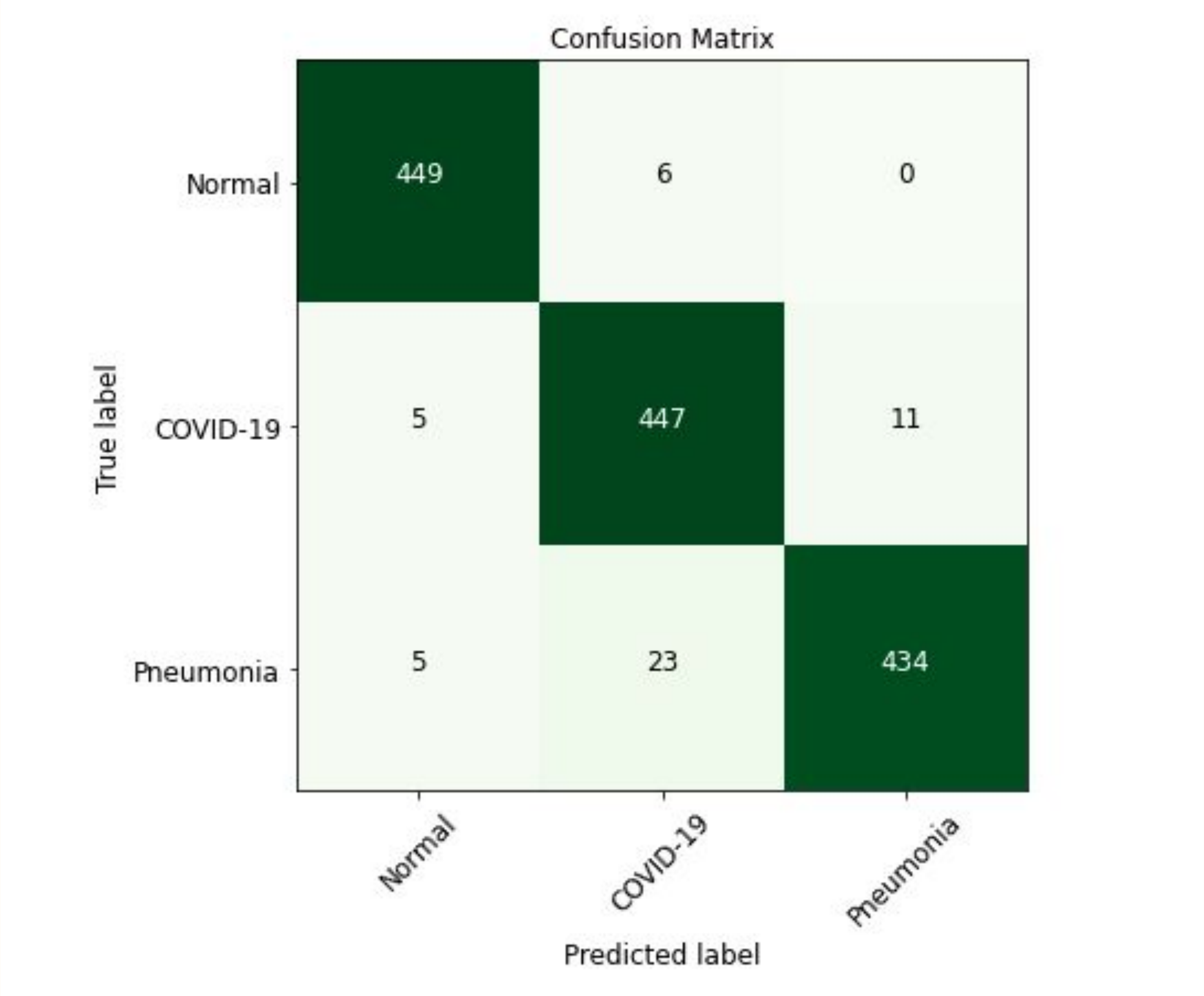
- Training and validation loss



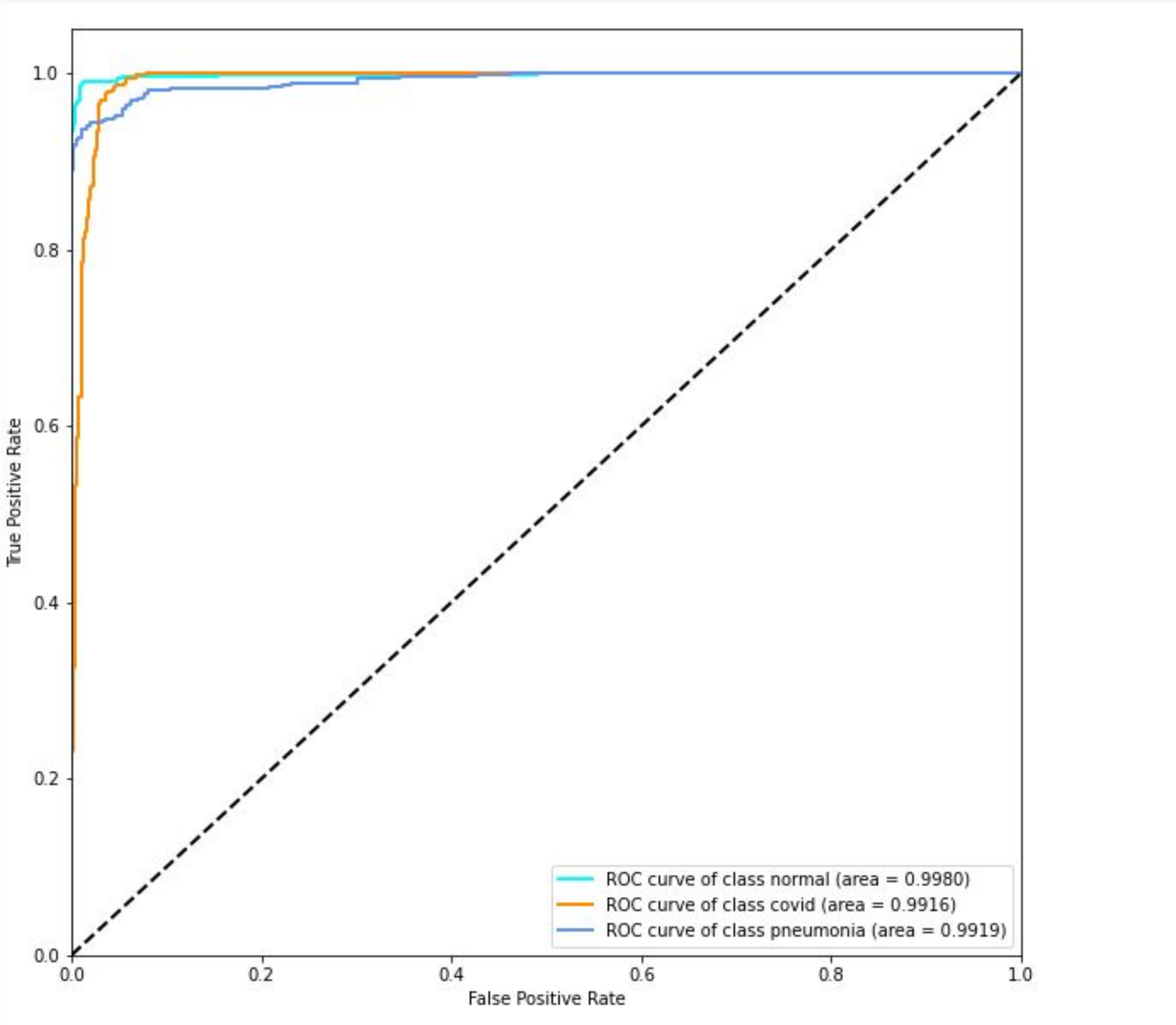
Result Analysis

VGG19-LSTM (Dataset 1)

- Confusion Matrix



- ROC curve



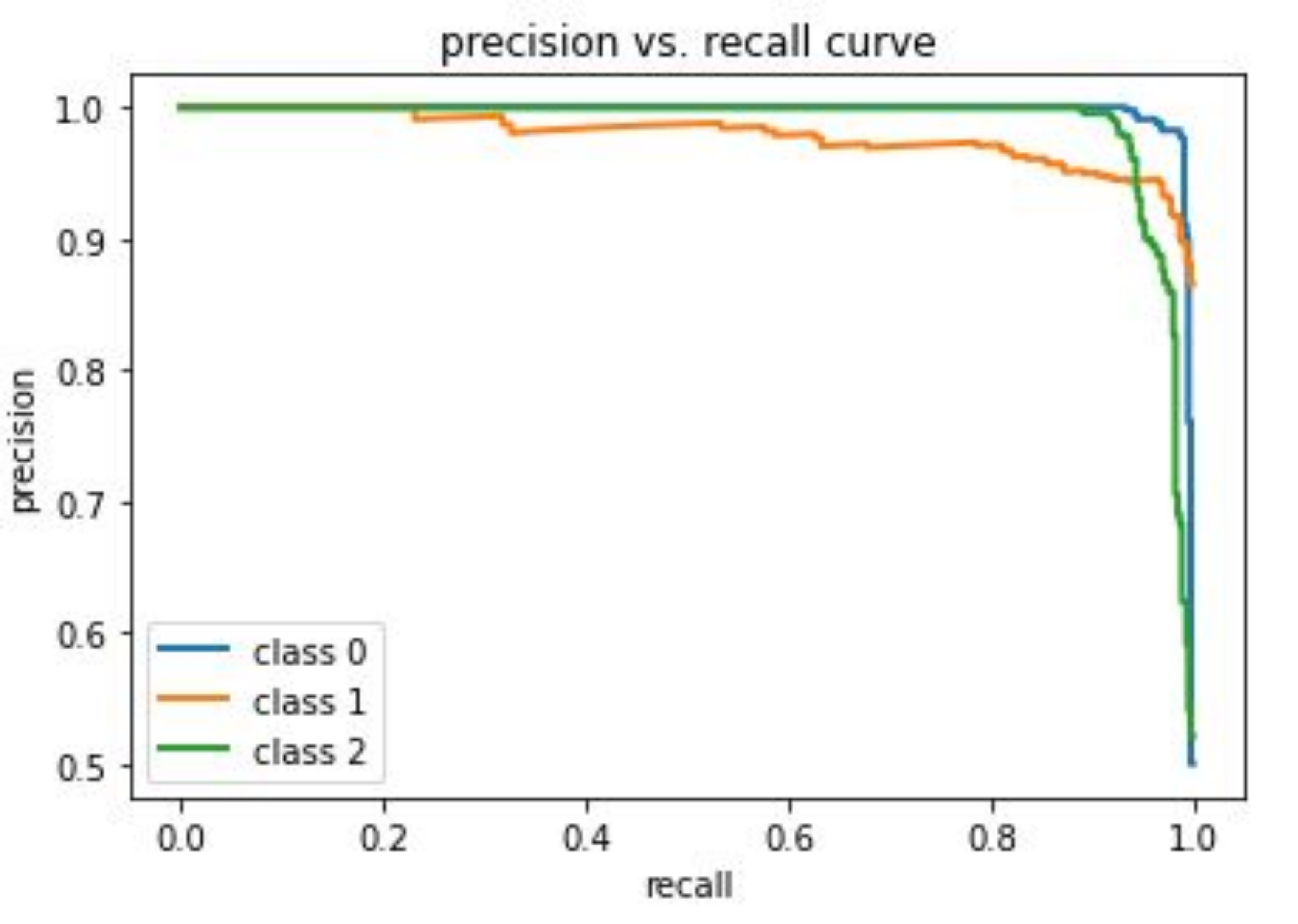
Result Analysis

VGG19-LSTM(Dataset 1)

- Classification report

	precision	recall	f1-score	support
normal	0.9804	0.9890	0.9847	455
covid	0.9474	0.9719	0.9595	463
pneumonia	0.9821	0.9481	0.9648	462
accuracy			0.9696	1380
macro avg	0.9699	0.9697	0.9696	1380
weighted avg	0.9699	0.9696	0.9696	1380

- Precision vs Recall Curve

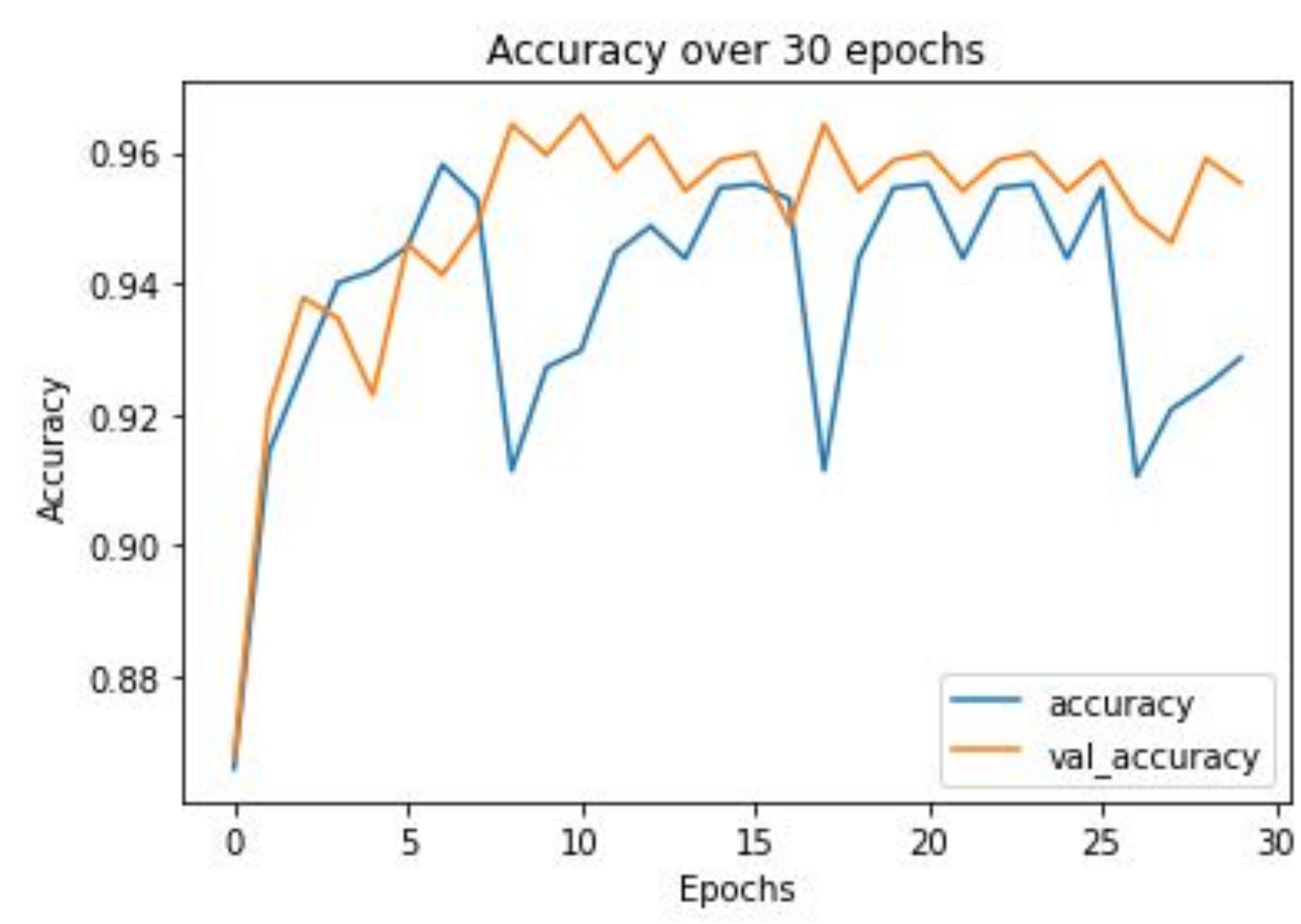


Result Analysis

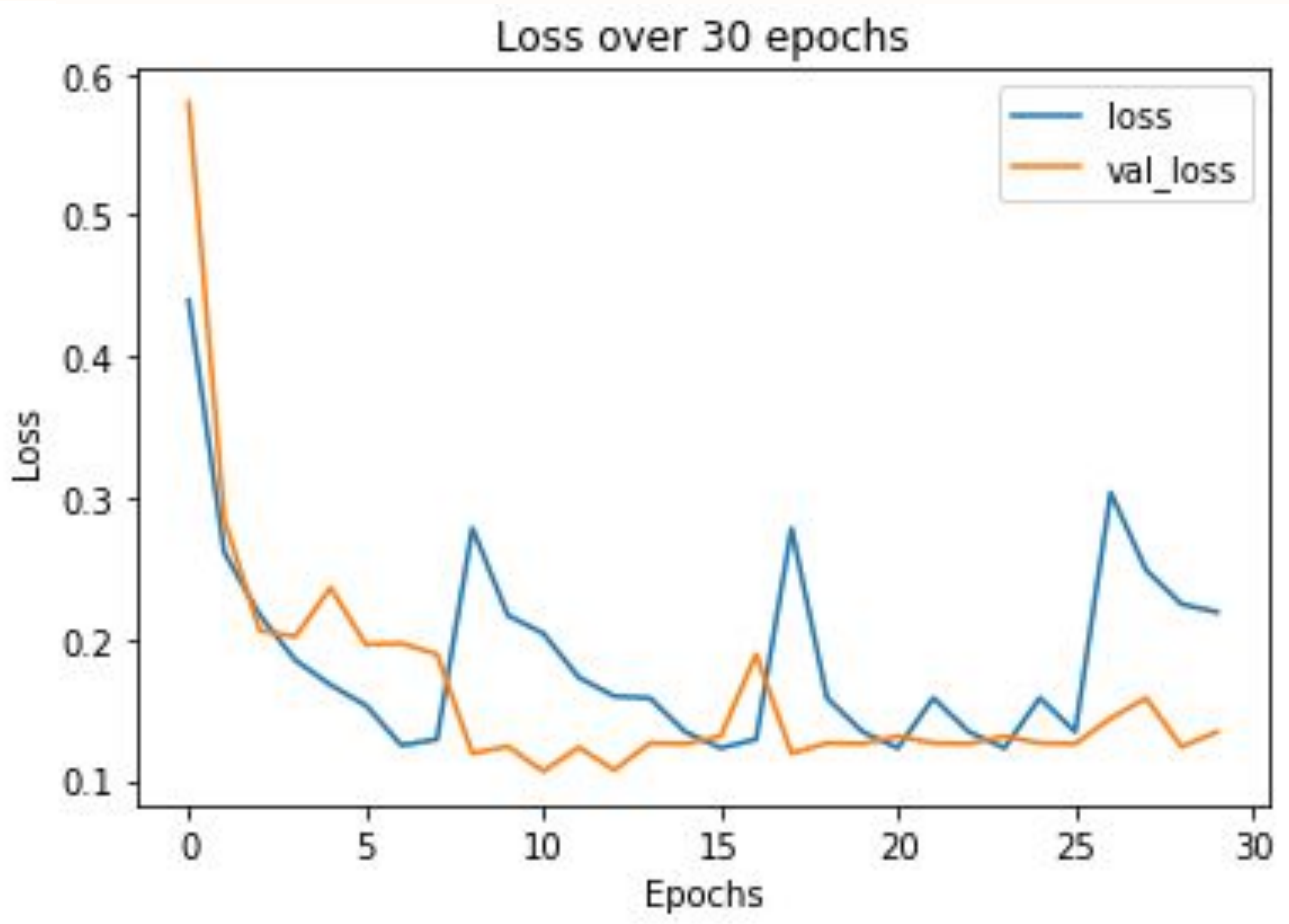
VGG16-LSTM(Dataset 1)

- x = number of epochs
  y_{left} = accuracy
  y_{right} = loss

- Training and validation accuracy



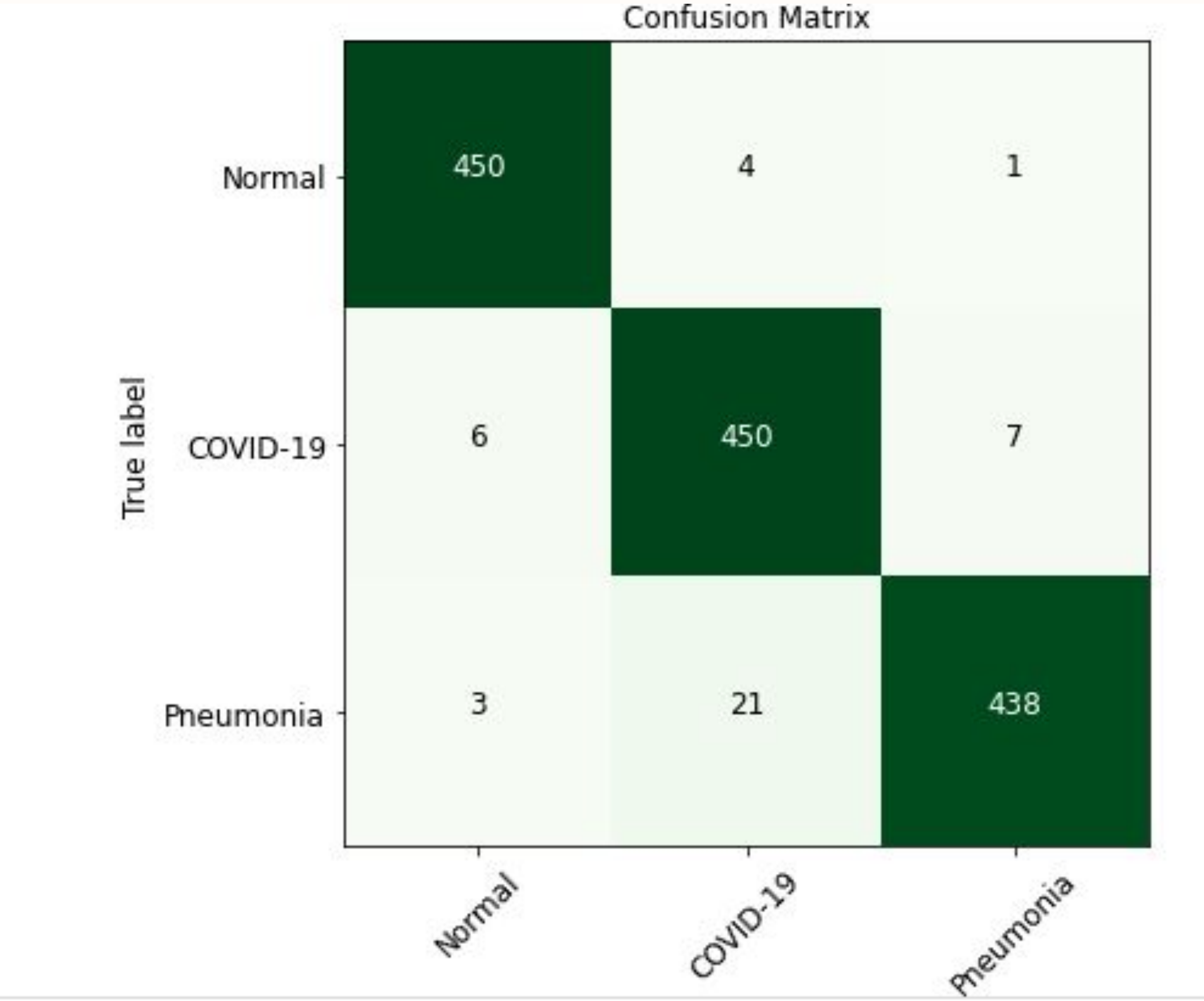
- Training and validation loss



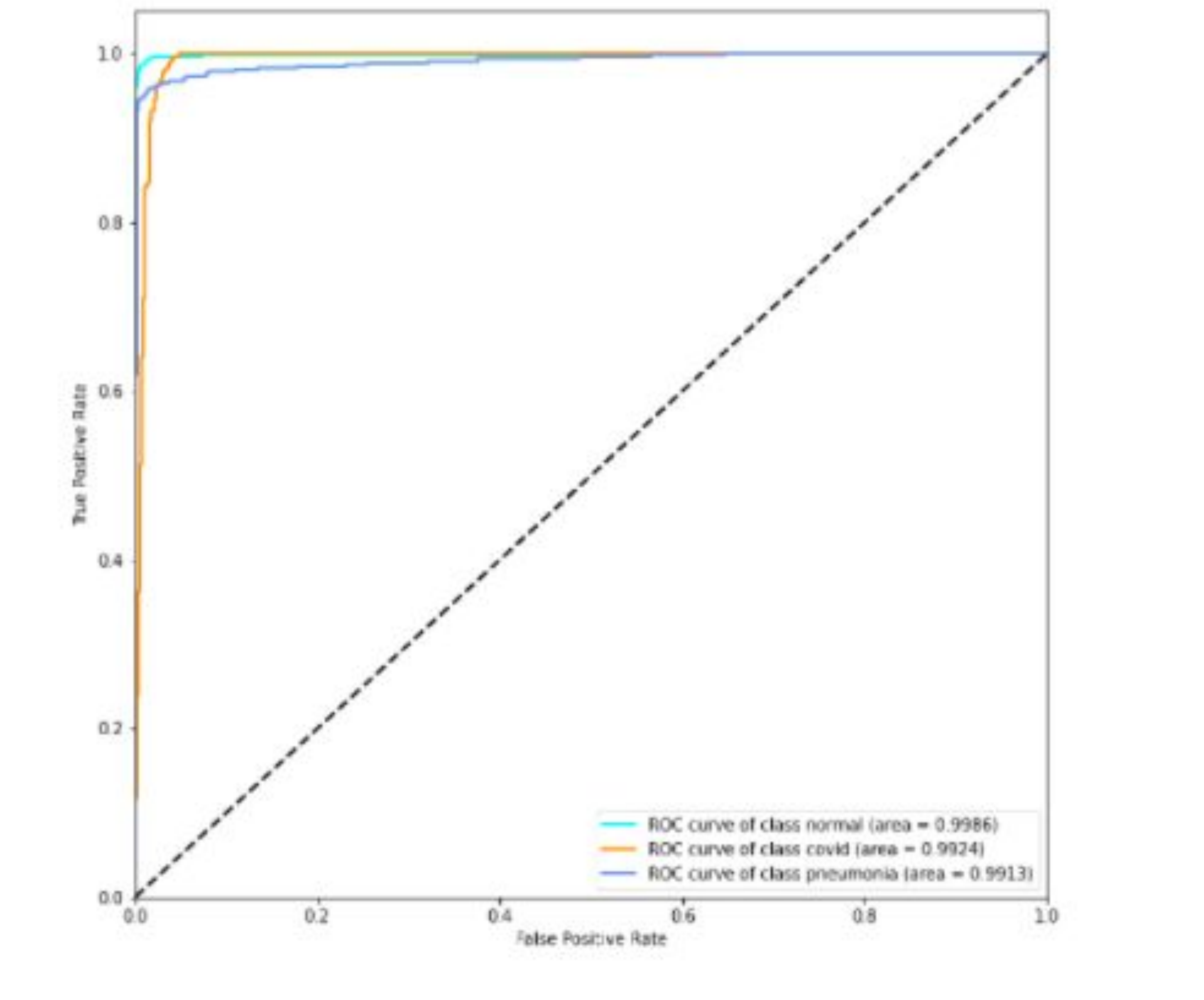
Result Analysis

VGG16-LSTM(Dataset 1)

- Confusion Matrix



- ROC curve

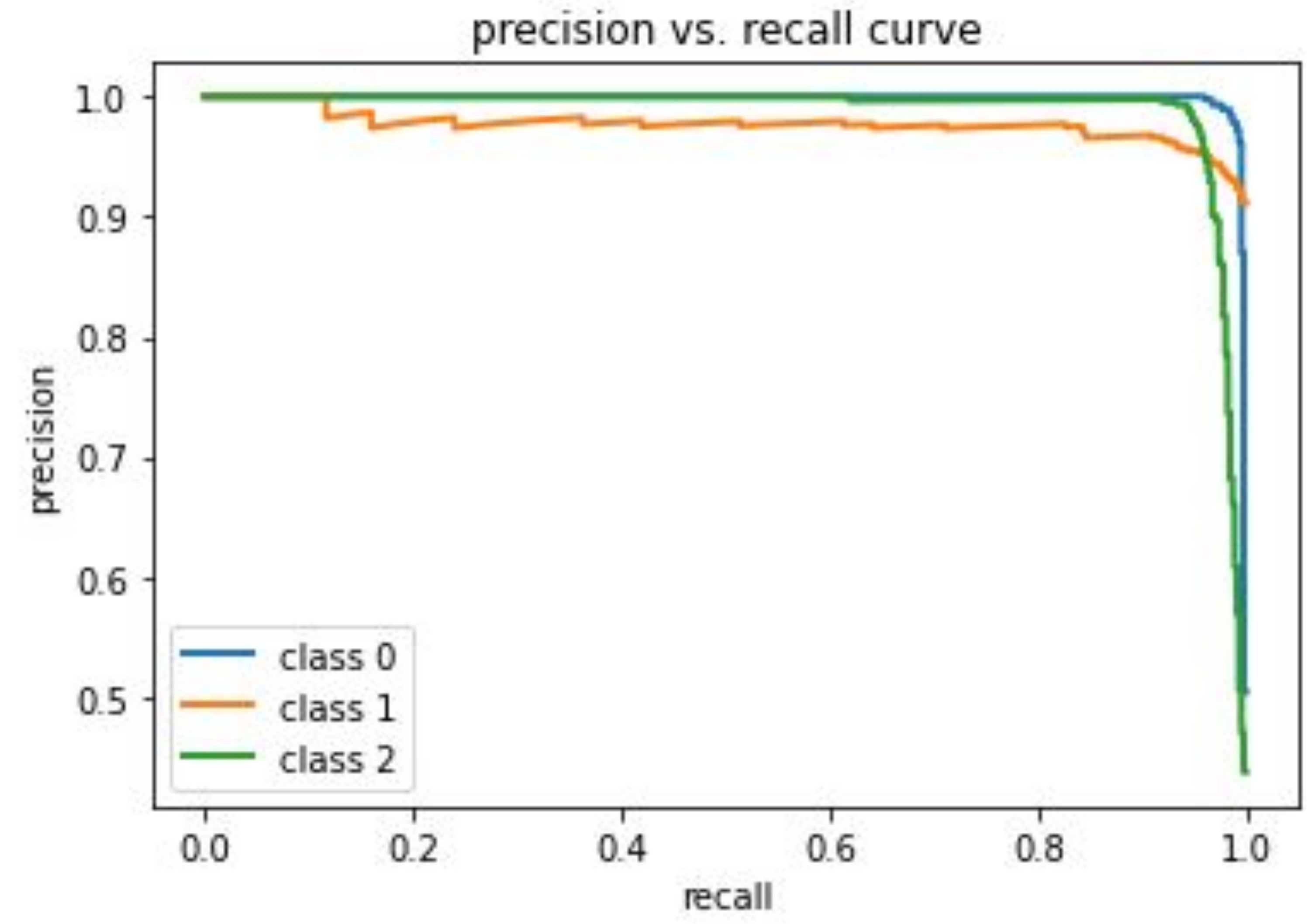


Result Analysis

VGG16-LSTM(Dataset 1)

- Classification report
- Precision vs Recall Curve

	precision	recall	f1-score	support
normal	0.9804	0.9890	0.9847	455
covid	0.9474	0.9719	0.9595	463
pneumonia	0.9821	0.9481	0.9648	462
accuracy			0.9696	1380
macro avg	0.9699	0.9697	0.9696	1380
weighted avg	0.9699	0.9696	0.9696	1380



Result Analysis

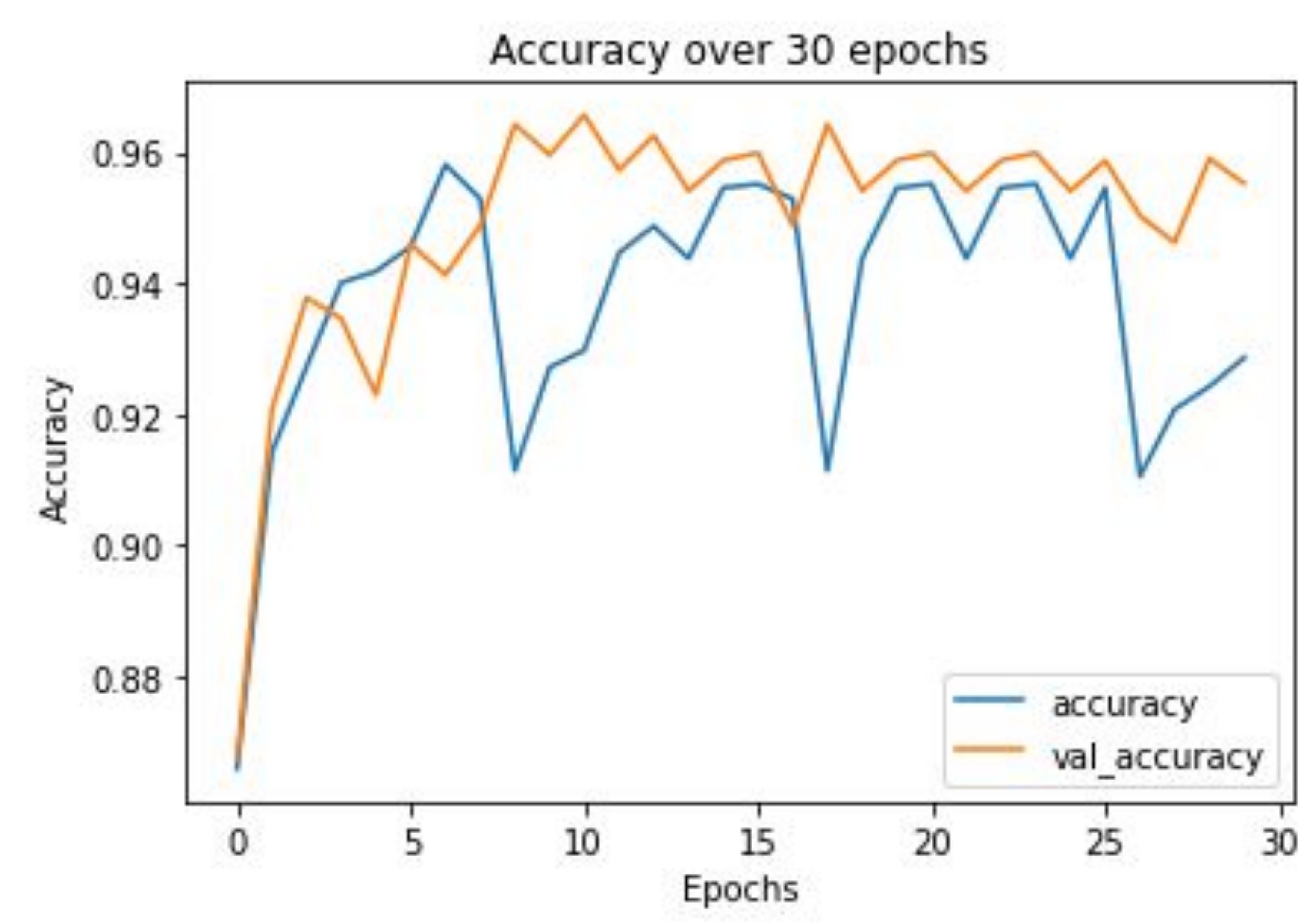
VGG16-BiLSTM(Dataset 1)

- x = number of epochs

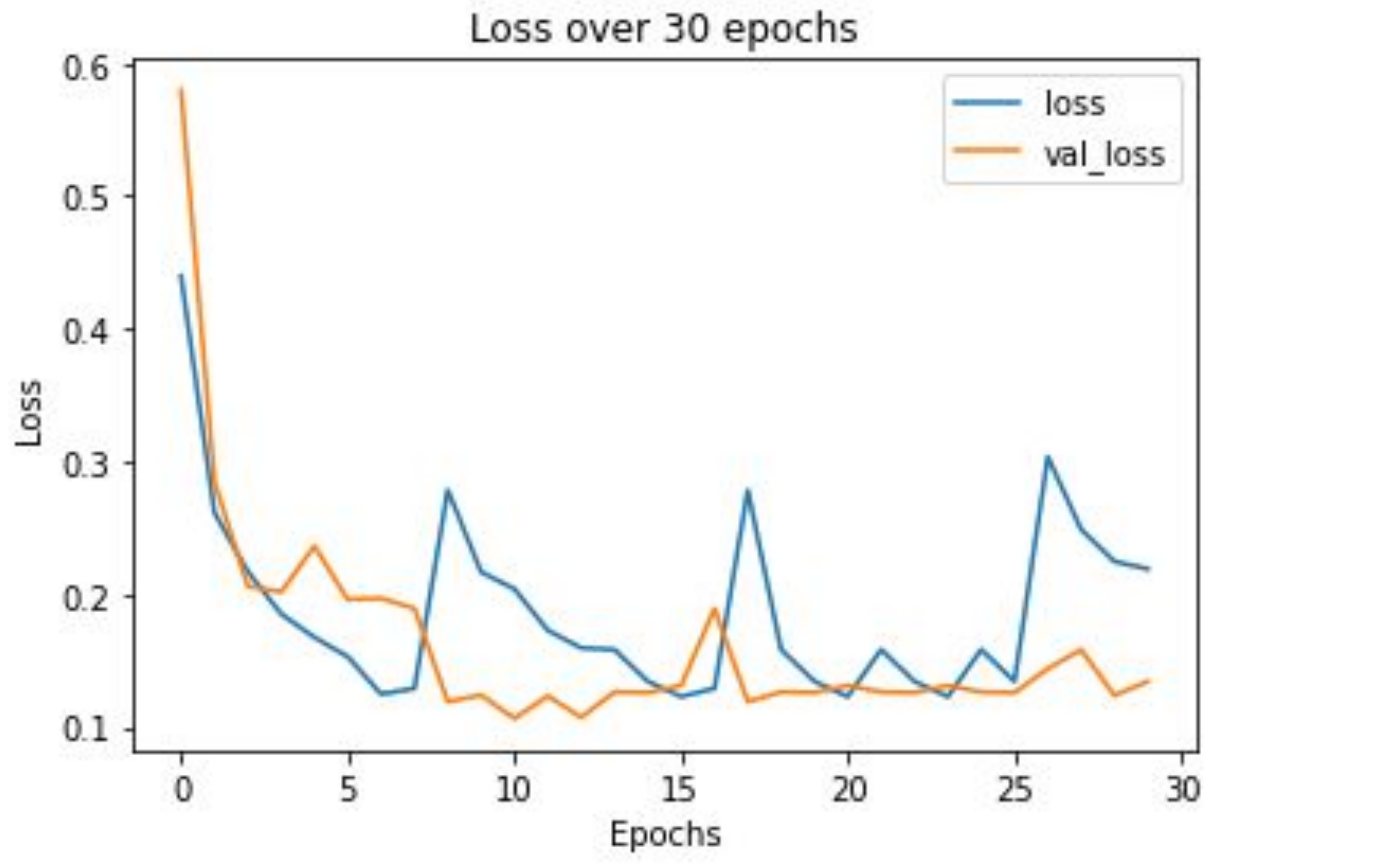
  y_{left} = accuracy

  y_{right} = loss

- Training and validation accuracy



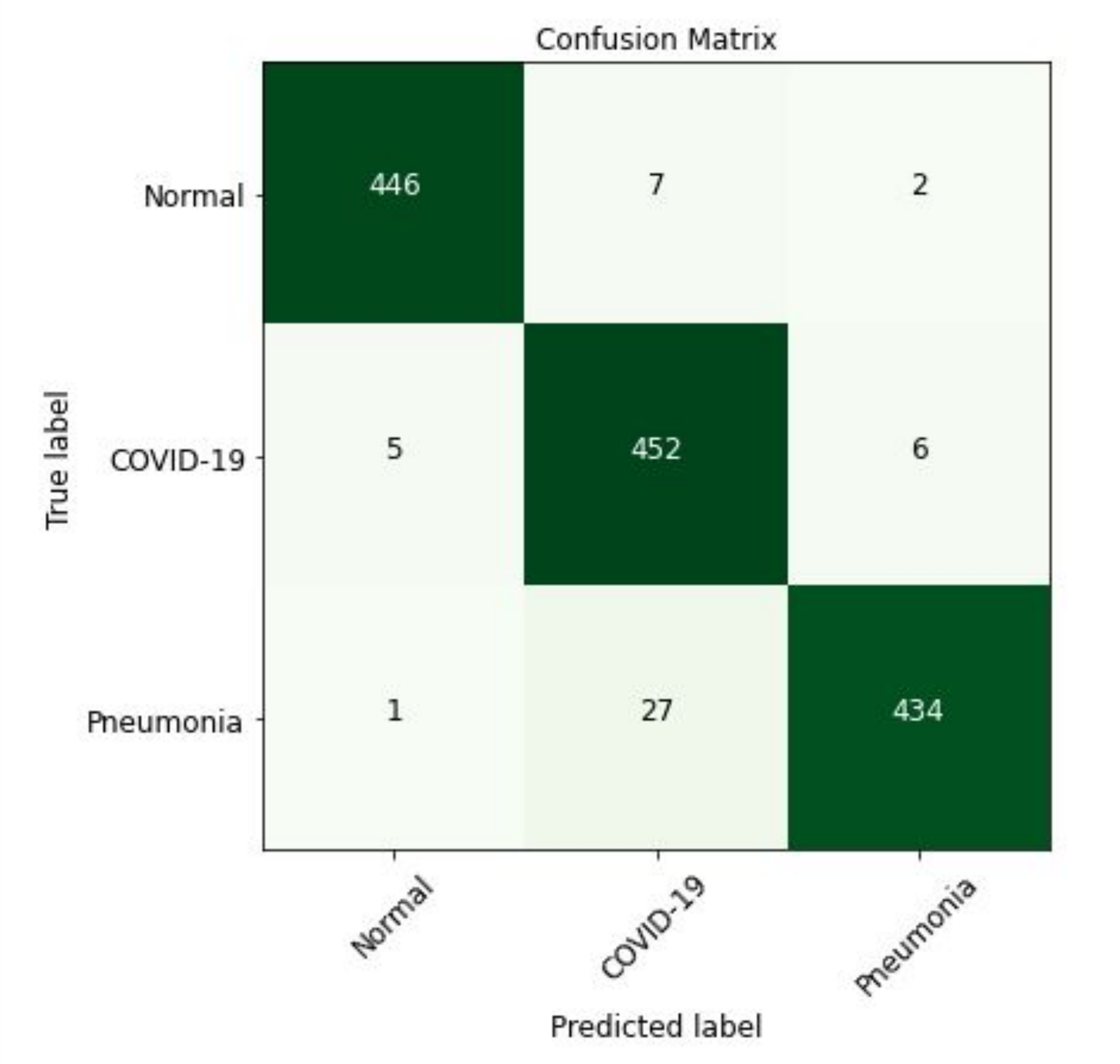
- Training and validation loss



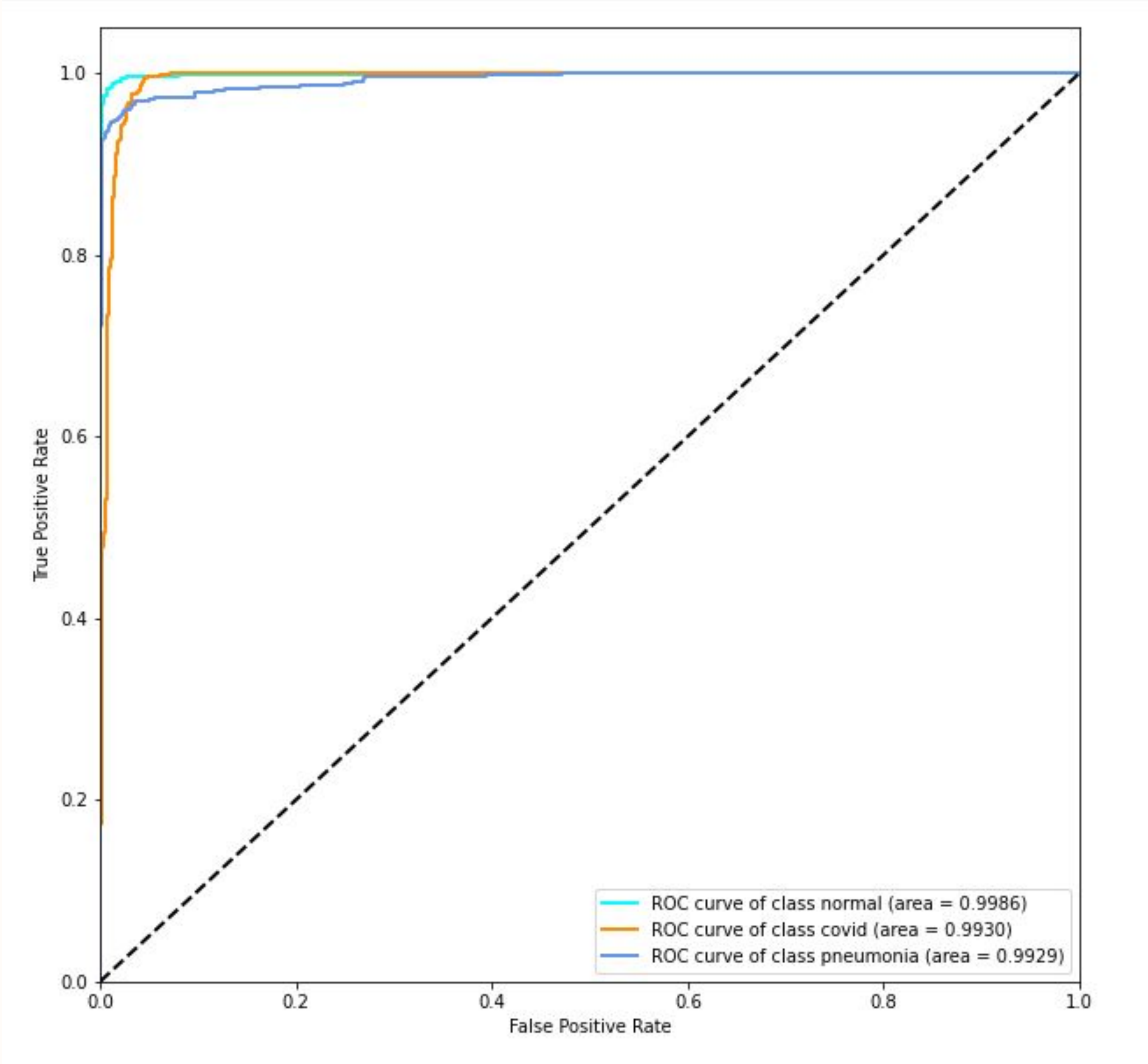
Result Analysis

VGG16-BiLSTM(Dataset 1)

- Confusion Matrix



- ROC curve



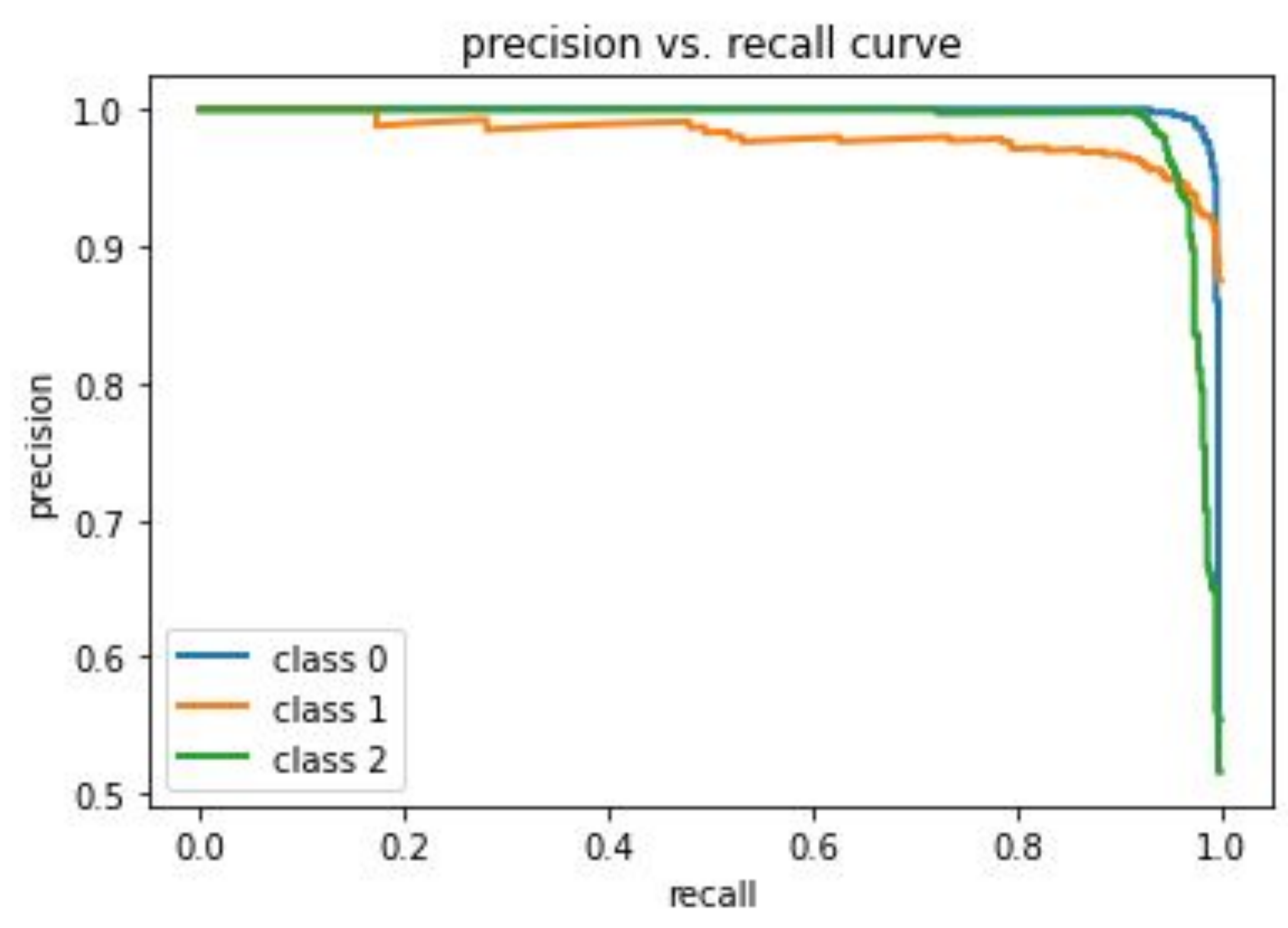
Result Analysis

VGG16-BiLSTM(Dataset 1)

- Classification report

	precision	recall	f1-score	support
normal	0.9867	0.9802	0.9835	455
covid	0.9300	0.9762	0.9526	463
pneumonia	0.9819	0.9394	0.9602	462
accuracy			0.9652	1380
macro avg	0.9662	0.9653	0.9654	1380
weighted avg	0.9661	0.9652	0.9653	1380

- Precision vs Recall Curve

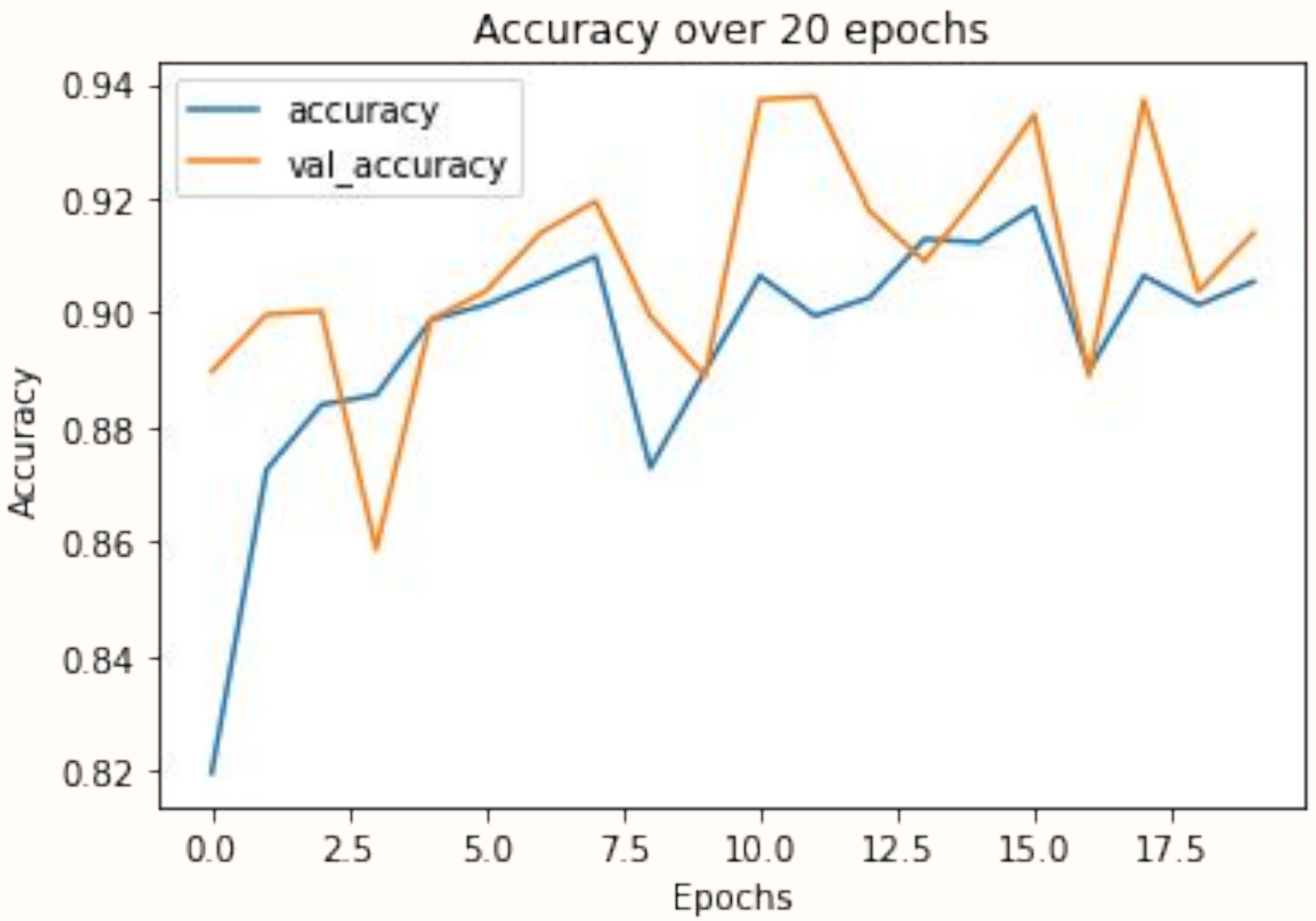


Result Analysis

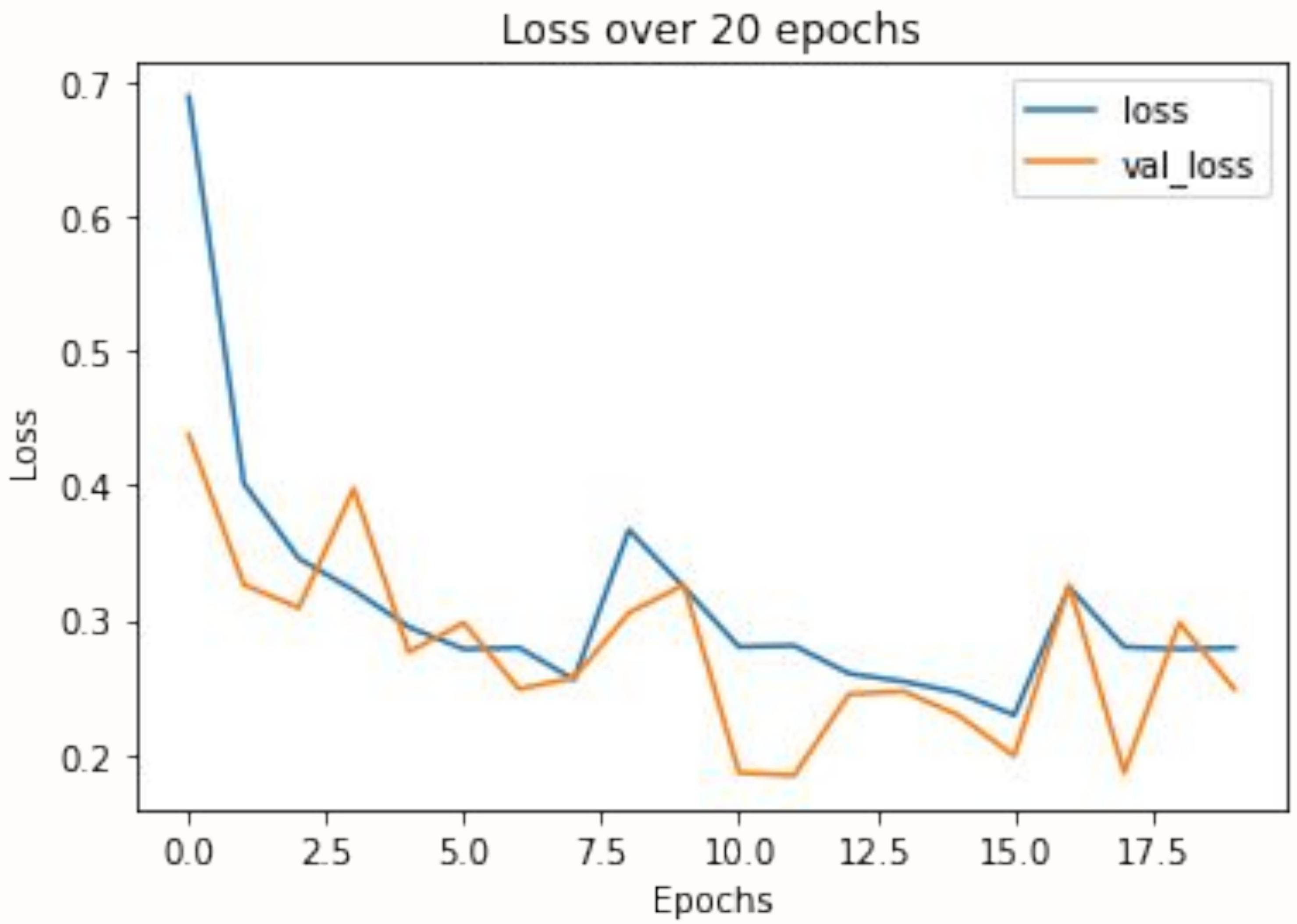
InceptionResNetV2-LSTM (Dataset 1)

- x = number of epochs
  y_{left} = accuracy
  y_{right} = loss

- Training and validation accuracy



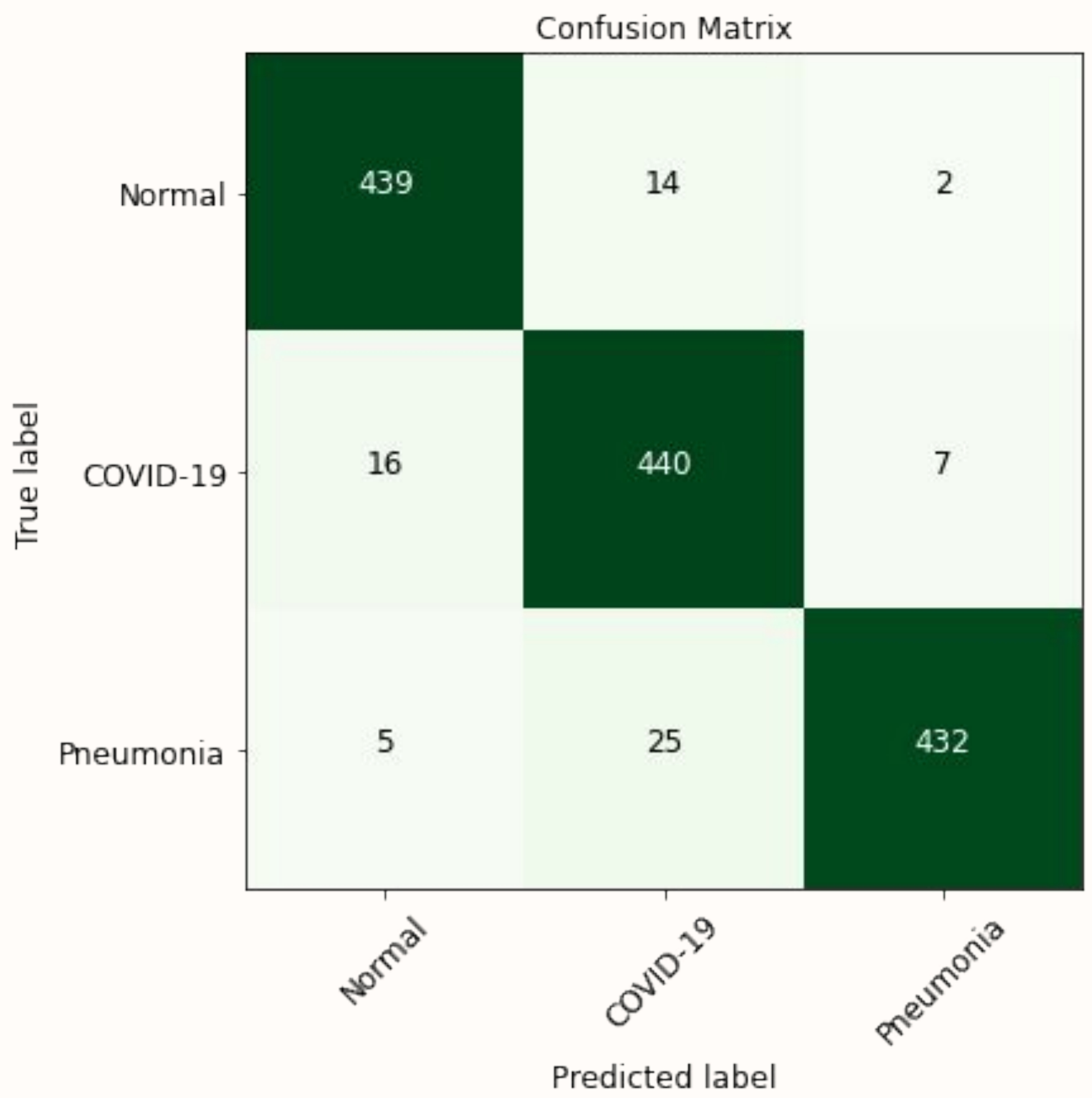
- Training and validation loss



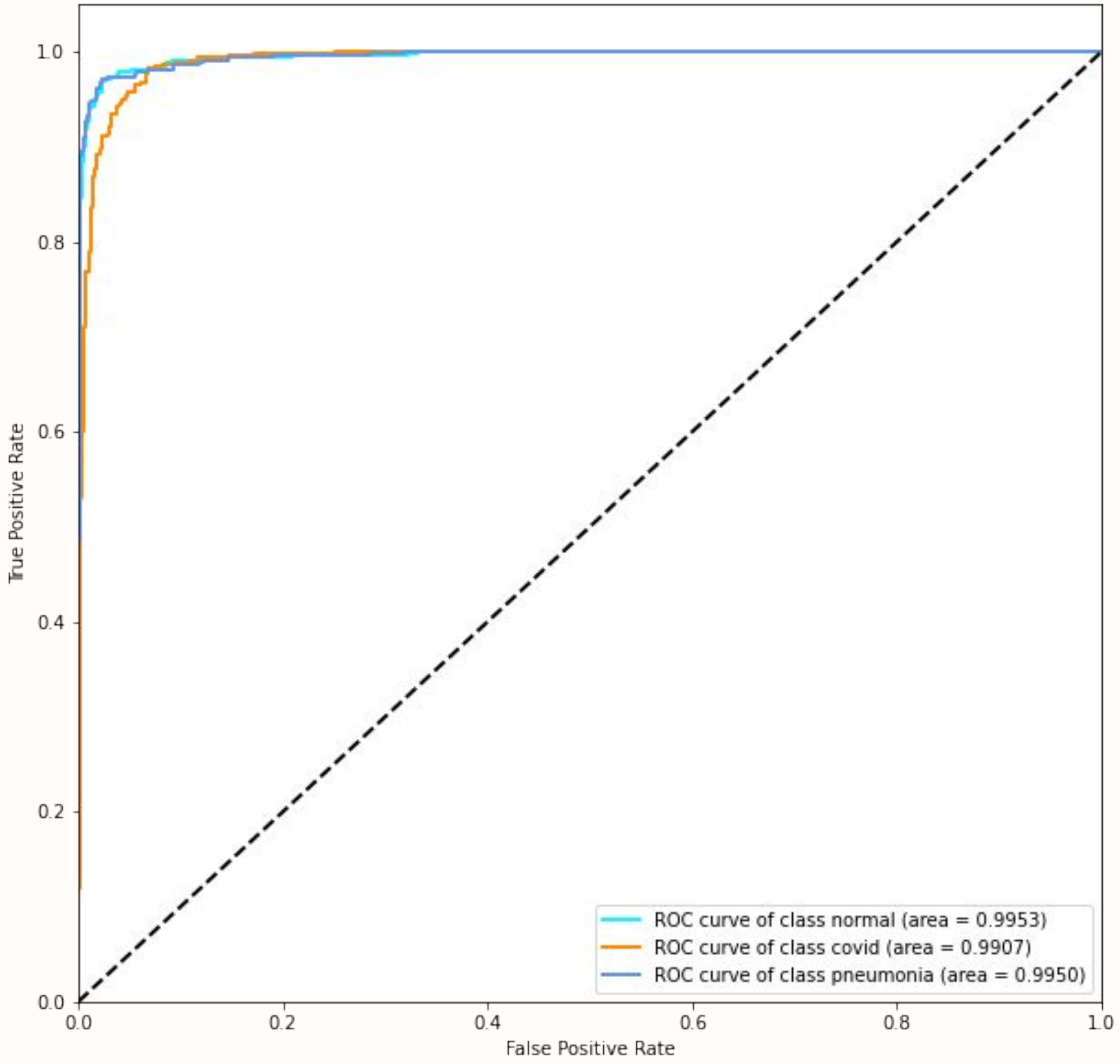
Result Analysis

InceptionResNetV2-LSTM(Dataset 1)

- Confusion Matrix



- ROC curve



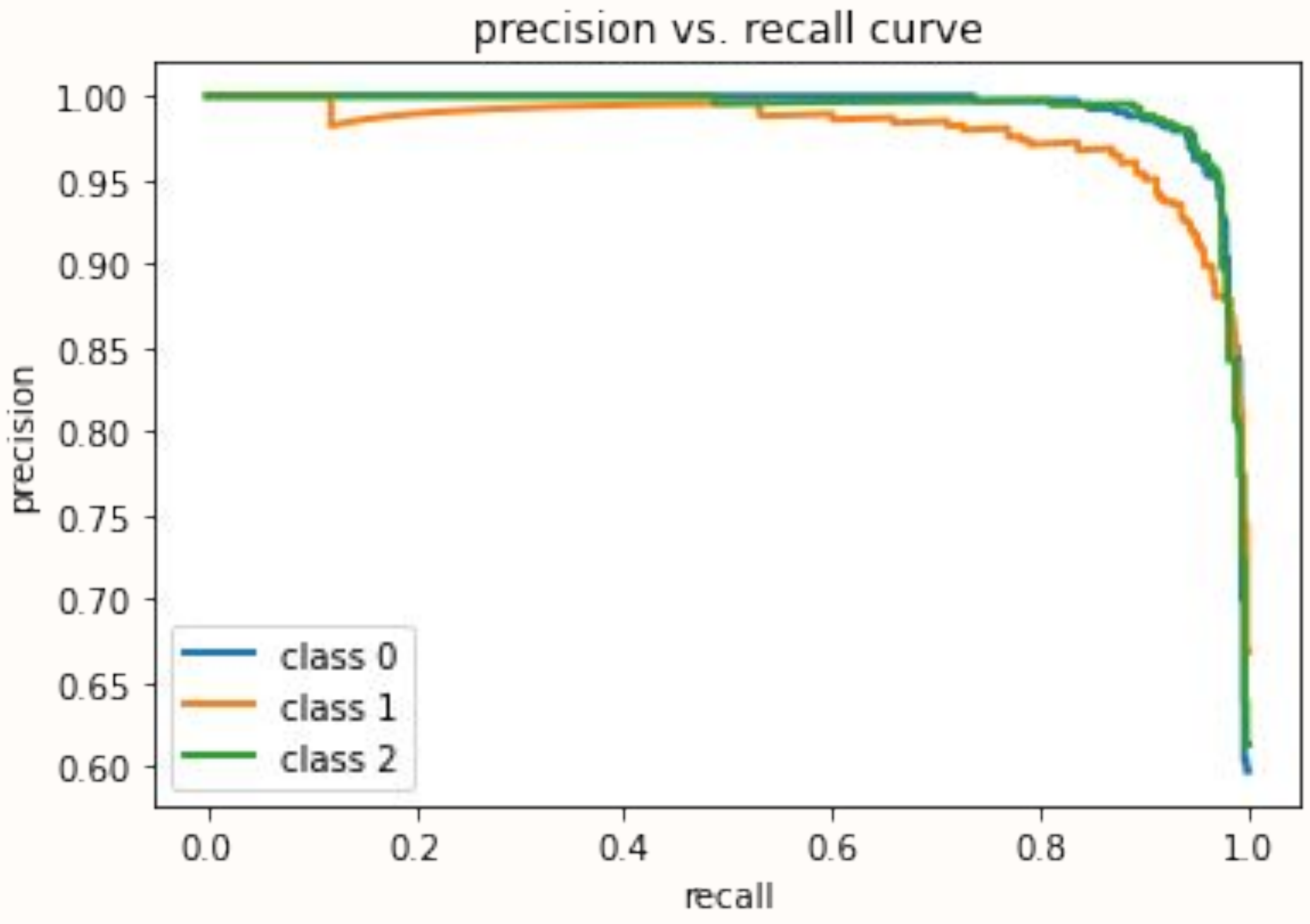
Result Analysis

InceptionResNetV2-LSTM(Dataset 1)

- Classification report

	precision	recall	f1-score	support
normal	0.9543	0.9648	0.9596	455
covid	0.9186	0.9503	0.9342	463
pneumonia	0.9796	0.9351	0.9568	462
accuracy			0.9500	1380
macro avg	0.9508	0.9501	0.9502	1380
weighted avg	0.9508	0.9500	0.9501	1380

- Precision vs Recall Curve



Result Analysis

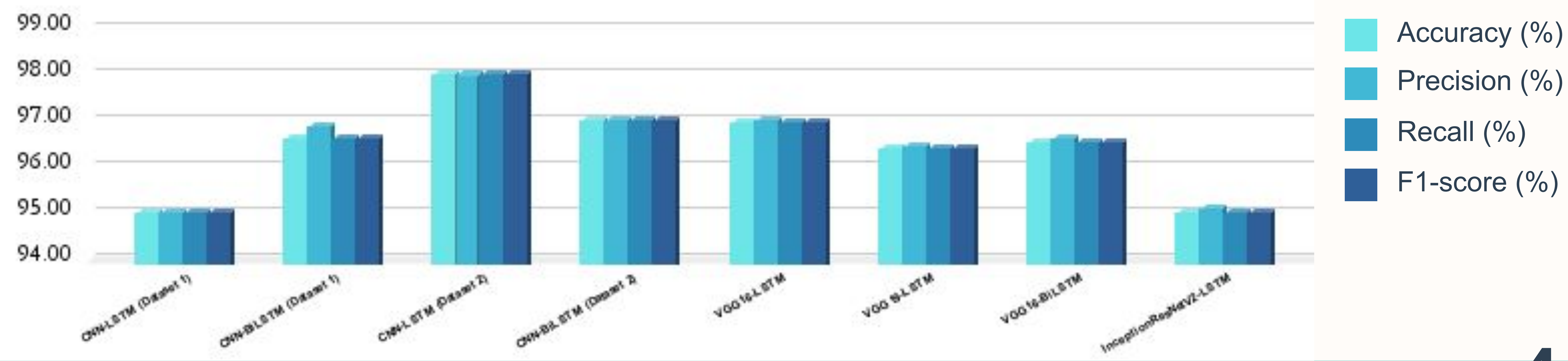
Time needed for training of the models

Model Name	Number of epochs needed	Time needed per epoch (sec)	Total training time (hours)
CNN-LSTM	32	115	1.02
CNN-BiLSTM	32	341	3.03
VGG19-LSTM	20	127	0.706
VGG16-LSTM	40	110	1.22
VGG16-BiLSTM	40	175	1.94
InceptionResNetv2-LSTM	10	568	1.57

Result Analysis

Comparative Results and Discussions

	Experiment 1				Experiment 2			
Model	**CNN-LSTM (Dataset 1)**	**CNN-BiLSTM (Dataset 1)**	**CNN-LSTM (Dataset 2)**	**CNN-BiLSTM (Dataset 2)**	**VGG16-LSTM**	**VGG19-LSTM**	**VGG16-BiLSTM**	**InceptionResNetV2-LSTM**
Accuracy (%)	95	96.6	98	97	96.96	96.38	96.52	95
Precision (%)	95	96.87	98	97	96.99	96.42	96.6	95.08
Recall (%)	95	96.6	98	97	96.96	96.39	96.5	95
F1-score (%)	95	96.6	98	97	96.96	96.39	96.5	95



Result Analysis

Comparative Results and Discussions

Comparision with other papers

Study	Method	Total Training Time (hours) (Epochs)	Accuracy(%)	Others(%)
[3]	CNN- LSTM, CNN	5.33 (125)	99.2%	Specificity : 99.2%, Sensitivity : 99.3%, F1-score : 98.9%
[6]	DNN,Bi-LSTM, VGG-16, ResNet-50, DenseNet-121	—- (100)	97.6%	Specificity : 99.2%, Sensitivity : 91.2%, Precision : 96.86%
[4]	DNN,CNN-LSTM, InceptionV3, Xception, ResNet50,VGG19	1.29 (150)	99.4%	Specificity : 99.4%, Sensitivity : 99.4%
[5]	CNN-LSTM, LSTM, GRU, RNN, DNN, CNN-RNN, CNN-GRU	—- (40)	98.94%	Precision : 99%, F1-score : 99%, Recall : 99%. Loss : 0.02%
Experiment 1 (for dataset 1)	CNN-LSTM CNN-BiLSTM	1.02 (32)	96.6%	Precision : 95%, F1-score : 95%, Recall : 95%.
Experiment 1 (for dataset 2)	CNN-LSTM CNN-BiLSTM	3.03 (32)	98%	Precision : 98%, F1-score : 98%, Recall : 98%.
Experiment 2	VGG16-LSTM VGG19-LSTM VGG16-BiLSTM InceptionResnetV2	0.706 (40)	96.96%	Precision : 96.99%, F1-score : 96.96%, Recall : 96.96%.

Future Direction

- Increase the capability of our system by using more data
- Generating larger datasets by synthetic data generation for unbalanced data
- Explore more advanced pre-trained models
- Use of advanced ensembling techniques
- Getting devices capable of working with larger datasets

Conclusion

Taking all of the limitations and constraints in mind we have come up with the idea of our proposed system which is to detect covid19 using chest x ray images. We believe that our proposed system will go a long way in achieving this goal and will help doctors and medical personnel and will add a significant value to the medical field.

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Thank You