

CoroNet: A Deep Neural Network for Detection and Diagnosis of Covid-19 from Chest X-ray Images

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Abstract: The novel Coronavirus also called Covid-19 originated in Wuhan, China in December 2019 and has now spread across the world. It has so far infected around 1.8 million people and claimed approximately 114698 lives overall. As the number of cases are rapidly increasing, most of the countries are facing shortage of testing kits and resources. The limited quantity of testing kits and increasing number of daily cases encouraged us to come up with a Deep Learning model that can aid radiologists and clinicians in detecting Covid-19 cases using chest X-rays. Therefore, in this study, we propose CoroNet, a Deep Convolutional Neural Network model to automatically detect Covid-19 infection from chest X-ray images. The deep model called CoroNet has been trained and tested on a dataset prepared by collecting Covid-19 and other chest pneumonia X-ray images from two different publically available databases. The experimental results show that our proposed model achieved an overall accuracy of 89.5%, and more importantly the precision and recall rate for Covid-19 cases are 97% and 100%. The preliminary results of this study look promising which can be further improved as more training data becomes available. 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.

Keywords: *Coronavirus; Covid-19, Pneumonia viral; Pneumonia bacterial; Convolutional Neural Network; Deep Learning*

INTRODUCTION

The 2019 novel Coronavirus or Covid-19 is a pandemic which was first reported in Wuhan, China in December 2019. A new virus which belongs to the family of viruses “Coronavirus” (CoV) was called “Severe Acute Respiratory Syndrome Coronavirus 2” (SARS-CoV-2) before it was named Covid-19 by World Health Organization (WHO) in February 2020. Covid-19 is contagious and spreads through respiratory transmission when an infected person coughs or sneezes. It can also spread when a person touches virus exposed surface or object and then touches his eyes, nose, or mouth. Due to its contagious nature, the virus spreads rapidly and infected around 60000 people within no time, and on 13 January, 2020, WHO confirmed first Covid-19 case outside China in Thailand. The outbreak was declared a Public Health Emergency of International Concern on 30 January 2020 [1]. It was not that far when the virus spread to other parts of the world and infected thousands of people in Iran, Italy, Germany etc. and finally on March 11, 2020, WHO declared Covid-19 as Pandemic. The number of daily cases began to increase exponentially and till now the pandemic has infected more than 1.8 million people and claimed around 114698 lives globally (as on 12 April 2020). The virus has engulfed more than 203 countries among which USA, Spain and Italy are severely hit with 560,433, 166,831 and 156,363 active cases and 22,115, 17,209 and 19,899 deaths respectively [2]. The country wise (Top 10) distribution of Covid-19 cases (as on 12 April 2020) is shown in Table I and the plot of daily cases is shown in Figure 1.

Once infected, a Covid-19 patient may develop various symptoms and signs of infection which include fever, cough and respiratory illness (like flu). In severe cases, the infection may cause pneumonia, difficulty breathing, multi-organ failure and death [2][3]. Due to the rapid and increasing growth rate of the Covid-19 cases, the health system of many advanced countries has come to the point of collapse. They are now facing shortage of ventilators and testing kits. Many countries have declared total lockdown and asked its population to stay indoors and strictly avoid gatherings.

A critical and important step in fighting COVID-19 is effective screening of infected patients, such that positive patients can be isolated and treated. Currently, the main screening method used for detecting COVID-19 is real-time reverse transcription polymerase chain reaction (rRT-PCR) [4][5]. The test is done on respiratory samples of the patient and the results can be available within few hours to 2 days. An alternate method to PCR screening method can be based on chest

Table I: Country-wise (Top 10) distribution of Covid-19 Cases (as on 12 April 2020) [2]

Country	Tot. Cases	Tot. Deaths	Cases/1M pop	Deaths/1Mpop
USA	560,433	22,115	1693	67
Spain	166,831	17,209	3568	368
Italy	156,363	19,899	2,586	329
France	132,591	14,393	2,031	221
Germany	127,854	3,022	1,526	36
UK	84,279	10,612	1,241	156
China	82,160	3,341	57	2
Iran	71,686	4,474	853	53
Turkey	56,956	1,198	675	14
Belgium	30,589	3,903	2,639	337

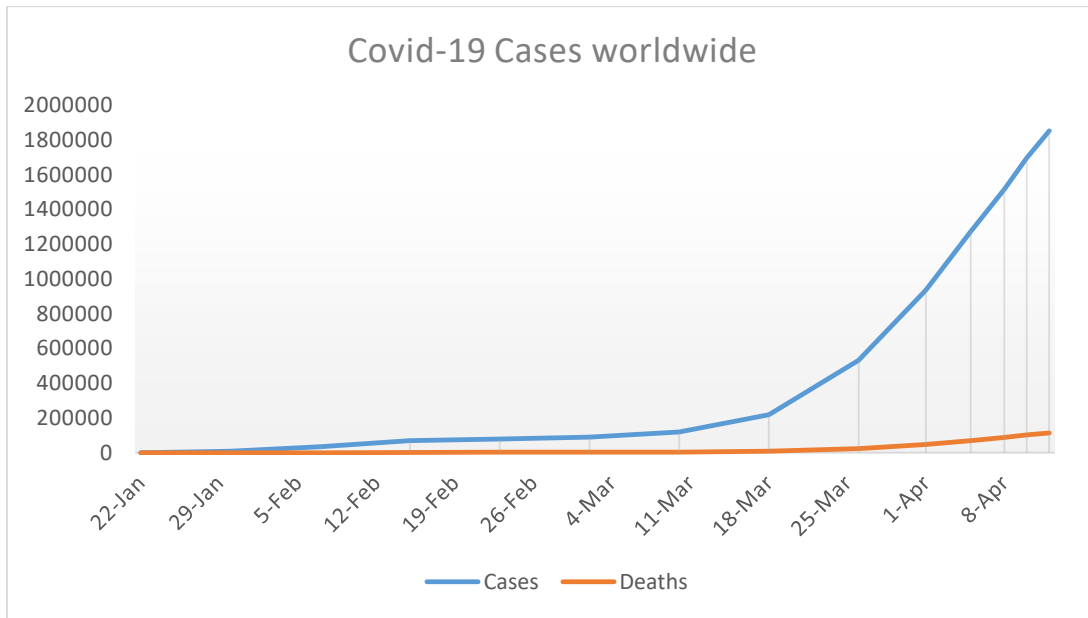


Figure 1: Covid-19 cases worldwide

radiography images. Various research articles published in Radiology journal [6][7] indicate that chest scans might be useful in detecting COVID-19. Researchers found that the lungs of patients with COVID-19 symptoms have some visual marks like ground-glass opacities—hazy

darkened spots that can differentiate Covid-19 infected patients from non Covid-19 infected ones [8][9]. The researchers believe that chest radiology based system can be an effective tool in detection, quantification and follow-up of Covid-19 cases.

A chest radiology image based detection system can have many advantages over conventional method. It can be fast, analyze multiple cases simultaneously, have greater availability and more importantly, such system can be very useful in hospitals with no or limited number of testing kits and resources. Moreover, given the importance of radiography in modern health care system, radiology imaging systems are available in every hospital, thus making radiography based approach more convenient and easily available.

Today, researchers from all around the world, from various different fields are working day and night to fight this pandemic. Many researchers have published series of preprint papers demonstrating approaches for Covid-19 detection from chest radiography images [10] [11]. These approaches have achieved promising results on a small dataset but by no means are production ready solutions. These approaches still need rigorous testing and improvement before putting them in use. Subsequently, a large number of researchers and data scientists are working together to build highly accurate and reliable deep learning based approaches for detection and management of Covid-19 disease. Researchers are focusing on deep learning techniques to detect any specific features from chest radiography images of Covid-19 patients. In recent past, deep learning has been very successful in various visual tasks which include medical image analysis as well. Deep learning has revolutionized automatic disease diagnosis and management by accurately analyzing, identifying, classifying patterns in medical images. The reason behind such success is that deep learning techniques do not rely on manual handcrafted features but these algorithms learn features automatically from data itself [12]. In the past, deep learning has had success in disease classification using chest radiography image. ChexNet [13] is a deep neural network model that detects Pneumonia from chest x-ray image. ChexNet achieved exceptional results exceeding average radiologist performance. Another similar approach called ChestNet [14] is a deep neural network model designed to diagnose thorax diseases on chest radiography images.

In this study, we present a deep learning based approach to detect Covid-19 infection from chest x-ray images. We propose a deep convolutional neural network (CNN) model to classify three different types of Pneumonia; bacterial pneumonia, viral pneumonia and Covid-19 pneumonia.

The proposed model is called CoroNet and will help us identifying the difference between three types of pneumonia infections and how Covid-19 is different from other infections. A model that can identify Covid-19 infection from chest radiography images can be very helpful to doctors in the triage, quantification and follow-up of positive cases. Even if this model does not completely replace the existing testing method, it can still be used to bring down the number of cases that need immediate testing or further review from experts.

DATASET

Deep learning is all about data which serves as fuel in these learning models. Since Covid-19 is a new disease, there is no appropriate sized dataset available that can be used for this study. Therefore, we had to create a dataset by collecting chest x-ray images from two different publically available image databases. Covid-19 x-ray images are available at an open source Github repository by Joseph et al [15]. The repository contains an open database of COVID-19 cases with chest X-ray or CT images and is being updated regularly. At the time of writing this paper, the database contained around 290 Covid-19 chest radiography images. Pneumonia bacterial, Pneumonia viral and normal chest x-ray images were obtained from Kaggle repository “Chest X-Ray Images (Pneumonia)” [16]. The dataset consists of 1203 normal, 660 bacterial Pneumonia and 931 viral Pneumonia cases. We collected a total of 1300 images from these two sources. We then resized all the images to the dimension of 224 x 224 pixels with a resolution of 72 dpi. Table II below shows the summary of the prepared dataset. The prepared dataset was then split into train and validation sets comprising of 80% and 20% of total data respectively. Figure 2 below shows some examples of chest x-ray images from the prepared dataset and Figure 3 shows the distribution of dataset for training and testing.

Table II: Dataset Summary

Disease	No. of Images
Normal	310
Pneumonia Bacterial	330
Pneumonia Viral	327
Covid-19	284

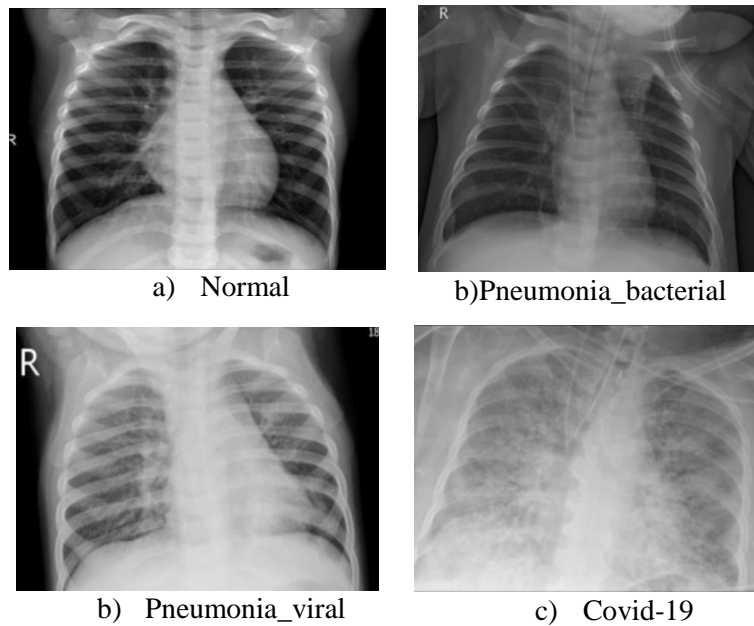


Figure 2: Examples of chest x-ray images from prepared dataset

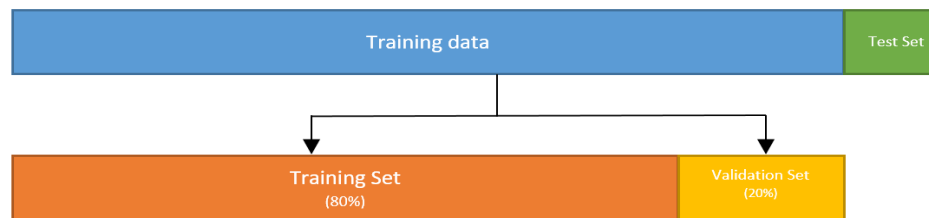


Figure 3: Distribution of images for training and testing

METHODOLOGY

In this section, we will discuss the work methodology for the proposed technique, model architecture, implementation and training. The work methodology is also illustrated in Figure 4.

Convolutional Neural Network (CNN)

Convolutional Neural Network also known as CNN is a deep learning technique that consists of multiple layers stacked together which uses local connections known as *local receptive field* and *weight-sharing* for better performance and efficiency. The deep architecture helps these networks learn many different and complex features which a simple neural network cannot learn. CNN's have shown excellent performance on several applications such as image classification, object detection, speech recognition, natural language processing, and medical image analysis.

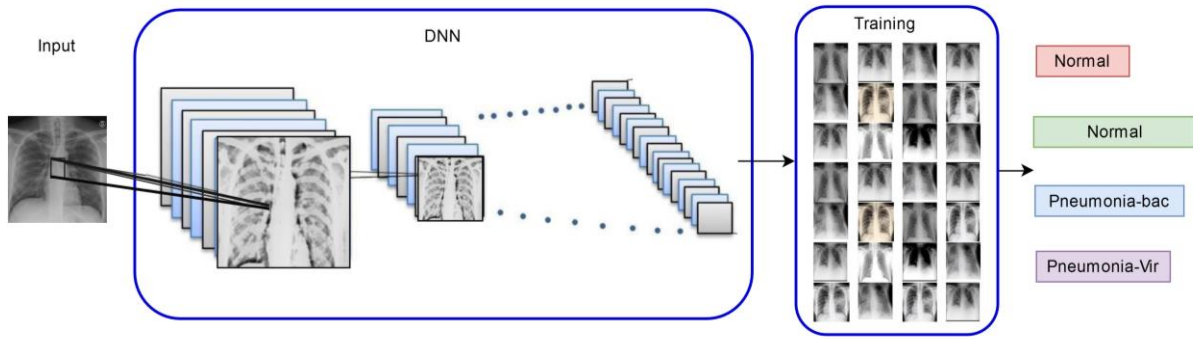


Figure 4: Overview of the proposed methodology

Convolutional neural networks are powering core of computer vision that has many applications which include self-driving cars, robotics, and treatments for the visually impaired. The main concept of CNN is to obtain local features from input (usually an image) at higher layers and combine them into more complex features at the lower layers [17] [18].

A typical Convolutional Neural Network architecture consists of the following layers:

a) Convolutional Layer

Convolution layer is the core building block of a Convolutional Neural Network which uses convolution operation (represented by $*$) in place of general matrix multiplication. Its parameters consist of a set of learnable filters also known as kernels. The main task of the convolutional layer is to detect features found within local regions of the input image that are common throughout the dataset and mapping their appearance to a feature map. The convolution operation is given as

$$F(i, j) = (I * K)(i, j) = \sum_m \sum_n I(i + m, j + n)K(m, n) \quad \dots Eq (1)$$

Where I is the input matrix (image), K is the 2D filter of size $m \times n$ and F represents the output 2D feature map. Here the input I is convolved with the filter K and produces the feature map F . This convolution operation is denoted by $I * K$.

The output of each convolutional layer is fed to an activation function. Activation function that takes the feature map produced by the convolutional layer and generates the activation map as its output. Activation function are used to introduces non-linearity to the network i: e it

transforms the linear output from convolution operation into non-linear one. Some activation functions even have squashing effect which takes an input (a number), performs some mathematical operation on it and outputs the activation level of a neuron between a given range e.g. 0 to 1 or -1 to 1. There are number of activation functions available but the one which is recognized for deep learning is Rectified Linear Unit (ReLU). ReLU simply computes the activation by thresholding the input at zero. In other words, ReLU outputs 0 if the input is less than 0, and raw output otherwise. It is mathematically given as:

$$f(x) = \max(0, x)$$

Rectified linear unit activation function produces a graph which is zero when $x < 0$ and linear with slope 1 when $x > 0$.

b) Subsampling (Pooling) Layer

In CNN, the sequence of convolution layer is followed by an optional pooling or down sampling layer to reduce the spatial size of the input and thus reducing the number of parameters in the network. A pooling layer takes each feature map output from the convolutional layer and down samples it i.e. pooling layer summarizes a region of neurons in the convolution layer. There most common pooling technique is Max Pooling which simply outputs the maximum value in the input region. Other pooling options are average pooling and L2-norm pooling.

c) Fully Connected Layer

The task of Convolution and pooling layers is to detect features from the input. Next step is to make a decision based on these detected features. In case of classification problem, the task is to compute the class scores. This is done by adding one or more fully connected layers at the end. In fully connected layer each neuron from previous layer is connected to every neuron in the next layer and every value contributes in predicting how strongly a value matches a particular class. The output of last fully connected layer is then forwarded to an activation function which outputs the class scores. Softmax and Support Vector Machines (SVM) are the two main classifiers used in CNN. Softmax function which computes the probability distribution of the n output classes is given as

$$Z^k = \frac{e^{x^k}}{\sum_{i=1}^n e^{x^n}} \dots \dots \dots eq (2)$$

Where x is the input vector and Z is the output vector. The sum of all outputs (Z) equals to 1. The proposed model CoroNet uses Softmax, to predict the class to which the input x-ray image belongs to.

All the layers discussed above are stacked up to make a full CNN architecture. In addition to these main layers mentioned above, CNN may include optional layers like batch normalization layer to improve the training time and dropout layer to address the overfitting issue.

Model Architecture and Development

CoroNet is a CNN architecture tailored for detection of Covid-19 infection from chest x-ray images. It is based on Xception CNN architecture [19]. Xception which stands for Extreme version of Inception [20] (its predecessor model) is a 71 layers deep CNN architecture pre-trained on ImageNet dataset. Xception uses depthwise separable convolution layers with residual connections instead of classical convolutions. Depthwise Separable Convolution replaces classic $n \times n \times k$ convolution operation with $l \times l \times k$ point-wise convolution operation followed by channel-wise $n \times n$ spatial convolution operation. This way the number of operations are reduced by a factor proportional to $1/k$.

CoroNet uses Xception as base model with a dropout layer and two fully-connected layers added at the end. CoroNet has 33,969,964 parameters in total out of which 33,969,964 trainable and 54528 are non-trainable parameters. Architecture details, layer-wise parameters and output shape of CoroNet model are shown in Table III. To initialize the model parameters, we used Transfer Learning to overcome the problem of overfitting as the training data was not sufficient.

Implementation and Training

The proposed model, CoroNet was implemented in Keras on top of Tensorflow 2.0. The model was pre-trained on ImageNet dataset and then retrained end-to-end on prepared dataset using Adam optimizer with learning rate of 0.0001, batch size of 10 and epoch value of 80. All the experiment and training was done on Google Colaboratory Ubuntu server equipped with Tesla K80 graphics card. Plots of accuracy and loss on the training and validation datasets over training epochs are shown in Figure 5.

Table III: Details of CoroNet Architecture

Layer (type)	Output Shape	Param #
Xception (Model)	5 x 5 x 2048	20861480
flatten (Flatten)	51200	0
dropout (Dropout)	51200	0
dense (Dense)	256	13107456
dense_1 (Dense)	4	1028

Total Parameters: 33,969,964
Trainable Parameters: 33,915,436
Non-trainable Parameters: 54,528

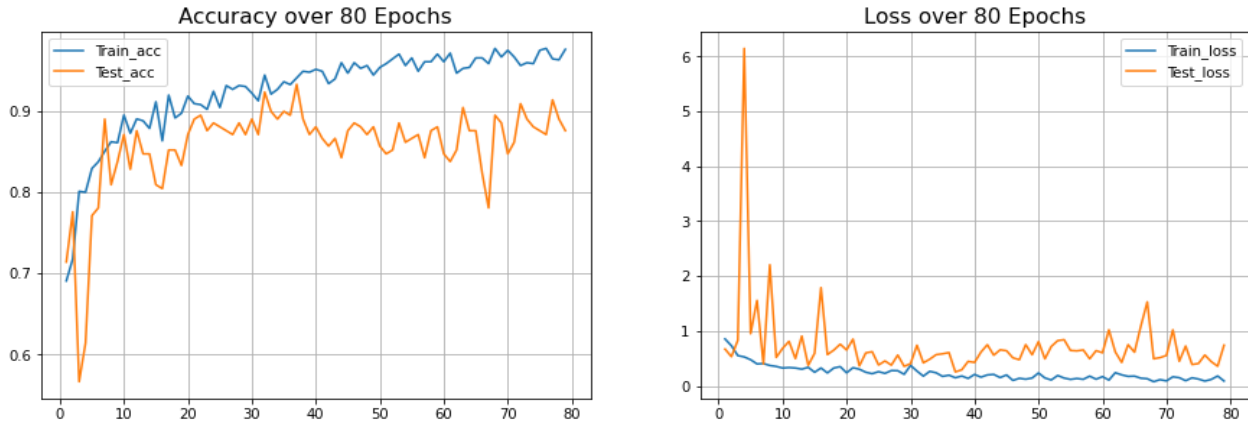


Figure 5: Plots of Accuracy and Loss on Training and validation sets over training epochs

RESULTS

The experimental result of the proposed model on the prepared dataset is presented in the form of confusion matrix in Table IV. The overall accuracy, class-wise precision, recall and F-measure computed by formulae given below are summarized in Table V.

$$\text{Accuracy} = \frac{\text{No. of images correctly classified}}{\text{Total no. of images}}$$

$$\text{Precision} = \frac{\text{Sum of all True Positives (TP)}}{\text{Sum of all True Positives (TP)+All False Positives (FP)}}$$

$$\text{Recall} = \frac{\text{Sum of all True Positives (TP)}}{\text{Sum of all True Positives (TP)+All False Negatives (FN)}}$$

$$\text{F-measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

The aforementioned performance metrics are the top metrics used to measure the performance of classification algorithms. The proposed model CoroNet achieved an overall accuracy of 89.5%, while as the accuracy and F-measure for Covid-19 class are 96.6% and 98% respectively. Figure 6 shows the result of CoroNet on some sample images from test set.

Table IV: Confusion Matrix of CoroNet

Class	Predicted Class			
	Covid-19	Normal	Pneumonia Bac	Pneumonia Vir
Covid-19	29	0	0	0
Normal	1	71	0	0
Pneumonia Bac	0	7	53	5
Pneumonia Vir	0	3	7	45

Table V: Performance of the CoroNet on each Infection Type

Class	Precision (%)	Recall (%)	F1 Score (%)
Covid-19	97	100	98
Normal	88	99	93
Pneumonia Bac	88	82	85
Pneumonia Vir	90	82	86
Overall Accuracy	89.5%		

DISCUSSION

By analyzing the confusion matrix, it can be observed that CoroNet achieved an overall accuracy of 89.5%. Even though CoroNet has been trained on a small dataset, the results look promising, indicating that given more data, the proposed model can achieve better results with minimum pre-processing of data.

Another positive observation from the results is the precision (PPV) and recall (Sensitivity) for Covid-19 cases which are 97% and 100% respectively. Recall value of 100% means that all the 29 examples of Covid-19 have been rightly classified as Covid-19. In other words, False Negative rate for Covid-19 is 0%. This is important because minimizing the missed Covid-19 cases as much as possible is the main aim of this research.

Furthermore, the precision and recall for normal class (88% precision, 99% recall) are slightly lower than Covid-19 cases but higher than non-Covid-19 cases. The performance for Non Covid-19 pneumonia classes (pneumonia-bacterial and pneumonia-viral) are comparatively lower than other two classes and contributes to the lower overall accuracy. If we combine the pneumonia-bacterial and pneumonia-viral into one single class as Non-Covid-19 class, then the overall accuracy increases significantly. The Confusion matrix of combined Non-Covid-19 classes is presented in Table VI. After combining the two non-Covid-19 pneumonia infections, the overall accuracy of CoroNet increased from 89.5% to 95%. Based on these findings, it is evident that despite limited training data, CoroNet performs exceptionally well in detecting Covid-19 cases using chest x-ray images and, as more data becomes available, the performance can be further improved.

Table VI: Confusion Matrix of CoroNet (Combined non-Covid-19)

Class	Predicted Class		
	Covid-19	Normal	Non-Covid-19
Covid-19	29	0	0
Normal	1	71	0
Non-Covid-19	0	10	110
Overall Accuracy	95%		

Performance Comparison

Covid-19 is a recent disease and there is not much literature and data available in public domain. The scarcity of data and literature in the public domain restricted our comparison to just one technique called Covid-Net [10]. Covid-Net is one of the early works done on Covid-19 which uses deep neural network to classify chest x-ray images. The results comparison of the two models is presented in Table VII. CoroNet which is trained on a dataset with slightly higher number of Covid-19 examples performed better than Covid-Net in terms of both accuracy as well as computational power. Covid-Net, with 116 million parameters achieved an accuracy of 83.5% while as our proposed model, CoroNet achieved an accuracy of 89.5% with just 33 million parameters (71% less parameters) which is a huge improvement in terms of computation. Thus, in comparison, CoroNet is much more efficient, provides good convergence and has highest performance accuracy.

Table VII: Performance Comparison Table

Class	Covid-Net [10]			CoroNet		
	Precision (%)	Recall (%)	F1 Score (%)	Precision (%)	Recall (%)	F-measure (%)
Covid-19	80	100	88.8	97	100	98
Normal	95.1	73.9	83.17	88	99	93
Pneumonia Bac	87.1	93.1	90	88	82	85
Pneumonia Vir	67.0	81.9	73.7	90	82	86
# of Parameters	116 million			33 million		
Accuracy	83.5%			89.5%		

CONCLUSION

As the cases of Covid-19 pandemic are increasing daily, many countries are facing shortage of resources. During this health emergency, it is important that not even a single positive case goes unidentified. With this thing in mind, we proposed a deep learning approach to detect Covid-19 cases from chest radiography images. The proposed method (CoroNet) is a convolutional neural network designed to identify Covid-19 cases using chest x-ray images. The model has been trained

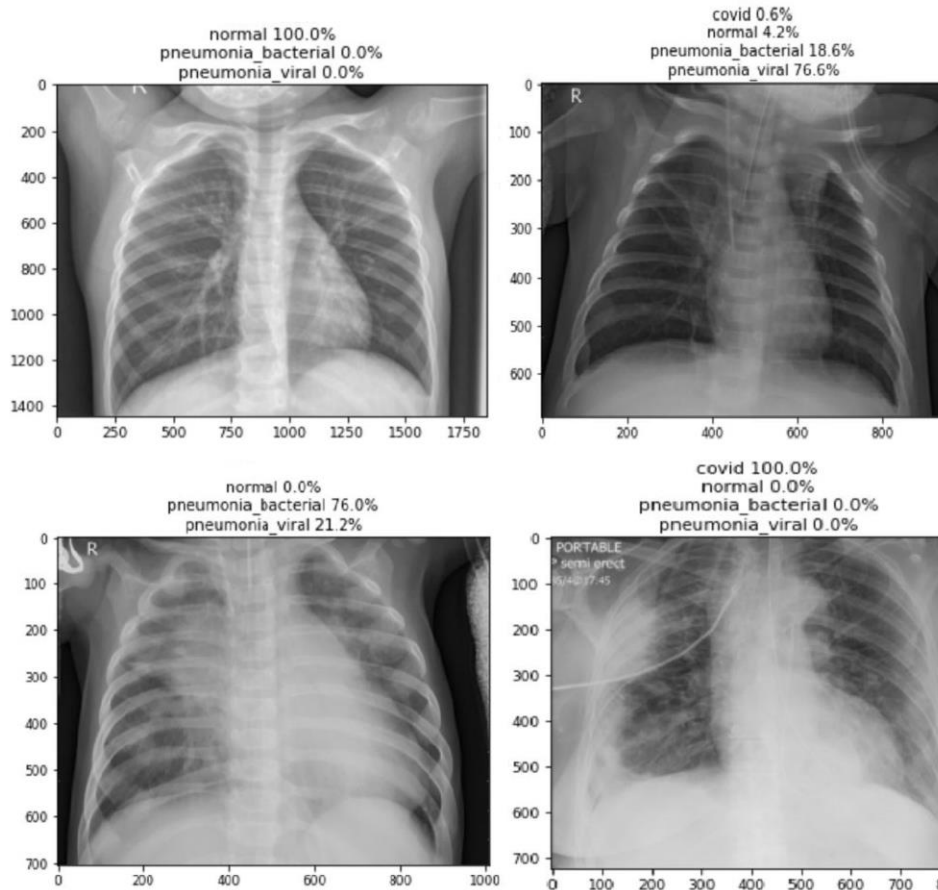


Figure 6: Result of CoroNet on test examples

and tested on a small dataset of few hundred images prepared by obtaining chest x-ray images of various pneumonia cases and covid-19 cases from different publically available databases. CoroNet is computationally less expensive and achieved promising results on the prepared dataset. The performance can further be improved once more training data becomes available. Notwithstanding the encouraging results, CoroNet still needs clinical study and testing but with higher accuracy and sensitivity for Covid-19 cases, CoroNet can still be beneficial for radiologists and health experts to gain deeper understandings into critical aspects associated with COVID-19 cases.

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