

Deep Learning Approach for COVID-19 Diagnosis Using X-Ray Images

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Research Article

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Abstract

During the times of pandemics, faster diagnosis plays a key role in the response efforts to contain the disease as well as reducing its spread. Computer-aided detection would save time and increase the quality of diagnosis in comparison with manual human diagnosis. Artificial Intelligence (AI) through deep learning is considered as a reliable method to design such systems. In this research paper, an AI based diagnosis approach has been suggested to tackle the COVID-19 pandemic. The proposed system employs a deep learning algorithm on chest x-ray images to detect the infected subjects. An enhanced Convolutional Neural Network (CNN) architecture has been designed with 22 layers which is then trained over a chest x-ray dataset. More after, a classification component has been introduced to classify the x-ray images into two categories (Covid-19 and not Covid-19) of infection. The system has been evaluated through a series of observations and experimentations. The experimental results have shown a promising performance in terms of accuracy. The system has diagnosed Covid-19 with accuracy of 95.7% and normal subjects with accuracy of 93.1 while it showed 96.7 accuracy on Pneumonia.

Keyword: COVID-19, Deep learning, CNN, X-ray images and Medical system

1- Introduction

Artificial intelligent (AI) has affected health care in many ways. It radically changing the ways people are accessing healthcare from an online medical check, over the phone services to robot-assisted surgeries[1]. Nowadays, machine learning has shown substantial importance in the applications of medical image processing[2]. More precisely, a field of machine learning called deep learning which encompasses more advanced and better-performed methods for training a neural network to diagnose diseases. Deep learning uses models which consist of multiple layers to learn the representations of data using many techniques. These techniques have dramatically improved the state-of-the-art in many computational applications[3]. COVID-19 a disease was first discovered in China December 2019 and then declared a pandemic by WHO in March 2020. AI would provide a computer-assisted system to classify the huge amount of data which is pooling from around the world. Training a system to detect with precision if a person is infected can save time and lives. This paper has proposed an AI-based method to diagnose COVID-19 patients. A deep learning approach has been introduced to train a neural network about chest x-ray images of infected subjects and then use the inferred knowledge to identify future cases. The rest of this paper has been organized as follows: Section 2 introduces related work in the field of lung diseases diagnosis. Furthermore, section 3 illustrates the materials and methodologies which have been used during this research. Section 4 demonstrates the experimental results while section 5 concludes the paper and proposes suggestions for future improvements.

2- Related Work

Nowadays, medical imaging analysis combined with machine learning has emerged as a promising solution to be applied in the field of diagnosis. Deep learning as a successor of conventional machine learning is being applied in the fields of diagnosis and prediction. Yong Xue et.al. [4] have introduced a detailed review of the applications of image analysis using deep learning for the purpose of diagnosing cancer as well as survival prediction. Computerized early detection of infections would increase the probability of healing and future follow up. Many researchers have devoted their work to design solutions that automate the process of analyzing and diagnosing lung diseases to reduce the human bias and misjudging. A lung cancer classification has been presented

by [5] with the aim of detecting lung tumor. The authors have used CT images which are then processed through number of steps to spot the infectious regions of the lung. The system has not employed deep learning which might have improved the performance in term of time complexity. Zhuo Liu et. al. [6] work has focused on the detection of lung cancer using reinforcement learning. They have used deep learning models with the aim of locating lung tumor and characterize them into different types of tumors. An advanced neural network framework has been introduced by [7] to optimize the diagnosis of tuberculosis diseases. The authors have claimed that the proposed architecture would produce good training results while improving the computational time performance. They also visualized the output using the saliency map as well as the grad- CAMs. A subjective test has been done by a radiologist to determine the system efficiency in detecting the infected areas of lung. Kim et. al. [8] proposed a method called "Class-selective Relevance Mapping" (CRM), which is capable of localizing and visualizing a particular region of interest (ROI) in, medical images. Their system would use image modalities to classify specific types of images to visually explain the learned behavior of a machine learning scenario.

3- Deep Learning

Deep learning is an approach of machine learning field inspired by an artificial neural network [9][10]. It used multi-layer sequencing to extract high-level features from raw images or data [11]. Depending on the problem domain and degree of complexity, the features have been selected, as well as the number of layers are increased. One of the most modern deep learning techniques is Convolutional Neural Network (CNN) [12]. CNN is a branch of deep learning network [13], it is majorly designed as a series of phases formed by layers. In the current research, we have proposed CNN model with an architecture that consists of 22 layers. Convolutional Layer is the first layer of CNN [14] [15]. It takes a filter(kernel) and pass it through all the points in the entire image and passing at any point into a single position (Output). The next layer is Pooling layer which performs a down-sampling of an image, it takes sub-samples of convolutional layer output and produces a single output. There are different pooling methods such as max pooling, mean pooling, average pooling etc. Furthermore, convolution layers and all the training layers, fully connected layers take the features from all neurons in the previous layer and operate with an individual neuron in the current layer to generate features output which might be used in the classification phase.

4- Materials and Methodology

This section describes the detailed design of the proposed system's architecture. The proposed model consists of two components, namely: the training component and classification component. The training part has been designed based on deep learning using convolutional neural network. The purpose of it is to train a labelled chest x-ray dataset of images which are partitioned into infected with COVID-19 and normal. The second component aims to identify if an input x-ray image is for an infected subject or no. figure (1) illustrates the design paradigm of the proposed solution.

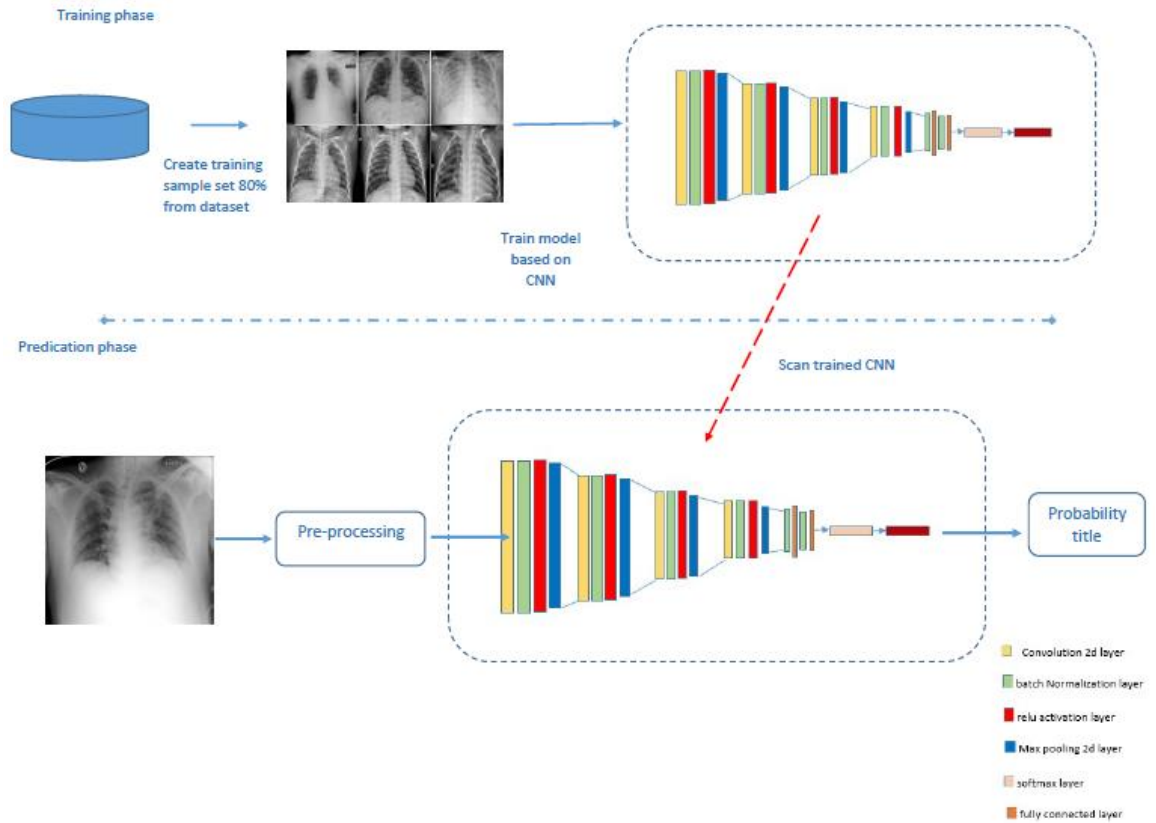


Figure 1 Proposed Model Schema for COVID-19 Detection

4.1 CNN Architecture Design

The proposed CNN architecture consists of 22 layers starting from the input layer to the classification layer. basically, the proposed model of CNN contains four phases of convolution layer for features extraction. Each one of them includes a convolutional layer, normalization layer, activation function and pooling.

- The first layer in the proposed CNN is an input layer which is used to determine the number of channels and input images dimensions. In this model, the properties for this layer were input size 224×224 and normalization used zero centers. by default, the layer performs normalization for the data, by subtracting the mean image of the training group for the entire group.
- After that the convolutional layer a 2-D convolutional layer applies to slide convolutional filters to the input image. The layer scans the input matrix (image) vertically and horizontally, to compute the result of the weights and the input, and then adding a bias term. The first convolutional layer starting with 8 filters, with [3,3] size. And set the default properties for others.
- The third part of the first block is the normalization layer; batch normalization layer was used with epsilon 0.00001. this layer is used to normalize each input channel across a mini-batch. Then, the layer changes the input raw data by a learnable offset as

well as changing the scales by a learnable scale factor. To increase the training performance of CNN and reduce the sensitivity to network initialization.

- Rectified Linear Unit ReLU Activation function is the most common activation function which is used in deep learning and CNN. ReLU is mathematically described in equation (1)

$$\text{ReLU} \quad f(x) = \max(0 \cdot x) \quad \dots \quad 1$$

- The next CNN layer is Pooling layer, the main function of this layer is to reduce the number of parameters. This operation applies to each features map individually. There are many pooling functions, in this model max-pooling are suggested.

The above layers are repeated with different parameters for four times, to extract the high-level features from the x-ray images. Then two fully connected layer with drop out layer in between for classification phase. Finally, the soft-max and class output layer to classify the entire image belong to which class, based on training phase. Table 1 shows the configuration of a proposed CNN.

Table 1 CNN Architecture Configuration

Layer	Configuration	Description
Conv_1	Filter size 3,3 Number of filter 8 Stride 1,1	Convolutional layer 1
batchnorm_1	Epsilon 0.00001	Batch Normalization layer 1
relu_1	relu_1	Activation function 1
maxpool_1	Pool size 2,2 Stride 2,2 Padding 0,0,0,0	Pooling layer 1
conv_2	Filter size 3,3 Number of filter 16 Stride 1,1	Convolutional layer 2
batchnorm_2	Epsilon 0.00001	Batch Normalization layer 2
relu_2	relu_2	Activation function 2
maxpool_2	Pool size 2,2 Stride 2,2 Padding 0,0,0,0	Pooling layer 2
conv_3	Filter size 3,3 Number of filter 32 Stride 1,1	Convolutional layer 3

batchnorm_3	Epsilon 0.00001	Batch Normalization layer 3
relu_3	relu_3	Activation function 2
maxpool_3	Pool size 2,2 Stride 2,2 Padding 0,0,0,0	Activation function 3
conv_4	Filter size 3,3 Number of filter 64 Stride 1,1	Convolutional layer 3
batchnorm_4	Epsilon 0.00001	Batch Normalization layer 3
relu_4	relu_4	Activation function 2
maxpool_4	Pool size 2,2 Stride 2,2 Padding 0,0,0,0	Activation function 3
dropout	Probability 0.5	Normalization
fc_1	Output size 3 Weight learn rate factor 1	Fully connected layer 1
dropout	Probability 0.3	Normalization
fc_2	Output size 3 Weight learn rate factor 1	Fully connected layer 2
Softmax	Classifier	
class output	Three classes output	Output

5- Experimental Result and Analysis

The proposed solution has been examined and evaluated by conducting a series of experiments which has been done under different scenarios.

5.1 Experimental Setting

The experimental settings have been organized as follows:

i. Dataset Collection

The proposed CNN model has been trained and evaluated based on collected chest x-ray images datasets. To evaluate the proposed model, we trained CNN based on these images. The Covid-19 collection of images were collected from two different datasets, First one chest x-ray images (pneumonia) [15], and the second one COVID-19 images collection [16] [17]. The chest x-ray dataset contains two label classes Normal and pneumonia, 1585 samples for Normal class and 4275 samples for pneumonia. The COVID-19 images collection consists of 123 samples of chest x-ray images. One of the most important challenges that we have faced during the course of this research was the limited number of chest x-ray for patients who are suffering from COVID-19. All the images were uninformed into 224×244, as well as enhanced by using

adaptive histogram equalization. figure 2 shows sample of normal chest x-ray and COVID-19 case.



(a) (b)
Figure 2 sample of chest x-ray (a) Normal (b) COVID-19

ii. Training and Implementation

The proposed model based on CNN was trained on the chest x-ray collected images. Initially, the CNN model was trained and evaluated based on sub-Covid19-collected images from the 123 images for each label class, then trained on all the dataset. The training option and parameters that used for training were as the following: Momentum: 0.9000, initial learning rate = 0.0100, Max Epochs=20 and Mini Batch Size=64. As well as using learning rate schedule with piecewise option, to updating the learning rate every certain number of epochs during the training phase. The solver of the training network was stochastic gradient descent with momentum “SGDM” optimizer. Table 2 shows the training option for the CNN.

Table 2 Training Option of Proposed CNN Based on SGDM

Training option	Parameters	Purpose
Momentum	0.9000	Contribution of previous step (iteration) .
initial learning rate	0.0100	The initial learning rate are used for training.
Learn Rate Drop Factor	0.2	Factor for dropping the learning rate. In this case =0.2 .
Learn Rate Drop Period	5	Number of epochs for dropping the learning rate. Every 5 epochs.
Max Epochs	20	Maximum number of epochs in training phase.
Mini Batch Size	64	Size of the mini-batch to use for each training iteration.
Shuffle	every-epoch	Shuffle the training and validation data once before training. To avoid discarding the same data every epoch

The proposed CNN was built and evaluated using the Matlab R2019 and Deep Network Designer.

5.2 Result and Discussion

To evaluate the performance of the proposed CNN model, we will analysis the result based on standard measurement, to understand the detection performance. The first measurement that we calculate is an accuracy of a method determines how correct the values are predicted, equation 2 shows the accuracy calculation.

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \dots\dots\dots 2$$

where TP, TN, FP and FN are truly positive, true negative, false positive, and false negative respectively. As well as confusion matrix was calculated. Figure 3 shows the confusion matrix of the chest x-ray collected dataset. As can see the correct predication of COVID-19 was 95.7% when 22 images are detected from 23 tested image. the second class of Normal the true detection was 93.1%, And finally, the third class achieved 96.7% success ratio.

		Target Class				
		COVID 19	Normal	PNEUMONIA		
Output Class	COVID 19	22 2.1%	1 0.1%	0 0.0%	95.7% 4.3%	
	Normal	0 0.0%	244 22.8%	18 1.7%	93.1% 6.9%	
	PNEUMONIA	3 0.3%	23 2.2%	757 70.9%	96.7% 3.3%	
		88.0% 12.0%	91.0% 9.0%	97.7% 2.3%	95.8% 4.2%	

Figure 3 Confusion Matrix of Proposed CNN the accuracy of classification for three label classes as shown in table 3 of the chest x-ray images.

Table 3 Accuracy of Infection Type

class	Accuracy
COVID-19	95.7
Normal	93.1
pneumonia	96.7

The dataset, that were used to test the performance of COVID-19 detection contain three classes COVID-19, Normal and pneumonia. The highest detection ratio was for pneumonia. And its acceptable ratio for COVID-19. Because of limited number of chest x-ray images which is belong to who's suffering from COVID-19 virus. The performance of CNN proposed model in training and validation based on chest x-ray images as shown in figure 4. The validation was traced on each epoch to calculated the performance based on accuracy at each epoch and iterations. Table 4 shows the validation accuracy during training.

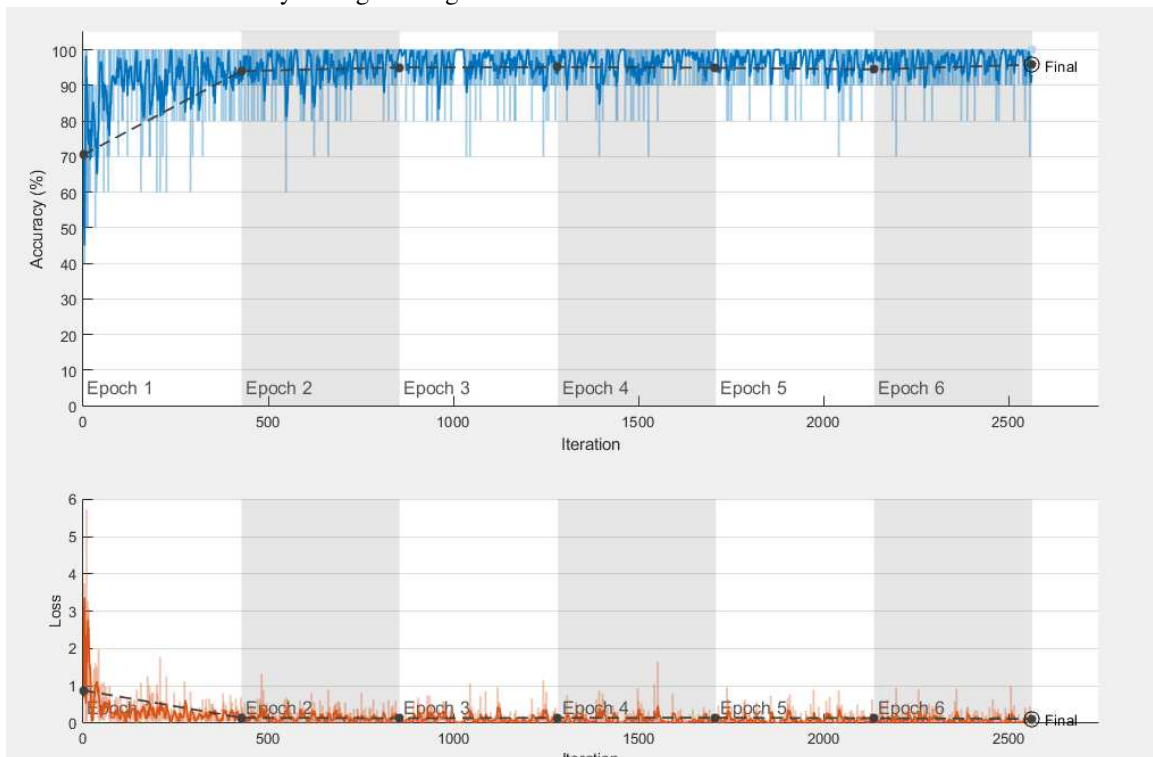


Figure 4 Performance in The Training and Validation Dataset

Table 4 validation accuracy based on each epoch

Dataset	Epoch	Validation Accuracy
Collection of chest x-ray	1	62.67%
	13	92.00%
	20	95.8

The success validation ratio was 92.00% during 13 iterations and the accuracy increased during training iterations, when the training terminated at maximum epoch 20, the accuracy was 95.8 overall for all three classes. To evaluate the proposed CNN, we have to compare the accuracy result with another pre-trained CNN. In this research work we picked Alexnet to compare with the proposed CNN, because the architecture design is a sequential same style with our model table 5 show the summary of comparison on same dataset.

Table 5 Summary of Accuracy Comparing With Different Methods

Paper proposed work	Dataset	Accuracy
AlexNet	collected chest x-ray images	95.00%
Proposed CNN	collected chest x-ray images	95.8%

From all tables above and figures, the proposed model achieved higher accuracy than pre-trained Alexnet in case of our selected chest x-ray image “Covid19-project dataset”.

6- Conclusion and Future Work

This work presents a CNN model for COVID-19 Diagnosis Using X-Ray Images. The proposed CNN consists of 22 layers. As well as the dataset were used for evolution the model collected from two public datasets: chest x-ray images (pneumonia) and COVID image collection. The CNN make predication based on deeper features extracted from x-ray images. The accuracy measurement was used to analyses the performance of the proposed model. the proposed model based on CNN achieved accuracy 95.8. and for COVID-19: 95.7, Normal :93.1 and pneumonia :96.7.

7. Conflict of Interests

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Figures

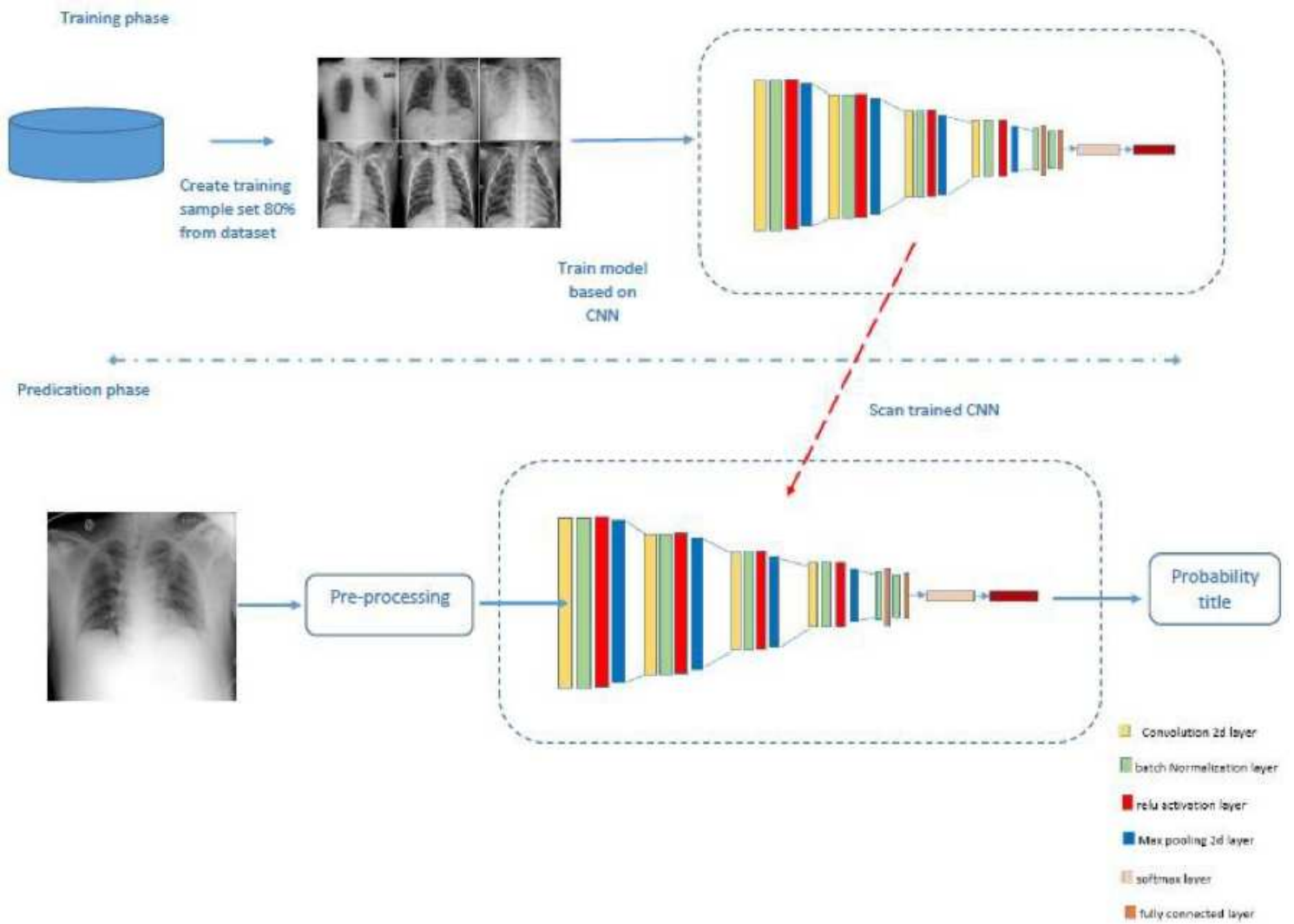


Figure 1

Proposed Model Schema for COVID-19 Detection

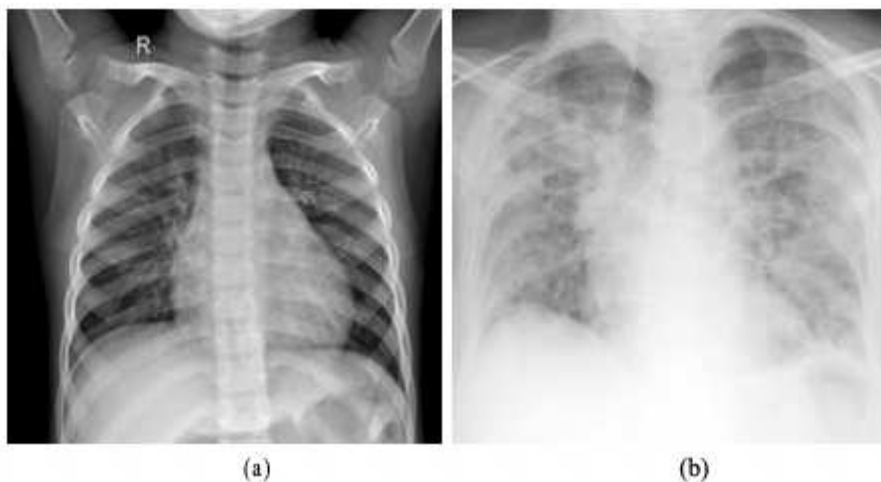


Figure 2

Sample of chest x-ray (a) Normal (b) COVID-19

Confusion Matrix

		Target Class				
		COVID 19	Normal	PNEUMONIA		
Output Class	COVID 19	22 2.1%	1 0.1%	0 0.0%	95.7% 4.3%	
	Normal	0 0.0%	244 22.8%	18 1.7%	93.1% 6.9%	
	PNEUMONIA	3 0.3%	23 2.2%	757 70.9%	96.7% 3.3%	
		88.0% 12.0%	91.0% 9.0%	97.7% 2.3%	95.8% 4.2%	

Figure 3

Confusion Matrix of Proposed CNN

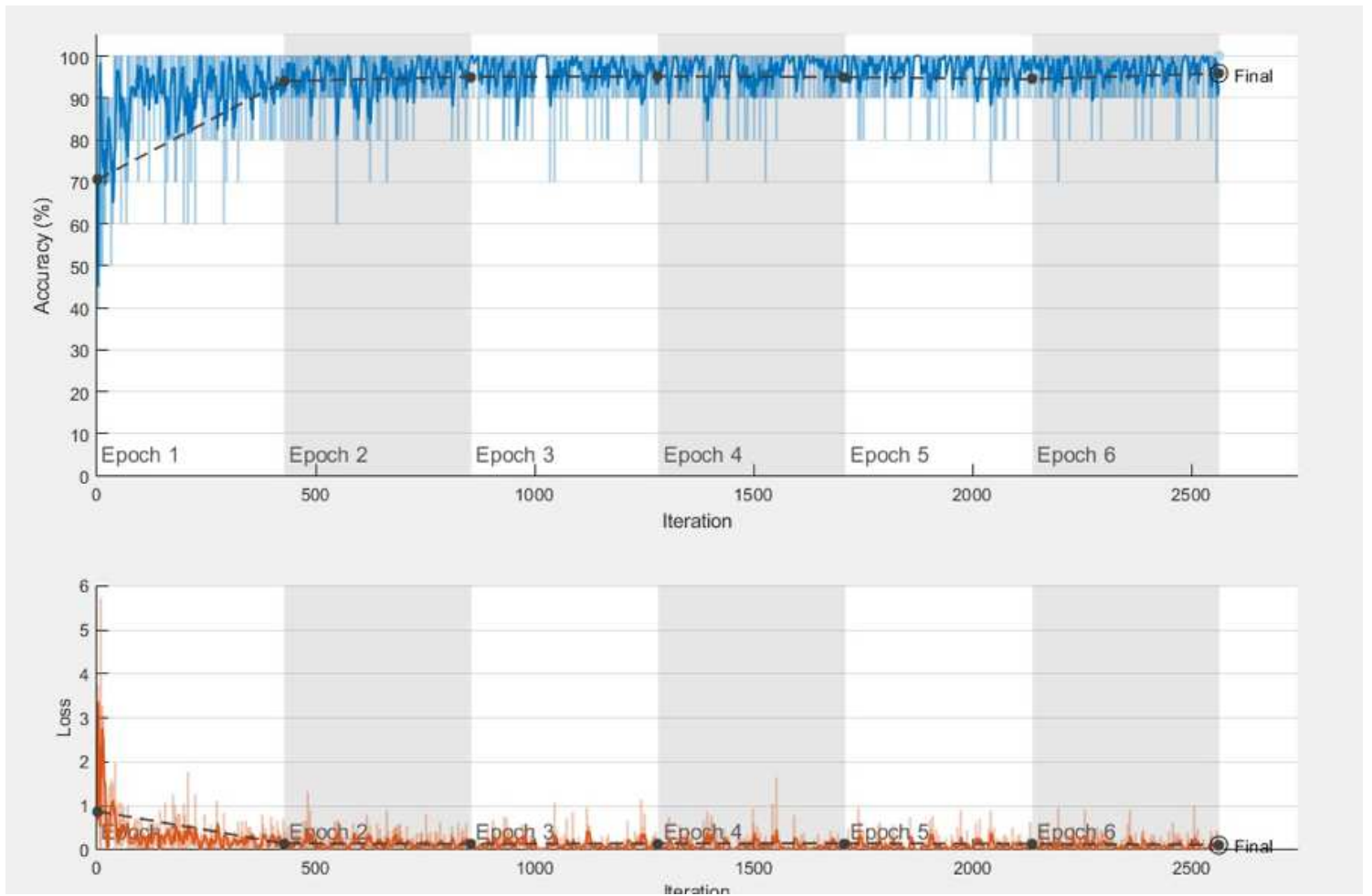


Figure 4

Performance in The Training and Validation Datase