Viral and Bacterial Pneumonia Detection using Artificial Intelligence in the Era of COVID-19

Mehmet Ozsoz
Near East University
Abdullahi Umar Ibrahim (Abdullahi.umaribrahim@neu.edu.tr)
Near East University https://orcid.org/0000-0003-3850-9921
Sertan Serte
Near East University
Fadi Al-Turjman
Near East University
Polycarp Shizawaliyi Yakoi
Cyprus International University

Research Article

Keywords: COVID-19, Non-COVID-19 Viral Pneumonia, Bacterial Pneumonia, AlexNet, Chest X-rays Images (CXR)

Posted Date: September 2nd, 2020

DOI: https://doi.org/10.21203/rs.3.rs-70158/v1

Abstract

Background: The outbreak of COVID-19 on the eve of January 2020 has led to global crisis around the world. The disease was declared pandemic by World Health Organization (WHO) in mid-March. Currently the outbreak has affected more than 150 countries with more than 20 million confirmed cases and more than 700,000 death tolls. The standard method for detection of COVID-19 is the Reverse-Transcription Polymerase Chain Reaction (RT-PCR) which is less sensitive, expensive and required specialized health expert. As the number of cases continue to grow, there is high need for developing rapid screening method that is accurate, fast and cheap.

Methods: We proposed the use of Deep Learning approach based on Pretrained AlexNet Model for classification of COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia and normal Chest X-rays Images (CXR) scans obtained from different public databases.

Result and Conclusion: For non-COVID-19 viral pneumonia and healthy datasets, the model achieved 94.43% accuracy, 98.19% Sensitivity and 95.78% Specificity. For bacterial pneumonia and healthy datasets, the model achieved 91.43% accuracy, 91.94% sensitivity and 100% Specificity. For COVID-19 pneumonia and healthy CXR images, the model achieved 99.16% accuracy, 97.44% sensitivity and 100% Specificity. For classification of COVID-19 pneumonia and non-COVID-19 viral pneumonia, the model achieved 99.62% accuracy, 90.63% sensitivity and 99.89% Specificity. For multiclass datasets the model achieved 94.00% accuracy, 91.30% sensitivity and 84.78% specificity for COVID-19, bacterial pneumonia and healthy. For 4 classes (COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia and healthy, the model achieved accuracy of 93.42%, sensitivity of 89.18% and specificity of 98.92%.

Introduction

Pneumonia is a common disease caused by different microbial species such as Bacteria, virus and Fungi as shown in Fig 1. The word “Pneumonia” comes from the Greek word “Pneumon” which translates to lungs. Thus, the word pneumonia is associated to lung disease. In medical terms, pneumonia is a disease that causes inflammation of either one or both lung’s parenchyma [1]. However, pneumonia often result from infection or not, such as food aspiration and exposure to chemicals. Based on infection, pneumonia occur as a result of inflammation caused by pathogens which lead the lung’s alveoli to fill up with fluid or puss and thereby leading to decrease of Carbon dioxide and Oxygen exchange between blood and the lungs, making it hard for infected persons to breathe. Some of the symptoms of pneumonia are: shortness of breath, fever, cough, chest pain etc. Moreover, the people at risk of pneumonia are elderly people (above 65 years), children (below the age of 5 years) and people with other complications such as HIV/AIDS, diabetes, chronic respiratory diseases, cardiovascular diseases, cancer, hepatic disease etc. [2, 3, 4, 5]. Table 1 presents classification of pathogens that causes pneumonia.

Table 1. Classification of pneumonia based on Pathogens

Pathogen	Specie
Bacterial	*Streptococcus pneumoniae*
	Legionella pneumophila
	Mycoplasma pneumoniae
	Chlamydophila pneumoniae
Viruses	*Influenza virus*
	Severe Acute Respiratory Syndrome Coronavirus (SAR-CoV-1 and 2)
	Middle East Respiratory Syndrome (MERS) Coronavirus
	Respiratory Syncytial virus (RSV)
	Adenovirus
	Hantavirus
	Rhinovirus
	Varicella-zoster virus
	Human metapneumovirus
	Enteroviruses
Fungi	*Pneumocystis jirovecii*
	Aspergillus spp
	Mucoromycetes
	Histoplasmosis
	Coccidioidomycosis
	Cryptococcus

1.1 Diagnosis and Treatment of Pneumonia

There are different approaches for the diagnosis of pneumonia, some of these approaches include Chest X-rays and CT Scan (which form the basis of our contribution), sputum test, pulse oximetry, Thoracentesis, blood gas analysis, bronchoscopy, pleural fluid culture, complete blood count etc. Mostly, pneumonia infection is treated based on the causative pathogen. For bacterial pneumonia, antibiotics are used, for viral pneumonia such as influenzas, SARS and MERS, antiviral drugs are used while antifungal drugs are used for fungal pneumonia [5, 6, 7].

1.2 COVID-19 and Pneumonia

COVID-19 is an extremely contagious disease caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SAR-CoV-2), it is the recent and buzzing disease that is caused by one of the family members of Coronaviridae family. In the past, 2 members of this family known as Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS) have caused global epidemic. The first case of COVID-19 was reported in Wuhan, Hubei province of mainland China on 31st December, 2019. The virus spread from city to city and from one country to another leading to global health crisis. However, it was not until March 11, 2020 that WHO declared it as pandemic [8, 9, 10].

COVID-19 can be transmitted through respiratory droplets that are exhaled or secreted by infected persons. Coronaviruses invade the lung's alveoli (an organ responsible for exchange of O_2 and CO_2, thus causing pneumonia. The symptoms of COVID-19 include dry cough, fatigue, fever, septic shock, organ failure, anorexia, dyspnea, myalgias, sputum secretion severe pneumonia, Acute Respiratory Distress Syndrome (ARDS) etc. [11, 12, 13, 14]. The pandemic caused by SAR-CoV-2 is alarming due to the fact there is no approved drug or vaccine [15].

In order to curb further spread of the virus, parliaments or governments of various countries and states imposed city lockdowns, flight cancellations, border restrictions, closure of workplaces, restaurants, postponement of sport, religious, cultural and entertainment event and activities, wearing of face mask, social distancing of 1-2m, and creating awareness on hygiene. Many countries are facing challenges regarding number of reported cases of COVID-19 as a result of the lack of RT-PCR test kit and delay in test kit. This delay is detrimental as it leads to more cases due to interaction between infected patients waiting for result with healthy population [16, 17].

1.3 Deep Learning (DL) and Transfer Learning (TL)

Deep Learning is a branch of machine learning (ML), a subset of Artificial intelligence (AI) inspired by the make-up of the human brain. It is termed as a sub-field of Machine Learning (ML) that works similar to the biology of human brains by taking data and processing the data through networks and neural networks. Many biomedical health issues such as cancer (brain tumor and breast cancer) detections are using computer aided diagnosis base on AI models. Precisely, DL Models can detect hidden features in images which are not apparent or cannot be detected by medical expert. In terms of DL, Convolutional Neural Network (CNN) is the leading DL tool that is popularly used in different sub-field of healthcare system due to their ability to extract features and learn to distinguish between different classes (i.e. positive and negative, infected and healthy, cancer and non-cancer etc. Transfer learning has provided easier approach to quickly retrain neural networks on selected dataset with high accuracy [18, 19, 20].

1.3.1 AlexNet

AlexNet model is a DL model proposed by Alex Krizhevsky which utilize Rectified Linear Unit (ReLu) in place of Sigmoid function which is used in traditional neural networks. The model achieved 84% accuracy in 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC). It contains 5 convolution (CONV) blocks or layer with convolutional filters size 3x3 without padding and 2x2 window size of 2X2 for Max pooling operation. The last 3 layers are 2 fully connected layers (FCL) and output layer. Other terms include Batch Normalization (BN) and Feature Map (FM). SoftMax activation function is utilized in the output layer for classification. Minibatch optimization is a gradient descent that is used to improve the model [21, 22].

1.4 Challenges

As the number of COVID-19 patient grows exponentially, there is high need massive detection which is critical for prevention and control. Medical practitioners all over the world required sophisticated system to accurately diagnose COVID-19. Different approaches are currently in used for detection of different types of pneumonia. However, detection of different strains of pathogens using molecular testing is still not up to standard of point of care diagnostics. Instead, specimens are collected from site of infections are transfer to equipped or specialized laboratories for diagnosis using RT-PCR sequencing approach which is the current gold standard [23]. This method is expensive and often lead to false result. Moreover, underdeveloped countries and remote areas with limited testing kit and equipped hospitals with ventilators have become the epicenter of the disease. Thus, there is high need for developing an alternative approach which is fast, cheap, simple and reliable. The use of X-ray has proven to be an alternative; however, this method is sometimes tedious for qualified radiologist [24]. These challenges can be addressed by computer aided detection method using DL approach which is accurate, fast and precise.

1.5 Contribution

Accordingly, our contributions have been summed up as follows.

- We suggested the use of Pretrained (transfer learning) AlexNet Model to detect COVID-19 pneumonia non-COVID-19 viral pneumonia, bacterial pneumonia and normal/healthy patients using CXR image.
- We trained the models separately to differentiate:

Between COVID-19 pneumonia and normal/healthy patient

Between non-COVID-19 Viral pneumonia and normal/healthy patient

Between Bacterial pneumonia and normal/healthy Patient

Between COVID-19 pneumonia and non-COVID-19 Viral pneumonia

Between COVID-19 pneumonia, Bacterial pneumonia and normal/healthy Patient

Between COVID-19 pneumonia, non-COVID-19 viral pneumonia, bacterial pneumonia and normal/healthy Patient

- We assessed the performance of the network based on accuracy, sensitivity and specificity

1.6 Related Work

The last decade has seen exponential rise for the application of DL in healthcare system. Different studies have shown that DL models can be used for pathological cancer images, diabetic retinopathy, CT scan of pneumonia and tuberculosis as well as microbial slide images. In the field of pathology, pathologist, Computer scientist and radiologist have been working together to detect diseases such as cancer, pneumonia and tuberculosis using computer aided diagnosis [25, 26, 27].

In terms of application of DL models for detection of Pneumonia using CT scan and Xray images, we provided literature review based on studies that:

1. Classified/distinguished between COVID-19, non-COVID-19 viral pneumonia (VP) and healthy CXR images or between COVID-19, bacterial pneumonia (BP) and healthy images (i.e. multiclass).
2. Classified/distinguished between COVID-19 and Non-COVID-19 viral pneumonia (VP) or COVID-19 and healthy CXR images (i.e. 2 classes).
3. Classified/distinguished between Non-COVID-19 Viral Pneumonia (VP) and Healthy CXR images

Chest Scan based on Chest X-ray or Computed Tomography (CT) scan is an approach radiologist used to distinguish between patient suffering from pneumonia and healthy person. The difference is based on the presence of white hazy patches which is known as “Ground-glass opacity” in infected patient which is absent in healthy person. However, as a result of scarcity of test for diagnosing COVID-19 as well as the high cost (120-130 USD), time consuming, low sensitivity, laborious of RT-PCR method, scientist turn to chest scan such as CT scans and X-rays as an alternative approach for diagnosis of severe pneumonia caused by SAR-CoV-2 and Bacterial Pneumonia [28]. Moreover, this approach has its own challenges such as shortage of expert (i.e. radiologist) that can interpret the result and the tediousness of interpreting thousands of CT scan and Xray images. These challenges are addressed by AI driven models which have shown high efficiency in assisting medical expert in classification and prediction of disease [29, 30].

Many studies have reported the use of CXR and CT scans along with Deep Learning models in order to achieve automated detection of COVID-19 pneumonia and other type of pneumonia such as non-COVID-19 viral pneumonia and bacterial pneumonia. Moreover, many studies have shown the viability of using TL models which are deep networks pretrained on the ImageNet database for classification of for classification of pneumonia from healthy CT scans [31, 32, 33].

The approach of TL in DL is utilized by Chowdhury et al., 2020 [17] to differentiate between COVID-19 and viral pneumonia based on dataset acquired from public database. The models were trained using 423 COVID-19, 1458 viral pneumonia and 1579 normal Chest X-ray images on 2 basis (I) augmentation and (II) without augmentation. The models achieved higher accuracies, sensitivities and specificities. A multi dilation CNN is utilized by Mahmud et al., 2020 [34] to classify COVID-19 and other forms of pneumonia. The study utilized a deep CNN as COVXNet with modifications base on varying dilation rates for feature extraction, optimization, stacking algorithms and gradient-based discriminative localization to train dataset containing 1493 Non-COVID-19 viral pneumonia, 305 COVID-19 pneumonia, 2780 bacterial pneumonia. The Model achieved 97.4% accuracy for COVID-19 vs normal, 96.9% for COVID-19 Vs non-COVID-19 viral pneumonia, 94.7% for COVID-19 vs bacterial pneumonia and 90% for multi-class.

In order to show the difference between COVID-19 and Community Acquired Pneumonia (CAP), Li et al 2020 [35] utilized 3-Dimensional DL framework know as COVID-19 detection neural network (COVNet) using 4352 CT scans (1292 of COVID-19, 1735 of CAP and 1325 normal CT scans). The model achieved

90% sensitivity and 96% specificity for detection of COVID-19 and 87% sensitivity and 92% specificity for detection of CAP. Apostolopoulos et al., 2020 [31] utilized TL approach on dataset that contain 1427 x-ray images (504 Normal Xray Images, 700 Bacterial Pneumonia and 224 COVID-19 Xray Images). The model was able to achieved 96.78% accuracy, 96.46% specificity and 98.66% sensitivity. The summary of application of AI for detection of pneumonia is presented in Table 2.

Table 2. Detection of different types of Pneumonia using AI-driven tools.

Classification	Reference	Type of pneumonia	Dataset	Result
COVID-19, non-COVID-19 VP, BP and normal CT scans	[35]	COVID-19 and Community Acquired Pneumonia (CAP)	4352 CT scans (1292 of COVID-19, 1735 of CAP and 1325 normal CT scans)	90% *SV and 96% *SF for detection of COVID-19 and 87% *SV and 92% *SF for detection of CAP
	[17]	COVID-19 and non-COVID-19 VP	423 COVID-19, 1458 viral pneumonia and 1579 normal Chest X-ray images	The models achieved higher accuracies, sensitivities and specificities
	[34]	COVID-19, non-COVID-19 VP, BP	1493 non-COVID-19 viral pneumonia, 305 COVID-19 pneumonia, 2780 bacterial pneumonia	The Model achieved 97.4% *AC for COVID-19 vs normal, 96.9% for COVID-19 Vs non-COVID-19 VP, 94.7% for COVID-19 vs BP and 90% for multi-class
Non-COVID-19 VP, BP and normal CT scans	[36]	Non-COVID-19 VP (strain not specified)	5856 X-ray images	Average *Ac of 94.81% training and 93.01% for validation
	[37]	Non-COVID-19 VP	453 CT scan images	The model achieved validation *AC of 82.9%, *SV of 84% and *SF of 80.5%, testing *AC of 73.1%, *SV of 74% and *SF of 67%.
	[38]	Viral pneumonia (strain not specified)	5863 Chest X-Ray Images	*AC of 95.30%
	[39]	VP (COVID-19, Influenza-A)	618 CT scan Images	*AC of 86.7%.
Non-COVID-19 VP and BP	[40]	Non-COVID-19 VP and BP (strains not specified)	5856 chest X-Ray	*Ac of 96.2% accuracy for BP and 93.6% for non-COVID-19 VP

*Ac is Accuracy, *BP is Bacterial pneumonia *Sv is Sensitivity, *Sf is Specificity *VP is Viral Pneumonia

Methods

In this section, we detail the proposed approach procedures and its main assumptions. The work process of the proposed approach is schematically shown in Fig 2. TL on DL Models have shown to perform efficiently even with small amount of dataset compare to Deep Learning models build from scratch which require large amount of dataset [41].

2.1. Dataset

Even though there are more than 20 million confirmed cases of COVID-19 globally, the amount of CT scan images that are available online are very few and limited. As shown in Fig 3, we obtained COVID-19 pneumonia, non-COVID-19 viral pneumonia, bacterial pneumonia and normal CXR images from the following website:

1. 153 images from GitHub (https://github.com/ieee8023/covid-chestxray-dataset)
2. 219 images from Kaggle (https://www.kaggle.com/tawsifurrahman/covid19-radiography-database). We removed 1 image due to low contrast, making the total number of images 371. We also obtained 1341 normal Xray images, 1345 non-COVID-19 viral pneumonia
3. 1341 normal, non-COVID-19 viral pneumonia, 4274 bacterial pneumonia from https://www.kaggle.com/sudalairajkumar/novel-corona-virus-2019-dataset
4. We obtained CXR images made available by Kermany et al., 2018 [42]. The dataset contains 3 folders (Training, validation and Testing with a total number of 5856 positive and negative cases. In each folder there is a subfolder with names Pneumonia and normal folders. The dataset description is based on X-ray images collected from retrospective pediatric patients between the age of 1 to 5. The number of each CXR images used are presented in Table 3.

Table 3. Dataset Description.

Type of Dataset	Number of Dataset
COVID-19 pneumonia	371
Non-COVID-19 viral pneumonia	4237
Bacterial pneumonia	4078
Healthy (i.e. Normal)	2882

2.1.1 Model Training

For training of datasets, we employed Matlab installed on personal computer with window-64-bit, 8GB random access memory (RAM), with an intel ® Core i7-3537U and graphical Processing unit (GPU). 30% of the dataset split as testing dataset are used evaluate the model performance as shown in Table 4. Pretrained AlexNet model is employed due to it high accuracy in carrying out feature extraction and image classification. The training is carried out using 20 epochs with 0.0001 learning rate.

Table 4. Dataset Split

Model	Training 70%				Testing (30%)			
Non-COVID-19 VP and Healthy	Non-COVID 19 VP		Healthy		Non-COVID 19 VP		Healthy	
	2966		2017		1271		965	
BP and Healthy	Bacterial		Healthy		Bacterial		Healthy	
	2853		2017		1225		965	
COVID-19 and Healthy	COVID-19		Healthy		COVID-19		Healthy	
	260		2017		111		965	
COVID-19 and Non-COVID-19 VP	COVID 19		Non-COVID-19 VP		COVID-19		Non-COVID-19 VP	
	260		2966		111		1271	
COVID-19, BP and Healthy	COVID-19	BP	Healthy		COVID-19	BP	Healthy	
	260	2853	2017		111	1225	965	
COVID-19, Non-COVID-19 VP, BP and Healthy	COVID-19	BP	Non-COVID-19 VP	Healthy	COVID-19	BP	Non-COVID-19 VP	Healthy
	260	2853	2966	2017	111	1225	1271	965

*BP: Bacterial Pneumonia VP: Viral Pneumonia

2.1.2 Parameters

To assess how the trained models performed, three parameters are employed; accuracy, sensitivity and specificity. Accuracy is termed as the ratio of correctly classified images over total number of images, it is also termed as the sum of sensitivity and specificity. For evaluating the loss and accuracy of a model the following formulas are utilized as shown in equation 1 and 2.

$$Loss = -\frac{1}{n}\sum_{i=1}^{n} \log PC \qquad (1)$$

$$Accuracy = -\frac{C}{N} \qquad (2)$$

Sensitivity (True Positive rate) is the proportion of positive image samples that are accurately identified as positive sample (i.e. it shows the percentage of positive samples that are identified correctly as positives). While Specificity (False positive rate (FPR)) is the proportion of positive samples that are identified incorrectly as positive samples (i.e. it shows the percentage of negative samples that are identified incorrectly as positives). The formula of sensitivity and specificity are shown in equation 3 and 4 respectively.

$$Sensitivity = -\frac{TPs}{TPs+FNs} \quad (3)$$

$$Specificity = -\frac{TNs}{TNs+FPs} \quad (4)$$

Where TPS = True Positives, FNs = False Negatives, TNs = True Negatives and FPs = False Positive

Results

In this section, the performance of the models are presented based on each type of pneumonia (COVID-19, bacterial and non-COVID-19 viral pneumonia) with healthy CXR images, COVID-19 and non-COVID-19 viral pneumonia and multiclass (1) COVID-19, bacterial pneumonia and healthy and (2) COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia and healthy as shown in Table 5 and Fig 4. Moreover, comparison between some state of art approaches with our models are presented based on COVID-19 and non-infected (healthy) CXR images and multiclass as shown in Table 6.

3.1 Performance Evaluation

The datasets are divided into two - 70% used in training and 30% used for testing. Performance of the models are evaluated based on testing accuracy, sensitivity and specificity. Firstly, we carried out a pilot study using 371 CXR images each for COVID-19, non-COVID-19, bacterial pneumonia and healthy Images. We obtained low accuracy, sensitivity and specificity due to low amount of dataset. We carried out this study to analyzed the linearity of the dataset by using same amount training and testing dataset due to the fact that we have only 371 COVID-19 CXR images.

Before we carried out a multiclass classification, we trained each type of pneumonia with healthy (non-pneumonia or non-infected) CXR images. For Non-COVID-19 viral pneumonia and Healthy datasets, we achieved 94.43% Testing accuracy, 98.19% sensitivity and 95.78% Specificity. In terms of bacterial pneumonia and healthy datasets, we achieved 91.43% Testing accuracy, 91.94% sensitivity and 100% Specificity. This shows that the model has learned to classified negative images (non-infected/healthy) accurately compare to positive CXR images (bacterial pneumonia). Moreover, majority of the recent studies focused on COVID-19 pneumonia and Non-infected CXR dataset. Our model achieved high evaluation performance with 99.16% Testing Accuracy, 97.44% sensitivity and 100% Specificity.

CXR scan images of a variety of viral pneumonia are similar, making it hard for radiologist to distinguish COVID-19 with other viral pneumonia. This limitation can lead to miss-diagnosis and at the same time can lead to non-COVID-19 viral pneumonia miss-diagnosed as COVID-19 pneumonia [17]. To addressed this limitation, we trained our model to distinguish between COVID-19 pneumonia and non- COVID-19

viral pneumonia. The model was able to achieved 99.62 Testing Accuracy, 90.63% sensitivity and 99.89% Specificity.

For multiclass dataset, before we train the whole classes, we examine the performance of the model based on 3 classes (COVID-19, bacterial pneumonia and healthy) to see how the model will perform before integrating non-COVID-19 viral pneumonia. The model achieved low accuracy compare to models trained to distinguish between 2 classes with 94.00% testing accuracy, 91.30% sensitivity and 84.78% specificity. Based on this result, we hypothesized to achieve lower performance based on 4 classes (COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia and healthy). However, the model achieved lower accuracy compare to 3 classes in terms of testing accuracy (93.42%) and sensitivity (89.18%) while the model achieved higher specificity (98.92%) compare to 3 classes as shown in Table 5 and Figure 4.

Table 5. Performance Evaluation

S/N	Dataset	Training Accuracy (%)	Testing Accuracy (%)	Sensitivity (%)	Specificity (%)
I	Non-COVID-19 viral pneumonia and healthy	96.43	94.05	98.19	95.78
II	Bacterial pneumonia and healthy	95.28	91.96	91.94	100.00
III	COVID-19 and healthy	99.71	99.16	97.44	100.00
IV	COVID-19 and non-COVID-19 viral pneumonia	99.57	99.62	90.63	99.89
V	COVID-19, bacterial pneumonia and healthy	97.40	95.00	91.30	84.78
VI	COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia and healthy	94.18	93.42	89.18	98.92

3.2 Comparison between our result with State of Art

As seen in Table 5, the performances of Pretrained AlexNet Models are compared with other proposed models. Compare to our work, the study carried out by Li et al 2020 [35] grouped viral and bacterial pneumonia as Community Acquired Pneumonia (CAP). However, our study disputes this approach, COVID-19 as viral disease resembles other viral pneumonia. The result we achieved when comparing COVID-19 and other viral pneumonia has shown lower sensitivity and specificity (90.63% and 99.89% respectively) compare to COVID-19 and healthy which achieved 97.44% sensitivity and 100% specificity. Our claim is also supported by Chowdhury et al 2020 [17] who stated that “Models performed extremely well when used for classifying COVID-19 and normal images compared to COVID-19 and other viral pneumonia. Both Bai et al., 2020 [43] and Narin et al., 2020 [32] have also reported high degree of similarity between COVID-19 and other viral pneumonia when considering physiological and clinical prospective.

With regards to the classification of COVID-19 and normal CXR images, it can be observed that our model provides significantly a better performance compare to studies that utilized small amount of dataset

such as Mahmud et al., 2020 [34] and models developed from scratch. The impressive performance of the model is attributed to the use of TL based on pretrained models which have shown to perform efficiently with less amount of data compare to models designed from scratch such as Tan et al., 2018 [19]. In terms of classification between Non-COVID-19 viral pneumonia and Healthy CXR images, several studies utilized same dataset made available by Kermany et al., 2018 [42]. Majority of these studies achieved higher performance of above 90% Accuracy such as Stephen et al. 2019 [36], Saravia et al., 2019 [38] and Rajaraman et al., 2018 [40]. However, our model achieved result within same range with 94.43% Accuracy.

Table 6. Comparison between our Result and State of Art

Class	Reference	Dataset	Result		
Multiclass (3-4)			Ac	Sv	Sf
	[35]	4352 CT scans (1292 of COVID-19, 1735 of CAP and 1325 normal CT scans)	-	90% for COVID-19 87% for CAP	96% for COVID-19 92% for CAP
	[17]	423 COVID-19, 1458 VP and 1579 normal Chest X-ray images	-	-	-
	[34]	1493 non-COVID-19 VP, 305 COVID-19 P, 2780 BP	90%	-	-
	Our Model (3 Classes)	371 COVID-19, 4078 BP and 2882 healthy	94.00%	91.30%	84.78%
	Our Model (4 Classes)	371 COVID-19, 4237 non-COVID-19 VP, 4078 BP and 2882 healthy	93.42%	89.18%	98.92%
2 Classes	[34]	305 COVID-19 P	97.4% for COVID-19 vs normal	-	-
	[34]	305 COVID-19 P and1493 non-COVID-19 VP	96.9% for COVID-19 Vs non-COVID-19 viral pneumonia,	-	-
	[34]	305 COVID-19 pneumonia and 2780 bacterial pneumonia	94.7% for COVID-19 vs bacterial pneumonia	-	-
	[36]	5856 CXR images	93.01%	-	-
	[37]	453 CXR images	73.1%,	74%	67%
	[38]	5863 CXR Images	95.30%	-	-
	[39]	618 CXR Images	86.7%.	-	-
	[40]	5856 CXR	96.2% for BP and 93.6% for Non-COVID-19 VP	-	-
	Our Model (Non-COVID-19 VP and healthy datasets	4237 Non-COVID-19 VP and 2882 healthy datasets	94.43%	98.19%	95.78%
	Our Model (BP and healthy datasets	4078 BP and 2882 healthy datasets,	91.43%	91.94%	100%
	Our Model (COVID-19 and healthy datasets	371 COVID-19 and 2882 healthy datasets	99.16%	97.44%	100%
	Our Model (COVID-19 and non- COVID-19 VP)	371 COVID-19 and 4237 non-COVID-19 VP.	99.62%	90.63%	99.89%

*Ac is Accuracy, *Sv is Sensitivity, *Sf is Specificity *P is Pneumonia *VP is Viral Pneumonia *BP is Bacterial Pneumonia *CXR is Chest X-ray

Conclusion

This work presents the utilization of Deep Neural Network based on TL approach (known as Pretrained AlexNet Model) for automatic detection of COVID-19 pneumonia, non-COVID-19 viral pneumonia and bacterial pneumonia. The models were trained based on 2 classes and multiclass. For 2 classes (each of COVID-19, non-COVID-19 viral pneumonia and bacterial pneumonia with healthy CXR Images, COVID-19 and non-COVID-19 viral pneumonia. For multiclass, the models are trained based on (1) 3 classes (COVID-19, bacterial pneumonia and healthy CXR images) (2) 4 classes (COVID-19, non-COVID-19 viral pneumonia and bacterial pneumonia and healthy CXR images. The models were evaluated using Accuracy, Sensitivity and Specificity. However, the outcome has shown that these models achieved 94.43% Testing Accuracy, 98.19% Sensitivity and 95.78% Specificity for non-COVID-19 viral pneumonia and healthy datasets. For bacterial pneumonia and healthy datasets, the model achieved 91.43% Testing accuracy, 91.94% sensitivity and 100% Specificity. In terms of COVID-19 pneumonia and healthy CXR images, the model achieved 99.16% Testing Accuracy, 97.44% sensitivity and 100% Specificity. For classification of COVID-19 pneumonia and non-COVID-19 viral pneumonia, the model achieved 99.62 Testing Accuracy, 90.63% sensitivity and 99.89% Specificity. For multiclass datasets the model achieved 94.00% testing accuracy, 91.30% sensitivity and 84.78% specificity for 3 classes (COVID-19, bacterial pneumonia and healthy) and testing accuracy of 93.42%, sensitivity of 89.18% and specificity of 98.92% for 4 classes (COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia and healthy).

The higher performance achieved for classification of COVID-19 pneumonia and non-COVID-19 viral pneumonia and COVID-19 pneumonia with healthy CXR images has shown that computer-aided detection approach can be used as an alternative or confirmatory approach against RT-PCR method which has shown to be less sensitive, time consuming and laborious. One of the limitations of this research is the fact that we used a small dataset of COVID-19 pneumonia. This challenge makes it difficult to generalized our result. In the future, we hope to acquire more dataset and to train the images using deeper Neural Networks such as Pretrained GoogleNet and ResNet.

Declarations

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Funding: No funding

Conflict of Interest: We declared no conflict of interests.

References

1. Sattar, S. B. A., & Sharma, S. (2019). Bacterial pneumonia.

2. Pound, M. W., Drew, R. H., & Perfect, J. R. (2002). Recent advances in the epidemiology, prevention, diagnosis, and treatment of fungal pneumonia. Current opinion in infectious diseases, 15(2), 183-194.
3. Virkki, R., Juven, T., Rikalainen, H., Svedström, E., Mertsola, J., & Ruuskanen, O. (2002). Differentiation of bacterial and viral pneumonia in children. Thorax, 57(5), 438-441.
4. Jones, R. N. (2010). Microbial etiologies of hospital-acquired bacterial pneumonia and ventilator-associated bacterial pneumonia. Clinical infectious diseases, 51(Supplement_1), S81-S87.
5. Ruuskanen, O., Lahti, E., Jennings, L. C., & Murdoch, D. R. (2011). Viral pneumonia. The Lancet, 377(9773), 1264-1275.
6. World Health Organization. (2014). Revised WHO classification and treatment of pneumonia in children at health facilities: evidence summaries.
7. Gao, J., Tian, Z., & Yang, X. (2020). Breakthrough: Chloroquine phosphate has shown apparent efficacy in treatment of COVID-19 associated pneumonia in clinical studies. Bioscience trends.
8. Fan, Y., Zhao, K., Shi, Z. L., & Zhou, P. (2019). Bat coronaviruses in China. Viruses, 11(3), 210.
9. Gómez, P., Semmler, M., Schützenberger, A., Bohr, C., & Döllinger, M. (2019). Low-light image enhancement of high-speed endoscopic videos using a convolutional neural network. Medical & biological engineering & computing, 57(7), 1451-1463.
10. Huang, Chaolin, Yeming Wang, Xingwang Li, Lili Ren, Jianping Zhao, Yi Hu, Li Zhang et al. "Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China." The lancet 395, no. 10223 (2020): 497-506.
11. Chen, S. G., Chen, J. Y., Yang, Y. P., Chien, C. S., Wang, M. L., & Lin, L. T. (2020). Use of radiographic features in COVID-19 diagnosis: Challenges and perspectives. Journal of the Chinese Medical Association, 83(7), 644-647.
12. Li, Qun, Xuhua Guan, Peng Wu, Xiaoye Wang, Lei Zhou, Yeqing Tong, Ruiqi Ren et al. "Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia." New England Journal of Medicine (2020).
13. Lai, C. C., Shih, T. P., Ko, W. C., Tang, H. J., & Hsueh, P. R. (2020). Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and corona virus disease-2019 (COVID-19): the epidemic and the challenges. International journal of antimicrobial agents, 105924.
14. Wang, Dawei, Bo Hu, Chang Hu, Fangfang Zhu, Xing Liu, Jing Zhang, Binbin Wang et al. "Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus–infected pneumonia in Wuhan, China." Jama 323, no. 11 (2020): 1061-1069.
15. Rothan, H. A., & Byrareddy, S. N. (2020). The epidemiology and pathogenesis of coronavirus disease (COVID-19) outbreak. Journal of autoimmunity, 102433.
16. Mueller, M., Derlet, P. M., Mudry, C., & Aeppli, G. (2020). Using random testing to manage a safe exit from the COVID-19 lockdown. arXiv preprint arXiv:2004.04614.

17. Chowdhury, M. E., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M. A., Mahbub, Z. B., ... & Reaz, M. B. I. (2020). Can AI help in screening viral and COVID-19 pneumonia?. arXiv preprint arXiv:2003.13145.
18. Yan, L. C., Yoshua, B., & Geoffrey, H. (2015). Deep learning. nature, 521(7553), 436-444.
19. Tan, C., Sun, F., Kong, T., Zhang, W., Yang, C., & Liu, C. (2018, October). A survey on deep transfer learning. In International conference on artificial neural networks (pp. 270-279). Springer, Cham.
20. Raghu, M., Zhang, C., Kleinberg, J., & Bengio, S. (2019). Transfusion: Understanding transfer learning for medical imaging. In Advances in neural information processing systems (pp. 3347-3357).
21. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097-1105).
22. You, Y., Zhang, Z., Hsieh, C., Demmel, J., & Keutzer, K. (2017). 100-epoch imagenet training with alexnet in 24 minutes. arXiv preprint arXiv:1709.05011.
23. Lippi, G., Simundic, A. M., & Plebani, M. (2020). Potential preanalytical and analytical vulnerabilities in the laboratory diagnosis of coronavirus disease 2019 (COVID-19). Clinical Chemistry and Laboratory Medicine (CCLM), 1(ahead-of-print).
24. Chen, N., Zhou, M., Dong, X., Qu, J., Gong, F., Han, Y., ... & Yu, T. (2020). Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study. The Lancet, 395(10223), 507-513.
25. Ching, T., Himmelstein, D. S., Beaulieu-Jones, B. K., Kalinin, A. A., Do, B. T., Way, G. P., ... & Xie, W. (2018). Opportunities and obstacles for deep learning in biology and medicine. Journal of The Royal Society Interface, 15(141), 20170387.
26. Kallianos, K., Mongan, J., Antani, S., Henry, T., Taylor, A., Abuya, J., & Kohli, M. (2019). How far have we come? Artificial intelligence for chest radiograph interpretation. Clinical radiology.
27. Wang, F., Casalino, L. P., & Khullar, D. (2019). Deep learning in medicine—promise, progress, and challenges. JAMA internal medicine, 179(3), 293-294.
28. Wang, W., Xu, Y., Gao, R., Lu, R., Han, K., Wu, G., & Tan, W. (2020). Detection of SARS-CoV-2 in different types of clinical specimens. Jama, 323(18), 1843-1844.
29. Shan, F., Gao, Y., Wang, J., Shi, W., Shi, N., Han, M., ... & Shi, Y. (2020). Lung infection quantification of covid-19 in ct images with deep learning. arXiv preprint arXiv:2003.04655.
30. Yang, W., & Yan, F. (2020). Patients with RT-PCR-confirmed COVID-19 and normal chest CT. Radiology, 295(2), E3-E3.
31. 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, 1.
32. Narin, A., Kaya, C., & Pamuk, Z. (2020). Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. arXiv preprint arXiv:2003.10849.
33. Wang, L., & Wong, A. (2020). COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images. arXiv preprint arXiv:2003.09871.

34. 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, 103869.
35. Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., ... & Cao, K. (2020). Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT. Radiology.
36. Stephen, O., Sain, M., Maduh, U. J., & Jeong, D. U. (2019). An efficient deep learning approach to pneumonia classification in healthcare. Journal of healthcare engineering, 2019
37. Wang S., Sun, J., Mehmood, I., Pan, C., Chen, Y., & Zhang, Y. D. (2020). Cerebral micro-bleeding identification based on a nine-layer convolutional neural network with stochastic pooling. Concurrency and Computation: Practice and Experience, 32(1), e5130.
38. Saraiva, A., Ferreira, N., Sousa, L., Carvalho da Costa, N., Sousa, J., Santos, D., & Soares, S. (2019). Classification of Images of Childhood Pneumonia using Convolutional Neural Networks. In 6th International Conference on Bioimaging (pp. 112-119).
39. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., ... & Lungren, M. P. (2017). Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225.
40. Rajaraman, S., Candemir, S., Kim, I., Thoma, G., & Antani, S. (2018). Visualization and interpretation of convolutional neural network predictions in detecting pneumonia in pediatric chest radiographs. Applied Sciences, 8(10), 1715.
41. Tajbakhsh, N., Shin, J. Y., Gurudu, S. R., Hurst, R. T., Kendall, C. B., Gotway, M. B., & Liang, J. (2016). Convolutional neural networks for medical image analysis: Full training or fine tuning?. IEEE transactions on medical imaging, 35(5), 1299-1312.
42. Kermany, D., Zhang, K., & Goldbaum, M. (2018). Labeled optical coherence tomography (OCT) and Chest X-Ray images for classification. Mendeley data, 2.
43. Bai, H. X., Hsieh, B., Xiong, Z., Halsey, K., Choi, J. W., Tran, T. M. L., ... & Jiang, X. L. (2020). Performance of radiologists in differentiating COVID-19 from viral pneumonia on chest CT. Radiology, 200823.

Figures

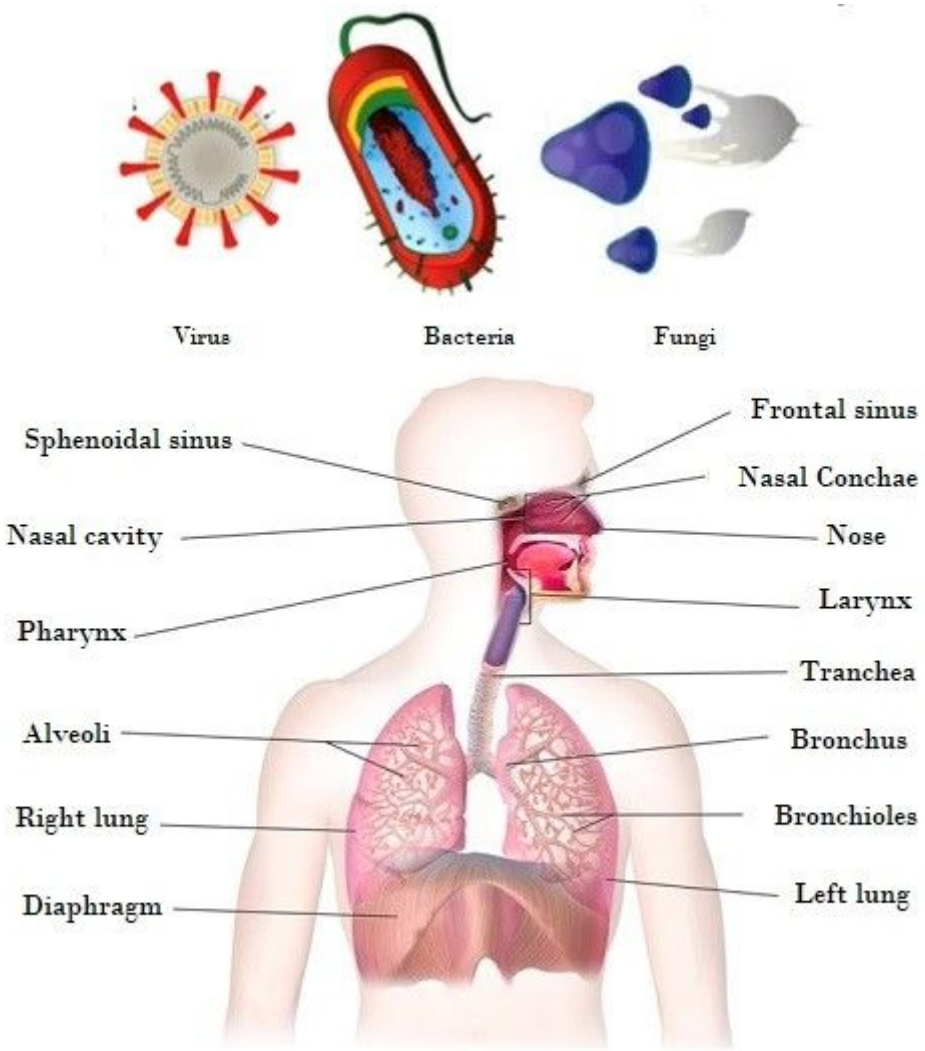

Figure 1

Classification of Pneumonia

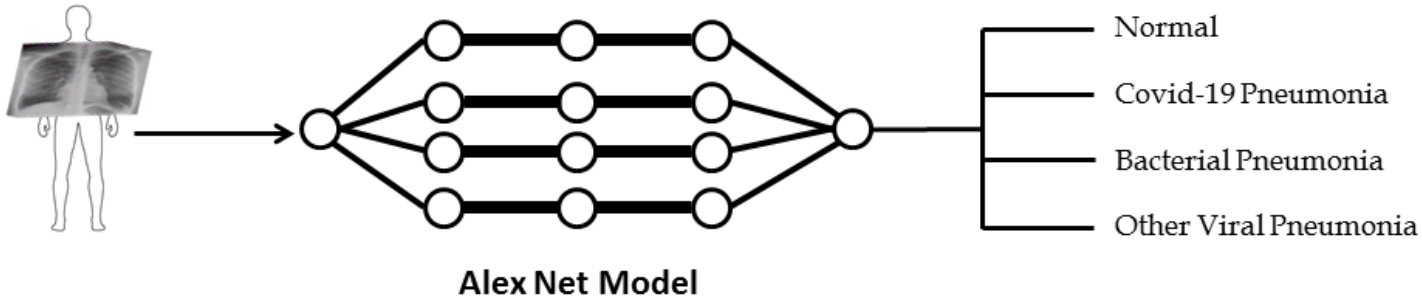

Figure 2

The complete workflow is represented schematically. CXR Images are used to train the network using Pretrained AlexNet Model for classification of classify (I) COVID-19 and normal (healthy) CXR scans (II) bacterial and normal CXR scans (III) viral pneumonia and normal CXR scan (IV) COVID-19 and bacterial CXR scans (V) COVID-19, bacterial pneumonia and normal CXR scans and (VI) COVID-19, bacterial pneumonia, viral pneumonia and normal CXR scans.

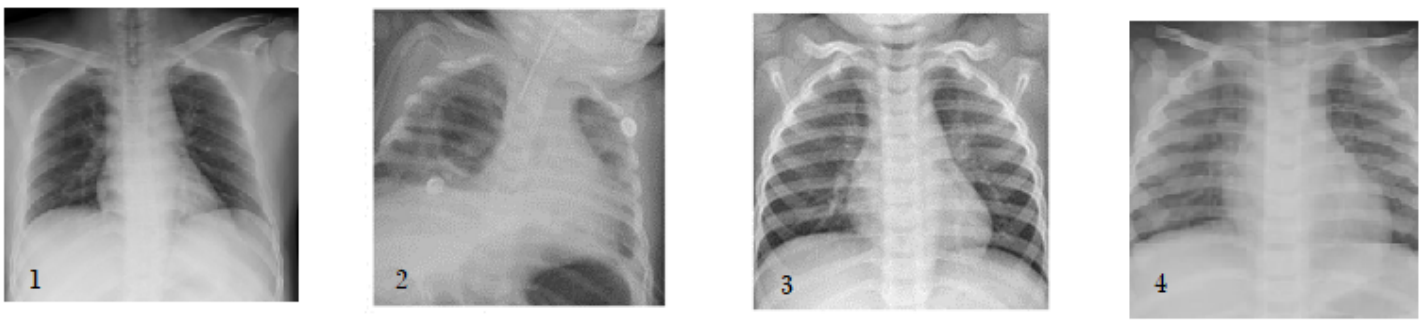

Figure 3

CXR scans. (1) COVID-19 (2) non-COVID 19 viral pneumonia (3) Normal CXR scan (4) bacterial pneumonia

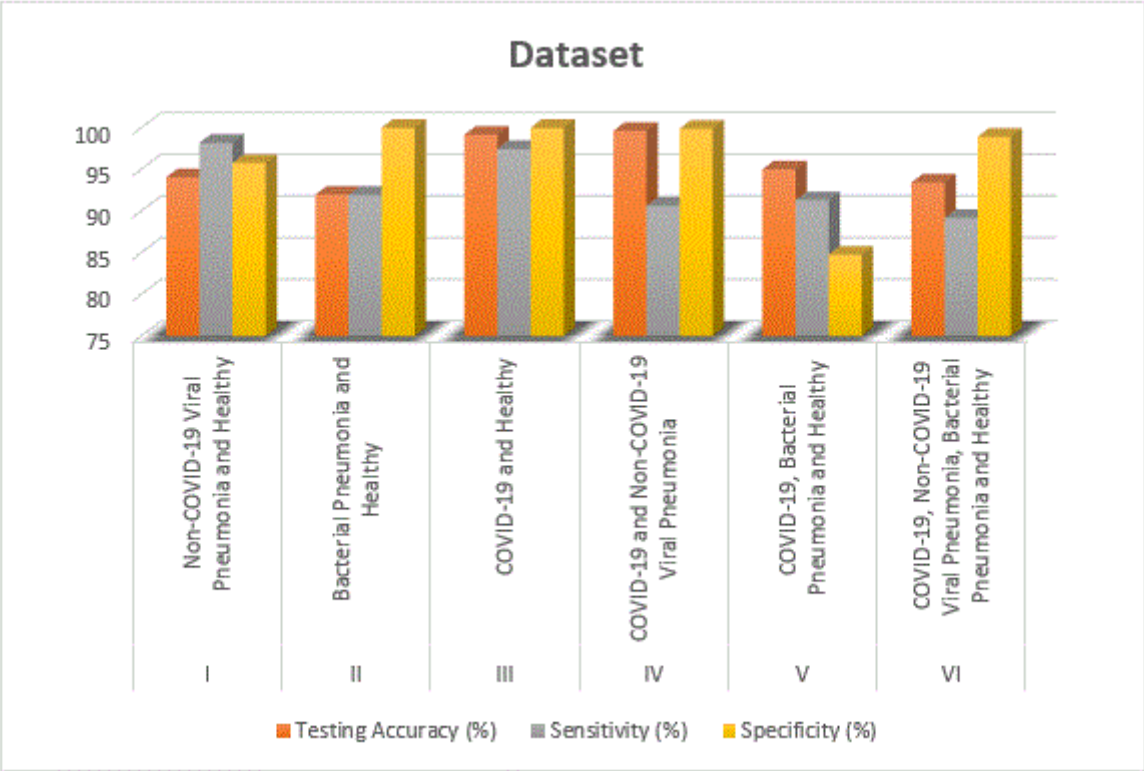

Figure 4

Performance Evaluation of models based on Accuracy, Sensitivity and Specificity

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- MATLABNEWEDITEDCODE.docx