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Covid-19 X-Ray Scan Images Classification by Deep Learning: Review

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ABSTRACT

Covid-19 is a rapidly spreading viral disease that infects not only humans, but animals are also infected because of this disease. The daily life of human beings, their health, and the economy of a country are affected due to this deadly viral disease. Covid-19is a common spreading disease, and till now, not a single country can prepare a vaccine for COVID-19. The virus hassince spread rapidly to become a global pandemic (WHO,2020) , with numbers of cases and associated deaths stillincreasing on a daily basis . At present, further research on an effective screening process is required for diagnosing the virus cases and segregating the affected people. Health professionals and scientists of many countries in the world are attempting to improve their treatment plan and capacity of test through implementing multifunctional testing to stop spreading the virus and for protecting themselves from the deadly virus [2]. A clinical study of COVID-19 infected patients has shown that these types of patients are mostly infected from a lung infection after coming in contact with this disease. Chest x-ray (i.e., radiography) and chest CT are a more effective imaging technique for diagnosing lung related problems. Still, substantial chest x-ray is a lower cost process in comparison to chest CT. Deep learning technology [7,8,13] is the most successful technique of machine learning, which provides useful analysis to study a large amount of chest x-ray images that can critically impact on screening of Covid-19.

Keywords : covid,deeplearning,x-ray,scan,pneuomania, machine learning

1.1 Research Background

The new SARS-CoV-2 coronavirus, which produces the disease known as COVID-19, kept the whole world on edge during the first months of 2020. It provoked the borders close of many countries and the confinement of millions of citizens to their homes due to infected people, which amounts to 868,000 confirmed cases worldwide at this moment (April 2020). This virus was originated in China in December2019. From March 2020, Europe was the main focus of the virus sprout, achieving more than 445,000 infected people. China, with a total of 3,312 deaths and more than 81,000 infected people, has managed to contain the virus almost three months after the start of the crisis in December 2019. Italy, which surpassed the Asian country in death toll on March 2020, became the most affected country, in number of deceased is followed by Spain, with more than10,000 dead based on a report made on April 2020. This number was constantly growing. There were different studies that predicted the growth of the curves of infections, based on different parameters such as exposed, infected or recovered human's number. These studies allowed to get an idea

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of the transmission dynamics that could occur in each country [16,26].

1.2 Materials and Methods

1.2.1 Dataset

In the study, chest X-ray images of 341 COVID-19 patients have been obtained from the open-source GitHub repository shared by Dr. Joseph Cohen et al. [19]. This repository is consisting chest X-ray / computed tomography (CT) images of mainly patients with acute respiratory distress syndrome (ARDS), COVID-19, Middle East respiratory syndrome (MERS), pneumonia, severe acute respiratory syndrome (SARS). 2800 normal (healthy) chest X-ray images were selected from "ChestX-ray8" database [49]. In addition, 2772 bacterial and 1493 viral pneumonia chest X-ray images were used from Kaggle repository called "Chest X-Ray Images (Pneumonia)" [42].

Narin Ali et al. [10] conducted experiments based on three binary created datasets (Dataset-1, Dataset-2 and Dataset-3) with chest X-ray images. Distribution of images per class in created datasets are given Table 1.1.

Table 1.1 Number of images per class for each dataset

Classes / Datasets	Bacterial Pneumonia	COVID-19	Normal	Viral Pneumonia
Dataset-1	-	341	2800	-
Dataset-2	-	341	-	1493
Dataset-3	2772	341	-	-

All images were resized to 224x224 pixel size in the datasets [10]. In Figure 1.1, representative chest X-ray images of normal (healthy), COVID-19, bacterial and viral pneumonia patients are given, respectively.

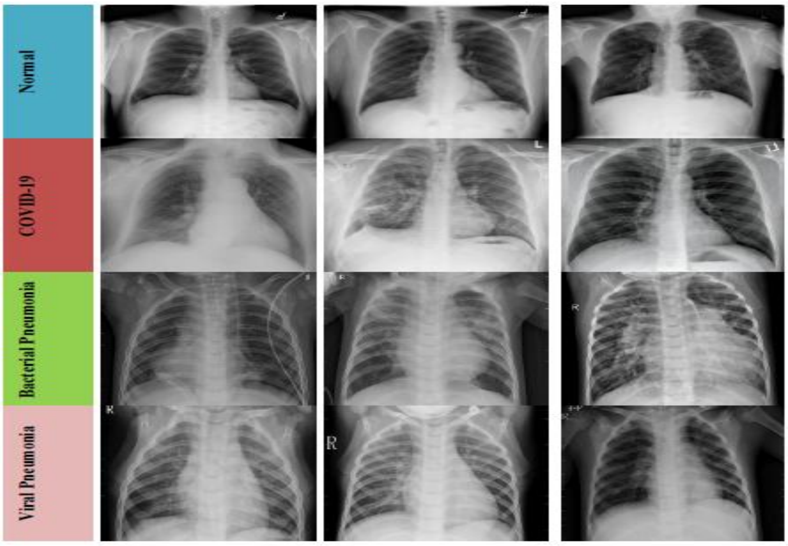

Figure 1.1 Representative chest X-ray images of normal (healthy) (first row), COVID-19 (second row), bacterial (third row) and viral pneumonia (fourth row) patients [10].

1.3 Architecture of Deep Learning

Deep learning is a sub-branch of the machine learning field, inspired by the structure of the brain. Deep learning techniques used in recent years continue to show an impressive performance in the field of medical image processing, as in many fields. By applying deep learning techniques to medical data, it is tried to draw meaningful results from medical data [16,21-23].

Deep learning models have been used successfully in many areas such as classification, segmentation and lesion detection of medical data. Analysis of image and signal data obtained with medical imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT) and X-ray with the help of deep learning models. As a result of these analyses, detection and diagnosis of diseases such as diabetes mellitus, brain tumor, skin cancer and breast cancer are provided with convenience [44,45].

A convolutional neural network (CNN) is a class of deep neural networks used in image recognition problems [27]. Coming to how CNN works, the images given as input must be recognized by computers and converted into a format that can be processed. For this reason, images are first converted to matrix format. The system determines which image belongs to which label based on the differences in images and therefore in matrices. It learns the effects of these differences on the label during the training phase and then makes predictions for new images using them. CNN consists of three different layers that are a convolutional layer, pooling layer, and fully connected layer to perform these operations effectively. The feature extraction process takes place in both convolutional and pooling layers. On the other hand, the classification process occurs in fully connected layer. These layers are examined sequentially in the following.

1.3.1 Convolutional Layer

Convolutional layer is the base layer of CNN. It is responsible for determining the features of the pattern. In this layer, the input image is passed through a filter. The values resulting from filtering consist of the feature map. This layer applies some kernels that slide through the pattern to extract low- and high-level features in the pattern [51]. The kernel is a 3x3 or 5x5 shaped matrix to be transformed with the input pattern matrix. Stride parameter is the number of steps tuned for shifting over input matrix. The output of convolutional layer can be given as:

$$x_j^l = f(\sum_{\alpha=1}^{N} w_j^{l-1} * y_\alpha^{l-1} + b_j^l \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1.1)$$

Where, x_j^l is the j-th feature map in layer l, w_j^{l-1} indicates j-th kernels in layer l-1, y_α^{l-1}represents the a-th feature map in layer l-1, b_j^lindicates the bias of the j-th feature map in layer l, N is number of total features in layer l-1, and (*) represents vector convolution process.

1.3.2 Pooling Layer

The second layer after the convolutional layer is the pooling layer. Pooling layer is usually applied to the created feature maps for reducing the number of feature maps and network parameters by applying corresponding mathematical computation. In this study, we used max-pooling and global average pooling. The max-pooling process selects only the maximum value by using the matrix size specified in each feature map, resulting in reduced output neurons. There is also a global average pooling layer that is only used before the fully connected layer, reducing data to a single dimension. It is

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connected to the fully connected layer after global average pooling layer. The other intermediate layer used is the dropout layer. The main purpose of this layer is to prevent network overfitting and divergence [53].

1.3.3 Fully Connected Layer

Fully connected layer is the last and most important layer of CNN. This layer functions like a multi-layer perceptron. Rectified Linear Unit (ReLU) activation function is commonly used on fully connected layer, while Softmax activation function is used to predict output images in the last layer of fully connected layer. Mathematical computation of these two activation functions is as follow:

$$ReLU = \begin{cases} 0, & x < 0 \\ x, x \geq 0 \end{cases} \quad \dots\dots\dots\dots\dots\dots..(1.2)$$

$$Soft\,\max(x_i) = \frac{e^{x_i}}{\sum_{y-1}^{m} e^{x_i}} \quad \dots\dots\dots\dots\dots..(1.3)$$

Where x_i and m represent input data and the number of classes, respectively. Neurons in a fully connected layer have full connections to all activation functions in previous layer.

1.3.4 Pre-Trained Models

In the analysis of medical data, one of the biggest difficulties faced by researchers is the limited number of available datasets. Deep learning models [4,16,21,22] often need a lot of data. Labeling this data by experts is both costly and time consuming. The biggest advantage of using transfer learning method is that it allows the training of data with fewer datasets and requires less calculation costs. With the transfer learning method, which is widely used in the field of deep learning, the information gained by the pre-trained model on a large dataset is transferred to the model to be trained.

The study involves a deep CNN based ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2 models for the classification of COVID-19 Chest X-ray images to three different binary classes (Binary Class-1 = COVID-19 and normal (healthy), Binary Class-2 = COVID-19 and viral pneumonia, Binary Class-3 = COVID-19 and bacterial pneumonia). In addition, we applied transfer learning technique that was realized by using ImageNet data to overcome the insufficient data and training time. The schematic representation of conventional CNN including pre-trained ResNet50, ResNet101, ResNet152, InceptionV3 and Inception ResNetV2 models for the prediction of normal (healthy), COVID-19, bacterial and viral pneumonia patients were depicted in Figure 1.2. It is also available publicly for open access at https://github.com/drcerenkaya/COVID-19-DetectionV2.

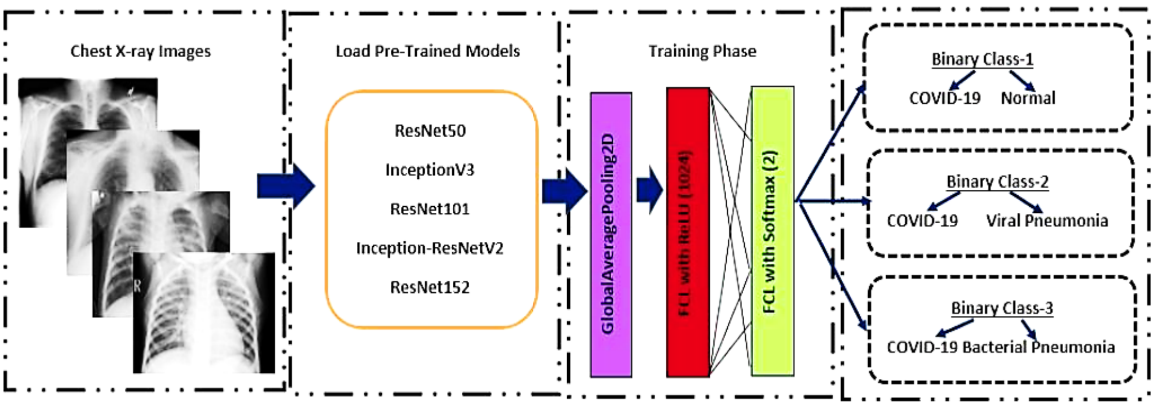

Figure 1.2. Schematic representation of pre-trained models for the prediction of normal (healthy), COVID-19, bacterial and viral pneumonia patients [10]

ResNet50

Residual neural network (ResNet) model is an improved version of convolutional neural network (CNN). ResNet adds shortcuts between layers to solve a problem. Thanks to this, it prevents the distortion that occurs as the network gets deeper and more complex. In addition, bottleneck blocks are used to make training faster in the ResNet model [46]. ResNet50 is a 50-layer network trained on the ImageNet dataset. ImageNet is an image database with more than 14 million images belonging to more than 20 thousand categories created for image recognition competitions [52].

InceptionV3

InceptionV3 is a kind of convolutional neural network model. It consists of numerous convolution and maximum pooling steps. In the last stage, it contains a fully connected neural network [48]. As with the ResNet50 model, the network is trained with ImageNet dataset.

Inception-ResNetV2

The model consists of a deep convolutional network using the Inception-ResNetV2 architecture that was trained on the ImageNet-2012 dataset. The input to the model is a 299×299 image, and the output is a list of estimated class probabilities [47].

ResNet101 & ResNet152

ResNet101 and ResNet152 consist of 101 and 152 layers respectively due to stacked ResNet building blocks. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [52]. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224x224.

1.7 Performance metrics

The performance of the proposed classification model was evaluated based on accuracy, sensitivity, specificity, precision, and F1 score [30]. Given the number of false positives (FP), true positives (TP), false negatives (FN) and true negatives (TN), the parameters are mathematically defined as follows:

Accuracy = $\frac{TP+TN}{TN+TP+FP+FN}$; Sensitivity =$\frac{TP}{TP+FN}$;
Specificity = $\frac{TN}{TN+FP}$; Precision = $\frac{TP}{TP+FP}$
F1= $2 \times \frac{Recall\ \times Precision}{Recall\ \times\ Precision}$

Moreover, the present study supports the use of confusion matrix analysis in validation [52] since it is strong to type of relationship and any data distribution, it makes a stringent evaluation of validity, and it provides extra information on the type and sources of errors. Before starting the analysis of the confusion matrix of each model, let's first see how it is structured and define all the parameters and variables [35] that can be extracted (Table 1.1).

Table 1.1 Confusion matrix structure

		Predicted		
		Bacteria Coronavirus		Normal
Actual	Bacteria	P_{bb}	P_{nb}	P_{cb}
	Normal	P_{bn}	P_{nn}	P_{cn}

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Coronavirus	P_{bc}	P_{nc}	P_{cc}

where:
P_{bb}: Bacteria class were correctly classified as Bacteria.
P_{cb}: Bacteria class were incorrectly classified as Coronavirus.
P_{nb}: Bacteria class were incorrectly classified as Normal.
P_{bc}: Coronavirus class were incorrectly classified as Bacteria.
P_{cc}: Coronavirus class were correctly classified as Coronavirus.
P_{nc}: Coronavirus class were incorrectly classified as Normal.
P_{bn}: Normal class were incorrectly classified as Bacteria.
P_{cn}: Normal class were incorrectly classified as Coronavirus.
P_{nn}: Normal class were correctly classified as Normal.

Using these parameters, we can define other variables [35]:

True Positives TP: True Negatives TN:

TP(Bacteria)	P_{bb}	TN(Bacteria)	$P_{cc} + P_{nc} + P_{cn} + P_{nn}$
TP(Normal)	P_{nn}	TN(Normal)	$P_{bb} + P_{cb} + P_{bc} + P_{cc}$
TP(Coronavirus)	P_{cc}	TN(Coronavirus)	$P_{bb} + P_{nb} + P_{bn} + P_{nn}$

False Positives FP: False Negatives FN:

FP(Bacteria)	$P_{bc} + P_{bn}$	FN(Bacteria)	$P_{cc} + P_{nc}$
FP(Normal)	$P_{nb} + P_{nc}$	FN(Normal)	$P_{bn} + P_{cn}$
FP(Coronavirus)	$P_{cb} + P_{cn}$	FN(Coronavirus)	$P_{bc} + P_{nc}$

Table 2.1 Inference drawn from the literature

Reference	Methodology	Purpose/Aim	Application Domain	Gaps	Inference
Jain, R., et.al (2021)	Deep learning-based CNN models, Inception V3, Xception, and ResNeXt models	Deep learning-based detection and analysis of COVID-19 on chest X-ray images	COVID-19 Analysis	The research doesn't focus on making a perfect mechanism. Instead, it looks for ways to fight this disease that are affordable.	The xception model gives the highest accuracy (i.e., 97.97%) for detecting Chest X-rays images as compared to other models.

Ahsan, et.al (2021)	HOG and CNN	COVID-19 detection from X-ray images of the chest using DL and feature fusion.	COVID-19 Detection	This research uses a small number of X-ray images. When combining datasets with substantial differences, it can be difficult to design a valid testing protocol.	CNN technique used in this study showed better classification performance.
Wang. et.al (2021)	The retrospective**,** diagnostic or prognostic study, and multicentre study.	A DL algorithm using CT images to screen for Coronavirus disease (COVID-19)	COVID-19 Screening	Low SNR and complex statistics integration have challenged the efficacy CT images constitute a difficult class challenge due to the extraordinarily massive number of variable items	These findings show the proof-of-concept for the use of AI to retrieve radiological features for the accurate and timely diagnosis of COVID-19.
Hasan, et.al (2021)	DL algorithm	DL Approaches for Detecting Pneumonia in COVID-19 Patients by Analysing Chest X-Ray Images	COVID-19 Detection	No conflicts	The model efficiently reduces the training loss and boosts accuracy
Turkoglu (2021)	CNN-based AlexNet design with the transfer learning approach	COVID-19 diagnostics system based on X-ray pictures	COVID-19 diagnostics	Finding suitable settings for the SVM classifier could be considered a performance restriction of	The proposed model obtained an accuracy of 99.18 % in the test findings.

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				the study. Another disadvantage of the study is the inability to identify suitable Relief algorithm parameters.	
Ghaderzadeh, & Asadi (2021)	DL algorithm	DL in the Detection and Diagnosis of COVID-19 Using Radiology Modalities	Detection and Diagnosis of COVID-19	One of the disadvantages of this procedure is the requirement for a lab kit, which is hard, if not impossible, to get in many nations during emergencies and outbreaks.	This review paper gives an overview of the existing of all models for COVID-19 diagnosis and detection using radiological modalities and DL processing.
Haider & Kowalski (2021)	HOG, CNN, and a modified anisotropic diffusion filtering (MADF) technique.	COVID-19 Detection from Chest X-Ray Images Using Feature Fusion and DL.	COVID-19 Detection	A virus with a prolonged detection time and a low detection rate.	Using merging the characteristics obtained by HOG features and CNN, this work created and constructed an intelligent system for COVID19 identification with high precision and minimal complexity.
Karakanis, & Leontidis (2021)	Lightweight deep neural networks	Lightweight DL models for detecting COVID-19 from chest X-ray	COVID-19 Detection	To assist in the prevention and identification	In comparison to other studies in literature as well as a ResNet8 model, the

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		images.		of COVID-19 from CXR, quick, accurate, and available tools are required. Furthermore, it may be necessary to adapt new testing techniques to new or current models.	models performed well.
Ghosh & Bandyopadhyay (2021)	A fine-tuned deep CNN model	Detection of Coronavirus using Chest X-Ray Images and DeepCNNs with Transfer Learning	COVID-19 Detection	An auxiliary automatic detecting system that will aid in immediate testing is urgently needed.	In comparison to prior studies in this domain, the suggested model achieved a validation accuracy of 99.39394 percent.
Ibrahim, et.al (2021)	A deep neural network based on the TL approach	Classification of pneumonia using DL on chest X-ray pictures during COVID-19.	Pneumonia Classification Using Deep Learning	COVID-19 pneumonia was studied using a short dataset.	The suggested model achieved good accuracy in terms of accuracy, sensitivity, and specificity.
Keidar, et.al (2021)	DNNS, namely VGG16, ReNet34, ReNet50, and ReNet152	DNN classification of COVID-19 X-ray images	COVID-Classification	Due to the lack of accessibility to the patients' clinical data, prior medical conditions and impairments were not included in the assessment of both the	The suggested model achieved good accuracy.

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				COVID-19 and control databases.	
Ismael & Şengür (2021)	Deep CNN models (ResNet101, ResNet18, VGG16, ResNet50, and VGG19)	COVID-19 identification using DL methods based on chest X-ray images.	COVID-19 Identification	-	The results of the experiments suggest that deep learning has the capacity to detect COVID-19 from chest X-ray pictures.
Hussain, et.al (2021)	CoroDet	A deepNN for COVID-19 identification and diagnosis from chest x-ray images.	COVID-Classification	Hardware limitations	The suggested model obtained a classification accuracy of 99.1 percent for 2 class classification, 94.2 percent for 3 class classification, and 91.2 percent for 4 class classification, which is better than state-of-the-art methods employed for COVID-19 detection to the best of my knowledge.
Kc, K., et.al (2021)	DCNN	Assessment of DL-based classification strategies for COVID-19 depending on chest X-ray images.	COVID-Classification	-	The test results suggest that just 62% of total variables were retrained to obtain this level of precision.
Hemdan, et.al (2020)	COVIDX-Net	To diagnose covid-19 in x-ray pictures, a set of deep learning classifiers was developed.	COVID-19 Diagnosis	X-ray pictures cannot easily identify soft tissue with poor contrast	This study revealed the usefulness of using deep learning models to categorize

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				to keep the patient's exposure dose to a minimum.	COVID-19 in X-ray pictures.
Apostolopoulos, et.al (2020)	Mobile Net, a state-of-the-art CNN	Extraction of potentially relevant COVID-19 biomarkers from X-ray pictures using a deep learning strategy.	COVID-19 biomarker	A small number of COVID-19-infected cases are included in the study. Second, the pneumonia incidence data are older samples that do not reflect pneumonia images from individuals who have been diagnosed with Coronavirus symptoms. Third, there is no major risk factor listed.	Classification accuracy of 87.66 % is attained between the seven classes.
Ozturk, et.al (2020)	Raw chest X-ray images and DarkCovidNet DL network	COVID-19 instances were detected automatically utilizing deep neural networks and X-ray images.	Automated detection of COVID-19	COVID-19 public image statistics have limited information.	The developed application can perform binary and multi-class functions with an accuracy of 98.08 percent and 87.02 percent, respectiv ely.
Khan, ***et.al (2020)***	CoroNet	A deepNN for COVID-19 identification and diagnosis from chest x-ray images.	COVID-19 Identificatio n	CoroNet requires more clinical research and testing, but it is more	The experimental results demonstrate that the proposed model accomplished an

				accurate and sensitive in COVID-19 patients.	overall accuracy of 89.6%

CONCLUSION

Despite all its promises, AI brings difficulties in many stages from its development to its use. The main reason is that, in most health-related systems, it starts with the need for real data rather than synthetic data, and as the AI models become more complex, algorithms lose their explainability. Legal approval of the process is based on the understandability of the systems in some cases. Much is written about black-box algorithms; there are cases where deep neural networks, in particular, are not possible to understand the result produced. This blur caused the European Union's General Data Protection Regulation clarification requests for transparency before an algorithm was used for patient care. These discussions on whether it is acceptable to use non-transparent algorithms for patient care are up to date. Prescribing a drug without a known mechanism of action, it is noteworthy that many aspects of drug administration are not explained, and it is another research side of the subject with social content.

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