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COVID-19 DETECTION AND CLASSIFICATION BY DEEP LEARNING : REVIEW

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Abstract

Coronavirus infection leads to serious acute respiratory syndrome when viral pneumonia of lungs develops. The individual who has been exposed to the new coronavirus experiences a variety of symptoms. The most common signs of a new coronavirus disease are dry cough, fatigue, and fever . The signs and symptoms of this illness differ from one being to another

. Some people may also experience other symptoms like headaches, sore throats, and lack of taste and smell, although the most serious signs of COVID progression include short breath, chest pain, and the inability to move or talk . RTPCR i.e., Reverse transcriptase-polymerase chain reaction, antibody testing, isothermal nucleic amplification, medical imaging, and serology testing are some of the methods that can be used to conclusively diagnose COVID. is the primary method for diagnosing COVID and a range of other viral diseases (RT-PCR)

Keywords: Covid, x-ray images, deep learning, classification, detection

1. Introduction

Infectious disease Covid-19 is a fast-spreading virus that infects both human beings and animals. As a result of this condition, animals may get infected with the virus. This fatal viral illness has an impact on not only the day-to-day lives of people but also their health and the economy of the nation in which they live. There is currently no vaccination available for COVID-19, regardless of the fact it is a global epidemic that is growing rapidly across the globe. Since then, the virus has swiftly spread over the globe, turning into a pandemic (WHO, 2020) [41], with the number of reported cases and fatalities connected with them continuing to rise on a daily basis [40]. At the moment, more research on an efficient screening technique is necessary in order to diagnose instances of the virus and separate those who have been infected from the rest of the population. To limit the spread of the fatal virus and defend themselves from it, medical practitioners and specialists in many nations across the world are introducing multifunction testing [2] to improve their treatment regimen and testing capacity. This is currently being done to enhance their capacity to detect the infection. When COVID-19-infected patients were studied in a clinical area, it was observed that they were often infected with respiratory illnesses. This conclusion was reached as a result of the findings of the study. Imaging techniques such as chest x-rays (also known as radiography) and chest CT scans are more accurate than other methods when it comes to detecting issues that are connected to the lungs. A thorough chest x-ray is less expensive than a chest CT, albeit [1, 5] [36-40]. The most successful method of machine learning uses deep learning technologies [7, 8, 13]. This is a great tool for analysing a large number of chest x-ray images, which could significantly affect the Covid-19 screening process.

1.1. *Materials and Methods*

1.1.1. Dataset

Dr. Joseph Cohen et al. [19] provided an open-source GitHub repository with 341 COVID patients' chest X-ray images. Images of patients with ARDS, COVID-19, Middle East Res- piratory Syndrome (MERS), pneumonia, and severe acute respiratory syndrome compose the bulk of this collection (SARS). The "ChestX-ray8" database [49] yielded 2800 images of normal chest X-rays. On the other hand, Kaggle's collection "Chest X-Ray Images (Pneu- monia)" had more than 2,700 images of pneumonia.

Dataset-1, Dataset-2, and Dataset-3 comprise pictures of chest X-rays, and they were tested by Narin Ali et al. [10]. Table 1.1 shows the breakdown of photographs in various datasets by class.

For each database, the number of images for each class.

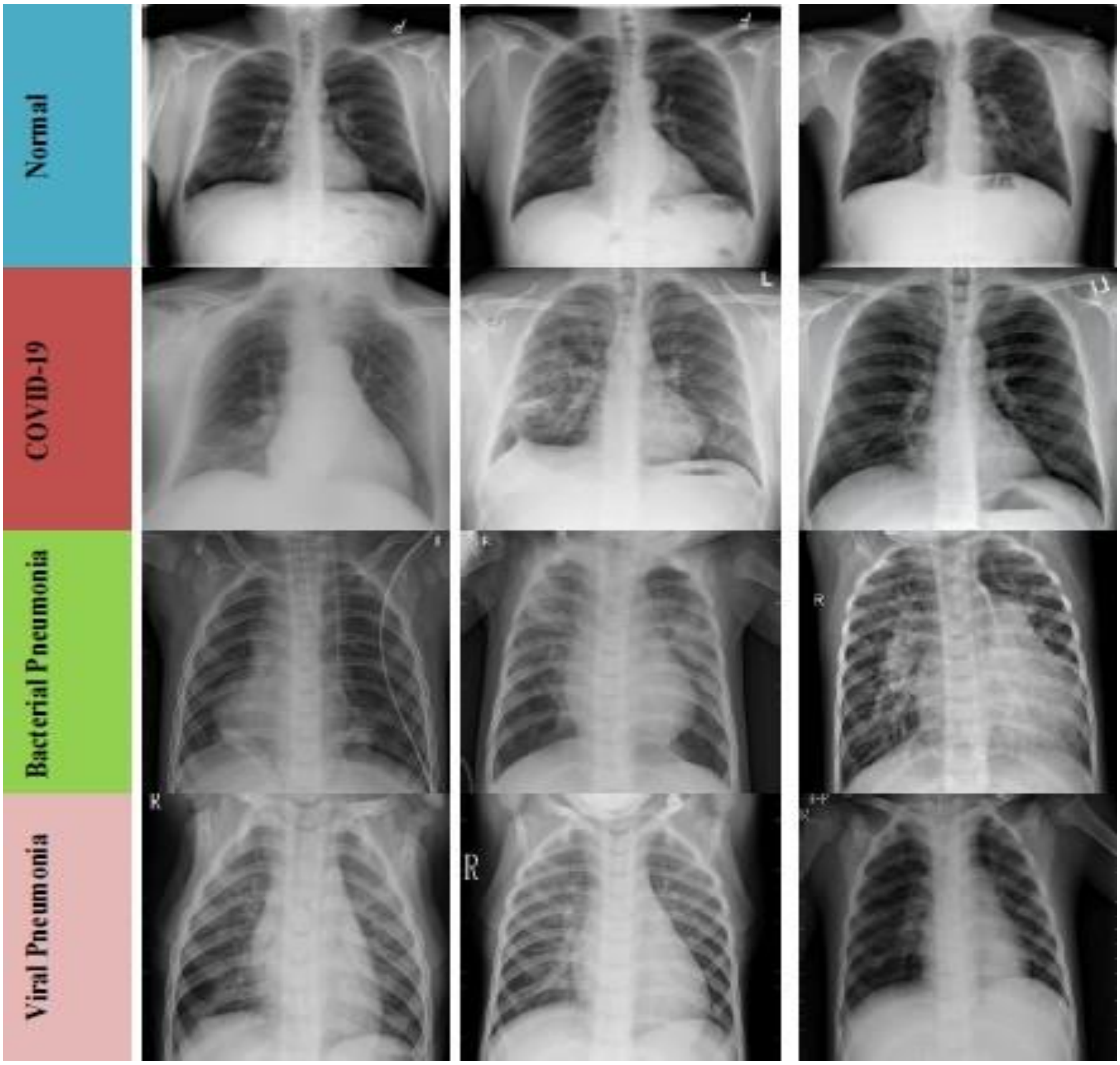
Classes / Datasets	Bacterial Pneumonia	COVID-19	Normal	Viral Pneumonia
Dataset-1	-	341	2800	-
Dataset-2	-	341	-	1493
Dataset-3	2772	341	-	-

Figure 1: Images In Datasets

All the visuals were downsized to 224x224 pixels for the datasets [10]. Patients with normal health, COVID-19, bacterial, and viral pneumonia are depicted in the X-ray images shown in Figure 1.1, respectively.

2. RELATED WORK

Stefanos Karakanis **and** Georgios Leontidis **[8] .** As a unique approach to identifying COVID-19, the researchers propose utilizing a conditional GAN to generate synthetic images to augment the little data already available. Two deep learning models that conform to a lightweight design and that are commensurate to the entire amount of data that is available are also proposed by the researchers. In addition to binary classification for COVID patients vs. normal cases, the testing focused on multi-classification. This added a third category for



Sayantan Ghosh and Mainak Bandyopadhyay [9]. To accurately diagnose binary classification (COVID-19 positive vs. COVID-19 negative) using raw chest X-ray pictures, this study proposed an exclusive deep CNN model with fine-tuned parameters. The model was built by the study's authors. Over 1300 image samples were used in 5 fold cross- validation training to get the model's accuracy metrics and the whole model architecture. The validation accuracy of the proposed model was 99.39394 percent, which is much greater than the accuracy of previous research in this subject.

Ali Narin, et.al [10]. Research and Development (R&D) There are five CNN-based models recommended by the authors of this study for the identification of people with the coronavirus that causes pneumonia by analyzing chest X-ray radiographs, including ResNetV2, and InceptionV3. This study used a 5-fold cross-validation method to estab- lish three binary categories each containing a total of four classifications: viral pneumo- nia, COVID-19, normal (healthy), and bacterial pneumonia. It was found that the pre- trained ResNet50 model outperformed three other models (Dataset-1: 96.1 percent accu- racy, Dataset-2: 99.5 percent accuracy, and

Dataset-3: 99.7 percent accuracy) in terms of classification accuracy. These findings were reached after an evaluation of the obtained performance data.

Ibrahim, et.al [11]. This research advocated the use of a deep learning approach based on a pre-trained AlexNet model for categorizing non-COVID-19, COVID-19 bacterium pneu- monia, COVID-19 viral pneumonia, and routine CXR images collected from multiple publi- cally accessible sources. Two-way, three-way, and four-way classifications have been taught to the model, including normal vs. COVID-19, healthy vs. non-COVID viral pneumonia, and healthy vs. COVID in the case of bacterial pneumonia. The four-way categorization was the most hardest to learn.. The suggested model was 94.43 percent accurate, 98.19 percent sensitive, 94.43 percent accurate, and 95.78 percent specific for CXR pictures of patients who did not have Corona viral pneumonia and were healthy, all at 95.78 percent reliability. The model's accuracy, sensitivity, and specificity were all more than 90% when comparing normal CXR pictures to those exhibiting bacterial pneumonia. For COVID-19 pneumonia and normal CXR images, the model was 99.16% accurate, 97.444% sensitive, and 100% specific. In specifically, the model had a prediction value of 100 percent. When it comes to correctly detecting viral pneumonia from CXR scans of COVID-19 and non-COPID-19 pneumonia, the model had a 99.62 percent accuracy rate, a 90.63 percent sensitivity rate, and a 99.89 percent specificity rate. Accuracy was 94%, sensitivity was 91%, and three-way classification efficiency was 84% for this model. The suggested model has a four-way classi- fication accuracy of 93.42 percent, a sensitivity of 89.18 percent, and a specificity of 98.92 percent.

Table 1: Different Studies Associated with COVID-19 Classification from CTScans

Mei etal. (2020)	Algorithm used Bidirectional	Image Source	Number Of Images	Accura
Pathak et al. (2020)	Long Short-Term Memory (LSTM)	Various lung CT images	-	cy 96.2%
Bai et al. (2020)	Image partition, slicing and Efficent NetB4	Confidential database	521 COVID-19 and 665 other lung infection cases	96%
Dey et al. (2020)	ROI partition and feature extraction and KNN	COVID-19 CT partition database (Radiopeadia)	200 COVID-19 and 200 healthy cases	87.8%
Farid et al. (2020)	Feature extraction, feature choice using composite ensemble scheme and CHFS-Stacked (jrip, random forest) with naive bayes classification	Kaggle repositories	51 COVID-19 cases	96.1%
Xu et al. (2020b)	Image quantization, slicing and 3D DenseNet	Confidential database	432 COVID-19, 76 viral influenza, 350 bacterial pneumonia and 418 healthy cases	_
Yan et al. (2020)	Image conversion, regularization and multi-scale CNN	Confidential database	206 COVID-19 cases and 412 healthy cases	98%

Ozkaya et al. (2020)	Feature extraction using pre-trained VGG- 16, GoogleNet and ResNet-50, feature merging fusion, scoring and SVM classifier	Italian Society of Medical and Interventional Radiology	53 COVID-19 cases	98.3%
Peng et al. (2020b)	DenseNet121	Images accumulated from PMC	606 COVID-19, 222 penumonia and 397 healthy cases	-
Pu et al. (2020)	Image augmentation and 3D CNN	Confidential database	498 COVID-19 and 497 CAP cases	99%
Song et al. (2020)	BigBiGAN	Confidential database	98 COVID-19 and 103 healthy cases	-
Sharma (2020)	Feature extraction and ResNet	COVID-CT images accessible from GitHub	800 COVID-19, 600 viral influenza and 800 healthy cases	91%
Wu et al. (2020)	ROI partition, slicing and multi- view merging ResNet150	Confidential database	368 COVID-19 and 127 influenza cases	76%
Wang et al. (2020b)	Image conversion, ROI partition and prior attention-66 framework	Confidential database	1,315 COVID-19, 2,406 ILD and 936 healthy cases	93.3%
Li et al. (2020c)	Image preprocessing, image augmentation and 3D ResNet18	Mulitple clinical institutions	251 COVID-19, 869 pneumonia and 1,475 healthy cases	-
Raajan et al. (2020)	Regularization and ResNet16	Open clinical Github libraries	216 COVID-19 and 1,341 healthy cases	95.1%
El Asnaoui et al. (2020)	Color regularization, Dynamic histogram equalization, Inception, ResNetV2 and DenseNet201	COVID-19 X- ray scan dataset created by Cohen JP	2,780 bacterial influenza,231 COVID-19 and1,583 healthy cases	92.2% (Inception-ResNetV2) 88.1%(DenseNet201) ResNetV2) 88.1% (DenseNet201)
Kang et al. (2020)	Regularization and NN	Various quarantine rooms located in China	1,495 COVID- 19 and 1,027 Community-Acquired Pneumonia (CAP) cases	94%

Rajaraman et al. (2020)	Preprocessing and In-cptionV3	Twitter and Montreal COVID-19 CXR databases	313 COVID-19 and 7595 pneumonia cases	99%
Li et al. (2020a)	ROI partition using U-net and COVNet	Confidential database	1,296 COVID- 19 and 1,735 CAP cases	- 91%
Harmon et al. (2020)	ROI partition, im-age augmentation and ensemble 3D DenseNet121	Confidential database	386 COVID-19 and 1,011 non- COVID-19 cases	
Jaiswal et al. (2020)	Image augmentation and DenseNet201	SARS-CoV-2 CT im-age database	1262 COVID- 19 and 1,230 healthy cases	96.3%
Lessmann et al. (2020)	Quantization, reg-ularization and CORADS-AI	ICU in the Nether-lands	237 COVID-19 and 606 healthy cases.	-
Alsharman et al. (2020)	Binarization, im- age conversion and GoogleNet	COVID-19 database	-	82.1%
Aswathy et al. (2020)	Thresholding, texture-based fea-ture mining, CNN	National Cancer Insti-tute and the Cancer Image Archive	1763 healthy and 63 pneumonia cases	99%
Sakagianni et al. (2020)	Automated ML cloud vision	COVID-19 jour-nal collected from MedRxiv and BioRxiv	349 COVID-19 and 397 healthy cases	-
Wang et al. (2020c)	ROI partition and COVID-19Net	Confidential COVID-19 CT image databases	754 COVID-19, 271 bacterial influenza, 29 viral influenza and 42 healthy cases	78.3%
Barstugan et al. (2020)	Feature extraction and SVM	Italian Society of Medical and Interven-tional Radiology	150 COVID-19 cases	98.8%
Singh et al. (2020a)	Multi-objective differ-ential evolutionary-based CNN	COVID-19 CT images	-	90.2%
Yu et al. (2020)	DenseNet201 with cu-bic SVM	Confidential database	202 COVID-19 cases	95.2%
Hu et al. (2020a; 2020b)	Image augmentation and CNN	Quarantine rooms of Wuhan Red Cross Community	150 COVID-19, 150 pneumonia and 150 healthy cases	96%
Song et al. (2020)	ROI partition, feature extraction using NN	Renmin Hospital of Wuhan University	88 COVID-19 cases	86%

Jin et al. (2020b)	ROI partition using U-Net and ResNet152 classifier	3 open CT image repositories	1,502 COVID- 19, 83 influenza-A/B, 1,334 CAP, 258 healthy cases	_
Warman et al. (2020)	Image augmentation and YOLOv3 frame-work	Open libraries	606 COVID-19, 224 viral influenza and 74 healthy cases	97%
Chen et al. (2020)	Image preprocessing and deep learner structure	Confidential database	51 COVID-19 and 55 healthy cases	95%
Butt et al. (2020)	Image preprocessing and 3D CNN	-	110 COVID-19 and 399 healthy cases	-
Wang et al. (2020d)	ROI partition, fea-ture mining using TL, completely linked net-work, mixture of de-cision tree and Ad-aBoost	Confidential database	44 COVID-19 and 55 pneumonia cases	83%
Xu et al. (2020a)	Image preprocessing and 3D CNN- based ROI partition	Confidential quaran-tine rooms in China	110 COVID-19, 224 influenza- A and 175 normal patients	87%
Bridge et al. (2020)	Generalized extreme value activation factor and Inception V3	COVID-CT- database	30 COVID-19 and 1,919 healthy cases	100%

3. CONCLUSION

This research work focuses on the latest deep learner-based recognition and prognosis of COVID-19 in which lung CT images have been used to identify and classify the COVID-19 Pneumonia with high accuracy. In the first phase of this research work, the TL mechanism is proposed for modifying the deep learner structures, achieving better learning and testing efficacy. In this mechanism, the pre-trained deep learner structures include ResNet18, Xcep- tion, InceptionV3, DenseNet121 and MobileNetV3 are employed as the building blocks for few particular proceses rather than executing the time-consuming learning by the random initial weights. Therefore, it supports to save the considerable power required for designing deep learner frameworks for COVID-19 classification and diagnosis problems.

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