Deep Learning Algorithms for Diagnosing Covid 19 Based on X-Ray and CT Images

Original Scientific Paper

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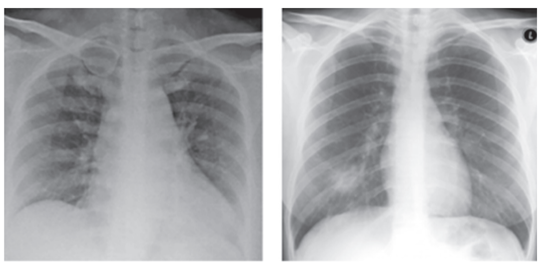
Abstract *– An outbreak of a highly pathogenic coronavirus, which can cause chronic respiratory illness and high mortality rates. It takes a considerable amount of time to perform the polymerase chain reaction (PCR) used in COVID tests. Its accuracy ranges from 30% to 70%. In contrast, CT and chest X-ray diagnostics are 98% and 80% accurate in detecting COVID, respectively. A deep learning algorithms was applied to CT and X-ray images to enable rapid and accurately diagnosis of COVID-19 within seconds. In this survey, we revised all state-of-the-art studies of COVID-19 based on CT and X-ray images. Also, we analysed multiple deep learning networks and compared the performance of each technique. The result of the comparison shows that the baseline neural network has better efficiency in the recognition of COVID-19. The detection accuracy of baseline networks ranges between 93% and 98.7%. This shows the efficiency of deep learning techniques in identifying COVID-19.*

Keywords*: COVID-19, chest X-rays, CT scans, deep learning networks*

1. INTRODUCTION

The onset of the once-in-a-century pandemic coronavirus or SARS-CoV in Wuhan, China, spread its roots within a split second and triggered the global issue. According to Global Statistics, over 2.3 billion pathological cases and 4.8 million deaths were recorded across 188 nations and territories as of October 1, 2021. COVID-19 is a infectious disease that is spread by the physical contact of an infected person, saliva droplets, and sometimes airborne [1]. It suppresses the immune system and causes serious respiratory disorders. The standard Polymerase chain reaction (PCR) test for the diagnosis of COVID-19 has only 30 to 70% efficiency and it consumes time. Modern diagnostic tools such as computed tomography (CT) and Chest X-ray also have effective results on Covid-19 [2]. Early detection of the syndrome and infection level prevents the severity, increases the recovery phase and particularly reduces the further spread of infection. Implementation of the deep learning technique in medical diagnosis allows the creation of approaches from beginning to end without the need for manual intervention, yielding predictable outputs from input data [3-5]. For recognizing suspected instances of the coronavirus, computer vision studies use DL techniques like convolution neural network (CNN), recurrent neural network (RNN), and supervised and semi-supervised models to classify the CT images or chest X-rays of the chest as normal or abnormal. Herein, CNN models such as ResNet, Mobile Net, LeNet, and some other backbone techniques such as VGG, inception, and Xception structures have shown extremely accurate performance in the areas of image identification and computer vision detection [6]. They are often used for computer vision tasks. CNN [7, 8], COVID Screen [9], and COVINet [10] are some of the deep learning networks that have been designed for identifying COVID-19 occurrences. Fig. 1. illustrates the difference between positive and negative COVID-19 chest X-ray images.



(a) (b)

Fig. 1. Chest X-Ray images of Covid-19 (a) positive, and (b) negative

Deep learning networks require adequate data to train, process, and classify the input image. In the field of medical image processing, in which there is only a finite amount of information available, that results in an insufficient training database. To solve this issue, the transfer learning methodology was established. [11, 12], employed transfer learning to train the model with minimal trials by transferring data from a previously trained network to a newer model for evaluation. Integration of AI with chest X-ray technology has latterly been proven to be more successful in detecting this problem. The models used for the analysis were ResNet, InceptionV3, InceptionResNetV2, VGG16, Mobile Net, Xception, and DenseNet121, which were fine-tuned through a new batch of layers substituted by the network's head. But most of the deep learning networks fail in the execution process. The pitfalls of deep learning and its execution failures are discussed in.

The main aspect of this work is to analyze all the up-to-date DL techniques based on the COVID-19 diagnosis. All the recent deep learning studies on the Covid-19 using chest X-rays and CT scans are reviewed with a detailed view of existing techniques along with their drawbacks. The key focus of the review is elaborated as follows:

- To study all advanced deep learning networks on predicting COVID-19 infection, particularly from CT and chest X-ray images.
- To present a detailed view of different data sources reliable on Covid-19.
- To discuss the challenges faced by the recent learning structure both in the training and testing process.
- To provide a future guideline for overcoming existing limitations and designing an effective system for detecting COVID-19 infection.

The remainder of this study is arranged as follows; section II explains a detailed study of COVID-19 datasets. Section III narrates a detailed description of deep architecture. Section IV comprises the comparison study and tabulation of up-to-date deep learning techniques on COVID-19, especially using CT and chest X-ray images on Covid infection. Section V explains the discussion of the survey, and the conclusion part is stated in section VI.

2. DATASET

A detailed study on the COVID-19 dataset is described in this section. Data harmonisation is the process of combining data from various sources such as CT scans and X-rays into a single cohesive data set by modifying data formats. It covers most of the reliable datasets on COVID-19. The COVIDx-CT dataset is significantly large. The data is obtained from the CNCB. It is limited to data from China's various provinces, implying that COVID-19 symptoms in CT imaging may not be appropriate for instances outside of China. The GitHub dataset comprises about 1140 normal and abnormal images of Covid-19 infection. The dataset includes bacterial, viral, Chlamydophila, E. coli, fungal, COVID, Influenza, Klebsiella, Legionella, Lipoid, MERS, Mycoplasma, No Finding, Pneumocystis, pneumonia, SARS, Strecoccus, Varicella, and viral infection images. There are two perspectives for COVID images: PA and AP views. The normal images were collected from the Kaggle website's Pneumonia dataset. There are more than 500 images, but they must be counted in the same way as COVID images.

Table 1. Dataset description

Datasets	Total images	Attributes (Patients / Age)	Classes	Severity level (positive class)
COVIDx-CT	201,103	3,745/ 18-80	Negative (100548) Positive (100555)	Normal-PCR+:9568 Mild:25137 Moderate:50274 Severe:15568
RSNA pneumonia CXR challenge	30,227	1546/ 3-35	Negative (15115) Positive (15112)	Normal-PCR+:945 Mild:3778 Moderate:7556 Severe:2833
Chest X-ray8	32,717	5428 / 20-45	Negative (16360) Positive (16357)	Normal-PCR+:661 Mild:4564 Moderate:8178 Severe:2954
MIMIC-CXR	377,110	65,379/ 25-60	Negative (188,555) Positive (188,555)	Normal-PCR+:19064 Mild:53569 Moderate:80138 Severe:35784
PadChest	160,000	67,000/ 18-55	Negative (15115) Positive (15112)	Normal-PCR+:871 Mild:3778 Moderate:7523 Severe:2940

COVID-19 ImageData Collection is the primary source for the COVID-19 class. It has 76 good and 26 negative PA perspectives. Most research use CXR from one or more public pulmonary illness data sets to create non-COVID classes. The following are some examples of these repositories: On Kaggle, one can find the RSNA Pneumonia CXR challenge dataset, Dataset ChestX-ray8, MIMIC-CXR dataset, PadChest dataset. Multiple kinds of research have demonstrated that better data leads to better models. All pre-processing procedures that raise the value and validity of data are referred to as smart data. These tactics include noise reduction, data augmentation, and data transformation.

3. MATERIALS AND METHODS

In this section, we have discussed the existing deep learning techniques developed during the past two years for the detection of Covid-19 infection and the diagnosis process. The analysis discusses the architectural modification and structural implementation of neural networks in the case of covid-19 diagnosis. The following networks were some of the recently developed deep learning architectures which show remarkable efficiency in covid-19 prediction.

3.1 DEEP LEARNING

Deep learning (DL) and machine learning (ML), two important AI disciplines, has recently sparked a lot of interest in medical applications. Some of the DL systems are designed using a pre-trained model that employs transfer learning, while others utilize custom networks. Machine learning and data science are also frequently employed in the disciplines of coronary diagnosis, prognosis, prediction, and epidemic forecasting. The intensity of the epidemic has also been reduced because of computer vision [29]. A DL model that is both dependable and accurate could be utilized as a triage tool and to assist in clinical decision-making. A widening number of recent studies assert to have attained remarkable sensitivity levels of > 95%, considerably higher than competent radiologists. In the modern environment, CNN is the main factor in exhibiting remarkable performance in the field of medical image analysis. ResNet, Xception, Inception, DenseNet, GoogleNet, and other CNNs are among the most useful. By extracting characteristics from the CXR images, the DL technique was able to distinguish between normal, pneumonia, and COVID-19. Because it is lightweight, the equipment required for this test is less cumbersome and portable. This sort of resource is more often accessible than necessary for RT-PCR and CT-scan testing. Furthermore, a patient's chest X-ray takes only 15 seconds, making it one of the most cost-effective and time-efficient evaluation techniques. The CNN is a deep learning network with ResNet, Mobile Net, LeNet and some other backbone techniques such as VGG, inception and Xception structures has developed multiple neural networks to detect the Covid infection and yields effective progress. The basic architecture of the CNN model is depicted in Fig. 2. Internet of Things (IoT), big data, and smart technologies are also effective in combating the spread of COVID 19.

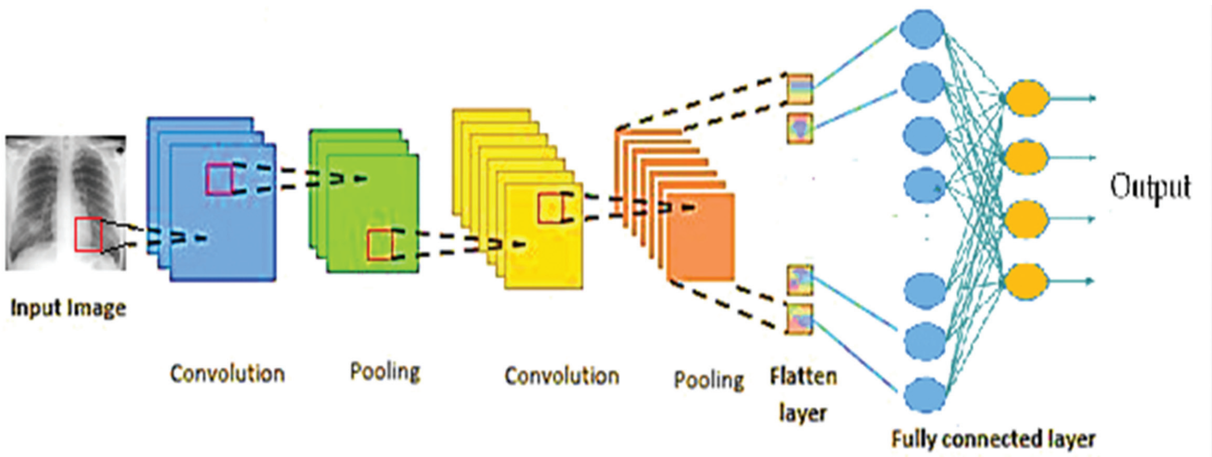


Fig. 2. Basic architecture of deep learning network

CNN can learn hierarchic characteristics, an essential trait, automatically. The initial several CNN layers frequently identify fundamental characteristics like horizontal, vertical, and diagonal borders. The output of these layers is transmitted to the intermediate layers, which extract more advanced characteristics like corners and edges. This implies that the characteristics calculated by the initial layers are generic and may be used for a range of issues, while the characteristics calculated by the latter layers are particular to the given dataset and tasks. CNN offers an important benefit from the need for a reduced number of neurons and hyperparameters compared with conventional feed-in neural networks. Several CNN baseline designs have been created and effectively used to solve complicated visual imaging tasks for image recognition applications. In this work, we opt to construct suggested models with pre-trained models like VGG16, InceptionV3, and Xception.

VGG 16 Net

A standard object-cognition model with up to 16 layers is the VGG16 Object-cognizing model. ImageNet performs VGG16, a deep CNN, on a variety of tasks and datasets. VGG16 is one of the most commonly used imaging models today. We thus suggest that this model be used.

Inception V3

InceptionV3 was one of the earliest batch standardization models. It also used the factorization method for more efficient calculations. InceptionV3 will parallel operations and execute convolutions and batch normalization in parallel before the results are concatenated instead of linearly performing processes, with additional parameters and complexities. InceptionV3 enables advanced treatment with directed acyclic graphs.

Xception

Xception is a CNN completely made of convolutionary layers, which are profoundly separate. Xception combines ResNets with a profoundly separable convolution to produce a light yet highly powerful network. Xception achieved greater precision than InceptionV3 with the ImageNet dataset. Table 2. shows the performance analysis of a pretrained deep learning networks on the Covid dataset.

Table 2. Performance analysis of pretrained deep learning model on Covid Chest X-ray 8 dataset.

Models	Labels	Precision	Sensitivity	Specificity	F1-score	Accuracy (%)
DenseNet121	Normal	0.93	1	1	0.96	97
	Pneumonia	1	0.92	0.96	0.96	
	COVID	1	1	1	1	
Xception	Normal	0.91	1	1	0.95	96
	Pneumonia	1	0.90	0.95	0.95	
	COVID	1	1	1	1	
MobileNetv2	Normal	0.91	1	1	0.95	95
	Pneumonia	1	0.86	0.93	0.92	
	COVID	0.95	1	1	0.98	
ResNet50v2	Normal	0.86	1	1	0.93	94
	Pneumonia	0.98	0.84	0.92	0.90	
	COVID	1	0.98	0.99	0.99	
NASNetMobile	Normal	0.86	0.98	0.99	0.92	93
	Pneumonia	0.95	0.84	0.92	0.89	
	COVID	1	0.98	0.99	0.99	
VGG19	Normal	0.83	0.98	0.98	0.90	92
	Pneumonia	0.96	0.86	0.93	0.91	
	COVID	1	0.90	0.96	0.95	

4. RESULT AND DISCUSSION

This section compares the available Covid infection approaches using CT and X-ray imaging in detail.

4.1 RESULTS OF PROPOSED MODELS

The functionality of the pretrained CNN models generated in this research is assessed. The experiments have been carried out with the tuned hyper-parameters are depicted in table.3, which produced the better results during training. Table 3 mention the comparison details of the existing baseline technique based on model size, training and inference time.

Table 3. Comparison of baseline technique based on model size, training time and FPS

Model	Parameters	Model Size	Training Time	FPS
U Net	31.07M	118.24MB	51min	1.88
E Net	343.7K	1.33MB	15min	4.03
U Net ++	9.16M	34.95MB	58min	1.81
Attention U Net	34.87M	133.05MB	63min	1.75
ANAM-Net	4.47M	17.21MB	27min	2.76

In terms of sensitivity, accuracy, and specificity. Anam-Net outperformed the better outcomes. On the other hand, UNet++ has a vast dense connection, which results in hierarchical encoder-decoder modules that enable efficient feature propagation for accurate segmentation. When compared to other models, the proposed Anam-Net with fewer parameters was able to provide reliable segmentation results. In the cross-data set assessment, Anam-Net did quite well (second best), as shown in Fig. 3, and was similar to the highest performing technique.

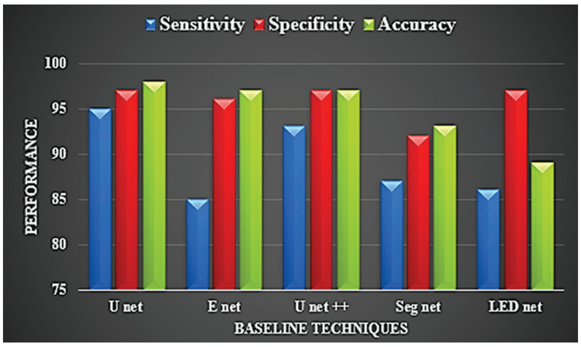


Fig. 3. Comparison of various baseline techniques based on sensitivity, specificity and accuracy based on COVIDx-CT dataset

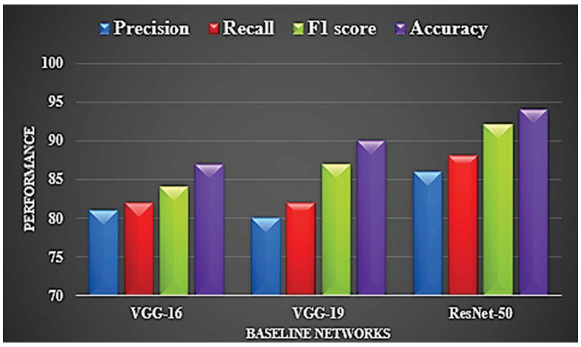


Fig. 4. Comparison of baseline technique based on precision, recall, F1 score and accuracy based on COVIDx-CT dataset

Necessity of DL in CXR

To diagnose COVID-19, many researchers and practitioners have relied on simple radiographic imaging or X-rays. Nonetheless, these images lack the requisite resolution and precision to diagnose COVID infection in the initial stage and they have some drawbacks in this regard. As a result, AI researchers went to the aid of medical specialists and deployed DL as a potent tool to progress the accuracy rate of COVID-19 detection using X-rays. The below figure 5. depicts the rate of using different radiological techniques for diagnosis and detection of COVID-19.

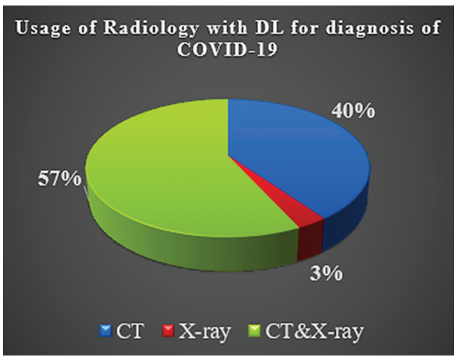


Fig. 5. Rate of using DL accompanied radiology

This showed that a greater proportion of persons will need to be examined in short durations by a few professionals with limited resources. The uniform database encompasses all severity levels, from normal with Positive RT-PCR to Mild, Medium, and Extreme. The performance measure for SD-Net on various Chest x-ray databases is listed in Table 4. And Table.5 represents the efficiency of the hybrid network and baseline network in Covid-19 classes based on CXR images respectively. Fig.6. represents the efficiency rate of CNN models in COVID-19 images.

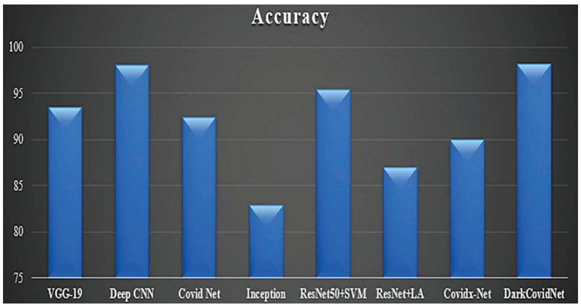


Fig. 6. Accuracy rate of CNN architectures of radiology modality images of COVID-19.

Table 4. Comparative analysis of hybrid Model based on CXR images

Metric	Sensitivity	Specificity	Precision	Accuracy
COVID Net-CXR	69.12	88.23	4.56	72.1
COVID-CAOS	74.89	65.12	68.56	69.56
RES Net without segmentation	68.63	80.23	75.23	79.25
RES Net with segmentation	2.01	79.34	78.52	75.89
FuCiT Net	78.94	81.56	76.01	77.23
COVID –SD Net	80.04	89.56	79.74	80.12

Table 5. Performance evaluation of five-fold cross-validation for Covid -19 classes based on CXR images

Model	Sensitivity	Specificity	Precision	F1-score
COVID-CAPS	0.953	0.351	0.710	0.822
COVID-CAPS (focal)	0.962	0.231	0.664	0.781
COVID-CAPS scaled	0.921	0.542	0.763	0.831
COVID-CAPS scaled (focal)	0.994	0.363	0.674	0.812
POCOVID-Net	0.882	0.764	0.852	0.873
POCOVID-Net (focal)	0.881	0.792	0.861	0.873
Mini- COVIDNet	0.923	0.684	0.821	0.863
Mini-COVIDNet (focal)	0.921	0.712	0.832	0.874
MobileNet-v2	0.964	0.612	0.813	0.881
MobileNet-v2 (focal)	0.912	0.643	0.813	0.860
NASNetMobile	0.921	0.494	0.734	0.822
NASNetMobile (focal)	0.952	0.521	0.751	0.842
ResNet50	0.841	0.572	0.761	0.801
ResNet50 (focal)	0.952	0.472	0.742	0.832

Table 6. Comparison of different frameworks for COVID-19 prediction on the X-RAY images

Author & year	Dataset	Data description	Preprocessing method	Network model	Partitioning	Validation results
Dong, S., et al [14](2021)	Public CXR dataset (COVIDx)	15134 (Normal-8851Pneumonia-6045COVID-19-238)	-	RCoNet	5-fold cross validation	Accuracy-92.98% Sensitivity-93.39% Specificity-93.51%
Tabik, S.,[15] (2020)	COVIDGR-1.0	Normal-426 COVID-19-426	Segmentation-based cropping, class-inherent transformation network (to increase the discrimination capacity)	COVID-SDNet	Traning-80% Testing-20%	N- specificity-80.79±6.98, N- precision-74.74±3.89, N- FI-76.94±2.82 p- sensitivity-72.59±6.77, p- precision-78.67±4.70, p- FI-75.71±3.35 Accuracy-76.18±2.70
Wang, L et al., [16](2020)	COVIDx 1.0, RSNA pneumonia detection challenge dataset	13800(Normal-8066,Pneumonia-5538,COVID-358)	-	COVID-Net	Training-98% Testing-2%	Sensitivity-80% Accuracy-92.6% Precision-88.9%
Ozturk, T et [17] al.,(2020)	chestX-ray8 data base,covid-19 X-ray image	Normal -500Pneumonia-500Covid-19-127	-	Dark covidnet	5-fold cross validation	Accuracy-95.13% Precision-98.03% Specificity-95.3% Sensitivity-85.35% FI-score- 96.51%
Ohata, E.F et al.,[18](2020)	Kaggle COVID-19 in X rays	Healthy-194 Covid-19-194	Transfer learning	Mobile net+SVM Densenet201+MLP	10-fold cross validation	mobilenetAccuracy&FI-score-98.5% densenetAccuracy&FIscore-95.6%

Author & year	Dataset	Data description	Preprocessing method	Network model	Partitioning	Validation results
Oh, Y., et al [19] (2020)	CXR dataset, JSRT,NLM	502(normal-191, bacterial-54, tuberculosis-57, viral-20, COVID_19-180)	Data augmentation via batchextraction	Densenet-103 Resnet-18	80%-training 20%-testing	Accuracy-91.9%,
Horry et al.,[20](2020)	COVID-19 X-ray image database, NH chest X-ray	400(COVID-19-100, pneumonia-100, normal-200	Equalization of sampling bias, segmentation-based noise reduction, data augmentation	VGG16, VGG19, Resnet50, Inception v3, Xception	Training 80% Tesing-20%	Sensitivity=80 Precision-83 FI-score-80
Panwar H et al., (2020)[21]	Chest xray data set	337(covid-19-192)	Resize the image, data augmentation	nCOVnet	70% - training 30%- testing	Accuracy-97%
Toğaçar, M [22] (2020)	Joseph Paul Cohen dataset, Kaggle	458(Covid-19-295, normal-65, pneumonia-98)	Fuzzy color technique	MobileNetV2, SqueezeNet	5-fold cross validation	Accuracy=98.25% FI-score-93.48
Hussain E [23] (2021)	Covid-R	7390 (Covid-19-2843Normal-3108, Pneumonia-1439)	Generating dataset	CoroDet	5-fold cross validation	2-class acuuracy-91.1% 3-class accuracy-94.2% 4-class accuracy-91. %
Jain, R (2021) [24]	Kaggle	6432 (583-normal, 576-covid-19,4273-pneumonia)	-	Inception V3, Xception Net,ResNeXt	90%testing, 10%validation	Accuracy-97.97%
Haghanifar, A (2020)[25]	NH CXR-14	CAP-4600, Normal-5000, COVID-19-780	Image augmentation, enhancement algorithm	COVID-CXNet	-	Accuracy-96.72%
Hemdan, E.E.D et al (2020)[26]	Public dataset of X-ray	50 (25-normal, 25-COVID-19	One-hot encoding	COVIDX-Net	80%-20%	Inception v3-50%, VGG19 &DenseNer201-90% MobileNetV2-60%
Basu, S.,et al(2020) [27]	NIH Chest X-ray Dataset,	Data A (normal-350, pneumonia-322, other-disease-300, Covid-305) Data B (57560, diseased-50819)	Domain Extensive transfer learning	CNN	5-fold cross validation	Accuracy-90.13%±0.14
Ouchicha, C(2020)[28]	Kaggle's COVID-19 Radiography Database	Pneumonia-1345, COVID-19-219, normal-1341	Cropping and resizing	CVDNet	K fold cross validation	Accuracy-97.02%
Gupta, A2021[29]	Kaggle, Chest X-ray dataset	COVID-19-316, normal-1341, pneumonia-1345	Fuzzy color image enhancement, stacking	InstaCovNet-19	80%-20%	3-class Accuracy-99.08%
Rajaraman, S (2020)[30]	Pediatric CXR dataset, RSNA CXR dataset, Twitter COVID-19 CXR dataset, Montreal covid-19 car dataset	-	Lung segmentation, Median filtering, rescaling	VGG-16, VGG-19, Inception-V3	90%-10%	Accuracy-99.01% AUC-95%

Table 7. Comparison of different approaches for COVID-19 detection on the CT images

Author& year	Dataset	Data description	Preprocessing method	Network model	Partitioning	Validation results
Farid et al [31] (2020)	Kaggle benchmark dataset	102(COVID-19=51, SARS=51)	Feature extraction	CNN	10-fold cross validation	Accuracy=94.11% Precision-99.4% FI-score-94% AUC=99.4%
Gunraj, H.,[32] (2020)	COVIDx-CT Dataset	Total-104009	Data augmentation	COVIDNet-CT	-	Accuracy-99.1% Sensitivity-98.76% Specificity-99.53%
Yazdani, S et al., (2020) [33]	COV-2 CT scan dataset	2482 (COVID-19-1252, normal-1230)	Data augmentation	COVID CT-Net	-	For 0.9 threshold Sensitivity- 0.850±0.002 Specificity = 0.962 ± 0.001 FI score = 0.900 ± 0.001

Author& year	Dataset	Data description	Preprocessing method	Network model	Partitioning	Validation results
Zheng et al (2020)[34]	Three different hospitals (Union hospital, Tongji Medical college, Huazhong University of science and technology)	Total-630	Lung segmentation, data augmentation	DeCoVNet	Traning-80% Testing-20%	Accuracy=90.1% Sensitivity=90.7 Specificity=91.1 Precision=84 NPC=98.2 AUC=93
Wang, S., etal(2021)[35]	3 different hospitals	259 (pneumonia-180,79-SARS-COV-2)	ROI separate, background area filling, reverse color, grayscale binarization	M- inception	Traning-80%, Testing-20%	Accuracy-89.5% Sensitivity-88% Specificity-87%
Fan, D.P., etal (2020)[36]	COVID-SemiSeg	638 (285 -normal, 353 –COVID-19)	Data augmentation	INF-Net	Training-50%, Testing-50%	Sensitivity-87% Specificity-97% Precision-50%
Zhou, T., (2021) [37]	previous publications, authoritative media reports, and public databases	2933	Resize	Ensemble CNN	5-fold cross-validation	Alexenet accuracy-98.16 Alexnet accuracy-98.16 Googlenet accuracy-98.25
Ni, Q., (2020) [38]	Individual patient,	12291 (COVID-193854, Pneumonia-6871, Normal-8566)		MVP-Net, 3D U-Net		FI score-97% Sensitivity-95%

4. 2 DISCUSSIONS

The aim of the study is to review and present various prominent COVID-19 diagnostic techniques based on CT and chest X-ray images. Although many of the characteristics described in the related works are emphasised here, some limits still required to be considered in future studies. Initially, the COVID-19 deep-learning diagnostic systems have been presented, but no underlying knowledge descriptions of deep-learning methods highlighting mathematical evaluations are provided. This work takes on a degree of domain expertise. Secondly, several features of the studied neural networks are not addressed here, especially for custom designs, such as layer numbers, layer speciation, study rate, epoch number, lots size, dropdown layer, optimization, and loss function. Third, while this study examines diagnosis COVID-19 from a computer viewpoint, this paper does not give qualitative diagnostic results in CT scans with chest X-rays. The study aims to evaluate and provide many well-known diagnostic methods for COVID-19 based on CT and chest X-ray images. Although many of the features were discussed in this study are stressed, some restrictions still need to be considered in future studies. First of all, COVID-19 deep-learning diagnostic tools are described, but no basic explanations of deep-learning processes are offered that emphasise mathematical representations.

5. CONCLUSION

As mentioned above, early detection and the DL method for COVID-19 are the fundamental stages in avoiding sickness and reducing the complexity of the infection. The addition of DL algorithms to radiological equipment increases computation speed with a low cost and efficient diagnosis. Implementation of these efficient tools reduces human error and predicts accurate results in critical cases. This review supports the concept that DL algorithms are a potential method in which diagnostic and therapeutic processes might be optimised and improved. Despite of deep learning is the most effective computational tools for pneumonia diagnosis, in particular COVID-19, the development of COVID-19 DL diagnostic techniqu4s should be careful to prevent overfitting and optimise the generalisation and utility of deep learning models.

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