Journal of Molecular and Pharmaceutical Sciences

Review

COVID-19 Diagnosis Empowered with Deep Semi-Supervised Learning Techniques Using X-Ray and CT Images

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Abstract

Background: The early detection and diagnosis of COVID-19 and the accurate separation of non-COVID-19 cases in a quick and cheap manner are among the main challenges in the COVID- 19 pandemic to ensure recovery treatment for patients which will help to save patient's lives. Deep learning techniques proved themselves to be a novel prediagnostic detection methodology of COVID-19. In particular, the deep supervised learning has successfully applied to analyse and detect COVID-19 on chest X-ray and CT scan images. However, the performance of such models is heavily dependent on the availability of a large labelled dataset. This is often a limitation because the creation of which is a very expensive and time consuming task, and especially imposes a great challenge for a novel disease. Semi-supervised learning has shown the ability to improve the detection accuracy of supervised models whilst requiring a small labelled datasets. This makes the semi-supervised an interesting alternative of significant practical importance for identifying COVID-19. **Material and Methods:** The present systematic review was conducted by searching the three databases of PubMed, Web of Science and Science Direct from December 1, 2019, to May 15, 2022, based on a search strategy. A total of 392 articles were extracted and, by applying the inclusion and exclusion criteria, 33 articles were selected as the research population. **Result:** In this study we reviewed studies which used deep semi-supervised learning methods on chest X-ray images and CT scans for the detection and diagnosis of COVID-19 and compared their performance. According to the findings, deep semi-supervised learning-based models are able to improve the diagnostic accuracy and robustness without exhaustive labeling. **Conclusion:** The application of deep semi-supervised learning in the field of COVID-19 radiologic image processing facilitates an accurate and reliable diagnosis. The use of deep learning technology and semi-supervised learning paradigm in the detection and diagnosis for COVID-19 reduce false-positive and negative errors, leading to an improved patient care and management.

Keywords:
COVID-19, Deep Learning, Semi-supervised Learning, Detection, Diagnosis, X-ray images, CT scan.

*Received October 17, 2023; accepted December 17, 2023

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Cited as: Bahi M, Boufenara M.N. COVID-19 Diagnosis Empowered with Deep Semi-Supervised Learning Techniques Using X-Ray and CT Images. J. Mol. Pharm. Sci. 02 (02), 2023, 39-58.

1 Introduction

The World Health Organization (WHO) declared that new coronavirus disease 2019 (COVID-19) was a Public Health Emergency of International Concern on January 30th 2020. COVID-19 is a viral disease that causes serious pneumonia and impacts our different body parts from mild to severe depending on patient's immune system. Researchers across the globe are working round the clock to find solutions and design strategies to control the pandemic and minimize its impact on human health and economy [1].

The early identification of COVID-19 cases is momentous as it not only helps start treatment of the cases immediately, but also facilitates containing the virus by isolating the patient from other humans. The current gold standard for identifying the positive cases of COVID-19 is based on a molecular test of the reverse transcription polymerase chain reaction (RT-PCR). It is aimed at detecting the RNA of the virusin respiratory samples such as nasopharyngeal swabs or bronchial aspirate. However, this test can take up to 2 days to complete, serial testing may be required to rule out the possibility of false negative results and there is currently a shortage of RT–PCR test kits. Therefore, there is still an urgent need for alternative efficient diagnostic methods that enable rapid and accurate testing of COVID-19 positive patients. Diagnosing COVID-19 based on medical imaging can be a reliable and accurate alternative, and is still under exploration. Several early works have reported that the sensitivity of the chest Computed Tomography (CT) and the chest X-ray imaging are noticeably greater than that of the RT-PCR test at the initial representations of the disease, making them great candidates for developing new and sophisticated methodologies for analysis and classification of COVID-19 cases [2]. Transmission of an X-ray digital image does not require transferring from the access point to the analysis point, so the diagnostic process is performed very quickly. Chest radiography is convenient and fast for medical triaging of patients. Chest CT scans and X-ray images have been reported to have sensitivity values of 98% and 69%, respectively [3]. Unlike, CT scans, X-ray imaging requires less scarce and expensive equipment, so significant savings can be made in the running costs. COVID- 19 detection by using CT scan and X-ray images is possible by manual interpretation of images expert radiologists. However, interpreting and analyzing these images might encounter some problems leading to reduced sensitivity. Moreover, it can be a time consuming and daunting task, especially when manually quantifying the infected regions on the CT scan and X-ray images. To cope with these limitations, there is a pressing need to develop intelligent algorithms to accurately and automatically detect COVID-19 cases using radiological images. As an accurate technique, deep learning has gained the attention of both clinicians and researchers for COVID-19 diagnosis. It is able to identify abnormal patterns of CT and X-ray images. Using this technique, it is possible to assess certain segment regions and take precise structures in chest CT images facilitating diagnostic purposes [5]. Deep Learning methods have been shown to detect COVID-19 and distinguish this condition from community-acquired pneumonia and other non-pneumonia lung diseases [6].

The bulk of literature addressing the task of classifying CT scans and X-ray images for COVID-19 is largely based on deep supervised learning e.g. [7], [8], [9], [10], requiring extensive data annotations by experts. However, it is fairly hard to acquire a large-scale dataset for COVID-19 with accurate labels in regard to the shortage of radiologists in clinics, the emergency of the disease, and etc. Therefore, by using deep supervised learning techniques are prone to labelling error and uncertainty that adversely affect the classification output. Semi-supervised is an attractive alternative approach when strong annotations are hard to come by, enabling the use of labeled and unlabeled data in a cooperative manner to improve model accuracy. The amount of unlabeled data keeps increasing in medical imaging. Semi-supervised learning provides a way to utilize the unlabeled data without the cost of data annotation, which is a bottleneck of the technical advance. Semi-supervised modelling can not only reduce the cost of data annotation, but also help in discovering hidden patterns and relations in the data [2]. Moreover, semi-supervised learning can easily be adapted for mutations of the virus at a later stage, with relatively small labelled samples.

In this study, we reviewed studies which used deep semi-supervised learning methods on chest X-ray images and CT scans for the purpose of COVID-19 diagnosis and compared their performance. To the best of our knowledge, this is the first time a COVID-19 deep semi-supervised learning review is presented.

2 Materials and Methods

This systematic literature review followed the guidelines of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework for preparation and reporting [11].

2.1 Literature Search Strategy

The search of the present review was conducted on three databases of PubMed, Web of Science and Science Direct for all the articles relevant to the scope of our research question from December 1, 2019 till May 15, 2022. Many queries were used to enhance the search-related quality to various deep semi-supervised learning techniques for detecting COVID-19 using CT scan and X-ray images. The Keywords were searched using Boolean operators "OR/AND." The search terms were as follows: (a) PubMed database search code is TOPIC: ((“Coronavirus” OR “COVID-19”) AND (“Detection” OR “diagnosis” OR “classification”) AND

(”CT-scans” OR ”X-Ray”) AND ”Deep semi-supervised learning”); (b) Web Of Science database search code is TOPIC: ((“Novel Coronavirus” OR “COVID-19” OR “coronavirus” OR “2019-nCoV” OR “new coron- avirus” OR “SARS-CoV-2”) AND (“Detection” OR “diagnosis” OR “prediction” OR “prognosis”) AND (”CT scan images” OR ”X-ray images”) AND (“ Deep learning” OR “Deep semi-supervised learning”)); (c) Science Direct database search code is TOPIC:(“Novel Coronavirus” OR “COVID-19” OR ”coronavirus” OR “2019-nCoV” OR “new coronavirus” OR “SARS-CoV-2”) AND (“Detection” OR “diagnosis” OR “pre- diction” OR “prognosis” OR “Analysis” OR “Classification” OR ”CT image” OR ” X-ray”) AND (“Deep learning” OR “Deep semi-supervised learning”).

We were looking for publications that evaluated the performance of any technique of deep semi-supervised learning based on inclusion and exclusion criteria. In the initial query, 392 articles were found; however, by removing duplicate articles from these, 267 articles have remained. Screening has been conducted based on title, abstract, and keywords, then 171 articles were excluded. We had sorted out 96 articles for complete text studies, and after studying each article, only 33 high-quality articles were selected for this systematic review. Figure 1 shows the flowchart of the study design.

2.2 Inclusion Criteria

The following inclusion criteria were used in the selection of the articles: (1) Studies that applied deep semi-supervised learning algorithms, (2) Studies that evaluated the measurement of model outcomes in comparison with ground truth or gold standards, and (3) Studies that used algorithms to analyze radiographic images (CT-scan, Chest X-ray, etc.).

2.3 Exclusion Criteria

The following studies were excluded: (1) Studies that used deep learning approach in not semi-supervised fashion, (2) Studies that used other artificial intelligence techniques like machine learning or classic computer vision approaches, (3) Studies that did not treat the problems directly related to the COVID-19 imaging, (4) Review studies and (5) All non-English articles were excluded as well.

3 Results and Discussion

3.1 Results

Initially, 392 abstracts and full-text articles were assessed, and ultimately, 33 studies meeting the inclusion criteria were selected. The PRISMA method was adopted in the process of selecting the articles. Due to the novelty of the disease, all the selected articles were published in 2020 and 2022. By reviewing 33 research papers on the application of CT scan and X-ray images in the diagnosis of COVID-19 by using deep semi-supervised learning methods, the current modality can be introduced to the scientific and medical community for the early and rapid diagnosis of this disease. These studies have used different analytical methods. For instance, Ankalaki et al. [13] have performed the identification of COVID-19, Pneumonia and Normal using DenseNet201 classifier from Chest X-Ray (CXR) images. A semi-supervised learning approach is used to segment the covid affected region, using DeepLabV3, and the ground truths for the segmentationis created by pre-processing the output class activation maps of DenseNet201. Their classification method of CXR images into COVID, Pneumonia and Normal classes yielded the accuracy of 82.35%. The performance of this model can be increased by fine-tuning the DenseNet classifier. Maghdid et al. [14], have builded a comprehensive dataset of X-rays and CT scan images from multiple sources as well as provided an effective COVID-19 detection technique using deep learning and transfer learning algorithms. Further, a modified convolution neural network (CNN) and AlexNet model as a pre-trained network are applied on the pre- pared X-rays and CT scan images datasets. The result of the experiments on both datasets, showed that the proposed models can provide accuracy up to 98% via pre-trained network (AlexNet) and 94.1% accuracy by using the modified CNN. They have offerd an efficient tool in detecting COVID-19 patients with high

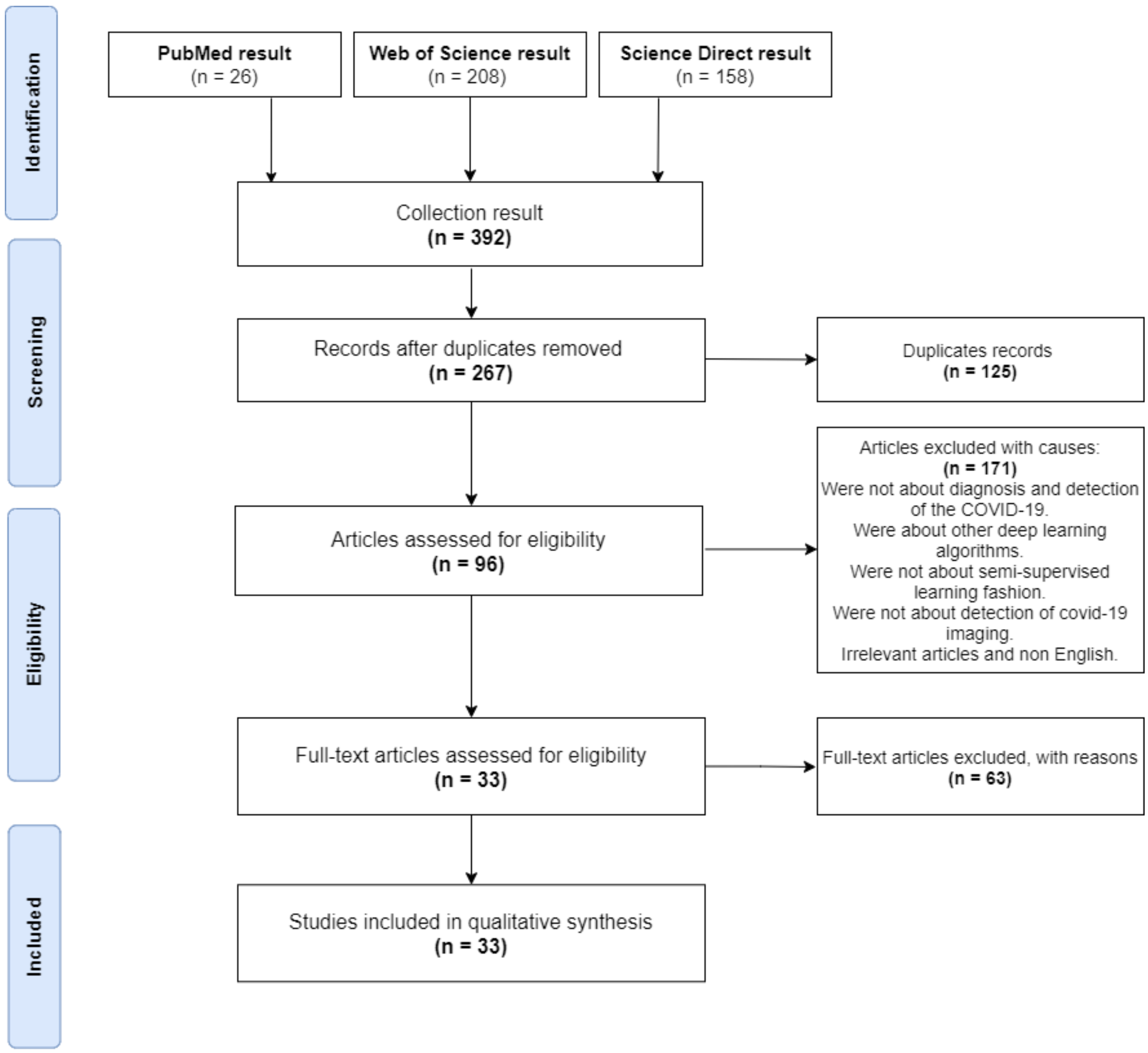

Fig. 1: PRISMA flow diagram of the review process and exclusion of papers.

accuracy and low response time. This is the first study in the literature that uses both pre-trained and CNN on both CT scan and X-ray images in identifying COVID-19. Albahli et al.[15] have developed an automated model that has the clinical potential for early detection of COVID-19 based on X-ray images. Three deep learning models namely Inception ResNetV2, InceptionNetV3, and NASNetLarge, were applied and fine-tuned. The best results have been obtained from InceptionNetV3, which yielded the accuracy levels of 98.63 and 99.02% with and without application of data augmentation in model training, respectively. Calderon-Ramirez et al.[16], have evaluated the performance of the semi-supervised deep learning archi- tecture known as MixMatch using a very limited number of labelled observations and highly imbalanced labelled dataset. Moreover, they demonstrated the critical impact of data imbalance to the model's accu- racy. They have proposed a simple approach for correcting data imbalance, re-weight each observation in the loss function, giving a higher weight to the observations corresponding to the under-represented class. For unlabelled observations, authors proposed the usage of the pseudo and augmented labels calculated by MixMatch to choose the appropriate weight. Application of their proposed model on chest X-ray images has led to accurate diagnosis of COVID-19 patients with accuracy of 93.4%. Relying on Generative Ad- versarial Networks (GAN), Alizadehsani et al. [17] proposed a Semi-supervised Classification using Limited Labelled Data (SCLLD) for automated COVID-19 detection from CT scan images. They have improved the detection accuracy of the proposed method by applying Sobel edge detection. Their method is capable of learning from a mixture of limited labelled and unlabelled data where supervised learners fail due to lackof sufficient amount of labelled data. This is the first study that presented a COVID-19 detection method based on semi-supervised learning. This method has achieved an accuracy of 99.60%, sensitivity of 99.39%, and specificity of 99.80%. A bifold COVID SCREENET architecture has been developped by Elakkiya et al. [18] for providing COVID-19 screening solutions using chest X-ray images. Transfer learning using nine pre-trained ImageNet models which includes Xception net , VGG16, Resnet50, Resnet50V2, Inception V3, Mobilenet V2, Densenet121, Resnet101V2 and Inception Resnet V2net, is adapted in the first fold and clas- sified using baseline Convolutional Neural Network (CNN). All the models extracted the features of training and testing data comprises of normal, pneumonia and COVID-19 chest X-ray images. Authors have proposeda Modified Stacked Ensemble Learning (MSEL) in the second fold by stacking the top five pre-trained models such as Xception, Resnet50V2, Mobilenet V2, Densenet121 and Resnet101V2, and then the predictions re- sulted. The experimental results of their approach achieved an accuracy of 100% in detecting and performing multi-class classification. Han et al. [19] have proposed an advanced, diagnostic tool for COVID-19 in CT scan images based on CNN architecture. The approach adopted a deep semi-supervised learning scheme that exploits both supervised and unsupervised learning. Both labeled and unlabeled CT images are employed. Labeled CT images are used for supervised leaning. Unlabeled CT images are utilized for unsupervised learn- ing in a way that the feature representations are invariant to perturbations in CT images. In distinguishing COVID-19 from non-COVID-19 CT images, the proposed method achieves an overall accuracy of 99.83%, sensitivity of 0.9286, specificity of 0.9832, and positive predictive value (PPV) of 0.9192. For discriminating between COVID-19 and common pneumonia CT images, their suggested method obtained 97.32% accuracy, 99.71% sensitivity, 95.98% specificity, and 0.9326 PPV. Moreover, they compared their approach with other supervised deep learning approach and they demonstrated that their proposed method is able to improve the diagnostic accuracy and robustness without exhaustive labeling. Tao et al.[20] proposed an ensemble deep learning model to detect COVID-19 from CT scan images. They used transfer learning was used to initialize model parameters and pretrain three deep convolutional neural network models named AlexNet, GoogleNet, and ResNet. These models were used for feature extraction on all images. Softmax was used as the classifica- tion algorithm of the fully connected layer. Application of their proposed model has led to accurate diagnosis of COVID-19 patients(Accuracy = 99.05%, Sensitivity = 99.05%, Specificity = 99.6%). Sahoo et al.[21] have proposed a semi-supervised deep learning approach named COVIDCon to detect COVID-19 cases accurately by analyzing digital chest X-rays and CT scans. COVIDCon has achieved 97.07% accuracy on the COVID-19 radiography dataset using just 1000 labeled data. In the case of CT scan dataset, COVIDCon has yielded an impressive accuracy of 99.13%, at 20000 labels. These results demonstrate the effectiveness of COVIDCon method for screening COVID-19 patients. An integrated semi-supervised shallow neural network framework comprising a Parallel Quantum-Inspired Self-supervised Network (PQIS-Net) for automatic segmentation of lung CT scan images followed by Fully Connected (FC) layers, was proposed by Konar et al.[22]. PQIS-Net model is aimed at providing fully automated segmentation of lung CT slices without incorporating pre-trained convolutional neural network based models. Their proposed diagnosis method for COVID-19 yielded an Accuracy of 98.4%, Precision of 98.6%, Recall of 98.5%, F1-score of 98.3% and an AUC of 98.3%. Table 1 summarizes the features of studies which adopted deep semi-supervised learning methods in CT images and chest X-ray of COVID-19 patients.

4 The Utility of DSSL in COVID-19 Screening

In recent years, deep learning models have demonstrated their potentials to be useful to radiologists and medical imaging experts for various disease detection and classification tasks. Deep learning consists of a group of algorithms applied to develop an expert system that can identify problems and yield predictions. These deep learning techniques produce intelligence into a computer that can elicit the patterns relative to specific data and then proceeds for automatic reasoning [23].

Since the outbreak of COVID-19, there have been increasing efforts on developing deep learning methods to perform screening of COVID-19. The extraordinary performance of such deep learning models based on supervised learning [24], however, requires large amounts of labeled data. A situation that may be challenging in medical image analysis, where data collection and annotation are time-consuming tasks and increase the workload on the radiologists. For this reason, semi-supervised learning (SSL) has been a hot research topic in deep learning in the last decade. It is well suited to deal with datasets which are poorly labelled, or have few labels, making deep semi-supervised learning attractive for computer aided medical imaging analysis.

Semi-supervised methods require the use of both labelled $Sl = (X_l, Y_l)$ and unlabelled samples $S_u = X_u = \{x_1, ..., x_{nu}\}$. Each labelled observation in $X_l = \{x_1, ..., x_{nl}\}$ has an associated label in the set $Y_l = \{y_1, ..., y_{nl}\}$ [16]. No labels are associated to the unlabelled set. DSSL can be classified into five categories, i.e., generative methods, consistency regularization methods, graph-based methods, pseudo labeling methods, and hybrid methods. An extensive survey on DSSL approaches can be found in [12].

Semi-supervised models can easily be adapted for mutations of the virus at a later stage, with relatively small labelled samples.

5 Discussion

This systematic review evaluated 33 studies in order to assist researchers to explore and develop knowledge-based systems based on deep semi-supervised learning in the detection and diagnosis of COVID-19 using CT scan or X-Ray images. To the best of our knowledge, the current review, is the first comprehensive study that reviewed a variety of deep semi-supervised learning methods to assess CT scan and X-ray images in the diagnosis and detection of this disease. The current review provided up-to-date information on deep semi-supervised algorithms and their application as an expression of radiographic imaging analysis of COVID-19. Image-based diagnostic methods in epidemics play a key role in the screening of affected cases [25]. Chest X-rays and CT scan are both among the main radiology modalities in the detection and diagnosis of COVID-19. While X-rays need less data memory, processing time requires a low radiation dose than a CT scan. Deep learning approach has been successfully applied to a wide range of problems in medical image processing and analysis. It can assess massive high-dimensional characteristics of X-Ray and CT scan images with high accuracy. Therefore, deep learning methods could facilitate automatic discrimination and detection of COVID-19 from other types of viral pneumonia. In general, deep learning architectures require large labelled datasets to provide good levels of generalisation. However, labeling data is heavily expensive and time consuming, and in the case of the virus outbreak gathering high quality and reliable labelled data can be challenging. Moreover, in the context of a new highly infectious disease, the datasets are also highly imbalanced, with few observations from positive cases of the new disease. Semi-supervised learning is an attractive way to utilize the unlabeled data without the cost of data annotation to improve model accuracy.

Author, Year	Data source	Data structure and size	Data preprocessing	Best model structure(s)	Performance measurements (on the best model)	References
ANKALAKI etal. (2020)	CXR images for COVID "https://github.com/ abzargar/COVID-Classifier /tree/master/dataset"	140 COVID-19 positive im- ages 100 normal images 140 pneumonia images (Chest X-ray images)	Input images are resized to 522 x 582 pixels; Generate the binary ground truth of CXR images to per- form semantic segmentation by splitting the 3 channels (namely, red, green and blue)	DeepLabV3 based on DenseNet201 classifier	Accuracy = 82.35%	[13]
Maghdid et al. (2021)	Image data collection GitHub repository; British Society of Thoracic Imaging (BSTI) dataset; Kaggle dataset; Italian Society of Medical Radiology and Interventional (SIRM) dataset;	170 X-ray images 361 CT images 85 COVID-19 posi- tive patients (X-Ray images) 203 COVID-19 positive pa- tients (CT-scan images) 85 normal patients (X-Ray im- ages) 153 normal patients (CT-scan images)	Cropping Resizing	Modified Convolu- tion neural network (CNN) and pre-trained AlexNet model	CNN model : Accuracy=94% Sensitivity=100% Specificity= 88% (for X-Ray images) Accuracy=94.1% Sensitivity=90% Specificity= 100% (for CT-scan images)AlexNet model : Accuracy=98% Sensitivity=100% Specificity= 96% (for X-Ray images) Accuracy=82% Sensitivity=72% (for CT-scan images)	[14]
Calderon-Ramirez et al. (2021)	COVID-19+ dataset: https://github.com/ieee8023 /covid-chestxray dataset Italian Society of Medical and Interventional Radiolog Chinese pediatric patients dataset Stanford Hospital, US : https://www.kaggle.com/nih-chest-xrays/sample/data Indiana Network for Patient Care : https://www.kaggle.com/ raddar/chest-xrays-indiana-university Costa Rican private clinic, Clinica Ima- genes Medicas Dr. ChavarriaEstrada.	200 COVID-19 positive im- ages 200 normal images 200 pneumonia images (Chest X-ray images)	All the datasets have been preprocessed to exclude arte- facts (manual labels) Images stored with 8 bits were replicated by 3 Data augmentation using flips and rotations Correcting data imbalance, re-weight each observation in the loss function, giving a higher weight to the obser- vations corresponding to the under-represented class Using the pseudo and aug- mented labels calculated by MixMatch to choose the ap- propriate weight for unla- belled data	MixMatch (CNN model)	Accuracy of 93.4%	[16]

(Continued)

Author, Year	Data source	Data structure and size	Data preprocessing	Best model structure(s)	Performance measurements (on the best model)	References
Aviles-Rivero etal. (2020)	COVID-19 image data col- lection Actualmed COVID-19 Chest X-ray Dataset Ini-tiative availabe on: https://github.com/agchung/ Actualmed-COVID-chestxray-dataset, 2020 ; COVID-19 Chest X-ray Dataset Initiative available on: https: // github.com/agchung/Figure1-COVID-chestxray-dataset, 2020; "RSNA CXR dataset;" ; COVID-19 Radiography Database available on: "https://www.kaggle.com/ tawsifurrahman/covid19-radiography-database, 2020."	13,975 Chest X-ray images across 13,870 patients 13,675 images for training 1579 im- ages for test 300 : COVID-19 positive images 5500 Pneu- monia images 8000 healthy patients (Chest X-ray im- ages)	The images are resized to the resolution 480x480 pix- els. Define the data in a non-Euclidean domain with a graph to produce pseudo-labels. Normalise the images to have zero mean and unit variance Feature extraction	GraphXCOVID is a combination between a model-based (energy model) and a deep learning framework	Accuracy = 94.6%F1 score = 95% Sensitivity = 94% POSITIVE PREDICTIVEVALUE (PPV)= 94.67%	[28]
Berenguer et al.(2020)	From 10 institutions throughout Europe and Latin-America (9 centers was pooled and comple- mented with scans from the open LIDC-IDRI)	1419 non-contrast enhanced CT scans 795 COVID-19 positive cases 624 COVID-19 negative cases (CT scan im- ages)	Lung segmentation using a 3D neural network based on the DeepMedic architecture The chest CT images in- tensities were cropped at [-1000; 400] HU in order to preserve brighter structures within the lungs, and re- sampled with variable in- plane resolution and 3 mm slice increment. Extracting the lesion seg- mentation masks. Side information in the form of an additional label image	Conditional Varia- tional Autoencoder (CVAE) with CNN architecture	Performance on the test set AUC = 97% Sensitivity = 94% Specificity = 82% F1-score = 88%	[35]

(continued)

Author, Year	Data source	Data structure and size	Data preprocessing	Best model structure(s)	Performance measurements (on the best model)	References
He et al.(2020)	COVID-19 articles on medRxiv and bioRxiv Lung Nodule Analysis (LUNA) database as a source of additional unlabeled CTscan data	349 COVID-19 Patients 397 non-COVID-19 patients 500 unlabelled images (CT scanimages)	The CT images were resizedto 224 × 224 pixels ; Data augmentation ; Applying dif- ferent random affine trans- formations including random cropping with a scale of 0.5 and horizontal flip ; Applying color jittering with random contrast and random bright- ness with a factor of 0.2.	CRNet ; DenseNet- 169 (Self-Trans) Combination of contrastive self- supervision into the transfer learning process	Accuracy = 86% F1 = 85% AUC = 94%	[36]
Khobahi et al.(2020)	COVID-19 image data col- lections RSNA Pneumonia detection dataset	99 COVID-19 patients ; 9579 pneumonia patients ; 8851 healthy subjects (X- Ray im- ages)	Relevant features extract- ing using AutoEncoders ex- tracted residual features ; Identification of the abnor- malities appearing in in- fected chest X-ray mani- festations ; Concatenating the features from differ- ent resolutions using Feature Pyramid based AutoEncoder (FPAE)	Combination of two models : Task- Base Feature Extraction Network (TFEN) based on Autoencoders Covid-19 Identi- fication Netwrok (CIN) based on CNN architecture	Accuracy =93.50% Precision = 93.63% Recall = 93.50% F1-score = 93.51%	[37]
Liu and Ji(2021)	Dataset 1 : ImageNet ; Dataset 02 The COVIDx : COVID-19 Image Data Col-lection; COVID-19 Chest X-ray Dataset Initiative ; Ac-tualMed COVID-19 ChestX-ray Dataset Initiative ;RSNA Pneumonia Detection Challenge dataset ; COVID-19 radiography database ; Dataset3 : COVID19-CT	16898 images in total 573 COVID-19 patients ; 5559 Pneumonia patients ; 8066 normal patients (X-ray im- ages) 349 COVID-19 pa- tients (positive CT-scan im- ages) 397 non COVID-19 pa- tients (negative CT-scan im- ages)	Each image is scaled to 256X256 and a patch of size 224X224 is randomly cropped as a training sample ; Horizontal flip is randomly performed for each cropped patch with a probability of 0.5. Data augmentation ; The center-cropped patch with size 224 for each image is used.	SSTL-M: Self - supervised transfer learning method.	Accuracy = 94.2% F1-Score = 95.3% AUC = 97.8% (on CT scan images)	[32]

(continued)

Author, Year	Data source	Data structure and size	Data preprocessing	Best model structure(s)	Performance measurements (on the best model)	References
Huang et al. (2021)	COVID-CT dataset available on (https://github.com/ UCS-DAI4H/ COVID-CT)	746 images in total 349 positive COVID-19 (CTimages) 397 non-COVID-19 (CT im-ages)	Resizing images to 256*256 pixels ; Random resizing and cropping to 224*224 ; Nor-malization ; Added Gaus-sian noise and flipped im-ages with horizontal param-eter 0.5 Feature extraction using ResNet50 to get a 2048-dimensional feature vector Reducing the number of fea-tures from 2048 to 64.	Evidential Covid-Net combines the ResNet architecture with an evidential layer based on deep neural network and belief functions	Accuracy = 81% F1-Score = 81.2% AUC = 87.5%	[38]
Hasan et al.(2021)	MosMedData dataset adminis- tered by municipal hospitals in Moscow, Russia,	NOR : 254 Not consistent with pneumonia, including COVID-19, and refer to a specialist MiNCP : 684 Mild novel COVID-19 positive ; MoNCP :125 Moderate novel COVID-19 positive ; SeNCP : 45 Severe novel COVID-19 positive CrNCP : 2 Critical novel COVID-19 positive (CT scan images)	Extracted 3D patches ; Progressive Resizing ; Unsupervised Lung Segmen-tation ; Data augmentation (both geometry- and intensity-based) ; class-rebalancing	3D-CNN	AUC= 91.4% (for binary classification) ; AUC =89.3% for multi-class classification ; Sensitivity= 87% ; Specificity = 86.9%	[29]
Tao et al.(2020)	”Domestic and foreign jour-nals such as Sciencedirect, Nature, Springer Link, andChina CNK”; ”Authoritative media re-ports such as the New York Times, Daily Mail (United Kingdom), The Times (United Kingdom), CNN, The Verge (United States), Avvenire (Italy), LaNuo-vaFerrara (Italy), People’sDaily, Toutiao News, andDr. Lilac”; ”The sirm.org public database” ”GitHub public database”	2500 positive COVID-19 im-ages; 2500 lung tumor images; 2500 normal images; (CT scan images)	Deleting images with large noise and coronal position. All images were normalized at the same time, converting the image to a size of 64 × 64.	The ensemble clas-sifier EDL-COVID composed of three deep convolutional neural network models: AlexNet, GoogleNet, and ResNet.	Accuracy = 99.05% Sensitivity = 99.05% Specificity = 99.6% F1-score = 98.59% MCC= 97.89%	[20]

(continued)

Author, Year	Data source	Data structure and size	Data preprocessing	Best model structure(s)	Performance measurements (on the best model)	References
Nwosu et al. (2021)	Chest X-ray dataset COVIDx	18,543 chest X-Ray images across 13,725 cases 108 positive COVID-19 patients; 9,584 pneumonia patients; 8,851 normal patients; (X-Ray images)	-	Two-path semi-supervised deep learning model, ssResNet, based on Residual Neural Network (ResNet)	Accuracy = 84.95% Macro average Precision (MacroP) = 61.18% Macro-average Recall(MacroR)= 66.76% Macro-average Fscore (MacroF) = 62.41%	[26]
Qi et al.(2021)	BIMCV dataset COVIDx dataset COVID-19-AR datasetMIDRC-RICORD-1c dataset	18,691 chest X-ray images from 16,817 subjects. 3,795 COVID-19 positive im-ages 6045 pneumonia images 8,851 normal (healthy patients), (X-Ray images)	Normalization ; Extraction of local phase image features using bandpass quadrature filters and L1 norm-based contextual regularization method ; Three different local phase CXR(x; y) image features are extracted: 1- Local weighted mean phase angle (LwPA(x; y)), 2- LwPA(x; y) weighted local phase energy (LPE(x; y)), and 3- Enhanced local energy attenuation image (ELEA(x; y)) ; A multi-feature image, is created by combining these three types of local phase images as three-channel input.	Multi-feature convolutional neural network (CNN) architecture	Accuracy = 93.61% Sensitivity = 94% Specificity= 94% F1-Score= 94%	[39]
Oluwasanmi etal.(2021)	COVID-19 Open Research Dataset Challenge (CORD-19) by the Allen Institute for AI ; COVID-19 Dataset from theUniversity of Montreal ; COVID-Chestxray-Dataset developed from various websites and publications: ”COVID-19 image datacollection”	700 positive COVID-19 patients; 700 normal patients (CT scan images)	Transforming images into a tensor, Images are normalized to a pixel range of 0 to 1 ; The image dimension is fixed at 224 224 3 ,representing the height, width, and color channel of the images ; The data are categorized binarily, with one representing COVID-19 infected and zero representing normal images.	Semi-Supervised Generative Ad -versarial Network(SSGAN) model	Accuracy = 94% Sensitivity = 96% Specificity = 92%	[31]

(continued)

Author, Year	Data source	Data structure and size	Data preprocessing	Best model structure(s)	Performance measurements (on the best model)	References
Fan et al. (2020)	Italian Society of Medical and Interventional Radiol- ogy ; COVID-19 CT Collection dataset ;	100 CT scan images (labeled data) 1,600 (unlabeled data)	Resizing images to 352 × 352 pixels Resampling images using dif-ferent scaling ratios, i.e., 0.75, 1, 1.25	Inf-Net (Lung Infec- tion Segmentation Deep Network)	Precision= 51.5% Sensitivity = 86.5% Specificity = 97.7%	[40]
HU et al.(2020)	"Hospital of Wuhan Red Cross Society;" "Shenzhen Hospital;" "TCIA dataset;" "Cancer Centre Archive(TCIA) Public Access;" "MD Anderson Cancer Cen-tre;" "Memorial Sloan-Kettering Cancer Center;" "MAASTRO clinic"	150 COVID-19 patients; 150 pneumonia patients; 150 normal patients (CT images)	Data augmentation ; Normalization ; Lung segmentation usingmulti-view; U-Net based segmentation network ; Clipping based on HU win- dows,	weakly supervised multi-scale deep learning based on Convoltional neural network (CNN)	Accuracy = 96.2% Sensitivity = 94.5% Specificity = 95.3% AUC = 97% Precision = 97.3%	[41]
Li et al. (2020)	More than 10 medical centers between Nov.11th, 2010 and Feb. 9th, 2020	305 images from 251 COVID-19 patients; 872 images from 869 pneu- monia patients; 1,498 images from 1,475 non- pneumonia patients (CT images)	Image processing method based on HU values; 18Data augmentation	3D ResNet-	Recall = 88% Precision = 89.6%F1 score = 87.88%	[42]
MOHAMME D et al. (2020)	COVID-19 image data col- lection, (collected from a few Chinese, Iranian and Italian hospitals) ; "Tianchi Lung diseases diagnosis competi- tion CT images"	302 CT scan images; 20 positive COVID-19 pa- tients; 282 negative COVID-19 im- ages	Resizing images to 256X256pixels ; Data augmentation (contrast stretching, the addition of Gaussian noise, blur, and spatial transformations such as zooming, scaling, rotation, and elastic deformation) ; Incorporating resampling strategy in case of positive instances(To further min- imize the skewness in data distribution) ; Stochastic enhancement and tone mapping	ResNext+ with LONG-SHORT TERM MEMORY (LSTM) architec-ture	Accuracy = 77.6% Precision = 81.9% Sensitivity = 85.5% Specificity = 79.3% Precision = 81.9%F1 score = 81.4%.	[43]

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Author, Year	Data source	Data structure and size	Data preprocessing	Best model structure(s)	Performance measurements (on the best model)	References
Wu et al. (2020)	Various hospitals in Iran, Italy, South Korea, and the United States between January 1, 2020 and March 30, 2020; "MedSeg, Radiopeadia"	234 COVID-19 patients(CT scan images)	All the images were resampled to 256 × 256 resolution in the axial plane ; Segmentation using 2D UNet	Deep learning method based on hybrid week labels	TPR(True Positive Rate) =0.555 FPR(False Positive Rate)=0.008	[44]
Peng et al. PMC **(2021)**	Collected from	606 COVID-19 patients; 222 Influenza; 397 Normal or other disease patients (CT images)	-	DenseNet121	AUC= 87% Sensitivity = 72.3% Specificity= 85.2%	[45]
Zhou et al. (2021)	First dataset: ChestXray-14 collected fromNational Institutes of Health(NIH) clinical center; Second dataset: COVID- ChestXray collected fromvarious public sources anddifferent hospitals aroundthe world	First dataset contains 112,120 X-Ray images; Second dataset contains 382 images in which 253 positiveCOVID-19 images 61 pneumonia images (Chest X-Ray)	-	Semi-supervised Open set Domain Adversarial network (SODA) based on CNN architecture	AUC-ROC score = 90.06%for COVID-19 AUC-ROC score = 90.82% for pneumonia	[46]
Calderon-Ramirez et al. (2020)	Covid-19+ dataset: available on "https://github.com/ieee8023 /covid-chestxray" which is created by Dr. Joseph Cohen, from the University of Montreal "Pediatric chines CXR dataset;"	102 positive COVID-19 images; 4273 pneumonia patients (including viral and bacterial); 1583 of normal patients (Chest X-Ray images)	Resizing images to 100*100 pixels; Data augmentation	Semi-supervised deep learning framework based on the Mix Match architecture	Accuracy = 96.6%	[27]
Li et al. (2021)	SPGC-COVID dataset: "2021 IEEE ICASSP Signal Processing Grand Chal-lenge"	116 positive COVID-19 patients; 41 pneumonia patients; 52 normal patients; Validation dataset includes: 55 positive COVID-19; 19 pneumonia patients; 24 normal patients (CT scan images)	Extracting digital feature descriptors of each image ; Dataset clustering	Ensemble learning (Fix-Match and sequence classifier)	Performance in validation set: Accuracy =86.73% Sensitivity = 87.27% (COVID-19); 68.42% (Pneumonia class); 100.0%(Normal class) Performance in test set: Accuracy = 80.00% Sensitivity= 88.57% (COVID-19 class); 35.00% (Pneumonia class); 97.14%(Normal class)	[47]

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Author, Year	Data source	Data structure and size	Data preprocessing	Best model structure(s)	Performance measurements (on the best model)	References
Wang et al.(2021)	Local hospitals	284 positive COVID-19 images; 281 community-acquired pneumonia images (CAP); 293 second pulmonary tuberculosis images (SPT); 306 healthy control images (HC) (CT scan images)	The resolutions of all images were 1024× 1024× 3. The color CCT images from four classes were converted into grayscale by retaining the luminance channel; The histogram stretching (HS) was utilized to increase the contrast of all images; Cropping was carried out to remove the checkup bed at the bottom area, and to remove the texts at the margin areas; Multiple data augmentation	CCSHNet with deep fusion using transfer learning and discriminant correlation analysis	Sensitivities of four classes: 95.61%(COVID-19); 96.25% (CAP); 98.30%(SPT); and 97.86% (HC) The precision values of four classes: 97.32% (COVID-19); 96.42% (CAP), 96.99%(SPT); 97.38%(HC) F1 scores of four classes: 96.46% (COVID-19); 96.33% (CAP); 97.64% (SPT); 97.62% (HC) The MA F1 score = 97.04%.	[48]
Elakkiya et al.(2021)	https://www.kaggle.com/tawsifurrahman/covid19-radiography-database (Chowdhury et al., 2020) ; https://www.kaggle.com/nih-chest-xrays/data (Wang et al. 2017); http://www.chestxray.com/index.php/education/normal-cxr-moduletrain-your-eye!10; https://data.mendeley.com/datasets/rscbjbr9sj/2 (Kermany et al. 2018); https://www.sirm.org/category/senz-categoria/covid-19/; https://radiopaedia.org/; https://www.eurorad.org/; https://www.ams.edu.sg/colleges/radiologists/covid-19-resource-site-forradiology-imaging(Cohen et al., 2020) ; Data from Three Govt. Hos- pitals (Thanjavur, Theni, Tirunelveli) at Tamilnadu	7725 chest X-ray images; 609 positive COVID-19 images; 4188 normal images; 2928 pneumonia images; (Chest X-Ray images)	The images are resizing and cropping to width and height of 224X224 and recolouring to the colour channel of 3; Data Augmentation using Image Data Generator and also augmented with albu-mentations to reach a total of 6758 samples	COVID*SCREENET* : Transfer learning and Modified Stacked EnsembleLearning	Accuracy of 100%	[18

Author, Year	Data source	Data structure and size	Data preprocessing	Best model structure(s)	Performance measurements (on the best model)	References
Calderon-Ramirez et al. (2021)	”Covid-19 image data collection : available at https://github.com/ieee8023/ covid-chestxray-dataset. [Online].” Radiopaedia and Italian Society of Medicine and Interventional Radiology	99 positive COVID-19; 99 negative covid-19 patients (Normal and pneumonia) (Chest X-ray images)	The images are resizing to 2500x2500 pixels	Uncertainty Estimation With Semi-supervised Deep Learning(SSDL)	Accuracy = 96.5% F1-score = 93%	[49]
Han et al.(2021)	The first dataset ”DataCOV”: acquired from CT COVID-19 challenge(https://covid-ct.grand- challenge.org) The second dataset (DataCOV-CV), obtained from the COVID-19 and common pneumonia chest CT dataset Other three publicly available lung CT datasets (LCTSC, RIDER, LUNGx)	The first dataset contains 349 CT images from 216 COVID-19 patients and 463 CT images from 55 non- COVID-19 patients The second dataset consists of 416 CT scans from 206 COVID-19 patients and 412 CT scans from 412 patients with common pneumonia (CP), including viral pneumonia, bacterial pneumonia, and fungal pneumonia (CT scan images)	Resizing images to 256 x 256pixels; Data augmentation; Following the center-crop of size 224 x 224 pixels, one ofthree operations–a Gaussianblur, a median blur, and anadditive Gaussian noise–are randomly selected and applied to make slight changes in the intensities of the image ; The lightness of the image is adjusted by adding a random value in a range of [–20, 20] per pixel.	Deep semi-supervised learning method based on CNN architecture	For distinguishing COVID- 19 from non-COVID-19 CT images : Accuracy = 99.83% Sensitivity = 92.86% Specificity = 98.32% Positive predictive value(PPV) = 91.92% ; For discriminating between COVID-19 and commonpneumonia CT images Accuracy= 97.32% Sensitivity = 99 .71% Specificity = 95.98% PPV = 93.26%	[19]
Minaee et al.(2020)	COVID-19 X-ray image database developed by Cohen JP; “ChexPert dataset”	40 COVID-19 patients; 3,000 normal patients (X-ray images)	Regularization	SqueezeNet	Accuracy = 97% Sensitivity = 97.5% Specificity = 97.8%	[30]
Albahli et al.(2020)	Open source COVIDx dataset	850 COVID-19 patients; 500 non-COVID-19 pneumo-nia cases; 915 normal patients (X-ray images)	Data augmentation	Inception-Net V3	Accuracy = 99.02%	[15]

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Author, Year	Data source	Data structure and size	Data preprocessing	Best model structure(s)	Performance measurements (on the best model)	References
Sahoo et al.(2021)	COVID-19 Radiography Dataset: developed by a team of researchers from Qatar University, the University of Dhaka and their collaborators from Pakistan and Malaysia with the help of medical doctors. "COVID-19 CT Scan Dataset: developed by the China Consortium of Chest CT Image Investigation(CC-CCII)"	219 COVID-19 positive images; 1341 normal images; 1345 viral pneumonia images (Chest X-ray images) 21777 positive COVID-19 CT images; 36894 pneumonia CT images; 24096 normal images; (CT scan imgaes)	Data augmentation; Consistency regularization; Multicontrastive learning; Resizing all images to 84x84pixels	COVIDCon model based on ResNeXt-101	Accuracy on X-ray dataset =97.07% AUC on X-ray dataset = 99.8% Accuracy on CT scandataset = 99.13% AUC on CT scan dataset =100%	[21]
Bridge et al. (2020)	"Toy dataset"; "Italian Society of Radiology"; "Shenzhen Hospital X-Ray dataset"; "ChestX-Ray8"; "COVID-CT-Dataset"	129 COVID-19 patients; 62,267 normal patients; 5,689 pneumonia patients (X-ray images) 30 COVID-19 patients; 1,919 normal patients (CT scan images)	Using the GEV activation function for unbalanced data	Inception V3	Accuracy =100% Specificity= 100% Sensitivity = 100%	[33]
Alizadehsani et al.,(2021)	CT scan images from Omid Hospital in Tehran Kaggle dataset	10000 lung CT scan images for training 17965 CT scan images for test 8535 COVID-19 positive 9430 non COVID-19 (CT-scan images)	The Sobel technique is used to detect the edges of the images ; Resizing of images to100x100 pixels; Normalization ;	Semi-supervised Classification using Limited Labelled Data (SCLLD) method based on Generative Adversarial Networks (GAN) model	Accuracy = 99.60% Sensitivity = 99.39% Specificity = 99.80% F1-score = 99.6% AUC= 99.60%	[17]
Konar et al. (2021)	Brazilian Dataset which is acquired from the real patients of Sao Paulo, City hos-pitals, Brazil. COVID-19 article on medRxiv; CCAP Dataset collected from IEEE Data port	First datasets containes: 1252 Covid19 images; 1230 non-COVID-19 Second dataset: 20 COVID-19 imagesThird dataset: 1806 COVID-19 images; 760 Viral Pneumonia; 1599 Bacterial Pneumonia; 784 Mycoplasma Pneumonia; 2094 Normal patients (CT scan images)	Data augmentation using rotation, scaling, shearing, and flipping operations; Remove the cavity regions from the slices in order to obtain lung region with uniform background; Normalization; Segmentation of lung CT slices using PQIS-Net; Resizing images to 512 X512pixels;	Parallel Quantum-Inspired Self-supervised Network (PQIS-Net) assisted semi-supervised shallow learning followed by Fully Connected (FC) layers	Accuracy = 98.4% Precision= 98.6% Recall = 98.5% F1-score = 98.3% AUC =98.3%	[22]

Different methods based on deep semi-supervised learning, such as DenseNet201, ResNet [26], MixMatch [27], GraphXCOVID [28], 3D-CNN [29], XceptionNet [15], SqueezeNet [30], Semi-Supervised Generative Adversarial Network (SSGAN) [31], have been used for the assessment of CT scan and X-Ray images of COVID-19 patients. Notably, the application of these methods on chest X-rays has offered promising results. Such a finding is particularly important since X-rays are easily accessible and low cost. In spite of the low expense of X-ray compared with CT images, the numbers of studies that assessed these two types of imaging using deep semi-supervised learning methods are not meaningfully different. However, few studies have used these methods on both types of imaging (Maghdid et al. (2021) [14], Liu and Ji (2021) [32], Sahoo et al. (2021) [21])

Many studies have shown that the use of deep semi-supervised learning methods can improve the rateof metric features of CT scan and X-ray images and enhance the sensitivity and specificity of radiographic images compared to the radiologists' diagnosis; therefore, the use of this inexpensive and affordable modality should be considered as a reliable method for the diagnosis and detection of COVID-19. The mean diagnosis of all the studies using the X-ray modality in deep semi-supervised learning had a sensitivity average ¿97%, a specificity ¿94%, and a higher rate of diagnosis than that reported in deep supervised learning and traditional methods. It can also be concluded that the specificity in CT scan images obtained by DSSL methods in case of COVID-19 was on average higher than 93% which, in many cases, has higher efficiency in terms of specificity compared to previous methods. The sensitivity of DSSL methods in CT scan images of COVID-19 was also higher than 92% which is higher than that of the supervised diagnostic methods. Semi-supervised models can boost the accuracy of Covid-19 early diagnosis from chest X-ray and CT scan images, particularly whenground truth data is limited.

One of the most promising deep semi-supervised learning approaches is transfer learning. The transfer learning is the concept of re-using a pre-trained network on huge dataset and transfer the learned model into a new model. This is very useful in COVID-19 detection using medical imaging, where there is a limited number of labeled data. Moreover, using such transfer learning algorithms provide insight into how one can think of design new architectures for the detection of COVID-19 cases. Among the included studies, Bridge et al. [33] even reached 100% classification accuracy on COVID-19 using the pre trained InceptionV3. Elakkiya et al. [18] achieved an accuracy of 99.66% using Xception net and 96.90% using pretrained Resnet50V2. Butin medical image analysis it is not always the fact of using the model with best accuracy, it is matter of factto consider the model with best sensitivity and specificity rate so as to avoid the questioning of false positive and false negative predictions. With this interpretation, the precision and recall rate of Resnet50V2 is 100% for COVID-19 class whereas for Xception net it is 100% and 97.92% respectively.

The MixMatch approach developed in [27] combined regularization and pseudo-labelled based learning, with intensive data augmentation. This method produced better results with an accuracy more than 96% compared to other regularized, pseudo-labelled based on deep semi-supervised learning methods as shown in table. Most of the other works first train a Convolutional Neural Network (CNN) on an existing large-scale chest x-ray or CT scan images dataset and then fine-tune the model on the newly collected COVID-19 images dataset, often at a much smaller scale. Generally, there are two methods of prediction of COVID-19 images, binary classification and multiclass classification. Binary classification is used to detect COVID-19positive and negative cases. However, this classification method is inaccurate due to the misclassification of COVID-19 images with other types of lung diseases (viral pneumonia, bacterial pneumonia) To solve this issue, researchers have differentiated the images of COVID-19 from other types of lung diseases using the method of multiclass classification. The accuracy of multiple classifiers is better than binary classifiers in detecting COVID-19 images.

The availability of public databases of CT scan and X-ray images of patients with COVID-19 has facilitated the application of deep semi-supervised learning methods on large number of images and execution of training and validation steps. However, since these images have come from various institutes using different scanners, preprocessing of the obtained data is necessary to make them uniform and facilitate further analysis [34]. Preprocessing is an essential step for reducing the impacts of intensity variations in CT slices and getting rid of noise. Subsequent thresholding and morphological operations have also enhanced the analytical performance. Data augmentation and histogram equalization are among the most applied preprocessing methods.

The results of included studies demonstrate the effectiveness and efficiency of deep semi-supervised learning for potential diagnosis of COVID-19 from chest X-rays and CT-Scans.

Utilizing the advanced deep learning techniques and semi-supervised learning, could be beneficial to the development of the diagnostic system for COVID-19. We have observed that with the emerging use of deep semi-supervised learning we can further aim for broader systematic reviews in the future.

6 Conclusion

The global outbreak of novel coronavirus has affected billions of lives and demands various cost-effective diagnostic tests about the presence of COVID-19 infection. Deep learning based methods are promising in automatically detecting COVID-19 disease on chest x-ray and CT scan images. However, there is a strong lack of high quality labelled data i.e., very low number of high quality labelled observations causes severe limitations on the development of deep learning based diagnosis technique. Deep semi-supervised learning makes use of more widely available unlabelled data, which can help to boost the accuracy of these techniques under restricted number of labels. Moreover, DSSL algorithms are able to avoid overfitting and to maximize the generalizability and usefulness of COVID-19 diagnostic models; these DSSL models is trained on large, heterogeneous datasets to cover all the available data space. Deep semi-supervised learning techniques could recognize COVID-19 lung pathology effectively by taking advantage of information from both labeled and unlabeled images. The use of these techniques in rapid diagnostic decision-making of COVID- 19 can be a powerful tool for radiologists to reduce human error and can assist them to make decisions in critical conditions and at the peak of the disease.

In the recent systematic review, the analysis of deep semi-supervised learning algorithms reported in the literature related to COVID-19 prediction, classification, and detection strategies using X-ray and CT scanimages has been presented. To our knowledge, this is the first systematic review on deep semi-supervised techniques for COVID-19 diagnosis using medical images. These studies based on DSSL showed excellent sensitivity and specificity for identification of COVID-19 and better global performances than the currentleading deep supervised technique, while requiring a very reduced set of labels.

Finally, it can be concluded that with the incorporation of deep semi-supervised learning algorithms in the equipment of radiology centers, it will be possible to achieve a faster, cheaper, and safer diagnosis of of the COVID-19 disease.

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