A Survey on Deep Learning Advances and Emerging Issues in Pneumonia and COVID19 Prediction

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***Abstract*—As the COVID19 pandemic evolves and coronavirus mutates to different variants, a high workload falls on the shoulders of doctors and radiologists. Identifying COVID19 through X-ray and Computed Tomography (CT) scanning in a short amount of time is vital because it helps doctors start the COVID19 treatment in the early stages. Deep Learning algorithms showed tremendous results in automating COVID19 detection using X-ray and CT scans. As there are not many survey papers on COVID19 detection using deep learning techniques, the goal of this paper is (1) to give a thorough discussion of COVID19 prediction considering Computer Vision problems like COVID19/pneumonia classification, detection, and segmentation, (2) to address new advances in deep learning like Transformers, GANs, and LSTMs, and (3) to cover technical issues like data security and data scarcity of X-ray and CT scans in COVID19.**

***Index Terms*—COVID-19 diagnosis; deep learning; federated learning; self-supervised learning; few-shot learning; differential privacy; data security; data scarcity**

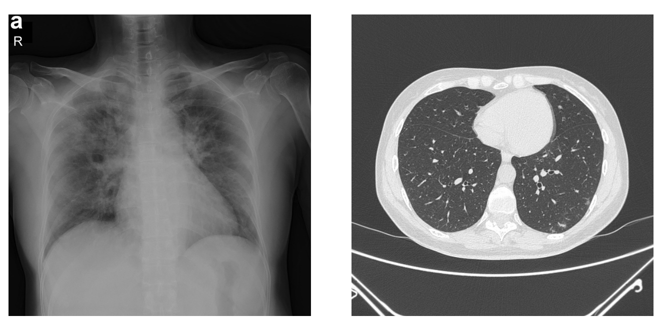
I. Introduction

According to World Health Organization [1], pneumonia is an acute respiratory infection in one or both lungs. An infected person with pneumonia may have a fever, chest pain, headaches, coughing that may produce mucus, etc. The leading causes of pneumonia are bacteria, viruses, and fungi. Pneumonia, both viral and bacterial, is highly infectious, meaning it can spread from person to person via sneeze or cough. Coronavirus is a virus, which can cause pneumonia. Coronavirus is one of the most severe diseases that has impacted many lives worldwide. For instance, as of August 4th of 2021, there are more than 200 million coronavirus cases and 4,262,651 deaths. Coronavirus is still evolving despite having several vaccines. While available vaccines help to mitigate the devastating effects of COVID19, they cannot guarantee complete protection. Therefore, it is crucial to identify COVID-19 pneumonia early due to the high transmission rate and high mortality rate among older adults.

The most fundamental testing procedure for early COVID-19 diagnosis is a real-time reverse transcription-polymerase chain reaction (RT-PCR). Additionally, signs of COVID-19 pneumonia can be detected through X-ray scanning (Fig. 1a) in 15 minutes. For a more deep analysis of chest abnormalities, medical personnel use CT scanning (Fig. 1b). As RT-PCR is a default option for identifying COVID-19 pneumonia, CT and X-Ray testing [2] are good complementary solutions to strengthen the COVID-19 pneumonia diagnosis. In developing countries, the cost of installing new machines for RT-PCR is not cheap [3] when X-ray and CT scanning machines are widely available. Also, CT results show higher sensitivity in the early COVID19 diagnosis than RT-PCR [4].

Looking and analyzing CT and X-Ray images one by one is a time-consuming task that requires much energy from a skilled radiologist. Therefore, it is essential to solve these cumbersome tasks by automating the prediction of COVID19 pneumonia and provide actionable intelligence to medical doctors and radiologists. Traditional approaches [5], [6] to automatic pneumonia detection rely on extracting hand-crafted features and then training statistical machine learning models. A typical limitation of these approaches is the requirement of domain expertise to analyze visual data, which is usually expensive and not scalable. However, we have recently witnessed a significant advancement of deep learning (DL) models by achieving state-of-the-art results in computer vision (CV) problems such as image classification, object detection, and object segmentation. These methods posses a superior capability of automatic feature learning from the visual data and outperform traditional models and this work focuses on surveying deep learning algorithms that solve COVID19/pneumonia detection, classification, and segmentation problems in CT scans and X-ray images.

Currently, several surveys on the automatic analysis of COVID19 pneumonia have been published [7]–



(a) COVID19 CXR (b) Very Early COVID19 CT

Fig. 1. COVID19 chest X-ray (CXR) and CT scan

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[9]. However, these surveys mainly focus on classifying COVID19/pneumonia from medical images, while other computer vision techniques like segmentation and localization (Fig. 2) are not well covered. More recently, a few surveys [7] discussed object segmentation problems in COVID19 pneumonia, they only gave general information on what is object segmentation but lack specifics of the methods. Moreover, the exhaustive surveys on COVID19/pneumonia classification mainly concentrate on Convolutional Neural Networks (CNNs) and fail to include the recent advances in deep learning including Transformers [10], GANs [11] and LSTMs [12] which have been widely used to tackle vision problems. Lastly, emerging issues related to COVID19 prediction, like lack of training data and data privacy, are not well discussed in existing works.

In this paper, to overcome the limitations of current surveys, contributions can be summarized as following:

- We investigate more specific computer vision techniques in COVID19/pneumonia prediction, including localization and segmentation. Primarily, we review various approaches for segmentation on different modalities (e.g., CT scans and X-ray images).
- We survey the recent advances in deep learning like Transformers, GANs, LSTMs, and examine how these deep learning architectures are employed.
- We survey papers related to a few-shot learning and self-supervised learning techniques in COVID19 prediction to overcome the data scarcity problem.
- We address the data security by reviewing Federated Learning frameworks and differential privacy which are considered as leading solutions for data privacy of patient information in COVID19 detection. As data security has colossal importance on the privacy of patient data, we decided to fill the stated gaps and provide a comprehensive review of COVID19/pneumonia prediction for researchers in this field as well.

This paper is organized as follows. Section II lists COVID-related X-ray and CT datasets with a brief explanation. Section III describes the general workflow of deep pneumonia prediction including data processing, feature learning, and summarizes widely used algorithms for image classification, detection, and segmentation. Section IV overviews the main COVID19-related tasks of classification, detection and segmentation; and presents a main network architectures within each task including Transformers, LSTMs and RNNs, GANs, and U-Nets. We also discuss technical issues like privacy security and scarcity of training data; and solutions such as federated learning, self-supervised learning, and few-show learning. Finally, section V provides the discussion with concluding points and references.

II. Datasets

In this section we describe a list of public medical data of CXR and CT scans for COVID19/pneumonia detection task.

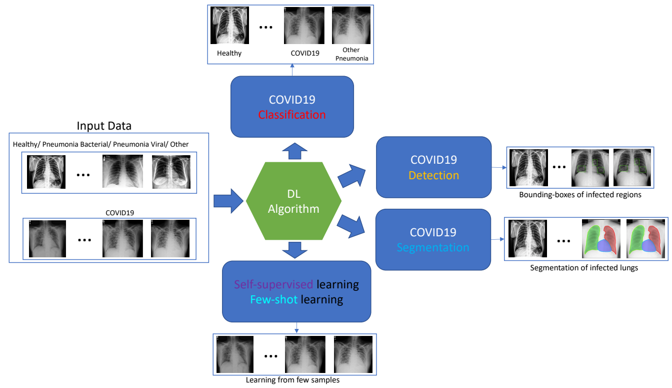

Fig. 2. Overall View of COVID19/Pneumonia Detection.

A. X-Ray Datasets

X-Ray is the cheapest and fastest method to identify COVID19 pneumonia. Thus, there are several useful datasets that are widely available to the reasearch community:

- RSNA Pneumonia detection challenge dataset [13] consists of 26k CXR images in DICOM format. It consists labels of *pneumonia* or *non-pneumonia*. The dataset also has bounding boxes of pneumonia-labeled images.
- The aim of the SIIM FISABIO RSNA COVID-19 Detection challenge [14] is to identify and localize COVID-19 abnormalities on chest radiographs. Datasets contain 6,334 chest scans (CXR) in DICOM format. Labels are Negative for Pneumonia, Typical Appearance, Indeterminate Appearance, and Atypical Appearance.
- NIH Chest X-ray Dataset [15] is one of the biggest datasets consisting of 14 common thorax disease. Dataset has 112,120 X-ray images of 30,805 patients with bounding boxes.
- Chexpert [16] is a large dataset from Stanford that has 224,316 chest radiographs (CXR) of 65,240 patients with 14 different pathologies in lungs.
- MIMIC-CXR-JPG [17] is a large dataset consisting of 371,920 chest x-rays (CXR) bound with 227,943 studies that came from the Beth Israel Deaconess Medical Center and MIT between 2011 - 2016. Labels are derived from Chexpert labeler and consist of 14 identical labels.
- RICORD dataset [18] is the collaborative intent of RSNA and Society of Thoracic Radiology in developing an expert annotated dataset. Dataset consists of 240 CT and 1,000 CXR images in DICOM format. Class labels are defined as typical, indeterminate, atypical, or negative appearance for COVID-19 pneumonia.

B. CT Datasets

Hospitals use computed tomography for deeper analysis. It helps to better identify the infected areas of COVID19 pneumonia. European Institute for Biomedical Imaging Research has listed the COVID19 imaging CT datasets of different organizations such as:

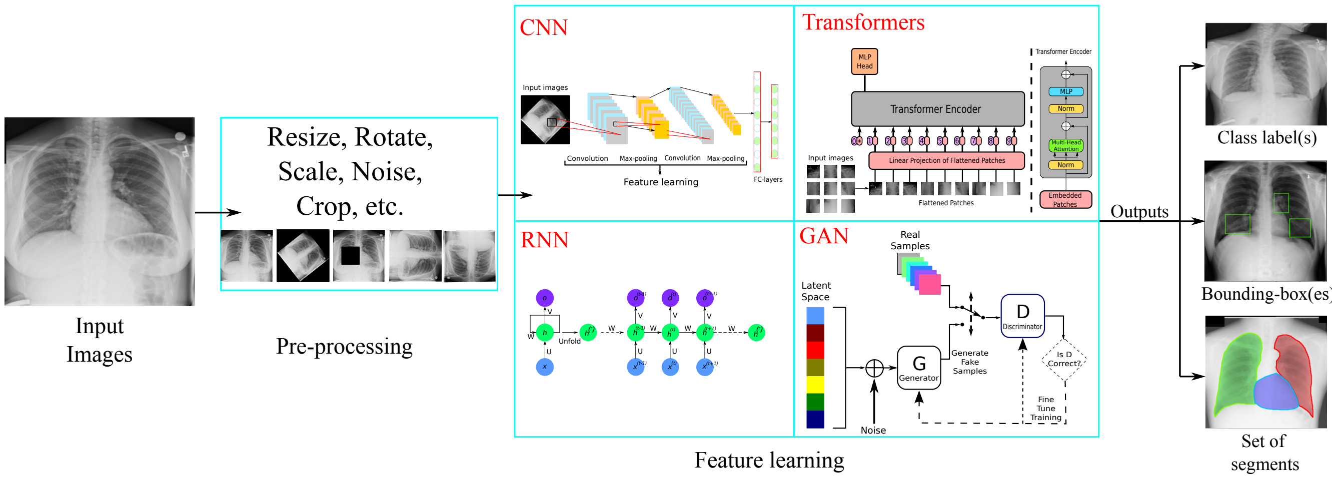

Fig. 3. General Workflow of COVID19 Pneumonia Prediction

- AIforCOVID database [19] with 983 patients from Italy with labels as COVID-19 severe and COVID-19 mild.
- MosMed COVID-19 Chest CT database [20] of 1,110 patients from Russia with labels CT0 (no severe damage), CT1 (damage until 25%), CT2 (damage from 25-50%), CT3 (damage from 50-75%) , CT4 (damage is above 75%) which shows the severity of the lungs.
- SIRM database [21] of 115 COVID19 detected patients from Italy.
- UCSD COVID-CT database [22] of 349 patients with COVID19 and non-COVID19 labels.

Listed datasets are continuously updated and new datasets are added. A complete list of datasets with links can be found in Tab. I.

III. General Deep Pneumonia Prediction

The general workflow of pneumonia prediction can be seen in Fig. 3. As a first step, raw DICOM files go through multiple transformations like resize, rotate, scale, etc. Afterward, preprocessed files are fed to DL algorithms like CNNs, Transformers, RNNs, and GANs to extract valuable features by reducing the dimension and automatically discover the representations needed for object classification, detection, and segmentation.

Image classification is a CV problem for finding objects in images and videos based on their unique properties. Classification of an image was a massive problem until DL algorithms showed marvelous results in many classification tasks since 2013. Practically, the image classification task can be applied in any place, which works with images, videos, or cameras involved. Surprisingly, image classification is becoming very popular in medicine [23]–[27].

Object detection task is used to identify and locate objects in images and videos by drawing bounding boxes. Object detection algorithms are applied in tasks like self-driving cars, video surveillance, etc. There are two types of object detection algorithms: one-stage and two-stage. One-stage approaches like YOLO [28] are more straightforward and faster, whereas two-stage algorithms like Fast R-CNN [29] and Faster R-CNN [30] have better accuracy but are slower in performance.

Image segmentation task is a process of grouping pixels together associated with an object type into multiple segments. There are three types of image segmentation: semantic segmentation [31], instance segmentation [32], and panoptic segmentation [33]. Semantic segmentation treats several objects of the same class as a single object. Nevertheless, instance segmentation divides multiple objects of the same type as distinct individual instances. For instance, in processing CXR

TABLE I
General Deep Pneumonia Prediction Datasets

Dataset name	# of images	Format	Type	# of labels
RSNA Pneumonia detection [13]	26,684	DICOM	CXR	2
SIIM FISABIO RSNA COVID-19 Detection [14]	6,334	DICOM	CXR	4
NIH Chest X-ray [15]	112,120	PNG	CXR	14
Chexpert [16]	224,316	JPG	CXR	14
MIMIC-CXR-JPG [17]	371,920	JPG	CXR	14
RICORD [18]	240 and 1,000	DICOM	CT and CXR	4
AIforCOVID [19]	983	DICOM	CXR	2
MosMed COVID-19 Chest CT database [20]	1,100	NIfTI	CT	5
SIRM [21]	115	JPG	CT	1
UCSD COVID-CT database [22]	349	PNG	CT	2

images, semantic segmentation means to segment lungs and bones separately. Panoptic segmentation handles both segmentation tasks mentioned above instance-wise and semantic-wise.

IV. Methodology

In this section, we divide the COVID19/pneumonia detection task into subsections as pneumonia classification, detection, and segmentation (Fig. 4). Each subsection consists of a family of algorithms applied for the COVID19/pneumonia detection task and then the existing works related to each of the algorithms. In this section, we give updates on CNN algorithms applied to the COVID19 prediction. Also, we survey new advances like Vision Transformer, RNNs/LSTMs for sequential data, and GANs. Furthermore, emerging issues related to data privacy and lack of training data are also discussed here.

A. Pneumonia/COVID19 Classification

1) CNN-based Classification: Recent advancements in CV were achieved through Deep CNNs. Every CNN consists of input, hidden, and output layers. The input layer has pixel information of an image; the output layer tries to predict the correct class label. The magic happens in the hidden layer where feature extraction and learning occur. Transfer learning technique uses pre-trained DL algorithms as a backbone in solving similar or related CV tasks, for instance, in medicine. The advantages of using CNNs are automation without human supervision and getting high prediction accuracy, but it takes an immense amount of data, time, and computation power to train a model.

Wang et al. in [23] proposed COVID-Net combined with projection-expansion-projection design pattern architecture achieving 93.3% accuracy in predicting COVID-19. However, Tang et al. in [34] achieved 95% accuracy by using an ensemble deep learning model of combined multiple COVID-Net model snapshots models. Pham et al. in [24] tested 16 pre-trained CNN algorithms to detect covid-19 on CT scans. Chowdhury et al. in [3] gave attention to cases like COVID-19 pneumonia vs. normal cases, and viral pneumonia and normal

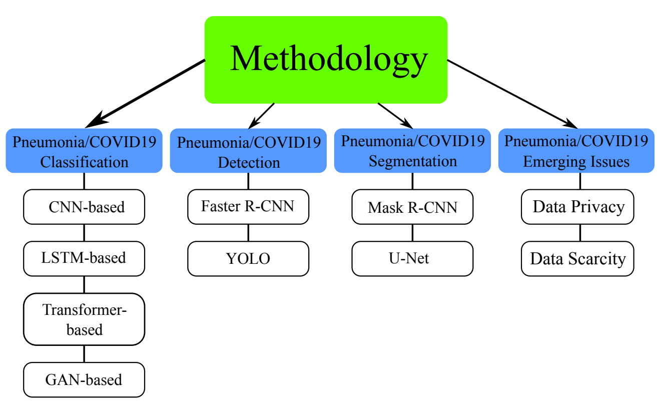

Fig. 4. COVID19/Pneumonia Detection Methodology.

chest X-ray images getting an accuracy of 99.7%. Ahuja et al. in [35] applied a wavelet transform augmentation to classify COVID-19 in CT scans. Authors achieved 99.4% accuracy using the pre-trained ResNet18 model.

2) LSTM-based Classification: RNNs are a type of ANNs that are primarily applied to sequential data. The idea behind RNNs is having an internal state which can represent context information, and information about past inputs which is kept for a fixed amount of time. LSTM algorithm [12] is an improved RNN that was designed to cover the vanishing gradient problem in RNNs. A significant advantage of using RNN/LSTM architecture is that it remembers information through time. However, it cannot access very long sequences, which results in a vanishing gradient problem. Below we give RNN/LSTM based COVID19 detection works.

Islam et al. [25] used CNN-LSTM combined architecture to predict COVID19. CNN was used to extract features, and LSTM was applied for classification purposes. Sedik et al. [36] took the same approach of using CNN combined with LSTM to detect COVID19 in CT and CXR images. Pustokhin et al. [37] developed a model called RCAL-BiLSTM, consisting of ResNet based Class Attention Layer with Bidirectional LSTM to detect COVID19. Authors achieved 94.88% accuracy.

3) Transformer-based Classification: CNNs have dominated the CV field for almost a decade. Researchers put several efforts into finding alternatives for CNNs, but success disappeared as CNNs gained more power by getting deeper. However, Dosovitskiy et al. [10] showed promise of Transformer architecture called Vision Transformer (ViT) in image classification without using CNNs. One of the advantages of using ViT is that it can handle very long sequential data, but the limitations are that it requires more data than CNNs to train a good model.

Park et al in [26] proposed Vision Transformer (ViT) algorithm to diagnose COVID19 pneumonia. They trained the backbone network utilizing PCAM, then trained the overall network using ViT and backbone. Sriram et al. in [38] proposed a new transformer-based algorithm with self-supervised pre-training using Momentum Contrast Learning. Authors achieved AUC of 0.786 and 0.848 for predicting an adverse event and predicting mortalities.

4) GAN-based Classification: Generative Adversarial Network (GANs) [11] is a DL-based generative model which mainly operates in unsupervised learning. GANs consist of a generator model responsible for generating new samples and a discriminator model that classifies whether the generated sample is real or fake. GANs are good at generating artificial samples when a dataset is limited, but generated samples need to be validated by a radiologist in medical imaging.

Yadav et al. in [27] proposed an unsupervised GAN-based algorithm with a support vector classifier (SVC) applied to CXR images. GAN algorithm was used as a feature extractor, and features were fed to SVC and logistic regression algorithms to make the final prediction. Authors of [39]–[41] applied GAN architecture as a data augmentation technique to generate more CT samples for COVID19 prediction. Results showed accuracies of 93%, 99.22%, and 99.60% respectively. Quan et al. [42] proposed a new model called XPGAN to improve COVID19 classification in X-ray images. GAN algorithm was used to augment CT scans to produce more X-ray images. Authors achieved an F1 score of 0.823.

B. Pneumonia/COVID19 Detection

Currently, there are not many updates focused on localizing COVID19 pneumonia in X-rays and CT scans. Therefore, this section briefly explains object detection algorithms and existing works on the COVID19 pneumonia detection task.

A region-based algorithm called R-CNN [43] is a two-stage object detection algorithm for object detection and segmentation tasks. The idea is to propose regions using Selective Search [44], classify proposed regions, and predict output labels with bounding boxes. The R-CNN algorithm, however, was quite slow, therefore the inventors of R-CNN devised the Fast R-CNN [29] method to address the issue. The only difference was to use convolution implementation of the sliding window to classify all proposed regions. Ren et al. proposed Faster R-CNN [30] algorithm to address the region proposal problem using a convolutional network, which proposes multiple objects available in an image. However, overlapping bounding boxes need to be handled separately, which is a time-consuming additional task.

Yao et al. [45] used Faster R-CNN to detect pneumonia in CXR images. Authors achieved mAP of 39.23% on the RSNA dataset and mAP of 38.02% on the ChestX-ray14 dataset. Li et a. [46] proposed NIA-Network, which is based on Faster R-CNN and Adversarial Learning (Gradient Reversal Layer) to detect COVID19 infection in CT scans. The authors showed an accuracy of 92.1%. Yang et al. [47] proposed to use a multiple deep learner approach for detecting pneumonia in CXR images. MDL approach is the combination of Mask R-CNN ResNet50, Mask R-CNN ResNet101, and Faster R-CNN ResNet101. Results showed a precision of 96% in predicting bounding boxes.

YOLO [28] is a one-stage algorithm that performs object detection in a real-time scenario. The idea of YOLO algorithms is to divide an image into multiple grids where each grid algorithm proposes its bounding box (es) with confidence scores. Afterward, class probabilities are predicted to establish class the class of an object(s). For instance, Al-antari et al. [48] applied YOLO algorithm for COVID19 detection on X-ray images.

C. Pneumonia/COVID19 Segmentation

Mask R-CNN [49] is a SOTA algorithm for image segmentation problems. Its task is to detect objects and generate a high-quality segmentation mask for each instance. Advantages of Mask R-CNN are: (1) easy to train, (2) outperforms existing object segmentation algorithms, (3) efficient because it adds a bit change to Faster R-CNN, (4) easy to generalize for other tasks.

Nayyar et al. [50] proposed a Mask R-CNN object detector to identify X-ray images that have pneumonia or some other type of lung disease. This method achieved an IoU score of 0.155. Ramesh et al. [51] applied Mask R-CNN for segmenting COVID-19 lung lesions on chest X-rays. The highest IoU score of 0.81 was achieved. In [52] Wu et al. used encoder-decoder architecture for segmentation task. Results showed a Dice score of 0.783, IoU score of 0.665.

U-net [53] is a DL algorithm for segmenting infected regions in biomedical images. Ronneberger et al. achieved high segmentation accuracy due to the rich feature extraction ability of CNNs and encoder-decoder architecture. In addition, U-Net allows access to global location and context simultaneously; however, learning may slow down in the middle because of the bottleneck in U-Net architecture.

Hasan et al. in [54] applied DenseNet based U-Net architecture to segment COVID19 infected regions in X-ray images. Average IoU scores of 0.90 and Dice coefficient 0.92 were achieved as a result. Munusamy et al. [55] proposed FractalCovNet architecture for segmenting the COVID19 infected regions in CT scans. As a result, mean Absolute Errors (MAE) of 0.064 was achieved. Zhou et al. [56] proposed a COVID19 segmentation algorithm which is based on U-Net with an attention mechanism. Experiments showed Dice score and Hausdorff Distance of 83.1% and 18.8 on 473 CT scans respectively. Combination of Dense GAN and U-Net with multi-layer attention (MLA) mechanism was applied in [57] to segment the lung lesions of COVID-19 in CT scans. U-Net with MLA served as a segmentation algorithm and Dense GAN assisted as a data augmentation technique.

D. Emerging Issues in COVID19 Prediction

In this section, we discuss emerging issues related to data privacy and lack of training data.

1) Pneumonia/COVID19 Data Privacy: Medical images consist of sensitive PHI, which is classified as confidential. Health care centers save the patient data in digital format into local servers by default. Most medical object detection (CV) models assume that all the data stay in a central server. However, it raises privacy issues, especially in DICOM files which consist of private information.

Federated Learning [58] is a solution that specifically eliminates the need to collect data which dramatically increases data privacy. First, the federated server holds only the global model. Each participating hospital downloads the model, and training happens locally. After the training process is finished, updated models are uploaded to the server, where aggregation happens, and computed the newly updated global model. This process is repeated several rounds by making the global model more robust because of the diversity of data. The data leakage problem is solved because the data stay locally without collecting it to a remote server. A huge benefit of using FL is that a model trains in a decentralized environment by keeping the data secure. Another technique for privacy protection is called Differential Privacy [59]. Differential privacy algorithms are used as an additional layer of data security by adding random noise to the data or a model. Nevertheless, using differential privacy and federated learning may result in a lower testing accuracy compared to centralized DL training.

Zhang et al. [60] proposed a dynamic fusion-based FL approach to detect COVID19 in X-rays and CT scans. Experiments showed 95% accuracy of detecting COVID19 while preserving data privacy. Kumar et al. [61] applied a blockchain-based FL framework with SegCaps and Capsule Network to detect COVID19. Results show 98.68% accuracy in a highly secure and private environment. Liu et al. [62] and Feki et al. [63] tested transfer learning techniques with FL to classify COVID19 in CXR images. FL approach applied in medical imaging holds a promising future in solving the COVID19 situation both efficiently and securely [64]. Ulhaq et al. [65] proposed theoretical framework which adds differential privacy into a federated machine learning model for predicting COVID19 cases to achieve scalable and robust results in a eminently protected setup. Authors of [66], [67] applied DP to deep learning models to predict COVID19 in CXR images and achieved promising results in privacy preserving environment. Data anonymity with vectorization was proposed in [68]. Authors showed that a vector-based model is more efficient in anonymization of location data while preserving data utility compared to point-based methods. Another work related to contact tracing was considered in [69]. Authors proposed a spatial k-anonymity privacy preserving algorithm to anonymize the geo-location data of COVID19 patients.

2) Scarcity of Pneumonia/COVID19 Data: Sharing medical data is prohibited by default due to privacy reasons. It raises the lack of training data, and researchers usually do not have enough data for training a good prediction model. ImageNet consists of a vast amount of images which are enough to train a DL model. However, due to having much personal information in DICOM files, researchers working with medical images deal with small datasets compared to ImageNet. So, to overcome this issue recently, researchers have considered self-supervised learning and few-shot learning techniques as probable solutions.

Self-supervised learning is a concept where machines try to learn things without human-annotated data. In the context of medical imaging, the final goal for an algorithm is to extract labels automatically from the input data. The most significant advantage of self-supervised learning is the reduction of the required amount of labeled data. However, a model might hit the overfitting problem if the data is minimal.

Abbas et al. in [70] applied a self-supervised learning algorithm to predict COVID19 in CXR images. A combination of deep CNNs, transfer learning, clustering algorithms gave 99.8% on two massive datasets by feeding unlabeled images. Authors in [71] mentioned the problem of weak annotation and insufficient data in medical imaging. To solve mentioned problems, the authors proposed weakly supervised learning with self-supervision and multiple instance data augmentations. Fung et al. [72] improved the Inf-Net model by applying self-supervision to segment coronavirus lesions from raw CT images. A proposed algorithm called SSInfNet outperformed U-Net and Inf-Net models. Finally, Park et al. [73] proposed to use self-supervised learning, Models Genesis, and convolution block attention module (CBAM) to diagnose COVID19 in CXRs.

Few-shot learning (FSL) is an ML technique that aims to build better models with less training data than traditional ML techniques requiring more data to train a model. Thus, FSL reduces the cost of data collection and labeling. FSL can produce consistent results compared to SOTA models, but the sensitivity of FSL to small data change leads to a lack of generalization ability. Although there are not many papers that applied FSL for COVID19 prediction, we give some applications below.

Ma et al. [74] applied FSL, domain generalization, and knowledge transfer for segmentation tasks on a limited COVID19 dataset. Jadon and Shruti in [75] proposed FSL with siamese networks followed by contrastive loss function to detect COVID19 in CXR images. Authors achieved 96.4% accuracy vs. logistic regression baseline model that showed 83%. Another attempt of using a siamese network with n-shot learning was proposed in [76]. Shorfuzzaman et al. used a pre-trained VGG-16 network encoder for feature extraction, Siamese network for classification purposes, contrastive loss, and various n-shot learning approaches to predict COVID19 cases. Authors achieved 95.6% accuracy with 96.0%, 98.0% for sensitivity and specificity, respectively.

3) Challenges: This paper shows that computer vision techniques proved to exhibit promising results in COVID19/pneumonia classification, detection, and segmentation problems to speed up the X-ray and CT scans analysis. However, in a real-world scenario, medical deep learning models have to deal with different datasets, and their performance is not satisfactory in some cases. For instance, Freeman et al. [77] surveyed popular DL models in breast cancer detection. Authors found that 94% of the models (34 out of 36) cannot outperform one radiologist. Thus, even though researchers try to solve the shortage of training data through self-supervised learning and few-shot learning, these solutions need further research, especially in medical imaging. To overcome the generalization issue, we can apply GANs as an augmentation technique. However, to test whether a model trained on synthesized data can make the correct prediction, results must be verified by an experienced radiologist. Unfortunately, verification of a deep learning model by a radiologist is an expensive task.

V. Conclusion

In this paper, we examine COVID19 prediction in-depth, taking into account CV issues such as COVID19/pneumonia classification, detection, and segmentation. We also look at new advances in deep learning developments such as Transformers, GANs, and LSTMs. Furthermore, while medical imaging has many advantages for detecting coronaviruses, it does have some privacy issues [78] because medical data contains a lot of private patient health information. We consider federated learning and differential privacy to address privacy concerns, which help train a model in a decentralized manner by adding some noise while not exposing a patient's privacy. Privacy concerns exacerbate the lack of training data in medical imaging. As a solution to limited data, we investigate self-supervised learning and few-show learning. In the future, more research and attention are needed to solve the privacy issues and the data scarcity problem. Moreover, the generalization ability of existing models is still a significant area of research.

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