Deep-Learning-Based COVID-19 Detection: Challenges and Future Directions

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Abstract—Coronavirus disease 2019 (COVID-19) is an ecumenical pandemic that has affected the whole world drastically by raising a global calamitous situation. Owing to this pernicious disease, millions of people have lost their lives. The scientists are still far from knowing how to tackle the coronavirus due to its multiple mutations found around the globe. The standard testing technique called polymerase chain reaction for the clinical diagnosis of COVID-19 is expensive and time consuming. However, to assist specialists and radiologists in COVID-19 detection and diagnosis, deep learning plays an important role. Many research efforts have been done that leverage deep learning techniques and technologies for the identification or categorization of COVID-19-positive patients, and these techniques are proved to be a powerful tool that can automatically detect or diagnose COVID-19 cases. In this article, we identify significant challenges regarding deep-learning-based systems and techniques that use different medical imaging modalities, including cough and breadth, chest X-ray, and computed tomography, to combat COVID-19 outbreak. We also pinpoint important research questions for each category of challenges.

Impact Statement—Deep learning (DL) is contributing significantly in combating against COVID-19 in various aspects of detecting and controlling COVID-19. Hence, DL based methods have been widely used for the detection of COVID-19. A plethora of research papers have been published, compiling and reviewing DL based techniques for the detection of COVID 19 through analyzing CT scans and X ray images. However, these studies lack to cover significant challenges and research questions in this field. The main objective of this paper is to identify challenges and research questions in detecting COVID-19 through deep learning which are not identified and fully elaborated by the researchers yet. The challenges highlighted in this paper will call an attention to the noticeable weaknesses and problems in the existing deep learning based COVID-19 detection systems and techniques. Moreover, the research questions for each challenge will guide the researchers to come up with novel solutions for COVID-19 detection.

Index Terms—Computed tomography (CT) scan, coronavirus, coronavirus disease 2019 (COVID-19), deep learning (DL), detection, diagnosis, severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), sound analysis, X-ray.
It has become challenging to perform the segmentation of COVID-19 images due to the low contrast of the COVID-19 infection and variation in shape, texture, and size. However, some researchers have identified a very slight difference between COVID-19 and pneumonia in images that light shades in computed tomography (CT) scan and X-ray images point out COVID disease and pneumonia is spotted by dark shades in the images [7], [8].

In the current health crisis and coronavirus pandemic, health industry, practitioners, and researchers are utilizing artificial intelligence (AI) and deep learning (DL) for tracking and controlling its growth and spread. DL is a subfield of machine learning (ML) that mimics the human brain and imitates the way humans gain certain type of knowledge, and thus, it is best suitable for problems such as image classification, anomaly detection, language translation, speech recognition, and disease classification. DL algorithms have the ability to process large amount of unstructured data. Moreover, DL algorithms are capable of solving pattern recognition problems with higher accuracy without human intervention. Fig. 1 demonstrates a number of AI contributions in fighting against COVID-19 and to curtail its adverse effects. Currently, the researchers are eagerly looking for new techniques and technologies based on DL for tracking the speed, detecting the growth rate of the coronavirus, and identifying the risk and severity of patients. Moreover, using AI, previous patient data can be adequately analyzed to anticipate the possibility of death.

There are some studies [9], [10], [11], [12], [13], [14], [15], [16], [17], [18] that have attempted to compile the literature related to COVID-19 detection and are highlighted in Table I. What is missing in them is that they all have contemplated and reviewed only one facet, either detection through CT scans or X-ray images or cough analysis and also they fail to cover the recent literature comprehensively. Moreover, these studies lack to cover important challenges and research questions in this field. The main objective of this article is to identify significant challenges and research questions in detecting COVID-19 through DL. Our contributions are threefold.

1) First, we describe in detail the general pipeline of image processing for COVID-19 detection.
2) Second, we describe in detail the DL-based detection of COVID-19 using different kinds of modalities.
3) Third, we identify, categorize, and present some important challenges in detecting COVID-19 through DL. The research questions for each category of challenges are also identified.

The rest of this article is organized as follows. Section II presents the general procedure followed for COVID-19 detection in image processing field using DL. Section III presents a taxonomy of modalities used for DL-based techniques for
TABLE I
CONTRIBUTIONS OF EXISTING RELATED SURVEYS

| Reference | Theme of the survey |
|-----------|---------------------|
| [9], 2022 | AI-based deep learning methods particularly COVID-19 classification using CNN are summarized. Performance challenges to demonstrate rapid virus diagnosis and detection potential are also highlighted. The cost-effectiveness of the surveyed methods for detecting COVID-19 in contrast with the other methods is also discussed. |
| [10], 2022 | An overview of novel deep learning-based applications for medical imaging modalities, computer tomography (CT) and chest X-rays (CXR), for the detection and classification COVID-19 is presented. Sources of used datasets for COVID-19 detection are collected that the researchers can easily access. |
| [11], 2022 | An overview of more than 100 DL-based approaches developed to combat COVID-19 is presented. |
| [12], 2022 | An in-depth survey of DL approaches based on image and region-level analysis of COVID-19 infection is presented. Most of the available commercial and non-commercial diagnostic tools, dataset resources and challenges faced in the pandemic are also highlighted. |
| [13], 2021 | A comprehensive survey of AI-powered methods is presented. |
| [14], 2021 | Deep learning-based research articles for the diagnosis of COVID-19 from CT or X-rays are studied and reviewed. |
| [15], 2021 | The approaches used in the detection of COVID-19 based on deep learning (DL) algorithms are discussed comprehensively. The advantages and disadvantages of different approaches used in literature are examined in detail. The databases and major future challenges of DL-based COVID-19 detection are also presented. |
| [16], 2021 | Summarized recent efforts about the COVID-19 outbreak for smart, healthy cities is provided. Three use cases in China, Korea, and Canada are also presented. A number of challenges and issues associated with existing studies are highlighted. |
| [17], 2021 | Machine learning methods to encounter the COVID-19 epidemic are comprehensively reviewed. |
| [18], 2020 | Research community efforts towards helping the individuals and the society to combat COVID-19 over the past 3-4 months using speech signal processing are summarized. |
| Our survey | We identify significant challenges regarding deep learning-based systems and techniques that use different medical imaging modalities, including Chest and Breast, Chest X-ray, and Computer Tomography (CT) to combat COVID-19 outbreak. |

COVID-19 detection. Section IV presents a taxonomy of significant challenges in detecting COVID-19 using DL and research questions for each category. Finally, Section V concludes this article.

II. ARCHITECTURAL DESIGN FOR DL-BASED COVID-19 DETECTION SYSTEMS/TECHNIQUES

In the automated diagnosis of COVID-19 in patients, DL is extensively used. Generally, several steps are followed by DL-based COVID-19 detection systems, including data collection, data preprocessing, segmentation, localization, feature extraction, feature selection, and classification. The DL-based COVID-19 diagnosis systems follow the general pipeline, and their general architectural design is illustrated in Fig. 2.

A. Image Acquisition

In the image acquisition stage, radiography images (CT scan or X-ray images) or sound data of the patient (speech, cough, and breath) are collected using different technologies and machines. CT scans range from the apex to the lung base, and during a single breath hold, they are acquired. CT images are reconstructed from the acquired raw data, and then, for subsequent readings and diagnosis, they are transmitted through picture archiving communications systems. An inevitable contact between the technicians and patients is required in the conventional imaging workflow, e.g., in positioning the patients, technicians assist in posing the patients, but to avoid the severe risks of infection in this pandemic of COVID-19, it is important to employ a contactless and automated image acquisition workflow. Sound data, such as breathing, cough, and speech, can also be collected using smartphone sensors or wearable sensors and can be utilized for COVID-19 diagnosis.

B. Preprocessing

The primary task of preprocessing is to emphasize the aspects of image and improve the quality of the raw images. This makes it in a form that is well suited for further processing by a machine vision system. In addition, it helps in image recognition tasks or DL training phase. In preprocessing, certain parameters of images are improved, such as smoothing the inner part of the region, improving the signal-to-noise ratio and removing the irrelevant noise and undesired parts in the background, enhancing the visual appearance of CT images image, and preserving its edges [19]. Since CXR images and CT scan images are collected from different sources, to ensure uniformity across different datasets, they are resized and transformed from RGB to grayscale. To speed up the convergence performance, the resultant images are then subjected to min–max normalization. In the case of speech data recorded in the installed applications and converted into a digital format, unwanted components, such as pauses, background noise, and stammering, are also removed from the digital signals in the preprocessing phase. Filtering and general signal processing techniques are applied to clear the areas to be processed for voice activity detection phase. After obtaining the actual signal, feature selection algorithms are applied to categorize the input signal into a specific characterized speech signal [20].

C. Segmentation

Segmentation is the process of dividing or partitioning a digital image into multiple segments. By dividing the image into segments, important segments can be picked for processing the image. For COVID-19 detection, the lung part in a CXR images is examined. For a successful detection, lung part in each image should be segmented. Moreover, in fighting against COVID-19, important information can be deducted by qualitatively evaluating and by the delineation of lung infections and longitudinal changes in CT scans of COVID-19 patients. It is indicated that the distinctive infection indication of ground-glass opacity (GGO) and consolidation can be detected through the segmentation of CT scans of COVID-19 patients [21]. It is laborious, tedious, and time consuming to manually project the lung infections with the dependence of the accuracy of infection annotation heavily on the knowledge and experience of the radiologist and often influenced by individual bias and clinical experiences as it is a subjective task. Thus, the automatic and accurate segmentation techniques provide a rapid screening of
COVID-19. DL-based techniques for COVID-19 detection have adopted different types of segmentation techniques, such as few shot segmentation [22] and semantic segmentation [23].

Some of the DL-based techniques are designed for the severity assessment of COVID-19 patients by leveraging segmentation of lung or lung lobe in CT images as a prerequisite procedure for diagnosis purposes [24], [25], [26], [27]. However, in most of these methods, the lung lobe segmentation and disease diagnosis are treated as two separate tasks, and their underlying correlation is ignored, which ultimately slows down the classification and detection or prediction process. Thus, it is instinctive that lung lobe segmentation and severity assessment/prediction are performed jointly, in which there is no need to detect and crop the lung field, and prediction performance is improved through faster learning [28], [29].

D. Feature Extraction

Feature extraction is an essential step toward classification because useful characteristics of the images are provided by extracted features. In feature extraction, an initial set of the raw data is divided and reduced to more meaningful groups. It aims to reduce the number of features in a dataset by creating new features from the existing ones and then discarding the original
features. Feature extraction is useful when dataset is large. In the case of CT scan and X-ray images, deep neural networks can provide extraordinary capabilities for feature extraction from a large-scale dataset. DL algorithms, such as convolutional neural network (CNN) (which is widely used in COVID-19 detection for feature extraction), can be used to segment the regions of interest and capture fine structures in chest CT images. Later, these self-learned features can be easily extracted [7]. In the system [30], the authors have extracted features form CT images by using ResNet50 and then applied the CNN for the classification. Moreover, in [31], a pipeline and multiview representation learning technique is proposed to classify COVID-19 using different types of extracted features from CT images.

In the case of the cough sounds dataset, cough features can be extracted, such as wet cough and dry cough, for COVID-19 detection [32]. However, it is time consuming to develop a classification model from a dataset with high dimensionality, which may also converge to local minima due to the large search space. In addition, cough features of COVID-19 may overlap with other diseases, so performance and accuracy can be immensely improved if a reduced set of relevant features from an audio sample is selected. It is, thus, challenging to extract cough features; however, some attempts have been made by some researchers.

E. Classification

In COVID-19 detection through image processing, DL mainly focuses on feature extraction and the classification of images in an automated manner [6], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42]. By using CXR images of patients, most researchers focused on DL techniques to detect COVID-19. Some of the researchers have attempted to detect COVID from non-COVID, which is called binary classification [43], [44], [45], [46], [47], [48]. Some of the researchers have proposed DL-based techniques for the severity assessment of COVID-19 patients. In these techniques, the binary classification problem is formulated for the task of severity assessment. Finally, a classification layer utilizes learned volume features for the severity assessment of COVID-19 patients, i.e., severe or nonsevere COVID-19 patients [28]. Others concerned with three-class classification (COVID versus normal versus pneumonia) [6], [33], [34], [35], [36], [37], [38], [39], [40], [49]. Only a few of the researchers focused on COVID-19 detection using four class classification (COVID versus normal versus bacterial pneumonia versus viral pneumonia) [41], [42].

III. Modalities Used for COVID-19 Detection Through DL

In this section, we devise a taxonomy for the modalities used by the research community for COVID-19 detection. The three types of modalities are medical images, sound, and smartphone-based data. The taxonomy is presented in Fig. 3.

A. COVID-19 Detection Through Medical Images

The chest CT is a valued feature of the assessment of patients with respiratory complications, as well as a great utility for elective surgical procedure monitoring and neurological examinations [50], [51]. In a chest CT examination procedure, X-rays are transmitted through the patient’s chest, which are then reconstructed into high-resolution medical images after being detected by radiation detectors. In the past, to successfully diagnose pneumonia either from CXRs or CT scans, AI-based techniques were employed [52], [53], [54]. At present, for the detection of COVID-19, thoracic CT scan and chest CT scans are extensively used by the clinical institutes around the world and are explored to be effective and complementary screening tool alongside RT-PCR [55]. Even more, CT scan provides more standard and intuitive information as compared to the RT-PCR test [56], [57], [58], [59].

On the basis of CT scans of COVID-19 patients, radiologists can make medical decisions by possibly determining how badly the lungs are compromised and how the illness of the individual progresses. To be adopted as a vital method for supporting the
diagnosis and management of patients with COVID-19 infection, there are certain patterns to look out for in thoracic CT scans, including air bronchograms, perilobular pattern, GGO, crazy paving and consolidation, and reverse halo [60]. More importantly, there is a need to know which part of the CT lung is most affected by COVID and specific patterns need to be looked upon, including bilateral, peripheral, interlobular septa thickening, multifocal patchy consolidation, basal predominant GGO, and crazy-paving pattern, with a peripheral distribution, which have been declared as the findings of COVID-19 infection at chest CT images [61]. Novel strategies and proposals are required for a simple classification and identification of COVID severity locations (CSLs) since few studies [62], [63] are not automated strategies for CSLs.

Although the analysis of CT scans provides more useful, faster, and reliable results in the COVID-19 classification and assessment, there are a few challenges to use CT scans for COVID-19 detection. First of all, it is challenging for radiologists to distinguish COVID-19 infections from non-COVID-19 infections using chest CT [64], [65] because some early studies have shown that a number of potential indicators for COVID-19 infections that are present in chest CT images may also be present in non-COVID-19 infections [62], [66], [67], [68]. Second, CT takes longer for imaging. CT imaging is highly costly, and the CT scanners are not available in many underdeveloped countries. Moreover, owing to high radiation in CT imaging, pregnant women and children may face health risks. Third, CT scanning equipment are not portable, and there is a need to sanitize the room and equipment between patients followed by a delay of at least an hour [69]. Otherwise, there is a danger of risk of exposing the persons under investigation (PUIs), hospital staff, and other patients to the COVID-19 virus [70] and its transmission from a patient to others due to CT scan tunnel contamination [71]. The comparison of most recent DL-based techniques for the detection of COVID-19 using CT scan images is presented in Table II.

Currently, in this pandemic of COVID-19, CXR images are also found to be very helpful in testing and evaluating COVID-19 patients. When attributable symptoms of COVID-19, such as fever, cough, or dyspnoea, are presented by the patients, doctors perform CXRs as they are cheaper and quick. The radiologists look for GGOs (in the case of COVID-19, it is usually the first radiological sign). They also look for the portion of lung appearing as a “hazy” shade of gray instead of being black with fine white lung markings for blood vessels [72]. In the studies for detecting COVID-19, the researchers have looked for predominant patterns in chest radiographs, such as peripheral opacities, interstitial opacities, airspace opacities, diffuse airspace opacities, lobar consolidation, craniocaudal gradient and bilateral diffuse reticular interstitial lung thickening, and the presence of pleural effusions [73], [74].

Compared with CT scan imaging, CXR imaging is more beneficial and effective for emergency cases, and owing to its less ionizing radiations, simplicity, portability (due to portable instrumentation), operational speed, and low cost, it is found to be promising. In CXR imaging, the personnel exposure is limited, and the PUIs can be imaged in more isolated rooms. Moreover, compared to CT scan, in obtaining CXR images, sanitation is much less complex [75]. Moreover, as CXR images are more easier to obtain, the existing CXR datasets are much larger than the CT datasets for COVID-19 diagnosis. However, according to some prior studies [76], when X-ray images were taken from people affected by the COVID-19, some inconsistencies were observed in those X-ray images. In addition, the CXR images have a high spatial resolution, but they are planer images and all the structures visualized at CXR are displayed on a single plane;
| Study | Year | Methodology | No of Samples | Dataset | Performance |
|-------|------|-------------|---------------|---------|-------------|
| [76]  | 2021 | The differentiable neural architecture search (DNAS) method combined with the Gumbel Softmax technique | 3,993 CT scans from 2,698 patients | Clean-CCICCI, ModMedData, and COVID-CTnet | Accuracy of Clean-CCICCI = 88.69% , ModMedData = 82.29% , and COVID-CTnet = 96.85% |
| [79]  | 2021 | Transfer learning strategy using custom-sized input tailored for each deep architecture, the LAMB optimizer utilized for training the networks | Total CT scans = 2,482 of 120 patients in the SARS-CoV-2 CT scan, Total CT scans = 746 in the COVID-19 CT, with 349 CT images COVID-19 and 397 non-COVID-19 and other pulmonary diseases. | The SARS-CoV-2 CT scan and the COVID-19 CT | Accuracy of SARS-CoV-2 dataset = 99.4%, COVID-19 CT dataset = 92.9% |
| [80]  | 2021 | Anamorphic depth (AD) embedding-based lightweight CNN, with the fully convolutional AD-block built within symmetric encoder-decoder architecture to segment anomalies in COVID-19 chest CT images, first lung extraction, data augmentation using horizontal flip and vertical flip, label weighting scheme during training, segmentation using AD block. | 929 axial chest CT images from 49 patients with COVID-19 provided by the Italian Society of Medical and Interventional Radiology | Italian Society of Medical and Interventional Radiology | Accuracy of Experiment 1 = 99.1%, Experiment 2 = 98.8% , Experiment 3 = 98.6% |
| [81]  | 2022 | Feature extraction using different layers of pre-trained ResNet50, feature selection using a new FS method, called Cluster-based Golden Ratio based Optimizer (CGRO) and clustering-based population selection applied to address premature convergence of GRO, then classification using SVM, KNN, and ELM. | SARS-CoV-2 contains 3492 chest CT scan images, 1262 of which are COVID-19 positive, and the remaining 1230 images are of healthy subjects COVID-CT contains 349 confirm COVID-19 cases and 397 healthy cases. | SARS-CoV-2, Muhannad Talo 2 class, and COVID-CT datasets | Accuracy of SARS-CoV-2 = 98.65%, Muhannad Talo 2 class = 99.64%, Muhannad Talo 3-class: 94.12% , and COVID-CT datasets = 99.31% |
| [82]  | 2022 | A new model is constructed by combining the ResNet50 backbone with SE blocks. First Data Pre-processing using binary image conversion, removing the connected regions that are in contact with the edges, a morphological erosion, data augmentation using horizontal flipping, random translation and finally classification using integrated ResNet50 and SENet. | A total of y 52973 slices of 659 persons. 2119 images of COVID-19, 594 images of bacterial pneumonia, 2315 images of typical viral pneumonia, and 582 images of healthy controls. | Sun Yat-sen Memorial Hospital and Renmin Hospital of Wuhan University | Accuracy 94% |
| [83]  | 2022 | A multi-stage attentive transfer learning framework is proposed. First captures semantic information from the whole lung and highlights the functionality of each lung region for better representation learning, self-supervised transfer learning from medical images (SSTL-M) to extract complex patterns from the used medical CT images by integrating self-attention layers (ATTNs) into convolutional neural networks (CNNs) such as ResNet50 and ResNet101. | 16898 images in total, among which 573 images are for COVID-19 cases, 5559 images are for regular pneumonia (non-COVID-19) cases and the rest 8066 are normal cases. | ImageNet, COVID-19 CT | Accuracy of R-50 with TL = 93.9% , Accuracy of R-101 with TL = 94.2% |
| [84]  | 2021 | A supervised domain adaption based COVID-19 CT diagnostic method is proposed. Siamese network structure that is trained by a novel cross-domain training mechanism. This cross-domain training mechanism enables an effective domain transfer via three different losses (Classification loss, Cross-domain pairing loss, Cross-domain detaching loss). | 6,000 source domains slices (synthetic data) and 60 target domain slices (real data) to form the training set, and we use 600 real CT scans as the test set. | Proprietary dataset | Accuracy = 80.40% |
| [85]  | 2021 | A DL based framework is developed by using pre-trained networks (DenseNet201, VGGG16, ResNet50V2, and MobileNet) as its backbone. First data augmentation using image rotation, n image shift, horizontal flipping, then classification using transfer learning. | A total of 2481 CT scan images The SARS-CoV-2 CT scan dataset contains 1252 CT scans of COVID-19 positive patients and 1229 CT scans of non-COVID-19. | Angelov et al p CL scan image dataset, SARS-CoV-2 CT scan dataset | Accuracy of DenseNet201 = 97% |
| [86]  | 2021 | SegNet-based network using the attention gate (AG) mechanism is proposed for the automatic segmentation of COVID-19 regions in CT image | 473 CT images | COVID-19 CT segmentation database | Sensitivity = 92.73% , Specificity = 99.51% |
| [87]  | 2021 | A new Multiple Kernel-ELM-based Deep Neural Network (Mk-ELM-DNN) method is proposed. First preprocessing using scaling and data augmentation using reflection and rotation. Deep Feature extractiing was using transfer learning of a DenseNet201 architecture, Then Normalization of the extracted features. Classification using Extreme Learning Machine (ELM) classifier based on different activation methods. The majority voting method is used for all predicted results and the final class label. | A total of 746 images; with 349 images of COVID-19 and 397 images of no-findings cases. | COVID-CT dataset | Accuracy = 98.36% |
| [88]  | 2021 | A fully automated and efficient deep learning-based method, called LungNet is proposed. The receptive-field-aware (RFA) module is proposed to segment the COVID-19 infection in lung CT images. RFA comprises convolution layers to extract COVID-19 features, dilated convolution consolidated with learnable parallel group convolution to enlarge the receptive field, frequency domain features obtained by discrete wavelet transform (DWT), which also enlarge the receptive field, and an attention mechanism to promote COVID-19-related features. | 20 labeled COVID-19 CT scans (1800 + annotated slices) | COVID-19 Lung CT Dataset | Accuracy = 98.92% |
| [22]  | 2021 | A semi-supervised few-shot segmentation (PSS) approach for efficient segmentation. There are three modules: the conditioner path, the adaptive interaction module, and the segmentation path. The conditioner path learns the visual information of the support set to infer infection on the query slice. The adaptive interaction module effectively conveys the learned representation in terms of feature maps. | CT-1 comprises 110 axial CT slices belonging to 60 patients, CT-2 comprises nine CT volumes consisting of 829 slices, with 373 annotated axial CT slices of COVID-19 | Two annotated CT datasets CT-1 and CT-2 publicly published by the Italian Society of Medical and Interventional Radiology | Sensitivity = 89.2% , Specificity = 97.5% |
thus, they do not allow 3-D slicing [77]. The comparison of most recent DL-based techniques for the detection of COVID-19 using CXR (X-ray) images is presented in Table III.

### B. COVID-19 Detection Through Mobile Sensors

In order to control pandemic, smartphone applications are a valuable commodity that could be tailored as respiratory monitoring systems [100]. There are some studies [101], [102], [103], [104] that have analyzed a variety of acoustic feature types and accuracy of algorithms based on ML by utilizing audio recordings collected via smartphones for the automatic detection of respiratory illness. In this pandemic of COVID-19, remote smartphone digital health technology has several advantages over traditional clinical visit for screening and diagnosing COVID-19. If COVID-19 infections are detected at earlier stages, the rate of its transmission can be reduced by alerting the individuals to take precautions more actively [105]. First, by using individual’s everyday smartphone devices at home, workplace, or vehicle, health screening implementation can be conducted on a large scale via an application, and respiratory health assessments can be performed remotely that can assist to quickly log the location/time of symptoms or incidence in real time. Second, overburdening at health-care emergency clinics can be reduced by remote evaluations and cross validation at medical clinics. The health-care-related expenses can be minimized while serving such practices. Third, screening access can be provided to those individuals who live in remote places or

| Study Year | Methodology | No of Samples | Dataset | Performance |
|------------|-------------|---------------|---------|-------------|
| [89] 2021 | Weighted averaging ensembling (WAE) | NA | COVIDX dataset | Sensitivity = 96%, PPV = 94.1% |
| [90] 2021 | CNN Classification | NA | Publicly available dataset | Accuracy = 99.44% |
| [91] 2021 | Transfer learning using ResNet-50 by training the network, 252 handpicked features extraction, classification | NA | Images from Mendeley and Kaggle Chest X-Ray Datasets | Accuracy = 97.4% |
| [92] 2021 | Transfer learning of pre-trained CNN models DenseNet321, InceptionResNetV2, MobileNetV2, VGG19 and InceptionV3 | NA | RSNA Pneumonia Detection Challenge dataset, COVID-19 Chest X-Ray Dataset Initiative and COVID-19 Image Data Collection | Accuracy = 95% |
| [93] 2021 | Pre-processing stage, image resizing and normalization of input images, the proposed 2D-CNN network for feature extraction, the classification operation using sigmoid and SVM separately | 333 chest X-ray images comprising of 77 images of COVID-19 patients and 256 images of normal subjects | Proprietary dataset recorded at Omida Hospital in Tehran | Accuracy = 99.02% |
| [94] 2021 | Transfer learning using VGG16, ResNet50, and EfficientNetB0 as feature extractor | 802 CXR images | Images from COVID-19 Image Data Collection publicly available on GitHub | Recall = 90% and Precision = 93% |
| [95] 2021 | Feature extraction by using eleven pre-trained CNN models, optimization using spotted hyena optimizer (SHO), 48 decision tree algorithm for classification | Chest X-ray images dataset of 50 normal patients and 50 COVID-19 patients | Chest X-ray images collected from the GitHub and Kaggle repositories | Accuracy = 98.54% |
| [96] 2021 | Feature extraction using histogram-oriented gradient (HOG), multiplicative speckle noise elimination using a modified anisotropic diffusion filtering (MADF) technique, segmentation using watershed segmentation technique for identifying fractured lung regions and classification by using CNN (VGG19). | 819 COVID-19-positive and 1341 normal chest X-ray images from a bench mark dataset, 660 images with 390 positive COVID-19 X-ray images from Cohen’s dataset, 770 images of the COVID-19 and 1500 normal images from publicly | Cohen’s dataset, other publicly available datasets | Accuracy = 99.49% |
| [97] 2021 | Pre-processing using gradient operations by applying operator such as Sobel, Roberts and Prewitt, Segmentation using watershed segmentation (MCWS) technique, three class classification using deep LSTM | A total of 1061 CXR images with 361 COVID-19, 200 Normal and 500 Pneumonia CXR images | Public Kaggle website dataset CXR images | Accuracy = 100% |
| [98] 2021 | Feature extraction using SqueezeNet and ShuffleNet CNN models and 4class classification using SVM | 300 images are COVID19, 300 images are bacterial pneumonia, 300 images viral pneumonia and 300 images are normal cases | A collection of CRIs created from the GitHub repository and Kaggle repository | Accuracy of 4-class = 94.44%, 3-class = 99.72 % and binary classification task = 100 % |
| [99] 2021 | Segmentation of the lung regions using classic segmentation model UNet with residual connection, Augmentation using Shifting, scaling and rotation operations, post-processing operations implemented by Scikit-image, filling holes and removing small objects, Classification using Mask Attention (MA) mechanism. | A total of 6792 CXR images with 1840 Normal images, 433 COVID-19 images, 394 TB images, 2760 BP images and 1345 VP images | A collection of CXR images from Montgomery County and Shriners No. 3 People’s Hospital | NA |
| [100] 2020 | Lung segmentation using ANN, data Augmentation using image rotation technique, classification using a transfer learning-based modified AlexNet (mAlexNet) architecture. | A total of 2905 CXR images with three classes 219 COVID-19 positive images, 1345 viral pneumonia images and 1341 normal images | Proprietary dataset COVID19 Radiology database | Accuracy = 98.14% |
C. COVID-19 Detection Through Sound Analysis

COVID-19 virus critically affects the human speech production system, and most of the symptoms of COVID-19 are associated with the functioning of the respiratory system. Thus, COVID-19 detection can be performed by analyzing three types of human generated audio or sound signals: speech signals, cough signals, and breathing signals. A characteristic symptom of COVID-19 is dry cough, in which no mucous or phlegm is produced with the cough. To help in the current scenario of COVID-19, in various studies [18], [114], [115], the authors have discussed possible opportunities, solutions, and use cases by leveraging human speech analysis. When respiratory muscles contract, the acoustic sound of a cough is generated. Cough (which can be wet, dry, or a wheezing, and whooping cough) is a sudden air expulsion from the nasal airways or throat, which is characterized by a distinctive sound [116]. A typical cough sound signal consists of three phases, i.e., a rapid explosive phase, an intermediate decaying phase, and a voiced phase, and dry cough is characterized by all these three phases due to the absence of any mucus or sputum.

Cough is a predominant symptom of COVID-19, and thus, for possible preliminary screening and diagnosing COVID-19, researchers have utilized human cough by identifying COVID-19-specific cough and differentiating it from other similar sounds, such as speech and laughter. They are motivated to analyze human cough for COVID-19 detection because prior studies [117], [118], [119], [120] have shown that cough from distinct respiratory syndromes has distinct latent features that are extracted by applying appropriate signal processing and mathematical transformations to train AI or DL models for diagnostic purposes. Understanding the impact of COVID-19 on healthy speech production and the changes in voice of COVID-19-infected patients, several initiatives have been taken as recently in a study [121], it has been shown that approximately 25–32% COVID-19 patients from the sampled populations in the U.K. and the USA have a hoarse glottal voice quality [107]. Another study was conducted on voice pathology, which was an indication of abnormally high rates of vocal dysphonia in COVID-19-positive individuals with mild-to-moderate severity because of the inflammation in tissues and glottic edema (vocal folds). [122]. The comparison of most recent DL-based techniques for the detection of COVID-19 using cough and speech analysis is presented in Table V.

IV. CHALLENGES IN COMBATING COVID-19

In fighting against COVID-19 pandemic, massive research proposals have been flooded regarding various aspects of COVID-19 detection, but still there are unresolved challenges and research questions in COVID-19 detection that need to be addressed through developing novel solutions. In this section, we devise a taxonomy for these challenges and categorize them according to COVID-19 data, diagnosis, and regulations. The challenges and future directions in combating COVID-19 pandemic are presented in Table VI and illustrated in Fig. 4.

A. Challenges Concerning COVID-19 Data

In this subsection, we present two potential challenges related to COVID-19 data that the researchers are facing in its detection. These challenges are security and privacy of COVID-19 patient’s data and lack of sufficient standards of COVID-19 datasets.

1) Security and Privacy of Patient’s Data: To control the situation in this pandemic of COVID-19 and to take immediate actions and decisions, there is a need to make up-to-date policies in the face of public health issues. In doing so, the authorities and governments aim to collect a range of personal information, such as ID, contact number, personal medical data, diagnosis reports, CT scan and X-ray images, travel trajectory, and daily activities and share it with public health departments. This collection and sharing of highly sensitive patient data have raised concerns regarding patient’s mobility, medical, and social behavior. This,
TABLE V

| Study | Year | Methodology | No of Samples | Dataset | Performance |
|-------|------|-------------|---------------|---------|-------------|
| [109] | 2021 | A primary screening test framework is proposed. It consists of identification algorithm based in EMG and a recognition method named DeepCough3D. DeepCough3D method generates a 3D audio tonus to leverage the strength of a convolutional neural network approach to identify the latent characteristics in Covid-19 cough sounds. First raw cough sound is preprocessed. Then, cough detection algorithm with the filtered audio signals is based on empirical mode decomposition (EMD). | 8,380 clinically validated cough samples with 2,339 Covid-19 positive and 6,041 Covid-19 negative | Cough samples collected from Hospital Costa del Sol Health Agency in Marbella, Spain and the National Laboratory for Research in Food Safety (LANLIA) laboratory in Nayari, Mexico. | AUC = 98.80% Sensitivity = 96.43% |
| [110] | 2020 | A system is proposed based on speech and sound analysis of different extracted acoustic features by utilizing RNN and LSTM architecture. | Speech corpus was collected from 60 healthy speakers and 20 COVID-19 patients | Proprietary dataset | Accuracy = 97 |
| [111] | 2020 | An AI speech processing framework that leverages acoustic biomarker feature extractors to pre-screen for COVID-19 from cough recordings. Cough recordings are transformed with Mel Frequency Cepstral Coefficient and input into a Convolutional Neural Network (CNN) based architecture made up of one Poisson biomarker layer and 3 pre-trained ResNet50's in parallel. | 2,660 COVID-19 cough samples | Proprietary dataset | Sensitivity = 98.5% Specificity = 94.2% AUC= 97% |
| [112] | 2020 | Extraction using the Mel scale, Log-based MelSpectrogram as well as filter banks. Classification using multi class LSTM and SVM. | 28 Pneumonia, 15 Pertussis, and 30 Typical back sounds. | Proprietary dataset | Accuracy = 100% |
| [113] | 2020 | An easy and early diagnosis based on the classification technique. First spectrogram evaluation analysis of processed cough sounds based on STFT. Feature extraction using STFT and MFCC feature extraction techniques. Feature selection using the sequential forward search (SFS) method. Then classification of COVID-19 cough is performed using support vector machine (SVM) algorithm. | 73 non-COVID and 48 COVID-19 coughs | Samples collected from mobile app upon the request of Stanford University and made available on “Cough” | Accuracy = 95.86% |

in turn, has also generated numerous privacy and security issues because of the open-source nature of data and mandatory usage of advisory and contact tracing applications. This is because such applications collect sensitive personal health data and do not give clear and transparent privacy notices while briefing about the functions of the application, integrating customs and travel records with national health-care database, using applications via Bluetooth for collecting the records of other people who have been in their close proximity within the past 21 days. Moreover, the collected information is erased and disposed of in an insecure manner. The location of the individuals who are required to undergo home quarantine is monitored via cellular signals from their mobile phones, which may also raise privacy concerns.

Although the usage of tracing apps and digital technologies for monitoring and curtailing the virus spread rates seems to be promising especially in the time of lockdown, these tools can raise privacy and security concerns just like many emerging technological advancements. Thus, the anonymization of individual’s information and ensuring the privacy preservation of COVID-19 patients’ personal and medical data is a challenging task [123], [124]. Another major concern is workforce shift from office based to more remote work arrangements on permanent basis; hackers are exploiting this disruption in normal work patterns to hide intrusion activities, and as a result, there is an increase in false positives in intrusion/risk alerts and complexity in filtering false positives from actual positives. Owing to successful cyberattacks, hospital operations are negatively affected and access to clinical services is delayed, leading to significant economic loss [125], [126]. In addition, sharing COVID-19 patients’ data for academic purposes has also resulted into public hatred and discrimination, as reported in [127]. Therefore, this situation demands the complete anonymity of medical and mobility data, and there is a need to carefully manage these concerns by implying security controls, such as encryption and anonymization, to deter data leaks and manipulation attempts from nontrusted third parties as well as to ensure that the results of COVID-19 detection are optimum. Moreover, during the design and refresh stages of contact tracing applications, privacy principles, such as “privacy by design” and “privacy by default,” should be considered. Although some efforts have been made by leveraging technologies such as blockchain [128], [129], [130], federated learning [131], [132], [133], [134], and incentive-based mechanisms [135] but still there is a room for the improvement in protecting COVID-19 patient’s data.

2) Lack of Sufficient Standard COVID-19 Datasets: Data are a key component in ML, and without sufficient data, for solving a problem, DL approaches may experience a limitation in their effectiveness, accuracy, and efficiency. Thus, in the current pandemic, the lack of standard and adequate COVID-19 clinical data prompted as a barrier and a severe challenge in the research of COVID-19 detection and diagnosis, limiting the performance of DL-based COVID-19 diagnostic and prognosis tools and techniques [136]. Owing to the rapid explosion of COVID-19, and urgency, scientific datasets were often constructed in a quick manner, and thus, the collected datasets are small and inadequate and may not be as precise as they should be. In this regard, an effort has been made in [137], where a generative adversarial network is used to generate more X-ray images and develop a COVID-19 diagnostic tool. With smaller datasets, researchers have exploited pretrained DL algorithms that usually worked well on larger datasets, but here on smaller datasets, their performance has diminished due to overfitting problems [138]. It is, thus, challenging to develop DL approaches for dealing with smaller as well as imbalanced datasets. Moreover, COVID-19 data are collected using smartphones or other voice recorders in unconstrained environments, which are generally noisy and contain reverberation. Hence, the available imaging data for
COVID-19 patients are in bad quality, noisy, incomplete, and in some cases, the labels are inaccurate and ambiguous [139]. It is complex to train a DL algorithm on such data, while resolving data redundancy, sparsity, and also the missing values. Consequently, insufficient time-series data and low-quality data result in biased and inaccurate predictions and unreliable results [140]. It is, thus, challenging for DL algorithms to diagnose and detect COVID-19 accurately and efficiently. In addition, because of using different datasets with different numbers of samples, definitively concluding which system yields the best result for COVID-19 detection is quite difficult. There is a need to establish organized framework and datasets to make them easily accessible for the researchers around the world.

### B. Challenges Concerning Smartphone-Based COVID-19 Detection/Diagnosis

In this subsection, we present two significant challenges related to COVID-19 detection/diagnosis through smartphones that the researchers are currently facing for its efficient detection.
These challenges are detecting and diagnosing COVID-19 patients with no or mild symptoms and user acceptance of remote health care and telehealth/telemedicine.

1) Detecting and Diagnosing COVID-19 Patients With No or Mild COVID-19 Symptoms: Currently, to control the worldwide disruptive and spreading novel coronavirus disease, smartphones, with their computing proficiency, have been used to detect COVID-19 by collecting and analyzing speech, cough, and breathing signals. Some interesting frameworks based on mobile smartphones are provided for developing COVID-19 detection softwares and algorithms [32], [40], [141], [142]. Moreover, smartphones are also capable of processing X-ray images and CT scans by using DL in smartphones for the detection of COVID-19 [143]. DL algorithms work well by providing better insights and accuracy in diagnosis with larger datasets, but using them on smartphones may degrade their performance because the computing capability of a mobile to treat a large amount of data is lower than a grand machine or a computer, and thus, to accomplish this task, lightweight algorithms are required to develop, which is a challenging task. There are also some other noticeable challenges in this regard. Experiments performed in [144] have shown that the quality of images in this way is not adequate for managing the smartphone-based applications. It is also challenging to get accurate and relevant speech data for developing DL models in terms of social distancing norms. To assist in this regard, chat bots play a significant role and automate the screening of COVID-19 making it faster, but it is also a challenging task to design chat bots while considering its positive and negative impacts.

In a recent pathology study [122], there is an indication of abnormally high rates of vocal dysphonia in COVID-19 patients with mild-to-moderate severity because of glottic edema and tissue inflammation. A major problem is that most of the smartphone-based studies [100] have not scrutinized speech data, but they have only examined recorded breathing/cough sounds for COVID-19 detection; the individuals with moderate COVID-19-like symptoms that tested negative are ignored. Thus, these studies are not effective in cases when individuals do not have difficulties in breathing or cough symptoms. It is, therefore, challenging to develop smartphone-based systems that can detect COVID-19 patients with no or mild symptoms such as cough.

2) User Acceptance of Remote Health Care and Telehealth/Telemedicine: Information and communication technologies are playing a significant role in assisting doctors, practitioners, and health-care professionals and workers for a faster diagnosis of viral infections and diseases. In the COVID-19 epidemic, owing to the need for social distancing and in-person contact restrictions, telehealth services application and remote care or remote diagnosis have accelerated and are used in the large-scale screening of patients, supervising patient care by experts, and for remote clinical encounters [145], [146]. It is made possible with the help of body wearable sensors, telehealth care, telemedicine, and AI-chatbots [147], [148]. By using telehealth, health-care professionals are able to provide medical services at a distance using video imaging and videoconferencing and other technologies. When emergency situations are detected, the smart homes equipped with environmental and personal sensors (interconnected using the Internet of Things) are capable of monitoring patient health and sending messages to responsible clinicians. In addition, health wearable devices have a myriad of different sensors that can collect distinct data types, such as steps, sleep, and heart rate pulse.

By processing the collected sensor data and applying DL and statistical methods, wearable devices are found to be promising technology to track viral infections overtime as well for detecting COVID-19 and proactively detect them before their onset. However, challenges are raised because environmental conditions and external factors affect the physiological measurements resulting into inherently unpredictable time-series data. This unpredictability in the data leads to low accuracy of models and systems, which, in turn, badly shatter the patient’s trust upon these systems. When patients and providers are unsatisfied with telemedicine, rather to be subjected a bad experience, they both may prefer to suffer the inconvenience and unavailability of in-person care. Moreover, mostly patients also prefer to see their own health-care provider as opposed to someone with whom they have no established relationship. Thus, patients trust upon telehealth should be developed, which is a challenging task [149]. Owing to the dramatic improvements in technology, digital availability has increased accessibility and quality of care, and at the time of epidemic conditions such as COVID-19, telemedicine has the potential to control the disease and management of clinical case and to improve research of epidemiological [150], [151], [152]. The patient’s general appearance, including patient’s respirations (effort of breathing, speech, and accessory respiratory muscle involvement), oropharynx observation, patient-directed lymph nodes to assess for notable lymphadenopathy, and the presence of a patient cough (dry or wet), can be noted via video [153]. Despite this, the concept of telehealth and telenursing is not a panacea, coming up with comes with risks including security breaches, and hindrances in its wide adoption still exist [154].

The most important hindrance in a wide adoption of telemedicine is the patients’ preference of face-to-face health care. A major problem is that there are some health issues, such as transplantation, therapies, etc., that can only be handled and evaluated in person, and using telemedicine, it may have trouble concentrating or working remotely. In addition, hurdles in implementing telehealth-care programs also largely depend on payments systems, insurance, and accreditation as there is a lack of supportive payment structures and heavy regulatory laws due to which telemedicine has yet to be widely implemented [146], [155]. Some other noticeable barriers that currently exist to telemedicine include a lack of knowledge about having telemedicine visits as an option, the lack of education about the efficacy and safety of telemedicine in light of current circumstances, and a lack of understanding about how to access telemedicine visits [156]. Although some patients are already embracing the telehealth mode of care delivery [157], [158], health-care professionals need to be aware of patients’ preferences for communication and to learn new skills for conducting telemedicine visits by developing programs to educate and mentor colleagues and trainees [159] and find the ways of using...
telehealth by which the need of patients can be met with the levels of attentiveness, expertise, and empathy that is provided during office clinical visits.

C. Challenges Concerning Ethics and Regulations

In this subsection, we present two critical challenges related to ethics and regulations in detecting COVID-19 that the research community is facing currently. These challenges are the lack of regulations and policies for detecting COVID-19 and controlling misconceptions, misinformation, and fake news about the pandemic.

1) Lack of Regulations and Policies for Detecting COVID-19:
The daily number of confirmed cases (infected and dead) is considerably increasing. To control this outbreak, governmental authorities are defining different policies and are playing a vital role by applying various approaches, such as screening and testing at a large scale, lockdown, social distancing, etc. For example, Korean government has started the quarantine policy from April 1, 2020 according to which it is compulsory to quarantine all the passengers for 14 days at designated facilities or registered addresses who are entering Korea. Moreover, all the passengers are obliged to send their daily self-diagnosis reports taken through self-diagnosis apps installed in their mobile phones. In case if people do not have mobile phones and cannot install the self-diagnosis apps, the Seoul Metropolitan Government has implemented an AI monitoring calling system, which can automatically check the health conditions of the people [160]. It is still challenging to make effective policies and regulations as individual citizens and businesses usually ignore what is asked of them.

There is a need for a rapid development of new policies and additional restrictive measures, to meet the novel circumstances. For a pandemic, the rationing policies vary from country to country on the basis of their health system, institution, and jurisprudence, and thus, the COVID-19 pandemic has also raised a host of ethical challenges, due to the rationing of scarce critical care resources by the health-care systems. Some countries have uniform policy, while some have no policies at all. Thus, there is need to ensure that remote health-care practices are carried out in an ethical, confidential, and safe manner by establishing laws and regulations around the world. Moreover, to preserve many of the current waivers that permit telemedicine services and to make telemedicine a viable solution, there is a need to advocate for legislative reform at the federal and state levels. From an ethical perspective, to avoid overt and implicit bias, there is a dire need to apply triage policies consistently to all the patients. From a legal perspective, allocation decisions and triage policies should not be unlawful against protected classes of individuals (e.g., on the basis of race, religion or color, national origin, and sex) so that discrimination can be avoided [161].

2) Controlling Misconceptions, Misinformation, and Fake News in the COVID-19 Epidemic:
In COVID-19 pandemic across the globe, medicine and science is combating against it with the assistance of digital technologies, but the health-care systems are in disarray and they are facing another critical problem, fake news or misinformation, which refer to fabrications, satires, and hoaxes mixed in real reports to mislead people’s judgment, especially during the pandemic. It is also stated by the WHO that pandemic is accompanied by an “infodemic” (information epidemic). Fake news is intentionally written to mislead readers to believe false information, which makes it difficult and nontrivial to detect based on news content. Fake news is divided into two categories: misinformation and disinformation. Misinformation refers to the false or misleading information that is inadvertently shared and disinformation refers to deliberate creation and sharing of false information that is purposely spread to deceive people and is known to be false [162], [163].

With the start of COVID-19 pandemic, the spreading of inaccurate information online, i.e., a cluster of fake news about possible remedies, vaccinations, and lockdown policies, is not only life threatening but also causing disruptions in society, creating confusion among people and even leading to deadly consequences in health problems. In addition, the prevalent misinformation is also disrupting the social order and the supply chain disrupted out of fear since people started to pile up stocks of masks and sanitizers [164]. The misinformation in the form of numerous harmful advice or cures being suggested regarding the prevention and treatment of COVID-19 is taken seriously, which has caused the deterioration of the patient’s condition as well as the emergence of new diseases [165]. For instance, it is suggested that drinking fish tank additives, bleach, or cow urine is suggested to be a cure for COVID-19, which is actually harmful for health [166]. Particularly, one major concern is the misinformation regarding COVID-19 vaccines, which is the main cause of vaccine hesitancy and is fueled by rumors of safety and conspiracies [167], thus influencing people’s willingness to follow the recommendations by health and political authorities on vaccination [168]. Owing to these rumors, people either refuse to vaccinate or delay its acceptance despite the availability of vaccination services [169]. This is mainly because the online social media lack gatekeeping and proper regulations, and thus, it is a place to disseminate misinformation and fake news rapidly [170] by providing a fertile ground for spreading a large amount of unfiltered content [171] and authorizing a misinformation phenomenon. Moreover, misleading news are presented purposefully by many online news portals in order to increase their popularity. This pandemic is seen as a good opportunity for the journalists, bloggers, or anyone with access to social media to increase the number of their followers or readership rates and to obtain extra attention by publishing COVID-19-related information. In doing this process, there is manipulation or fabrication of valid information, which creates fake news or stories in order for it to appear more interesting to the public [172]. Consequently, the public’s perception of reality is possibly manipulated and aggravated through the dissemination of fake news content [173].

During this epidemic, these fake news and rumors are creating panic among the masses, and thus, it is very crucial to detect [174] fake news. In most of the existing methods for fake news detection, false news is identified by combining richer data, which provide data repository, including news contents,
social contents, as well as dynamic information. However, such methods cannot be applied in new fields due to the lack of universality. Hence, researchers have proposed semisupervised and unsupervised methods [175], [176], [177], [178], which try to make a tradeoff between the amount of training data and the final training accuracy. It is still a challenging task to detect COVID-19 fake news as the COVID-19 fake news is multilingual. Moreover, the accuracy of some of the abovementioned recent systems has not yet reached acceptable levels because of the insufficient learning of limited corpus contents and the incomplete hard samples mining. The size and features of data used by the researchers are not enough for building models for accurate classification. Moreover, for the accurate classification of fake news detection, very less research has been done toward the application of linguistic and DL techniques. In addition, the model’s understanding of common sense is diminished due to the excessive further training, resulting in some incomprehensible mistakes. There is a need to design an effective detector that can efficiently and accurately differentiate between the real/actual news and fake news according to its title or summary. For evaluating the proposed works in the current pandemic, there is a need to apply the existing natural language processing (NLP) techniques for fake news identification on COVID-19 social media datasets [179]. From the ethical point of view, the authorities and people should be aware of their ethical duties so as to ensure that only ethical and valid information is being shred on social media [172].

D. Challenges Concerning the Usage of DL Models for COVID-19 Detection

In this subsection, we present two significant challenges that arise specifically when DL models are used for the detection of COVID-19. These challenges are the lack of generalization and the lack of interpretability and clinical translation of DL models for COVID-19 detection.

1) Generalization of DL Models: In the past months, DL models based on AI tools have been proposed for the automatic detection of COVID-19, which have utilized publicly available datasets of CXRs or CT scans for training and evaluation. However, their higher accuracy results for classifying COVID-19 are often obtained on cross-validation studies without an independent test set coming from a separate dataset. Moreover, they have biases such as the two classes to be predicted come from completely two different datasets [180]. The problem with these DL models is that when different kinds of prior knowledge are injected into AI, this may limit the generalization ability [181]. This results in models to perpetuate already existing biases in the training datasets, even exacerbating racial disparities already seen in COVID-19 [182]. The major gap in most of the recent studies of DL-based COVID-19 detection is that these models have been trained on narrow datasets and have not been tested in terms of their clinical utility on large datasets. This generalization problem is caused due to the imbalanced collection of CXR images. CXR images of COVID-19 patients differ in terms of patient features, radiographic features, and amount of data because they are collected with various radiographic devices and environments by different institutions. Thus, decisions of DL models, which are trained on these imbalanced datasets, are not much accurate because they do not consider minor differences in COVID-19-positive cases, pathological regions, or the lung regions, making it hard to generalize to new or unusual samples.

Thus, it has become challenging to categorize how well a trained model will generalize to new data distributions. There is need to develop AI-based models that must generalize to unseen data from different populations, and for this, the collected datasets from external sites should be adequately sized. An attempt has made in [98] to address the problem of generalization and interpretability while distinguishing COVID-19 from tuberculosis (TB), viral pneumonia (VP), and bacterial pneumonia (BP). They have utilized the attention mechanism at the first stage, and the predicted masks are used as spatial attention maps for the adjustment of the features of the CNN at the second stage.

2) Interpretability of DL Models: For COVID-19 rapid diagnosis, medical imaging is supported by AI models, as recently many efforts have been made to develop DL models for the detection of COVID-19 [183]. When AI is involved in detecting COVID-19 by releasing the need for human involvement in image reading, COVID-19 diagnosis has become more efficient. For the assessment of chest images of COVID-19 patients, different DL models and ML models, including CNN, Ensemble, ResNet, VGG16, Truncated Inception Net, Inception Net V3, MobileNet v2, Xception KNN etc., have been used producing promising results when applied on X-rays or CT scans. These methods are capable of diagnosing COVID-19 patients from non-COVID pneumonia cases as well as predicting the severity of COVID-19 pneumonia and the risk of short-term mortality [184]. However, the accuracy of AI models is not the only thing to see because current DL models for COVID-19 diagnosis generally lack clinical interpretability and transparency [185], and due to this complexity of AI models and their low reproducibility, their applications in clinical practice has weakened [186]. Models based on DL suffer from the black-box problem leading to unexplainable features and the absence of transparency and interpretability. In these methods, it is not possible to identify the exact imaging features, and what factors lead to a particular model prediction is difficult to tell. This lack of interpretability produces incorrect decisions and biased results in real diagnostic procedures.

In order to enhance the interpretability of DL models, an effort has been made in [187]. In their proposed model called SSInfNet, the lung imaging phenotypes are extracted from the output of the model, and statistical mediation analysis is applied in which the identified lung CT imaging mediators are used to explore the potential causal association of the patient’s age, gender, and underlying diseases with COVID-19 severity. Another attempt has been made in [7], where the gradient-weighted class activation mapping method [188] is used to improve interpretability to visualize the important regions leading to the decision of the DL model. Although the authors have used a heatmap to visualize the important regions in the scans, this study has limitation that heatmaps are still not sufficient to visualize the unique features that are used by the model to distinguish COVID-19 from community-acquired pneumonia. Thus, it is still challenging to develop interpretable DL models for COVID-19 detection. There is a need that the uncertainty and interpretability in the
predictions should be well understood, and future studies should focus on developing strategies and approaches that are precise and interpretable and are capable of providing interpretation besides black-box predictions.

V. CONCLUSION
COVID-19 has profound effects on human well-being and has significantly impacted global health-care and socioeconomic systems. It has become a major global concern because it is spreading at a fast rate, and the number of disease-related deaths continues to grow globally. To find a viable cure against COVID-19, medical and scientific researchers are working restlessly by harnessing AI and DL in numerous ways. In contribution to fight against COVID-19, DL algorithms, more suitably CNN and its variants, have been successfully applied for the screening, diagnosis, prediction, severity checking, drug discovery, and treatment of COVID-19. This survey offers the identification of significant challenges in DL-based COVID-19 detection. In this survey, we have first presented and explained a general pipeline of image processing with regard to DL-based COVID-19 detection. Then, we have presented the taxonomy of modalities used for the DL-based COVID-19 detection methods and explained each category. Moreover, we have also identified and presented potential challenges and devised a taxonomy for the DL-based detection of COVID-19. Important research questions for each category of challenges are also identified. This survey opens a promising path and a reference guide for the researchers contributing in the battle against COVID-19.

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