Automated Detection and Forecasting of COVID-19 using Deep Learning Techniques: A Review

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Abstract—Coronavirus, or COVID-19, is a hazardous disease that has endangered the health of many people around the world by directly affecting the lungs. COVID-19 is a medium-sized, coated virus with a single-stranded RNA, and also has one of the largest RNA genomes and is approximately 120 nm. The X-Ray and computed tomography (CT) imaging modalities are widely used to obtain a fast and accurate medical diagnosis. Identifying COVID-19 from these medical images is extremely challenging as it is time-consuming and prone to human errors. Hence, artificial intelligence (AI) methodologies can be used to obtain consistent high performance. Among the AI methods, deep learning (DL) networks have gained popularity recently compared to conventional machine learning (ML). Unlike ML, all stages of feature extraction, feature selection, and classification are accomplished automatically in DL models. In this paper, a complete survey of studies on the application of DL techniques for COVID-19 diagnostic and segmentation of lungs is discussed, concentrating on works that used X-Ray and CT images. Additionally, a review of papers on the forecasting of coronavirus prevalence in different parts of the world with DL is presented. Lastly, the challenges faced in the detection of COVID-19 using DL techniques and directions for future research are discussed.

Index Terms—COVID-19, Diagnosis, Deep Learning, Classification, Segmentation, Forecasting.

I. INTRODUCTION

The novel COVID-19 virus came to light in December 2019 in Wuhan Province, China, where it originated from animals and quickly spread around the world [1]. In January 2020, world health organization (WHO) announced the epidemic of COVID-19 as a threat to public health. In March 2020, it announced the Corona pandemic [2]. Coronaviruses include various types that mainly occur in animals. A type of Coronavirus, called SARS-CoV-2, is transmitted from bats to humans, threatening human health throughout the world [2]. SARS-CoV2 might stay alive on different surfaces from a few hours to several days. Clinical studies show that the incubation period of this virus is 1-14 days [2]. Recently, a new type of Coronavirus called Delta with a short incubation period has involved many people, and it has more dangerous complications [3].

The easiest way to transmit SARS-CoV-2 is through the air and physical contact, such as hand contact with an infected person [4]. The virus inserts itself into the lung cells through the respiratory system and replicates there, destroying these cells [5]. COVID-19 comprises a ribonucleic acid (RNA) and is very difficult to diagnose and treat due to its mutation characteristics [6]. The most common symptoms of SARS-CoV-2 include fever, cough, and shortness of breath, dizziness, headache, and muscle aches [2]. The virus is so perilous and can provoke the death of people with weakened immune systems [7]. Infectious disease specialists and physicians around the world are working to discover a treatment for the disease. COVID-19 is currently the leading cause of death for thousands of countries worldwide, including the USA, Spain, Italy, China, the United Kingdom, Iran, and others. Figure 1 shows the latest number of infected people worldwide due to COVID-19.

Currently, various methods have been proposed for fast diagnosis of the Coronavirus. Among the proposed methods, WHO has introduced the real-time reverse transcription polymerase chain reaction (RT-PCR) test as the gold standard of early diagnosis of COVID-19[8]. Also, imaging methods like X-Ray, CT, and ultrasound are of significance for COVID-19 diagnosis.

According to the WHO, all diagnoses of corona disease must be confirmed by RT-PCR [9]. However, testing with RT-PCR is highly time-consuming, and this issue is risky for people with COVID-19. Hence, first, medical imaging is carried out for the primary diagnosis of COVID-19, then the RT-PCR test is performed to aid the physicians in making final accurate detection. Two medical imaging techniques, X-ray, CT-scan, and ultrasound are employed to diagnose COVID-19 [10], [11].

X-ray modality is the first procedure to diagnose COVID-19, which has the advantage of being inexpensive and low-risk from radiation hazards to human health [12]. In the X-ray
method, detecting COVID-19 is a relatively complicated task. In these images, the radiologist must attentively recognize the white spots that contain water and pus, which is very prolonged and problematic. A radiologist or specialist doctor may also mistakenly diagnose other diseases, such as pulmonary tuberculosis, as COVID-19 [13].

The X-ray procedure has a high error rate. CT modality has a higher contrast compared to X-Ray [11]. CT data of the patients suffering from SARS-CoV-2 demonstrate pulmonary parenchyma destruction, including interstitial inflammation and extensive consolidation accurately [14]. To detect the Coronavirus, numerous CT slices are recorded from each patient, which their analysis is challenging. To this end, the specialists try to remove the slices that do not contain important information.

Lung ultrasound is another Coronavirus diagnosis method [15]. Ultrasound plays an important role in diagnosing and treating the Coronavirus because it is not a radiative method. Also, ultrasound can assess different organs and systems, including the heart, arteries, and kidneys, that might have been damaged due to COVID-19 [15].

In recent years, applications of AI in medicine have led to a variety of studies aiming to diagnose varied diseases, including brain tumors from magnetic resonance (MR) images [16], [17], multiple types of brain disorders such from electroencephalography (EEG) [18], breast cancer from mammographic images [19], [20] and pulmonary diseases such as Covid-19 from X-Ray [10] and CT [11]. In the last decade, DL, a branch of ML, has changed the expectations in many applications of AI in data processing by reaching human-level accuracies [21] in many tasks, including medical image analysis [22].

In this paper, an overview of COVID-19 diagnostic approaches utilizing DL networks is presented. Section II explains the search strategy, and various DL models developed for COVID-19 detection are described in Section III. Section IV of the DL techniques used for the detection, segmentation, and prediction of COVID-19 patients. Section V discusses the reviewed papers on diagnosis, segmentation, and prediction of COVID-19 patients. Challenges in diagnosing, segmentation, and prediction of COVID-19 patients are provided in Section VI. Finally, the summary and future work are delineated in Section VII.

II. SEARCH STRATEGY

In this study, valid databases, including IEEE Xplore, ScienceDirect, SpringerLink, ACM, and ArXiv, have been used to search for Covid-19 papers. Moreover, a more detailed Google Scholar search is employed. The articles are selected using the keywords “COVID-19”, “Corona Virus”, “Deep Learning”, “Segmentation”, “Forecasting”, “Attention Deep Learning”, “Transformer Deep Learning”, “Data Fusion”, and “Graph Deep Learning”. The latest selection of papers is done with the mentioned keywords on September 19th, 2021. Figure 2 indicates the number of papers published or indexed by COVID-19 using DL techniques using various databases.

III. DEEP LEARNING TECHNIQUES FOR COVID-19 DETECTION

Conventional machine learning and DL are the two main branches of AI, but DL is essentially a more advanced version of conventional ML. Various DL network architectures have been extensively used in research papers to diagnose the COVID-19 accurately using publicly available databases. Many of well-known DL architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), Autoencoders (AEs), deep belief networks (DBNs), generative adversarial networks (GANs), and also some hybrid networks such as CNN-RNN and CNN-AE have been developed for automated detection of COVID-19. Figure 3 shows the subcategories of DL networks.

IV. COMPUTER AIDED DIAGNOSIS SYSTEM (CADS) FOR COVID-19 DETECTION

In prior research papers, many CADS have been developed applying DL methods on X-ray and CT images; these systems
can be categorized by their application into two categories: (i) classification and (ii) segmentation. In classification-based CADS, the main objective is to identify COVID-19 patients, which involves the process of extracting and selecting the most informative features and classifying using DL. However, in the second type, an image of an infected person is given to the system for segmentation of an area of interest. Manual segmentation of medical images takes considerable time; thus, applying machine learning models is crucially paramount. Among the most important segmentation models, the several types of fuzzy clustering methods [23], [24] and DL ones such as U-Net [25] can be denoted. In the CADS, with the segmentation approach, patients’ CT-Scan images and their manual segments labeled by doctors are fed to the DL network. Then, during the training process, the DL network is trained on manual segments to segment raw input images. The components of DL-based CADS for COVID-19 detection are shown in Figure 4. In the following section, we will first mention the important data available for COVID-19; then, the DL methods used in the review research are introduced.

A. Public Databases used for COVID-19 Detection and Forecasting

Several public databases (X-ray and CT images) are available for the detection and segmentation of COVID-19, some of them are listed in Table I. Also, the datasets related to predicting the COVID-19 spread in leading countries of the world are shown in Table II.

B. Deep Learning Methods

This section is devoted to describing the methods applied in papers briefly. First, well-known network structures for both classification and segmentation are discussed; then, models which are applied for forecasting are explained and lastly, new trends and state-of-the-art methods are presented.

1) Classification Models: CNNs and Pre-trained Models

The primary issue in training the deep models is the concern of overfitting that occurs from the gap between the limited number of training samples and a large number of learnable parameters. Convolutional networks try to overcome this by using convolutional layers [32]. CNNs require minimal pre-processing by considering the 2-dimensional (2D) images as input, and hence it is designed to retain and utilize the structural information among neighboring pixels or voxels. A differentiable function is utilized to transform one volume of actions by each layer to the other as it is a sequence of layers structurally.

While convolutional layers work as some sort of workaround for the issues of deep neural networks, training CNNs properly still needs a massive amount of data, and also designing their structure is itself a time-consuming process. To overcome these problems, researchers usually use a pretrained version of well-known network architecture. Figure 5 shows how the pre-trained networks are used; also, some of the most used network architectures are: AlexNet [33], Visual Geometry Group (VGG) network [34], GoogLeNet [35], ResNet [36], DenseNet [37], and, SqueezeNet [38].

2) Generative Adversarial Networks (GAN): A primary problem in training deep models is limits in dataset size. Using generative models for data augmentation is one solution to this issue. Due to the high quality of generated data, GANs have attracted attention in the medical imaging community [39]. The basic idea in training a GAN is a simple minimax game, in which one network tries to distinguish between real data and generates one, and the other tries to create data undistinguishable by the first network [40], therefore creating images similar to real data.

3) Segmentation Models: A wide variety of DL models have been developed for the segmentation of the lung region to detect COVID-19 in patients accurately. Among these models, FCN network [41], SegNet [42], U-Net [25], and ResNet2Net [43]...
DL models are widely used for the segmentation of lungs. In this section, some of these models are briefly discussed.

**SegNet**
Generally, in segmentation techniques, a network created for classification is chosen, and the FC layers of that network are removed; the resulting network is called the encoder network. Then a decoder is created to transform these low-resolution maps to the original resolution. In SegNet [42], the decoder is created such that for each down-sampling layer in the encoding section, an up-sampling layer is positioned in the decoder. These layers, unlike the deconvolution layers of FCN networks, are not capable of learning, and the values are placed at the locations from which the corresponding max-pooling layer is extracted, and the rest of the output cells become zero.

**U-Net**
The U-Net network [25], like SegNet, consists of the identical numbers of pooling and up-sampling layers, but the network utilizes trainable deconvolution layers. Also, in this network, there is a corresponding skip connection between the up-sampling and down-sampling layers. Figure 6 shows a general form of U-Net architecture used to segment the lung in COVID-19 patients.

**4) Forecasting Models:** **Recurrent Neural Network (RNN)**
A feed-forward neural network is extended to create RNN, aiming to capture the long term dependencies and features from the sequential and time-series data. The most commonly used RNN is the long-short term memory (LSTM), which composed of a memory cell, a forget cell, the input gate, and output gate. These gates make the decision that which information needs to be remembered or discarded from the memory cell and also organizes the activation signals from different sources.

LSTM decides whether to keep or remove the memory by using these gates; also, unlike vanilla RNN, LSTM can preserve the potential long term dependencies. One LSTM variant is Gated Recurrent Unit (GRU) [45], which integrates the forget and input gates into a single update gate and combines the memory cell state and the hidden state into one state. Update gate makes a decision on the amount of information to be added or discarded, and the reset gate decides on how much earlier information is to be forgotten. This technique makes GRU simpler than LSTM.

**5) Advanced AI methods for Diagnosis of COVID-19:** **Deep Attention Learning**
The DL methods based on attention mechanisms have attracted attention recently [46]. The models based on attention mechanism are concentrated on a subset of inputs (focus on certain parts of the input) that contain information regarding the tasks [46]. Recently, attention models have been used in various applications, including classification, segmentation, and diagnosis of COVID-19. In [46], a DL model based on attention with the attention module of VGG-16 has been used to classify COVID-19 using X-Ray images.

**Deep Transformer Learning**
Transformer models are another type of DL method, and some of their techniques include spatial transformer networks, graph transformer networks, recurrent spatial transformer networks, and Polar transformer networks. In [47], COVID-19 has been diagnosed using ultrasound data based on the vision transformer (ViT) model.

**Deep Fusion Techniques**
With the emergence of DL models, it has been tried to combine data fusion techniques and DL networks with medical objectives. In [48], CT data have been extracted using four CNNs to classify Corona data. Then, feature integration and ranking techniques have been used to obtain effective features. Finally, the SVM classifier has been used.

**Graph Deep Learning**
The graph models based on DL are another class of new DL techniques that have been recently used in detecting the coronavirus. In [49], first, a 3D-CNN has been used to extract features from CT images. Then, a COVID-19 graph in GCN has been designed based on the features. Finally, these three DL models are combined to detect the COVID-19.

**V. Discussion**
The main focus of this work is to review the research papers that have worked on DL models for detection, segmentation of the lungs and also forecasting the spread of the COVID-19. The summary of works done on classification, segmentation, and forecasting are presented in Tables III, IV, and V, respectively. Figure 7 depicts the total number of investigations conducted in the field of classification, segmentation, and forecasting of COVID-19 using DL models. It can be noted from the figure that most works have been done on the detection of COVID-19 patients, and the least works are done on forecasting due to the shortage of available public databases.
| Work | Dataset | Modalities | Number of Cases | Preprocessing | DNN toolbox | DNN | Number of Layers | Classifier | Post Processing | K-Fold | Performance Criteria (%) |
|------|---------|------------|----------------|---------------|-------------|-----|------------------|-----------|------------------|--------|--------------------------|
| [20] | COVID-19 X-ray | 45 COVID-19, 1203 Normal, 931 Bacterial Pneumonia, 660 Viral Pneumonia Patients | Data Augmentation (DA), Rescaling, Normalizing | Fastai Library | COVID-ReNet (ResNet-50) Modified Version | Softmax | NA | NA | None | None | Accuracy: 99, Sens: 100, Spec: 100, F1-Score: 100 |
| [21] | Combination of Different Datasets X-ray | 50 COVID-19, 50 Normal Images | Rescaling | NA | ResNet50 Modified Version | Softmax | NA | 5 | Accuracy: 99, Sens: 100, Spec: 100 |
| [22] | Combination of Different Datasets X-ray, CT-Scan | 85 COVID-19 X-ray, 203 COVID-19 CT-Scan, 85 Normal X-ray, 153 Normal CT-Scan | Cropping, resizing | NA | AlexNet Modified Version | Softmax | NA | NA | Accuracy: 99, Sens: 100, Spec: 96 |
| [23] | Cohen’s Group X-ray | 25 COVID-19, 25 Normal Cases | Rescaling | Cortex with Tensor-Flow 2 Backend | COVID-Net (VGG19, DenseNet201) Standard Version | Softmax | NA | NA | None | None | Accuracy: 99, Sens: 100, Spec: 91 |
| [24] | Combination of Different Datasets X-ray | 70 COVID-19 subjects, 1088 Pneumonia Subjects | Rescaling, DA | NA | ResNet18 Modified Version | Softmax | 8 | 5 | Accuracy: 99, Sens: 100, Spec: 96 |
| [25] | BiBim COVID X-ray | 5801 HC, 6895 Pneumonia, 3231 COVID-19 | Filtering | PyTorch | Fused ResNet50 Modified ResNet50 | Softmax | – | 5 | Accuracy: 99, Sens: 91, Spec: 99 |
| [26] | COVID-19 X-ray | 76 COVID-19, 1583 Normal, 4298 Pneumonia Cases | DA, RDR format, Normalizing | MATLAB | COVIDDiagosis.Net Standard Version | Decision-Making System | Class Activation Mapping Visualization | NA | Accuracy: 99, Sens: 99, Spec: 98, F1-Score: 98 |
| [27] | Combination of Different Datasets X-ray | 66 COVID-19, 1853 Normal, 2768 Bacterial Pneumonia, 1564 Viral Pneumonia Images | Resizing, Standardizing, DA | Keras | ResNet50-V2 Modified Version | Softmax | 9 | 9 | None | None | Accuracy: 99, Sens: 99, Spec: 99 |
| [28] | Combination of Different Datasets X-ray | 295 COVID-19, 65 Normal, 98 Pulmonary Images | Feature Color Method, Image Stacking Technique | MATLAB | MobileNetV2 Standard Version | Softmax | 16 | 16 | None | None | Accuracy: 99, Sens: 99 |
| [29] | Clinical CT-Scan | 386 COVID-19 Patients, 127 Patients with Other Pneumonia | Segmentation, Rescaling, Multi-view Fusion | Keras | ResNet50 Modified Version | Dense Layer | NA | NA | None | None | Accuracy: 97, Sens: 91, Spec: 99 |
| [30] | Clinical X-ray | 3250 HC, 1281 COVID-19 infected, and 4637 X-ray images | Resizing, Normalization | NA | Fused-DenseNetTiny Modified DenseNet | Softmax | – | – | None | None | Accuracy: 99, Sens: 99, Spec: 99, F1-Score: 99 |
| [31] | Clinical CT-Scan | 106 COVID-19, 96 Non-COVID-19 Patients | Different Methods | NA | ResNet101, Alexnet Standard Version | Softmax | NA | NA | None | None | Accuracy: 99, Sens: 100, Spec: 99 |
| [32] | Combination of Different Datasets X-ray | 105 COVID-19, 11 SARS, 80 Normal Samples | DA, Histogram, Feature Extraction using AlexNet, PCA, K-means | MATLAB | DXToC (ResNet18) Standard Version | Composition-Phase | NA | Accuracy: 99, Sens: 99, Spec: 99, F1-Score: 99 |
| [33] | RyDELS-20 X-ray | 90 COVID-19, 10 MERS, 11 SARS, 10 Varicella, 12 Streptococcus, 11 Pneumococcus Samples | Different Features, Early Fusion, Late Fusion, Different Resampling Algorithms | NA | Inception-V3 Modified Version | Softmax | 12 | 12 | None | None | Accuracy: 99, Sens: 99, Spec: 99, F1-Score: 99 |
| [34] | Pneumonia Dataset X-ray | 624 Images in 2 Categories: Normal and Pneumonia | GAN | MATLAB | ResNet18 Standard Version | Softmax | NA | NA | None | None | Accuracy: 99, Sens: 99, Spec: 99 |
| [35] | Different Datasets X-ray | 311 HC, 1979 COVID-19 | Feature Fusion based on VGG19 | VGG19 Softmax | 5 | – | 5 | 5 | None | None | Accuracy: 99, Sens: 99, Spec: 99 |
| [36] | COVID-19 X-ray | NA | NA | NA | COVID-CAPS 9 Capsule Layer | Softmax | NA | NA | None | None | Accuracy: 99, Sens: 99, Spec: 99 |
| [37] | Combination of Different Datasets X-ray | 284 COVID-19, 110 Normal, 339 Bacterial Pneumonia, 327 Pulmonary Viral Images | Rescaling | Keras with Tensor-Flow Backend | ConvNet Modified Version | Softmax | NA | NA | None | None | Accuracy: 99, Sens: 99, Spec: 99 |
| [38] | Kaggle X-ray | 5360 X-ray Images in Two Classes: Normal and Pneumonic: 145 Chest X-ray Images of COVID-19 | Rescaling | Keras with tensor-Flow Backend | DenseNet160 Standard Version | Softmax | NA | NA | None | None | Accuracy: 99, Sens: 99, Spec: 99 |
| [39] | COVID-19 X-ray | 13, 804 Images from 13, 645 Individuals | Intensity Normalization, DA | Keras with Tensor-Flow Backend | EfficientNet B3 | Softmax | 50 | 50 | None | None | Accuracy: 99, Sens: 99, Spec: 99, F1-Score: 99 |
| [40] | 3 Different COVlD-19 Datasets X-ray | Different Number of Cases | Different Methods | Keras with Tensor-Flow Backend | DenseNet161 Modified Version | Softmax | 5 | 5 | None | None | Accuracy: 99, Sens: 99, Spec: 99, F1-Score: 99 |
| [41] | Clinical X-ray | 27 Normal, 220 COVID-19, 11 SARS and 15 Pneumococcal Images | Filtering | Keras, TransFlow | Feature Fusion (FM-RF-DLP model) Modified Inception v3 | Softmax | – | 10 | None | None | Accuracy: 98, Sens: 98, Spec: 98, F1-Score: 98 |
| [42] | Combination of Different Datasets X-ray | 99 COVID-19 Cases From the COVID19 Chest X-ray Dataset, 207 Images From Both Dataset | Balancing dataset, DA | Keras | GSA-DenseNet121- COVID-19 Modified Version | Softmax | NA | NA | None | None | Accuracy: 99, Sens: 99, Spec: 99, F1-Score: 99 |
| [43] | COVID-Net-%K Dataset X-ray | 536 COVID-19 Images, 5800 Non-COVID19 | DA, Down Sampling | PyTorch | SqueezeNet Standard Version | Softmax | NA | NA | None | None | Accuracy: 99, Sens: 99, Spec: 99, F1-Score: 99 |
| [44] | Combination of Different Datasets X-ray | 207 COVID-19 Images, 3,685 Non-COVID-19 Images | DA | NA | DenseNet161 Modified Version | Softmax | NA | NA | None | None | Accuracy: 99, Sens: 99, Spec: 99, F1-Score: 99 |
| [45] | Clinical CT Scan | 307 HC, 349 COVID-19 | Transforming CT Images to 2D images, Resizing | NA | Feature Fusion (FM-RF-DLP and RFPCA) Different Layers | Softmax | – | 10 | None | None | Accuracy: 99, Sens: 99, Spec: 99, F1-Score: 99 |
| [46] | Clinical CT Scan | 2331 COVID-19, 2080 Pneumonia, 5193 Tuberculosis, 3088 HC | Different Methods | Na | DenseNet121 ResNet532V2 and VGG16 | Softmax | – | – | None | None | Accuracy: 99, Sens: 99, Spec: 99, F1-Score: 99 |
| [47] | Combination of Different Datasets X-ray | 225 COVID-19 Images, 108,948 Frontal View Images From 32,717 Unique Patients | DA | Keras with Tensor-Flow Backend | CN | FCMLP Grad-CAM | 5 | 5 | None | None | Accuracy: 99, Sens: 99, Spec: 99, F1-Score: 99 |
| Combination of Different Datasets | X-ray | 180 COVID-19 Images, 6054 Pneumonia, 8851 Normal | NA | Keras | Concatenation of Segmentation and RecomputeV2 | Modified Version | Softmax | NA | 5 | Acc=99.56 |
| Combination of Different Datasets | X-ray | NA | Different Methods | PyTorch | COVID-DA | Modified Version | NA | Grad-CAM | NA | Pre=99.15 | Acc=99.5 |
| Combination of Different Datasets | X-ray | NA | Cropping, CLAHE Method, Resizing, DA | NA | CovidIDNet | 15 | Softmax | NA | NA | Acc=98.4 | Sens=99.4 | Spec=99.5 |
| COVIDs | X-Ray | S101 Pneumonia, S105 Normal, 313 COVID-19 Cases Images | – | TensorFlow | EDL-COVID | COVID-Net | NA | NA | – | – | Acc=99.5 | Sens=99.5 |
| Clinical | CT-Scan | 88 COVID-19 Patients, 100 Bacteria Pneumonia Patients, 86 Healthy Persons | Different Methods | OpenCV | DNN (ResNet-50 Backbone) | Modified Version | Aggregation | Softmax | NA | Acc=99.5 | Acc=99.4 | Pre=99.6 |
| Clinical | CT-Scan | 400 COVID-19 Patients | Segmentation, Resizing, Cropping, Normalization | PyTorch | Deep Fusion Architecture | Radiomics and Quantitative 3D Radiomics Models | Ensemble Learning | Grad-CAM | 5 | Acc=98.6 | Sens=99.4 | Spec=99.2 |
| Combination of Different Datasets | X-Ray, CT-Scan | 400 COVID-19 Patients | 200 COVID-19, 200 Healthy, 200 Bacterial Pneumonia, 200 Viral Pneumonia | NA | Caffe | ResNet101 | Standard Version | Softmax | NA | 10 | Pre=99.75 | Sens=99.50 | Spec=99.64 |
| COVIDs | X-Ray | 13975 X-Ray Images from 13975 Patients | – | PyTorch | RCNet | 4 Module | – | Uncertainty Estimation | – | – | Acc=99.75 | Sens=99.33 | Spec=99.24 |
| COVID-19 | X-Ray Dataset | 5,885 X-Rays normal or Pneumonia | DA | – | ResNet-50 | Standard Version | ASMX U-5 MLP | – | – | Acc=99.7 |
| Combination of Different Datasets | X-ray | 114 COVID-19 | Segmentation using U-Net, Standard Preprocessing, Weakly-Labeled DA | Keras with TensorFlow Backend | VGG-16 | Standard Version | Softmax | Grad-CAM | NA | Acc=99.26 |
| Clinical | CT-Scan | 105 COVID-19, 101 Non-COVID-19 | Standard Preprocessing: Annotating Pseudo-Infection Anomalies using RCDU-Net | NA | CovidCTNet | 19 | Softmax | NA | NA | Acc=99.15 | Sens=99.45 | Spec=99.45 |
| KRG Data Repository | X-ray | 150 COVID-19 | Filtering, Segmentation using Thresholding | NA | CNN | 11 | Softmax | NA | NA | Acc=99.0 |
| Combination of Different Datasets | CT-Scan | 521 COVID-19, 521 Non-COVID-19 | DA, Random Cropping Operation | NA | CNN with ShelfNetV2 as the backbone | Standard Version | Linear Layer | NA | NA | Acc=99.71 | Sens=99.52 | Spec=99.58 |
| Different Datasets | X-Ray | 142 COVID-19, 141 Normal, 141 Pneumonia | ReLU, Shuffling, Normalization | Keras with TensorFlow Backend | GRU-CNN | 7 | Softmax | Grad-CAM | NA | Pre=100 | F1-score=100 | Pre=100 | F1-score=85 | ACC=99.4 |
| Different Datasets | CT-Scan | 349 COVID-19, 397 Non-COVID-19 | DA, Self-Trans Method | PyTorch | DemoNet-109 | Standard Version | Softmax | Grad-CAM | NA | Pre=99.75 | Sens=99.49 | Spec=99.88 |
| Clinical | CT-Scan | 3389 COVID-19, 1593 Non-COVID-19 | Standard Preprocessing, YOLO-Net Toolkit for Segmentation and Lung Mask Generation | PyTorch | 3D ResNet34 with Online Attention Module | Modified Version | Ensemble Learning | Grad-CAM | 5 | Acc=99.73 | Sens=99.9 | Spec=99.11 | ACC=99.44 |
| COVIDs | X-ray | 238 COVID-19, 14096 Non-COVID-19 | DA | TensorFlow | DemoNet-121 | Modified Version | Softmax | Grad-CAM | 10 | Pre=100 | Sens=99.96 | Pre=99.66 |
| Clinical | CT-Scan | 146 COVID-19, 149 Non-COVID-19 | – | PyTorch | DenseNet | Standard Version | Softmax | CAM | NA | Acc=99.55 | Sens=99.70 | Spec=99.37 |
| Combination of Different Datasets | X-ray | 158 COVID-19, 158 Non-COVID-19 | – | MATLAB | ResNet50 | Standard Version | SVM | NA | NA | Acc=99.58 | Sens=99.72 | Spec=99.47 |
| Combination of Different Datasets | X-ray | 455 COVID-19 Images, 2109 Non-COVID-19 Images | Resizing, DA | Keras with TensorFlow Backend | MobileNet V2 | Modified Version | Softmax | NA | NA | 10 | Pre=99.95 | Sens=99.36 | Spec=99.42 |
| Combination of Different Datasets | X-ray | 403 COVID-19 Images, 721 Non-COVID-19 Images | Resizing, Normalizing, DA using CovidGAN Based AG-GAN | Keras | VGG16 | Standard Version | Softmax | PCA Visualization | NA | Acc=99.80 | Sens=99.50 | Spec=99.70 |
| Different Datasets | CT-Scan | 558 COVID-19 | 2D CNNs for the Segmentation | PyTorch | DOPLENet | Proposed Architecture | Softmax | Noise-Resistant Loss Functions | – | – | Pre=99.72 |
| Combination of Different Datasets | CT-Scan | 69 COVID-19 Images, 70 Normal, 70 Pneumonia Images, 79 Pneumonia Images, 79 Pneumonia Images, 79 Pneumonia Images | DA using GAN | MATLAB | Grad-CNN | Standard Version | Softmax | NA | NA | Acc=100 | Pre=100 | F1-score=100 |
| Different Datasets | CT-Scan | 1118 COVID-19 Images, 96 Pneumonia Images, 107 Healthy Images | Different Methods | MATLAB | CNN (Feature Extraction) | LSTM | NA | NA | NA | Acc=99.60 |
| Clinical | Ultrasound | 69 COVID-19, 58 TR, 50 Bacterial Pneumonia, 50 Bacteriological Pneumonia, 50 Bacteriological Pneumonia | Cropping | Keras with TensorFlow Backend | VGG-16 | – | Softmax | – | – | Acc=99.55 | Sens=99.70 |
| Combination of Different Datasets | X-ray | 224 COVID-19 images, 504 Healthy Cases, 400 Bacteria, 314 Viral Pneumonia | ReLU, Shuffling, DA | PyTorch | CNN (DenseNet121 Backbone) | Modified Version | Segmentation | Healmeke Generation using LRP | NA | Acc=99.75 | Pre=99.8 | F1-score=99.4 |
| Different Datasets | X-ray | 219 COVID-19 Images, 1341 Normal Lung Images, 1341 Viral Pneumonia Images | Manually editing, Reshaping, DA | PyTorch | CNN (DenseNet121) | Modified Version | Segmented | Exhausting Generation using LRP | NA |
| Different Datasets | X-ray | 40 COVID-19 Images, 88.079 Non-COVID-19 Images | Standard Preprocessing | TransformPyTorch | DenseNet | Modified Version | Segmented | t-SNE, Salience Maps | NA | MAE=1.14 |
| Combination of Different Datasets | X-ray | 190 COVID-19, 1345 Viral Pneumonia, and 1341 Normal Chest X-ray Images | Resizing, Normalization, DA | MATLAB | SparseNet | Modified Version | Softmax | NA | 5 | Acc=98.3 | Sen=96.7 | Spe=91.0 | Pre=100 |
|----------------------------------|-------|-------------------------------------------------------------------|-----------------------------|--------|-----------|-----------------|--------|----|----|-------|---------|--------|----------|
| COVID-CT - Dataset              | CT-Scan | 345 COVID-19, 307 Non COVID-19                                     | Resizing, DA using EXGAN, Normalizing | TensorFlow | ResNet50 | Modified Version | Softmax | NA | NA | Acc=97.91 | Sen=80.85 | Spe=91.43 |
| Combination of Different Datasets| X-ray | 181 COVID-19 cases, 8584 Normal Chest X-ray Images, 8851 Normal Cases | DA | keras | Concatenation of the ResNet and ResNet50 | Modified Version | Softmax | NA | 5 | Acc=91.4 |
| Kaggle                           | X-ray | 70 COVID-19 and 80 Normal Images                                   | Resizing, DA | NA | VGG16, VGG19 | Modified Version | Softmax | NA | NA | Acc=97.93 | Sen=98.10 | Spe=99.84 |
| Combination of Different Datasets| X-ray | 215 COVID-19, 4645 CAP, 8851 Normal Images                         | DA | PyTorch | Pre/Deep ResNet | Modified Version | Softmax | NA | NA | Trainable | Model: Acc=98.4 |
| Combination of Different Datasets| X-ray | 89 COVID-19, 70 Normal, 79 Pneumonia Bacteria, 79 Pneumonia Virus Images | Resizing, NeuripsThe Up Image Domain Conversion, Normalizing | MATLAB | GeoNet | Standard Version | Softmax | NA | NA | Acc=97.82 | Sen=97.62 | Spe=78.53 |
| Combination of Different Datasets| CT-Scan | 117 Healthy X-ray Images, 20 Healthy CT Scan Images                | Resizing, Normalizing | keras | DenseNet121 | Standard Version | Softmax | NA | 10 | Acc=95.40 | Sen=99.06 | Spe=85.13 |
| Combination of Different Datasets| X-ray | 181 COVID-19 Images, 384 Healthy Images                            | Normalizing, Resizing       | VGG-19 | Modified Version | Softmax | NA | NA | NA | Acc=96.3 |
| Clinical                         | CT-Scan | 151 COVID-19 Patient, 498 Non-COVID-19 Patient                   | Resizing, Padding, DA       | NA | 3D-CNN | 15 | Softmax | NA | 10 | Acc=95.78 | Sen=90.94 |
| Public Datasets & Private Datasets| CT-Scan | 1,684 COVID-19 Patient, 1,055 Pneumonia, 914 Normal Patients      | Resizing | NA | Inception V1 | Modified Version | Softmax | Interpretation by 5 Radiologists, t-SNE Method | 10 | Acc=95.78 | Sen=90.94 |
| Combination of Different Datasets| CT-Scan | 445 COVID-19 Images and 439 Normal or Pneumonia Infected Patients Images | ResNet50 (Feature Extraction) | NA | CNN | 14 | Softmax | NA | 10 | Acc=95.78 | Sen=94.39 | Spe=91.45 |
| Combination of Different Datasets| X-ray | 342 COVID-19 Images, 142 Normal Images                             | Resizing, DA | NA | NOXNet (VGG-16) | Modified Version | Softmax | NA | NA | Acc=97.32 | Sen=97.62 | Spe=78.53 |
| Combination of Different Datasets| X-ray | 326 COVID-19 Images, 864 Non-COVID-19 Images                      | Manual Annotation, Data Balancing and Augmentation Strategies, Normalizing, Resizing | NA | CNN with VSO predictor | 54 | Tensor of Prediction (Top) | NA | 5 | Acc=97.40 | Sen=99.06 | Spe=85.13 |
| Combination of Different Datasets| X-ray | 250 COVID-19, 2,755 Other Pulmonary Diseases, 3,320 Healthy Images | Resizing, DA | NA | VGG-16 | Modified Version | Softmax | Grad-CAM | NA | Acc=96.3 |
| Combination of Different Datasets| X-ray | 179 COVID-19, 179 Pneumonia, 179 Normal Images                    | Create a Noisy Snapshot Dataset | PyTorch | Modified Version | Softmax | NA | t-SNE, Grad-CAM | NA | Acc=96.3 |
| Another Reference                | CT-Scan | 75 Patients with COVID-19                                         | MODE Algorithm for Hyper-Parameter Tuning | MATLAB | CNN | 7 | NA | NA | 20 | Acc=94.92 | Sen=90.80 | Spe=85.03 |
| POCUS                            | Ultrasound | 1283 COVID-19, 731 Bacterial Pneumonia, 1312 BC                   | Cropping, Resizing          | keras | InceptionV3 | Standard Architecture | Softmax | – | 5 | Acc=98.81 | Sen=90.13 | Spe=86.84 |
| Clinical                         | CT-Scan | 88 COVID-19 Patients, 165 Non-COVID-19 Patients                  | Visual Inspection Google Collaboratory | BigBiGAN | NA | Linear Classifier | NA | NA | Acc=97.2 | Sen=92.02 | Spe=80.63 |
| Clinical                         | Ultrasound | 1580 LUS Scan with 287,540 Frames                                | Cropping, Resizing, Filtering, Smoothing | TensorFlow | Text-Stream Inflated 3D ConvNet | – | Softmax | – | 5 | Acc=96.05 | Sen=90.65 | Spe=86.03 |
| UCSF-AI4H                        | CT-Scan | 340 Patients with Confirmed COVID and 307 Healthy Subjects       | Resizing, Normalizing | keras | DenseNet121 | Standard Version | Softmax | No-SVM | 10 | Acc=95.81 | Recall@90.80 | Prec@90.76 |
| Different Datasets               | CT-Scan | 219 COVID-19, 1341 Normal, 1345 Viral Pneumonia Images           | Resizing, Normalizing, DA  | PyTorch | DenseNet-201 | Modified Version | Softmax | Sigmod | 10 | Acc=95.81 | Recall@90.80 | Prec@90.76 |
| Different Datasets               | X-ray | 536 COVID-19 Images, 619 Viral Pneumonia, and 668 Normal Images   | White Balance Algorithm, CLAHE, Normalizing, Resizing | keras | TensorFlow | COVIDLe | 38 | Softmax | t-SNE, S Maps, Grad-CAM, LIME | 5 | Binary Acc=95.5 | Male-Class Acc=96.43 |
| POCUS                            | Ultrasound | 1103 Images (678 Covid-19, 277 Pneumonia, 42 Healthy)             | Cropping, Videok as Video feature images | TensorFlow | Mini CovidNet | – | Softmax | – | 5 | Acc=96.6 | Sen=92.02 | Spe=74.51 |
| Combination of Different Datasets| X-ray | 327 Patients                                                     | Resizing, DA, Normalizing | NA | VGG16 | Modified Version | Softmax | NA | 5 | Acc=94.1 |
| COVIDIs                          | X-ray | 383 COVID-19 Images, 5331 Pneumonia Images, 4866 Normal Images    | NA | NA | UAPs using FGSM | Standard Version | Softmax | UAPs using FGSM | NA | Acc=92.8 | Sen=90.64 |
| Combination of Different Datasets| X-ray | 127 COVID-19 Images, 127 Pneumonia Images, 127 Healthy Images     | NA | keras | ResNet50 | Modified Version | SVM | NA | NA | Acc=95.53 | Sen=99.13 | Spe=90.62 |
| Combination of Different Datasets| X-ray | 738 Images of COVID-19, 4000 Normal, 4600 Images of CAP           | DA, Normalization, Resizing, CLAHE, BEASF | NA | CNN | NA | Grad-CAM, LIME | NA | NA | Acc=98.68 | Sen=99.84 |
| Clinical                         | Ultrasound | 2986 Frames from 450 Hospitalized Patients                      | Cropping, DA | MATLAB | ResNet50 | Standard Architecture | Softmax | – | – | Acc=97.95 |
### TABLE IV: Summary of DL segmentation methods used for COVID-19 detection.

| Work | Dataset | Modality | Number of Cases | Preprocessing | DNN toolbox | DNN | Number of Layers | Classifier | Post-Processing | K-Fold | Performance Criteria (%) |
|------|---------|----------|----------------|---------------|-------------|-----|-----------------|------------|-------------------|--------|------------------------|
| [ID1] Datasets | Different Clinical Datasets | CT-Scan | 157 International Patients | Dotnet and Measure Moles, Lung Crop using U-net, DA | NA | ResNet50 | Standard | SegNet | Grad-Cam, 3D Visualization | NA | ACC=99.5, Sens=98.2, Spec=92.2 |
| [ID2] Datasets | Clinical | CT-Scan | 549 COVID-19 Patients | HTIL Strategy | NA | V-Net | 8 Block | NA | NA | Quantitative Metrics | NA | ACC=99.4, Mean POI Estimation Error=0.3 |
| [ID3] Datasets | Combination of Different Datasets | CT-Scan | 630 COVID-19 Images, 689 Non-COVID-19 Images | Restoring, DA | PyTorch | DenseNet169+ASPP Layer | Standard | NA | NA | NA | ACC=98.4, Acc=83 |
| [ID4] Datasets | Different Datasets | CT-Scan | 110 Axial CT-Scan Images From 60 Patients | Restoring, Gray Scaling (GSL), DA | NA | ResNet6+blocks=16 Layers | Sigmod | Visualization | 10 | Acc=99 | Sens=94 |
| [ID5] Datasets | Different Datasets | CT-Scan | Different Number of Cases | Lung Segmentation using U-net with a VGG-16 Based Encoder, DA | NA | ResNet50 | Standard | Sigmod | Grad-Cam, Combine the Four Gran Maps to Create 3D Localization Maps, K-Means | NA | ACC=99.4, Spe=94 |
| [ID6] Datasets | COVID-CS Dataset | CT-Scan | 184 CT-Scan Images of 120 COVID-19 Patients and 350 Uninfected Control | DA, Segmentation using Encoder-Decoder Model | NA | ResNet | Standard | Softmax | Visualization of Activation Mapping | NA | Acc=99.05, Spe=93 |
| [ID7] Datasets | Italian Society of Medical and Interventional Radiology | CT-Scan | 473 CT Slices for COVID-19 | Restoring, GL, Intensity Normalization | Keras | U-Net | 50 | Sigmod | Visualization | NA | Dice=0.975, Sens=99.5, Spec=99.3 |
| [ID8] Datasets | 6 Different Datasets | X-ray | Different Number of Cases | Histogram, Segmentation using U-Net, Intensity Normalization | PyTorch | ResNet18 | Standard | Softmax | t-SNE Clustering | NA | Acc=99.05, Spe=99.10 |
| [ID9] Datasets | COVIDS Dataset (Prostate) | CT-Scan | 5MM COVID-19 Subjects | Standard Preprocessing | PyTorch | KISU-Net | 2 RU-Net | Sigmod | Softmax | Different Methods | NA | Dice=99.5, ASD=88.6 |
| [ID10] Datasets | COVID-19 Dataset | CT-Scan | 60 Patients with COVID-19 | Restoring, DA | PyTorch | MiniSeg | Proposed Structure | Sigmod | Softmax | NA | ACC=97.64, Spe=97.42, DSC=97.78, HD=88.07 |
| [ID11] Datasets | Combination of Different Datasets | CT-Scan | 311 COVID-19 Images, 7255 Normal, 6012 Pneumonia of Unknown Type, 2780 Bacterial Pneumonia Images | Segmentation using U-Net, Standard Preprocessing | NA | VGG-16, VGG-19, Inception-V3 | Modified Version | Weighted Average Ensemble Method | Grad-CAM | NA | Acc=99.01, Sens=99.01, Spec=99.95 |
| [ID12] Datasets | COVID-SemSeg | CT-Scan | 100 Labeled Images, 1560 Unlabeled Images of COVID-19 | Pseudo Label Generation | PyTorch | Semi-Supervised Inf-Net-Multi-Class Segmentation | Modified U-Net as Ensembles | Sigmod | Softmax | NA | Dice=0.954, Sens=96.6, Spec=96.7, MAE=3.2 |
| [ID13] Datasets | Dataset I | X-ray | 466 Normal, 382 Bacteria, 433 Viruses | Adaptive Histogram, CLAHE Method, Meds, U-Net, DA | Keras | Cascade-MNEM-Net | Modified Version | Sigmod | Grad-CAM | NA | Acc=99.5, Acc=99.7 |
| [ID14] Datasets | Dataset II | CT-Scan | 210 COVID-19, 350 Others | Standard Preprocessing | PyTorch | COVID-SegNet | Standard | Softmax | NA | ACC=100, Sens=75.1, Spec=72.6 |
| [ID15] Datasets | Clinical | CT-Scan | 21,658 Images From 861 COVID-19 Patients | Lungs Mask, Intensity Normalization | CNN | COVID-Net | 11 Blocks | Sigmod | Softmax | NA | Dice=98.75, Sens=87.6, Spec=80.8 |
| [ID16] Datasets | Clinical | CT-Scan | 10 Axial Sections, 3D-Net of COVID-19 Pneumonia Patients | Under Sampling of the Majority Class | Keras with Transfer Learning | FCN-8s | NA | NA | NA | Acc=80 | Pre=80 |
| [ID17] Datasets | Combination of Different Datasets | CT-Scan | 449 COVID-19 Patients, 160 Normal, 98 Lung Cancer, 397 Other Pathology | Restoring, Intensity Normalization | Keras with Transfer Learning | DenseNet and Feat. Extractor (2D U-Net) and MLP | 24, 24, 15 | Sigmod | Softmax | NA | ACC=96, Sens=94, Spec=97 |
| [ID18] Datasets | Clinical | CT-Scan | 313 COVID-19, 220 Non-COVID-19 | Normalization, Restoring, DA, 3D Long Mask Generation using 2D U-Net | PyTorch | DoConvNet | 20 | Softmax | Softmax | NA | Acc=99.08 |
| [ID19] Datasets | Clinical | CT-Scan | 877 COVID-19, 991 Non-COVID-19 | Visual Data Annotation and Quality Normalization, 3D U-Net for Segmentation, DA | PyTorch | ResNet50 | Standard Version | Softmax | Softmax | NA | Acc=99.7, Spe=99.2, AUC=99.1 |
| [ID20] Datasets | Clinical | CT-Scan | 1131 COVID-19 Scans, 3342 Non-COVID-19 Scans | Lobe Segmentation using 3D-U-net, Cropping, Restoring, DA | Keras with Transfer Learning | 3D-ResNet with Pre-Attention Mechanism | Modified Version | Softmax | Heatmap Visualization | 5 | Acc=98.73, Sens=87.65, Spec=80.53 |
| [ID21] Datasets | Clinical | CT-Scan | 17 COVID-19 Patients, 4 With COVID-19 Suspected, and 14 With Healthy | Labelling Process, DA, Reg-STN Model | NA | CNN | NA | Loss Function | Segmentation | 5 | NA |
| [ID22] Datasets | Clinical | CT-Scan | 296 COVID-19 Images, 1375 CAP 3252 Non-Pneumonic Images | Lung Processing using U-net | NA | COVNet | Modified Version | Softmax | Grad-CAM | NA | ACC=99.96, Sens=99.86, Spec=99.96 |
| [ID23] Datasets | Clinical | CT-Scan | 120 COVID-19 images | Segmentation Using U-Net, Different Preprocessing Methods | NA | ResNet18 | Modified Version | Softmax | Calculate the Proportion of Infection Regions in Lung | NA | Acc=99.7, AUC=91.8, m-Dice=74.1 |
| [ID24] Datasets | Clinical | CT-Scan | 100 COVID-19 and 100 healthy controls | DBL Landmarks, DEIN Segmentation, Alignment, Restoring | PyTorch | DenseNet | Modified Version | Softmax | Softmax | NA | Different Parameters |
| [ID25] Datasets | Clinical | CT-Scan | 558 COVID-19 Patients | 2D CNNs for the Segmentation | PyTorch | Stacked COPELNet-EEMA for Adjective teachers-Teacher COPELNet | Propose Architecture | NA | NA | Propose Loss Function | NA | Dice=40.32, RV=15.96 |
| [ID26] Datasets | Combination of Different Datasets | CT-Scan | 33 COVID-19 Patients, 52 Healthy Patients, 36 Patients with Other Lung Pathologies | Restoring, Intensity Normalization, Creating Feature Map using U-Net | NA | Different Architectures | NA | NA | NA | NA | ACC=98.5, Spearman Correlation=98 |
The X-ray, ultrasound, and CT modalities have been used to develop DL models. Figure 8 shows the total number of times each modality is used in reviewed studies. It can be observed that most of the researchers have used X-ray images. This may be due to cheaper registration fees, and the fact that slice selection is not needed. Also, very few research papers have used combined modalities of X-ray and CT images due to the absence of such a comprehensive database.

Various DL models developed for the automated detection of COVID-19 patients are shown in Figure 9. It can be noted from the figure that; different types of convolutional networks have been commonly used. Also, for the automated segmentation of lungs, various types of U-Net are more common.

Nowadays, a variety of toolboxes have been used to implement DL models. The number of toolboxes used for automated detection of COVID-19 by researchers is shown in Figure 10. It can be noted that the Keras toolbox is the most widely used in reviewed papers; this can be due to its simplicity and also the availability of pre-trained models in this library, which are also used frequently by researchers.

The last part of this study is devoted to the classification algorithms developed using DL architectures. The softmax is most employed for automated detection of COVID-19 patients (Tables III to V). Figure 11 shows the number of various classification algorithms used for automated detection of COVID-19 patients using DL techniques.

VI. CHALLENGES

With the rapid growth and spread of COVID-19 globally, researchers have confronted many serious challenges in designing and implementing CADS to diagnose and also forecast the spread of the disease. The most significant challenges associated with COVID-19 are data availability, DL networks architecture fixing, and hardware resources. Lack of availability of a huge public database comprising X-ray and CT images is the first challenge. Due to the limited number of patient data, many researchers have used pre-trained networks such as GoogLeNet and AlexNet. Nevertheless, the number of studies conducted on forecasting is limited as it also requires a vast database.

One of the problems of employing pre-trained networks is that these models are often trained on the ImageNet database, which is entirely different from medical images. Hence, implementing efficient CADS to accurately and swiftly diagnose COVID-19 from X-ray or CT images is still a challenging work. Physicians are not just convinced with X-ray or CT-scan images of patients to accurately diagnose COVID-19; they may use both modalities simultaneously. However, complete and comprehensive databases of the X-ray and CT-scan hybrid modalities for CADS research and implementation have not been provided for researchers in the machine learning scope. For this reason, researchers combine different X-ray and CT-Scan datasets from various datasets, which may disrupt network training. Yielding the combined X-Ray and CT-Scan datasets pave the path to help quickly identify COVID-19 alongside DL networks. The third challenge in the data section
Table V: Summary of DL models developed for the forecasting spread of COVID-19.

| Week | Dataset | Preprocessing | DNN | Number of layers | k-Fold | Test Processing | Performance Criteria |
|------|---------|---------------|-----|-----------------|--------|-----------------|----------------------|
| 159  | Johns Hopkins University and Canadian Health Authority | LSTM | 3 | NA | NA | LSTM 5 | RMMSE = 27.187 |
| 160  | Johns Hopkins University, Lockdown dates of Countries Datasets | LSTM | 10 | NA | RMSE=27.576 |
| 161  | Johns Hopkins University and Canadian Health Authority | LSTM | 5 | NA | NA | LSTM 3 | RMMSE = 27.187 |
| 162  | Johns Hopkins University and Canadian Health Authority | LSTM | 3 | NA | NA | LSTM 5 | RMMSE = 27.187 |
| 163  | Johns Hopkins University and Canadian Health Authority | LSTM | 4 | NA | NA | LSTM 5 | RMMSE = 27.187 |
| 164  | Johns Hopkins University and Canadian Health Authority | LSTM | 3 | NA | NA | LSTM 5 | RMMSE = 27.187 |
| 165  | Johns Hopkins University and Canadian Health Authority | LSTM | 4 | NA | NA | LSTM 5 | RMMSE = 27.187 |
| 166  | Johns Hopkins University and Canadian Health Authority | LSTM | 3 | NA | NA | LSTM 5 | RMMSE = 27.187 |
| 167  | Johns Hopkins University and Canadian Health Authority | LSTM | 4 | NA | NA | LSTM 5 | RMMSE = 27.187 |
| 168  | Johns Hopkins University and Canadian Health Authority | LSTM | 3 | NA | NA | LSTM 5 | RMMSE = 27.187 |
| 169  | Johns Hopkins University and Canadian Health Authority | LSTM | 4 | NA | NA | LSTM 5 | RMMSE = 27.187 |

Fig. 11: Illustration of number of various classifier algorithms used in DL networks for automated detection of COVID-19 patients.

The non-reporting of phenotypic information, such as age and gender, is a significant challenge in the implementation of DL algorithms. The utilization of this information can amend and enhance the performance of DL algorithms.

Table IV summarizes the DL-based segmentation algorithms aimed at identifying areas suspected of COVID-19 in the X-ray and CT-scan images. One of the obstacles with databases is the absence of manual or ground truths for COVID-19 image segmentation areas. Therefore, many researchers have delineated these areas with the help of radiologists and trained the models such as U-Net, which is time-consuming. Consequently, the presence of dedicated databases of segmented images will help to get the best-performing model. Also, it becomes easy to compare the performances with other authors who have worked on the same images.

In order to predict the prevalence of corona using DL methods, the nature of the COVID-19 is still relatively unknown, and the probability of mutation is a big issue. Therefore, to predict the prevalence of the disease, many factors like the average age of the society, policies to impede the spread of the disease by countries, climatic conditions, and infection of neighbor/friend/family member.

Lack of access to appropriate hardware resources is another challenge. Implementing DL architectures in CADS for corona diagnosis demands strong hardware resources, which unfortunately is not ordinarily accessible for many researchers. Although tools such as Google Colab have partially obviated this problem, employing these tools in real medical applications is still challenging. For this reason, in most studies, researchers have not provided practical CADS systems such as web or Windows software to detect COVID-19.

VII. CONCLUSION AND FUTURE WORKS

COVID-19 is an emerging pandemic disease that, in a short period of time, can severely endanger the health of many people throughout the world. It directly affects the lung cells, and if not accurately diagnosed early, can cause irreversible damage, including death. The disease is accurately detected by the specialists using X-ray, CT and ultrasound images together with RT-PCR results. Specialized physicians use RT-PCR as the gold standard for COVID-19 diagnosis based on WHO guidelines. The accurate diagnosis of COVID-19 is made using medical imaging methods, including X-Ray, CT, and Ultrasound beside RT-PCR. COVID-19 diagnosis by medical imaging always has some challenges for physicians. The high number of medical images associated with each patient, doctor’s fatigue, and low contrast of the images are among some problems challenging the COVID-19 accurate diagnosis. The accurate diagnosis of COVID-19 has high importance, and lack of fast and accurate diagnosis can cause severe damages such as death.

To address this problem, researchers are working on some advanced DL techniques to diagnose COVID-19 accurately in the shortest possible time. In this study, a comprehensive review of the accomplished studies of COVID-19 diagnosis was carried out using DL networks. Frist, the public databases available to detection and prediction of COVID-19 are presented. In the following, the state-of-art DL techniques employed for the diagnosis, segmentation, and forecasting of the spread of COVID-19 are presented in Tables III, IV, and V respectively.

In another section of the paper, some advanced DL methods such as transformers, fusion, and graph have been introduced. In this section, an introduction to the method has been presented first, then COVID-19 diagnosis papers based on these methods are introduced. In the following, important information of each paper, including various types of DL research for COVID-19 (classifications, segmentation, and predictions), have been explored and compared. In the following, the number of modalities used in
COVID-19 diagnosis, DL models, DL toolboxes, and classification algorithms are introduced. The most critical challenge of COVID-19 diagnosis using DL techniques is mentioned in section 4. As mentioned, the most critical challenges of COVID-19 diagnosis are dataset, software, and hardware. One of the challenges to develop a robust and accurate COVID 19 diagnosis system is the availability of an extensive public database. We strongly feel that, with more public databases, better DL models can be developed by researchers to detection and prediction of the COVID-19 accurately.

Recently, using fusion techniques such as feature fusion has had many improvements in medical applications [163]. In future works, it is possible to use deep feature fusion techniques besides medical imaging modalities to diagnose COVID-19. In addition to that, it is possible to use some advanced DL methods such as zero-shot learning in order to diagnose COVID-19 [164]. In a section of the paper, there were some discussions about attention and transformer techniques. As it is mentioned, each of these methods has a lot of different techniques [165]. So, various attention and transformer models can diagnose COVID-19 in future works.

REFERENCES

[1] J. F. Chan, S. Yuan, K.-H. Kok, K. K.-W. To, H. Chu, J. Yang, F. Xing, J.-W. Liu, C.-C.-Y. Yip, R. W.-S. Poone et al., “A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster,” The Lancet, vol. 395, no. 10223, pp. 514–523, 2020.

[2] N. Ghassemi, A. Shoiebi, M. Khodatars, J. Heras, A. Rahimi, A. Zare, R. B. Pachori, and J. M. Gorriz, “Automatic diagnosis of covid-19 from ct images using cyclegan and transfer learning,” arXiv preprint arXiv:2104.11949, 2021.

[3] J. Lopez Bernal, N. Andrews, C. Gower, E. Gallagher, R. Simmons, S. Thelwall, J. Stone, E. Tressier, N. Groves, G. Dabera et al., “Effectiveness of covid-19 vaccines against the b. 1.617. 2 (delta) variant,” N Engl J Med, pp. 585–594, 2021.

[4] P. Feng, X. Xu, Y. Li, L. Cheng, X. Zhou, and B. Ren, “Transmission routes of 2019-ncov and controls in dental practice,” International Journal of Oral Science, vol. 12, no. 1, pp. 1–6, 2020.

[5] S. Tian, W. Hu, L. Niu, H. Liu, H. Xu, and S.-Y. Xiao, “Pulmonary pathology of early phase 2019 novel coronavirus (covid-19) pneumonia in two patients with lung cancer,” Journal of Thoracic Oncology, 2020.

[6] T. C. Lan, M. F. Allan, L. Malsick, S. Khandwala, S. S. Nyeo, M. Bathe, A. Griffiths, and S. Rouskin, “Structure of the full sars-cov-2 nac gene in infected cells,” bioRxiv, 2020.

[7] A. Remuzzi and G. Remuzzi, “Covid-19 and italy: what next?” The Lancet, 2020.

[8] C. Sohrabi, Z. Alsafi, N. O’Neill, M. Khan, A. Kerwan, A. Aljubari, C. Ioossifidis, and R. Agha, “World health organization declares global emergency: A review of the 2019 novel coronavirus (covid-19),” International Journal of Surgery, 2020.

[9] “https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases,” 2020.

[10] F. J. F. Montalbo, “Diagnosing covid-19 chest x-ray with a lightweight truncated denseinet with partial layer freezing and feature fusion,” Biomedical Signal Processing and Control, vol. 68, p. 102583, 2021.

[11] D. Singh, V. Kumar, and M. Kaur, “Densely connected convolutional networks-based covid-19 screening model,” Applied Intelligence, vol. 51, no. 5, pp. 3044–3051, 2021.

[12] W. H. Self, D. M. Courtneyn, C. D. McNaughton, R. G. Wunderink, and J. A. Kline, “High discordance of chest x-ray and computed tomography for detection of pulmonary opacities in ed patients: implications for diagnosing pneumonia,” The American Journal of emergency medicine, vol. 31, no. 2, pp. 401–405, 2013.

[13] G. D. Rubin, C. J. Ryerson, L. B. Haramati, N. Sverzellati, J. P. Kanne, S. Raoof, N. W. Schluge, A. Volpi, J.-J. Yim, I. B. Martin et al., “The role of chest imaging in patient management during the covid-19 pandemic: a multinational consensus statement from the fleischer society,” Chest, 2020.

[14] S. M. El-Kenawy, S. Mirjalili, A. Ibrahim, M. Alrahmawy, M. El-Said, R. M. Zakie, and M. M. Eid, “Advanced meta-heuristics, convolutional neural networks, and feature selectors for efficient covid-19 x-ray chest image classification,” IEEE Access, vol. 9, pp. 36019–36037, 2021.

[15] B. Barros, P. Lacerda, C. Albuquerque, and A. Conci, “Pulmonary covid-19: Learning spatiotemporal features combining cnn and lstm networks for lung ultrasound video classification,” Sensors, vol. 21, no. 16, p. 5486, 2021.

[16] N. Ghassemi, A. Shoiebi, and M. Rouhani, “Deep neural network with generative adversarial networks pre-training for brain tumor classification based on mr images,” Biomedical Signal Processing and Control, vol. 57, p. 101678, 2020.

[17] M. Talo, O. Yildirim, U. B. Baloglu, G. Aydin, and U. R. Acharya, “Convolutional neural networks for multi-class brain disease detection using mri images,” Computerized Medical Imaging and Graphics, vol. 78, p. 101673, 2019.

[18] N. Ghassemi, A. Shoiebi, M. Rouhani, and H. Hosseinnejad, “Epileptic seizures detection in eeg signals using lstm and ensemble learning; in 2019 9th International Conference on Computer and Knowledge Engineering (ICCKE). IEEE, 2019, pp. 403–408.

[19] M. Mohammadpoor, A. Shoiebi, H. Zare, and H. Shojaee, “A hierarchical classification method for breast tumor detection,” Iranian Journal of Medical Physics, vol. 13, no. 4, pp. 261–268, 2016.

[20] D. Arefan, A. A. Mohamed, W. A. Berg, M. L. Zuley, J. H. Sumkin, and S. Wu, “Deep learning modeling using normal mammograms for predicting breast cancer risk,” Medical physics, vol. 47, no. 1, pp. 110–118, 2020.

[21] A. Esteva, B. Kuprel, R. A. Novaoa, J. K. S. M. Swetter, M. H. Blau, and S. Thrun, “Dermatologist-level classification of skin cancer with deep neural networks,” nature, vol. 542, no. 7639, pp. 115–118, 2017.

[22] M. M. Azourou, M. Buda, A. Saha, and M. R. Bashir, “Deep learning in radiology: An overview of the concepts and a survey of the state of the art with focus on mri,” Journal of magnetic resonance imaging, vol. 49, no. 4, pp. 939–954, 2019.

[23] T. M. Tuan, T. T. Ngan, C. N. Giap et al., “Seminisupervised fuzzy clustering methods for x-ray image segmentation,” in Handbook of Data Science Approaches for Biomedical Engineering. Elsevier, 2020, pp. 251–289.

[24] A. Shoiebi, N. Ghassemi, H. Hosseinnejad, and M. Rouhani, “An efficient brain mr images segmentation hardware using kernel fuzzy c-means,” in 2019 26th National and 4th International Iranian Conference on Biomedical Engineering (ICBME). IEEE, 2019, pp. 93–99.

[25] O. Ronneberger, P. Fischer, and T. Brox, “U-net: Convolutional networks for biomedical image segmentation,” in International Conference on Medical image computing and computer-assisted intervention. Springer, 2015, pp. 234–241.

[26] J. P. Cohen, P. Morrison, L. Dao, K. Roth, T. Q. Duong, and M. Ghassemi, “Covid-19 image data collection: Prospective predictions are the future,” arXiv preprint arXiv:2006.11988, 2020. [Online]. Available: https://github.com/ieee8023/covid-chestxray-dataset

[27] J. Zhao, Y. Zhang, X. He, and P. Xie, “Covid-ct-dataset: a ct scan dataset about covid-19,” arXiv preprint arXiv:2003.13865, 2020.

[28] J. Born, G. Brändle, M. Cossio, M. Disdier, J. Goulet, J. Roulin, and N. Wiedemann, “Pocovid-net: Automatic detection of covid-19 from a new lung ultrasound imaging dataset (pocus),” arXiv preprint arXiv:2004.12084, 2020.

[29] J. M. Banda, R. Tekumalla, G. Wang, J. Yu, T. Liu, Y. Ding, and G. Howell, “A large-scale covid-19 twitter chatter dataset for open scientific research—an international collaboration,” arXiv preprint arXiv:2004.03688, 2020.

[30] R. Hu, G. Ruan, S. Xiang, M. Huang, Q. Liang, and J. Li, “Automated diagnosis of covid-19 using deep learning and data augmentation on chest ct,” medRxiv, 2020.

[31] Z. Q. L. Linda Wang and A. Wong, “Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases,” IEEE Access, vol. 8, 2020.

[32] Y. Yang, Y. Hu, X. Zhang, and S. Wang, “Two-stage selective ensemble of ctcnn via deep tree tunning for medical image classification,” IEEE Transactions on Cybernetics, 2021.

[33] H. S. Maghidi, A. T. Asaad, K. Z. Ghafoor, A. S. Sadiq, and M. K. Khan, “Diagnosing covid-19 pneumonia from x-ray and ct images
using deep learning and transfer learning algorithms,” arXiv preprint arXiv:2004.00038, 2020.

[34] Y. Zhou, G. G. Yen, and Z. Yi, “A knee-guided evolutionary algorithm for compressing deep neural networks,” IEEE transactions on cybernetics, vol. 51, no. 3, pp. 1626–1638, 2019.

[35] M. Loey, F. Smarandache, and N. E. M Khalifa, “Within the lack of clinician covid-19 x-ray dataset: A novel detection model based on gan and deep transfer learning,” Symmetry, vol. 12, no. 4, p. 651, 2020.

[36] M. Ghafoor, S. A. Tariq, T. Zia, I. A. Taj, A. Abbas, A. Hassan, and A. Y. Zomaya, “Fingerprint identification with shallow multifeature view classifier,” IEEE transactions on cybernetics, 2019.

[37] B. Xiao, Z. Yang, X. Qiu, J. Xiao, G. Wang, W. Zeng, W. Li, Y. Nian, and W. Chen, “Pam-densenet: A deep convolutional neural network for computer-aided covid-19 diagnosis,” IEEE Transactions on Cybernetics, 2021.

[38] S. Minae, R. Kafeh, M. Sonka, S. Yazdani, and G. J. Soufi, “Deepcvd: Predicting covid-19 from chest x-ray images using deep transfer learning,” arXiv preprint arXiv:2004.09363, 2020.

[39] X. Yi, E. Walia, and P. Babyn, “Generative adversarial network in medical imaging: A review,” Medical image analysis, vol. 58, p. 101552, 2021.

[40] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial nets,” in Advances in neural information processing systems, 2014, pp. 2672–2680.

[41] D. Nie, L. Wang, E. Adeli, C. Luo, W. Lin, and D. Shen, “3-d fully convolutional networks for multimodal isointense infant brain image segmentation,” IEEE transactions on cybernetics, vol. 49, no. 3, pp. 1123–1136, 2019.

[42] Q. Yan, B. Wang, D. Gong, C. Luo, W. Zhao, J. Shen, Q. Shi, S. Jin, L. Zhang, and Z. You, “Covid-19 chest ct image segmentation—a deep convolutional neural network solution,” arXiv preprint arXiv:2004.10987, 2020.

[43] Y.-H. Wu, S.-H. Gao, J. Mei, J. Xu, D.-P. Fan, C.-W. Zhao, and M.-M. Cheng, “Jcs: An explainable covid-19 diagnosis system by joint classification and segmentation,” arXiv preprint arXiv:2004.07054, 2020.

[44] T. Zhou, S. Canu, and S. Ruan, “An automatic covid-19 ct segmentation network using spatial and channel attention mechanism.” arXiv preprint arXiv:2004.06673, 2020.

[45] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, “Empirical evaluation of gated recurrent neural networks on sequence modeling,” arXiv preprint arXiv:1412.3555, 2014.

[46] C. Sitaula and M. B. Hossain, “Attention-based vgg-16 model for covid-19 chest x-ray image classification,” Applied Intelligence, vol. 51, no. 5, pp. 2850–2863, 2021.

[47] S. Perera, S. Adhikari, and A. Yilmaz, “Pocformer: A lightweight transformer architecture for detection of covid-19 using point of care ultrasound,” arXiv preprint arXiv:2105.09913, 2021.

[48] U. Ozkaya, Ş. Öztürk, and M. Barstugan, “Coronavirus (covid-19) classification using deep features fusion and ranking technique,” in Big Data Analytics and Artificial Intelligence Against COVID-19: Innovation Vision and Approach, Springer, 2020, pp. 281–295.

[49] X. Liang, Y. Zhang, J. Wang, Q. Ye, Y. Liu, and J. Tong, “Diagnosis of covid-19 pneumonia based on graph convolutional network,” Frontiers in Medicine, vol. 7, p. 1071, 2021.

[50] M. Farooq and A. Hafeez, “Covid-resnet: A deep learning framework for screening of covid-19 from radiographs,” arXiv preprint arXiv:2003.14495, 2020.

[51] A. Narin, C. Kaya, and Z. Pamuk, “Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks,” arXiv preprint arXiv:2003.10849, 2020.

[52] E. E.-D. Hemdan, M. A. Shouman, and M. E. Karar, “Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images,” arXiv preprint arXiv:2003.11055, 2020.

[53] J. Zhang, Y. Xie, Y. Li, C. Shen, and Y. Xia, “Covid-19 screening on chest x-ray images using deep learning based anomaly detection,” arXiv preprint arXiv:2003.12338, 2020.

[54] X. Qi, L. G. Brown, D. J. Foran, J. Nosher, and I. Hachachinoglu, “Chest x-ray image phase features for improved diagnosis of covid-19 using convolutional neural network,” International journal of computer applications, vol. 107, p. 206, 2020.

[55] F. Ucar and D. Korkmaz, “Covididiagnosis-net: Deep bayes-squeezenet based diagnostic of the coronavirus disease 2019 (covid-19) from x-ray images,” Medical Hypotheses, p. 109761, 2020.
[77] S. Tang, C. Wang, J. Nie, N. Kumar, Y. Zhang, Z. Xiong, and A. Barnawi, “Edl-covid: Ensemble deep learning for covid-19 cases detection from chest x-ray images,” IEEE Transactions on Industrial Informatics, 2021.

[78] Y. Song, S. Zheng, L. Li, X. Zhang, X. Zhang, Z. Huang, J. Chen, H. Zhao, Y. Jie, R. Wang et al., “Deep learning enables accurate diagnosis of novel coronavirus (covid-19) with ct images,” medRxiv, 2020.

[79] S. Wang, D. Dong, L. Li, H. Li, Y. Bai, Y. Hu, Y. Huang, X. Yu, S. Liu, X. Qiu et al., “A deep learning radiomics model to identify poor outcome in covid-19 patients with underlying health conditions: a multicenter study,” IEEE Journal of Biomedical and Health Informatics, 2021.

[80] I. Razzaq, S. Naz, A. Rehman, A. Khan, and A. Zaib, “Improving coronavirus (covid-19) diagnosis using deep transfer learning,” medRxiv, 2020.

[81] S. Dong, Q. Yang, Y. Fu, M. Tian, and C. Zhuo, “Rcnet: Deformable mutual information maximization and high-order uncertainty-aware learning for robust covid-19 detection,” IEEE Transactions on Neural Networks and Learning Systems, 2021.

[82] S. Rajaraman and S. Antani, “Training deep learning algorithms with weakly labeled pneumonia chest x-ray data for covid-19 detection,” medRxiv, 2020.

[83] T. Javaheri, M. Homayounfar, Z. Amoozgar, R. Reiazi, F. Homayounieh, E. Abbas, A. Laali, A. R. Radmand, M. G. Harih, S. A. J. Mousavi et al., “Covidnet: An open-source deep learning approach to identify covid-19 using ct image,” arXiv preprint arXiv:2005.03059, 2020.

[84] M. Jamil, I. Hussain et al., “Automatic detection of covid-19 infection from chest x-ray using deep learning,” medRxiv, 2020.

[85] R. Hu, G. Ruan, S. Xiang, M. Huang, Q. Liang, and J. Li, “Automated diagnosis of covid-19 using deep learning and data augmentation on chest ct,” medRxiv, 2020.

[86] O. D. T. Catalá, I. S. Igual, F. J. Pérez-Benito, D. M. Escrivá, V. O. Castelló, R. Llobet, and J.-C. Peréz-Cortés, “Bias analysis on public x-ray image datasets of pneumonia and covid-19 patients,” IEEE Access, vol. 9, pp. 42 370–42 383, 2021.

[87] X. He, X. Yang, S. Zhang, J. Zhao, Y. Zhang, E. Xing, and P. Xie, “Sample-efficient deep learning for covid-19 diagnosis based on ct scans,” medRxiv, 2020.

[88] X. Ouyang, J. Hao, L. Xia, F. Shan, J. Liu, Z. Mo, F. Yan, Z. Ding, Q. Yang, B. Song et al., “Dual-sampling attention network for diagnosis of covid-19 from community acquired pneumonia,” IEEE Transactions on Medical Imaging, 2020.

[89] L. Sarker, M. Islam, T. Hannan, and A. Zakaria, “Covid-densenet: A deep learning architecture to detect covid-19 from chest radiology images,” Preprints, 2020.

[90] S. Yang, L. Jiang, Z. Cao, L. Wang, J. Cao, R. Feng, Z. Zhang, X. Xue, Y. Shi, and F. Shan, “Deep learning for detecting coronavirus disease 2019 (covid-19) on high-resolution computed tomography: a pilot study,” Annals of Translational Medicine, vol. 8, no. 7, 2020.

[91] P. K. Sathy and S. K. Behera, “Detection of coronavirus disease (covid-19) based on deep features,” Entropy, vol. 22, no. 5, p. 517, 2020.

[92] I. D. Apostolopoulos and T. A. Mpsisiana, “Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks,” Physical and Engineering Sciences in Medicine, p. 1, 2021.

[93] P. R. Bassi and R. Attux, “A deep convolutional neural network for covid-19 detection using chest x-rays,” arXiv preprint arXiv:2005.01578, 2020.

[94] J. P. Cohen, L. Diao, P. Morrison, K. Roth, Y. Bengio, B. Shen, A. Abbasi, M. Hoshamd-Kochi, M. Ghassemi, H. Li et al., “Predicting covid-19 pneumonia severity on chest x-ray with deep learning,” arXiv preprint arXiv:2005.11856, 2020.

[95] M. E. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M. A. Kadir, Z. B. Mahbub, K. R. Islam, M. S. Khan, A. Iqbal, N. Al-Emadi et al., “Can ai help in detecting viral and covid-19 pneumonia?” arXiv preprint arXiv:2003.13145, 2020.

[96] M. Loey, G. Manogaran, and N. E. M. Khalifa, “A deep transfer learning model with classical data augmentation and egan to detect covid-19 from chest ct radiography digital images,” 2020.

[97] M. Rahimzadeh and A. Attar, “A modified deep convolutional neural network for detecting covid-19 and pneumonia from chest x-ray images based on the concatenation of inception v3 and resnet50v2,” Informatics in Medicine Unlocked, p. 100360, 2020.

[98] N. Bansal and S. Sridhar, “Classification of x-ray images for detecting covid-19 using deep transfer learning,” 2020.

[99] B. D. Goodwin, C. Jaskolski, C. Zhong, and H. Asmari, “Intra-model variability in covid-19 classification using chest x-ray images,” arXiv preprint arXiv:2005.02167, 2020.

[100] N. E. M. Khalifa, F. Smarandache, and M. Loey, “A study of the neuroptic set significance on deep transfer learning models: An experimental case on a limited covid-19 chest x-ray dataset,” Preprints, 2020.

[101] S. H. Kassani, P. H. Kassani, M. J. Wesolowski, K. A. Schneider, and R. Deters, “Automatic detection of coronavirus disease (covid-19) in x-ray and ct images: A machine learning-based approach,” arXiv preprint arXiv:2004.10641, 2020.

[102] S. Vaid, R. Kalantar, and M. Bh Sanders,” Deep learning covid-19 detection bias: accuracy through artificial intelligence,” International Orthopaedics, p. 1, 2020.

[103] J. Pu, J. Leader, A. Bandos, J. Shi, P. Du, J. Yu, B. Yang, S. Ke, Y. Guo, J. B. Field et al., “Any unique image biomarkers associated with covid-19?” European Radiology, p. 1, 2020.

[104] K. Yang, X. Liu, Y. Yang, X. Liao, R. Wang, X. Zeng, Y. Wang, M. Zhao, and T. Zhang, “End-to-end covid-19 screening with 3d deep learning on chest computed tomography,” 2020.

[105] Y. Pathak, P. K. Shukla, A. Tiwari, S. Stalin, S. Singh, and P. K. Shukla, “Deep transfer learning based classification model for covid-19 disease,” IRBM, 2020.

[106] H. Panwar, P. Gupta, M. K. Siddiqui, R. Morales-Menendez, and V. Singh, “Application of deep learning for fast detection of covid-19 in x-rays using nnovnet,” Chaos, Solitons & Fractals, p. 109944, 2020.

[107] M. A. Al-antari, C.-H. Hua, and S. Lee, “Fast deep learning computer-aided diagnosis against the novel covid-19 pandemic from digital chest x-ray images,” 2020.

[108] L. Brunese, F. Mercaldo, A. Reginelli, and A. Santone, “Explainable deep learning for pulmonary disease and coronavirus covid-19 detection from x-rays,” Computer Methods and Programs in Biomedicine, p. 105608, 2020.

[109] X. Li, C. Li, and D. Zhu, “Covid-mobileexpert: On-device covid-19 screening using snapshots of chest x-ray,” arXiv preprint arXiv:2004.03042, 2020.

[110] D. Singh, V. Kumar, and M. Kaur, “Classification of covid-19 patients from chest ct images using multi-objective differential evolution-based convolutional neural networks,” European Journal of Clinical Microbiology & Infectious Diseases, pp. 1–11, 2020.

[111] J. Diaz-Escobar, N. E. Ordóñez-Guillén, S. Villareal-Reyes, A. Galaviz-Mosqueda, V. Koher, R. Rivera-Rodriguez, and J. E. Lozano Rizk, “Deep-learning based detection of covid-19 using lung ultrasound imagery,” PloS one, vol. 16, no. 8, p. e0255886, 2021.

[112] J. Song, H. Wang, Y. Liu, W. Wu, G. Dai, Z. Wu, P. Zhu, W. Zhang, K. W. Yeom, and K. Deng, “End-to-end automatic differentiation of the coronavirus disease 2019 (covid-19) from viral pneumonia based on chest ct,” European journal of nuclear medicine and molecular imaging, pp. 1–9, 2020.

[113] S. E. Ebadi, D. Krishnaswamy, S. E. S. Bolouri, D. Zonoobi, R. Greiner, N. Meuser-Herr, J. L. Jaremko, J. Kapur, M. Noga, and K. Punithakumar, “Automated detection of pneumonia in lung ultrasound using deep video classification for covid-19,” Informatics in Medicine Unlocked, p. 100087, 2021.

[114] A. Saeedi, M. Saeedi, and A. Maghsoudi, “A novel and reliable deep learning web-based tool to detect covid-19 infection form chest ct-scan,” arXiv preprint arXiv:2006.14419, 2020.
