COVID-19 Detection: A Systematic Review of Machine and Deep Learning-Based Approaches Utilizing Chest X-Rays and CT Scans

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Abstract

This review study presents the state-of-the-art machine and deep learning-based COVID-19 detection approaches utilizing the chest X-rays or computed tomography (CT) scans. This study aims to systematically scrutinize as well as to discourse challenges and limitations of the existing state-of-the-art research published in this domain from March 2020 to August 2021. This study also presents a comparative analysis of the performance of four majorly used deep transfer learning (DTL) models like VGG16, VGG19, ResNet50, and DenseNet over the COVID-19 local CT scans dataset and global chest X-ray dataset. A brief illustration of the majorly used chest X-ray and CT scan datasets of COVID-19 patients utilized in state-of-the-art COVID-19 detection approaches are also presented for future research. The research databases like IEEE Xplore, PubMed, and Web of Science are searched exhaustively for carrying out this survey. For the comparison analysis, four deep transfer learning models like VGG16, VGG19, ResNet50, and DenseNet are initially fine-tuned and trained using the augmented local CT scans and global chest X-ray dataset in order to observe their performance. This review study summarizes major findings like AI technique employed, type of classification performed, used datasets, results in terms of accuracy, specificity, sensitivity, F1 score, etc., along with the limitations, and future work for COVID-19 detection in tabular manner for conciseness. The performance analysis of the four majorly used deep transfer learning models affirms that Visual Geometry Group 19 (VGG19) model delivered the best performance over both COVID-19 local CT scans dataset and global chest X-ray dataset.

Introduction

The word "novel" is used often with coronavirus to mean that it is a new strain in the family of perilous viruses [1]. According to WHO, coronavirus belongs to a large family of viruses ranging from common cold to unsafe diseases (www.who.int). Such diseases can infect both humans and animals. The coronavirus COVID-19 strain started spreading in Wuhan, China, in December 2019, since then it has become a serious health problem in the world. The coronavirus COVID-19 strain has its place in two different coronaviruses called Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS). Respiratory complications like pneumonia, kidney disorder, and liquid formation in the lungs are among the symptoms of coronavirus infection. Coronavirus (CoV) is the dangerous one due to its serial interval (5 to 7.5) and reproductive rate (2 to 3) [2]. The CoV has its roots in the single-stranded RNA viruses (+ ssRNA) family, mostly seen in animals [3,

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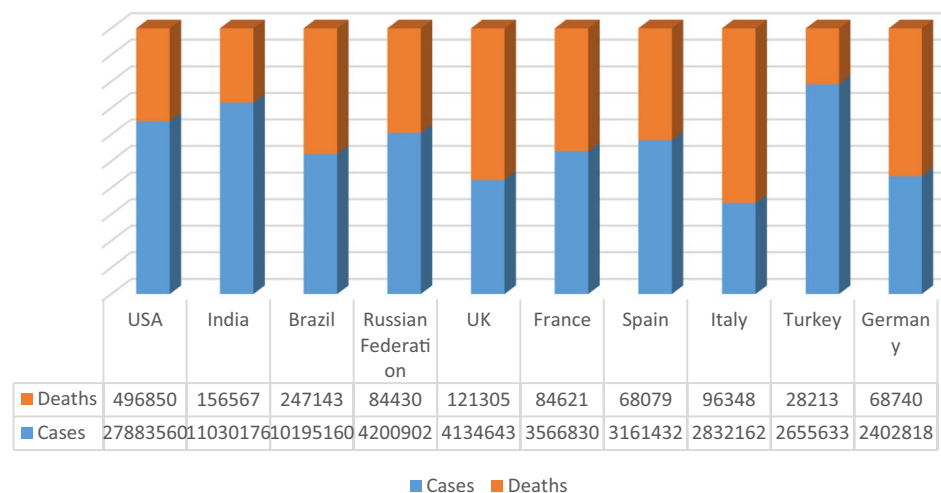
Table 1 Details related to the origin of CoV

Cov	Year	Origin	Mortality rate
SARS	2002	Guangdong Province, China	10%
MERS	2013	Saudi Arabia	34%
COVID-19	2019	Wuhan, China	2.0%

4]. These viruses have no species barriers and can cause epidemics like MERS and SARS which were seen in the last two decades. The SARS-CoV began in China, blew out to twenty-four countries and caused 8000 cases and 800 deaths. The MERS-CoV started in Saudi Arabia and reported 2500 cases and 8700 deaths. About 2% of the population are healthy carriers of CoV and these viruses are accountable for approximately 5 to 10% of acute respiratory infections [5]. The virus behind COVID-19 pandemic is called Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) [6]. The CoV details are given in Table 1.

COVID-19 is a new species discovered in 2019 that has not been previously identified in humans. Bats have been recognized as natural reservoirs and vectors of a variety of viruses including coronaviruses have crossed species barriers to infect humans as well as different kinds of animals, including avian, rodents, and chiropters [7]. The CoV is so named due to their solar corona (crown-like) appearance when observed under an electron microscope. COVID-19 is an acute resolved disease, but it can also be deadly as depicted in Fig. 1, based on the data from the WHO. Severe disease onset might result in death due to massive alveolar damage and progressive respiratory failure [8]. Respiratory droplets of size greater than 5–10 μm acts as a mode of airborne transmission (https://apps.who.int/iris/handle/10665/331601). COVID-19 carries a higher growth factor than SARS and MERS due to the fact that interaction without safety measures can be extremely contagious and it causes

lighter symptoms in most cases. The top ten COVID-19 infected countries statistics in terms of infected cases and deaths are presented with the help of Fig. 1.

Faster spreading rate is a major concern for COVID-19 pandemic and thus detecting who has the COVID-19 virus infection at an early stage is critical [9] to curtail its spread. Viral nucleic acid detection using real-time polymerase chain reaction (RT-PCR) is the accepted standard diagnostic method [10, 11]. However, this test has suboptimal sensitivity and specificity and many hyper-endemic regions and countries are not able to provide sufficient RT-PCR testing for tens of thousands of suspected subjects in a short period of time. Other concerns about RT-PCR are its painfulness, lack of swabs, need of reagents, delays in producing results and substantial false-negative rate. Considering these concerns, other approaches to diagnosis are worthy of investigation [12]. All such approaches should be accurate, fast, and effective tools for detecting COVID-19 infection to provide the prerequisite for rigorous detection, contact tracing and isolation of infected subjects at primary stage of infection. Artificial intelligence techniques are now exceptionally found to be beneficial for training, forecasting, and evaluation purposes. Neural networks are widely employed for developing prediction models. But neural networks still have limitations like slow convergence and learning capability [13]. ALzubi et al. [14] demonstrated the fact that deep learning is a beneficial technique to improve the diagnostic pace, since it can be used for making predictions and clinical decisions in medical system. These researches also stated that linking medical image and diagnostic parameters is an efficient scheme that will assist doctors to perform patients' diagnosis utilizing big data. To assist doctors to evaluate the COVID-19 disease and to optimize prevention and control measures as earliest as possible, medical imaging can be considered a vital technique to diagnose COVID-19 infections using radiological images such as X-rays or computed

Fig. 1 The top ten countries statistics related to infected cases and deaths

	USA	India	Brazil	Russian Federation	UK	France	Spain	Italy	Turkey	Germany
Deaths	496850	156567	247143	84430	121305	84621	68079	96348	28213	68740
Cases	27883560	11030176	10195160	4200902	4134643	3566830	3161432	2832162	2655633	2402818

Cases   Deaths

tomography (CT) scans. It has been established that anomalies can be found in COVID-19 patients in chest CT scans in the shape of Ground-Glass Opacities (GGO) [15]. Much research has demonstrated that a system using chest CT scans can be created for diagnosing and quantifying COVID-19 cases [16]. To detect COVID-19, X-ray images can also be utilized instead of CT scans. Hence, medical images like chest X-rays (CXR) and CT images can be studied to give comparatively instant diagnostic information by identifying possible patterns that may lead to the automatic diagnosis of the disease. Chest X-ray is the universally used imaging modality in the diagnostic checkup of patients with thoracic abnormalities, due to its fast imaging speed, low radiation, and low cost [17], universal availability in both emergency and hospital settings, where interpretation is often done without expert radiologists.

Unlike laboratory tests that involve probing the patient's respiratory system, X-rays can be taken without the increased risk of aerosolizing the pathogen. The X-rays may also facilitate the triage of patients into highest risk, high risk, and lower risk of further complications besides indicating the severity of disease at one or more time points. Unlike computed tomography (CT) scans, chest X-rays cannot provide 3D anatomy but can differentiate pneumonia even though it is probably understood as the most challenging plain film to interpret correctly [18]. Accurate interpretation is vital for patient management in the severe situation, and to help identify clustering occurrences of COVID-19. CT, being a noninvasive imaging approach, can portray certain characteristic manifestations in the lung which are associated with COVID-19 [19, 20]. CT can be used as an effective way for early diagnosis of COVID-19 but CT may determine similar imaging features between COVID-19 and other types of pneumonia, thus making it difficult to differentiate between them. CT imaging is significantly more time consuming than X-ray imaging, and also involves complex sanitization procedures between switching patients. Moreover, sufficient high-quality CT scanners may not be commonly available, making it difficult for a timely viral pneumonia screening. The role of medical imaging is vital for the fast diagnosis of COVID-19 [18]. The first image based approach used in Spain (https://healthcare-in-europe.com/en/news/imaging-the-coronavirus-disease-covid-19.html). Hence, the combination of AI and chest imaging can facilitate the detection of complications of COVID-19 [21].

Recent research work shows that computer vision [22], machine learning [23–25], and deep learning [26, 27] can be used for automatic diagnosis of different ailments in the human body [28, 29]. The deep learning method is used as a feature extractor that enhances classification accuracies [30]. Although radiography can be quickly performed and generally available due to commonality of chest radiology imaging systems in hospitals, the interpretation of radiography

images by radiologists is still a major concern due to the human capacity in detecting the subtle visual features present in the images. Deep learning can discover patterns in chest X-rays that can be missed by radiologists [31–34]. Deep learning, which has been used to detect tuberculosis in chest X-rays, could also be used for identifying lung abnormalities related to COVID-19 [35] due to its high capability of feature extraction [36–38]. This will help clinicians in deciding the order of treatment of high-risk COVID-19 patients. Deep learning was used to detect and segregate bacterial and viral pneumonia on pediatric chest radiographs [39, 40]. Efforts have also been made to detect various imaging features of chest CT scans [41, 42].

Deep learning (DL) is a branch of machine learning (ML) which is inspired by the way the human brain works and utilized for feature extraction as well as classification of images. Main strength of DL is that it is an unsupervised learning i.e., it can learn from unlabeled data. DL has been vastly used in industries, self-driven cars, face recognition, object detection, image classification, etc. [43] due to characteristics like unlabeled data utilization, working without feature engineering, prediction with high accuracy and precision. Convolutional neural network (CNN) is a DL algorithm that has been used extensively in solving problems like document analysis, different types of image classification, pose detection, and recognizing various actions [44]. Medical imaging is one of the areas where CNN has been showing encouraging results [45], and thus, convolutional neural networks (CNNs) have been doing well in detecting several diseases like coronary artery disease, malaria, Alzheimer's disease, different dental diseases, and Parkinson's disease. Likewise, CNN has considerable prospects for differentiating COVID-19 from non-COVID-19 infections with medical images like chest X-rays and CTs using public databases of chest X-rays and CTs. The chest X-rays and CT scans of COVID-19 positive cases and normal are presented with the help of Fig. 2.

The real motivation behind writing this review paper is to illustrate the latest trends and development in the domain of COVID-19 detection and classification approaches based on deep learning. Apart from this, an analysis and comparison is also done utilizing the five majorly used deep transfer learning models as per the literature review for the COVID-19 detection in the analysis and evaluation section. All these five models are trained and evaluated on the locally developed COVID-19 CT scan dataset and two global chest X-ray image dataset in order to observe their performance.

This state-of-the-art review paper is organized into a total of five sections. Initially, the "Introduction" section is all about illustrating the general introduction to the COVID-19 disease and its impact over the world in the present scenario. The "Research Methodology" section deals with the research methodology adopted to conduct this review study. The

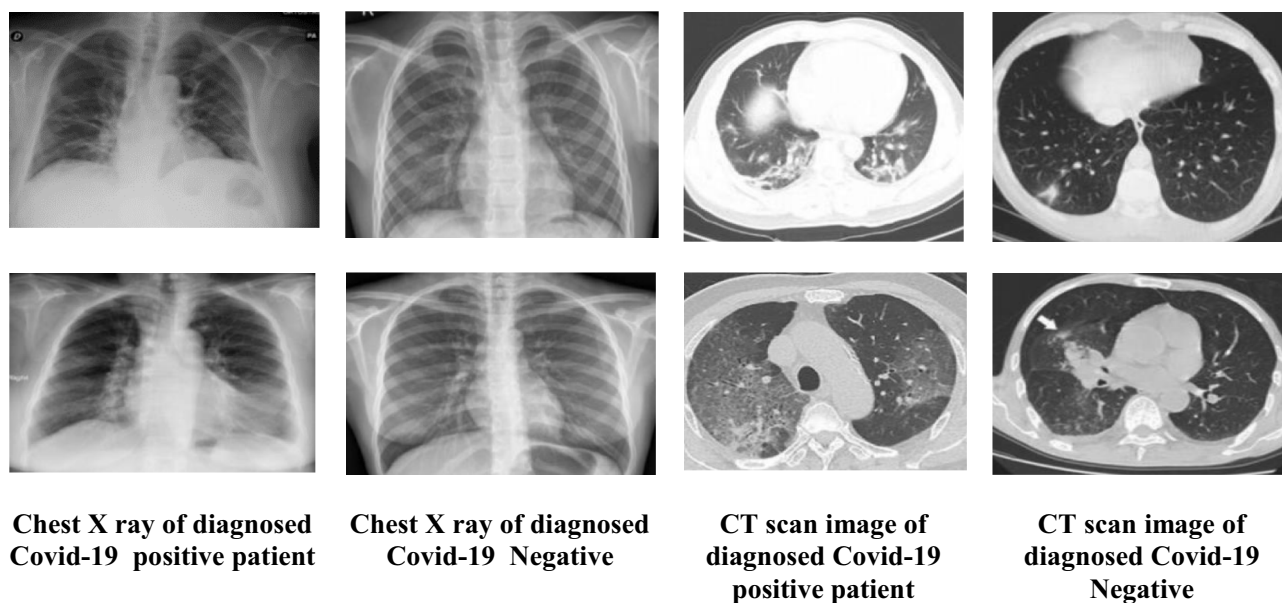**Chest X ray of diagnosed Covid-19 positive patient**

Chest X ray of diagnosed Covid-19 Negative

CT scan image of diagnosed Covid-19 positive patient

CT scan image of diagnosed Covid-19 Negative

Fig. 2 The chest X-ray and CT scan images of COVID-19 positive, normal people

"Literature Review" section deals with the brief review and comparison of major automated deep learning and machine learning-based COVID-19 detection approaches proposed by the various researchers since March 2020. The "Majorly Used COVID-19 Chest X Ray, CT Scan, and Ultrasound Image Dataset Description" section elaborates the various COVID-19 chest X-rays and CT scan datasets available online for research. The "Analysis and Evaluation" section presents an analysis and evaluation among the four majorly used deep transfer learning models over the COVID-19 local CT scan and global chest X-ray datasets.

Research Methodology

The presented review study aims to assess the existing research done in the domain of deep learning application for the detection of COVID-19 utilizing the chest X-rays and CT scan images. Various databases e.g. IEEE Xplore, PubMed, Web of Science etc. are searched exhaustively with the specific search items. The research studies included in this review study are based on the following selection criteria:

- Only deep learning-based approaches for the COVID-19 binary or multiclass classification are included.
- The considered research studies were limited to the period from March 2020 to August 2021.
- The research studies utilizing either the chest X-ray or CT scan imaging modalities are included. Other medical imaging modalities are excluded.

- Only classification or detection approaches are included, whereas prediction approaches utilizing big data are not excluded from this study.
- Research studies which mentioned the future direction or at least offered some narrative to improve the existing work.

After the elimination of duplicate and redundant works, more than 50 unique studies were considered in this review study. Table 2 below summarizes the search items employed for the searching of research studies for the COVID-19 classification and detection.

Literature Review

Since March 2020, a substantial amount of research has been carried out in the domain of COVID-19 detection based on deep learning. These deep learning models are trained and tested either using chest X-ray images or CT scan images or sometimes both. This fact is very well proved by the Figs. 3 and 4 representing the data collected from major research databases like PubMed and Web of Science. These two graphs simply illustrate the number of COVID-19 detection research studies done using either CT scan or Chest X-ray datasets and established on deep learning, deep transfer learning. Figures 5 and 6 demonstrate the general COVID-19 detection approaches based on machine learning, deep learning, and deep transfer learning whereas Fig. 7 depicts deep learning in conjunction with traditional machine learning classifiers, also known as the hybrid models.

Table 2 The list of research article sources and search items used

Research studies sources	Search terms
Web of science	Under Advance search tab TS = (Covid19* "and" Chest X ray* "and" Deep learning* "and" machine learning*) TS = (Covid19* "and" CT scan* "and" Deep learning* "and" machine learning*)
IEEE Xplore	"Covid19" AND "Deep learning" AND "CT scan" "Covid19" AND "CNN" AND "CT scan" "Covid19" AND "Deep transfer learning" AND "CT scan" "Covid19" AND "machine learning" AND "CT scan" "Covid19" AND "Deep learning" AND "Chest X ray" OR "X ray" or "X ray Scan" "Covid19" AND "CNN" AND "Chest X ray" OR "X ray" or "X ray Scan" "Covid19" AND "Deep transfer learning" AND "Chest X ray" OR "X ray" or "X ray Scan" filter applied: journals only Publication year: 2020 to 2021
PubMed	"Covid19" AND "Deep learning" AND "CT scan" AND "machine learning" "Covid19" AND "CNN" AND "CT scan" "Covid19" AND "Deep transfer learning" AND "CT scan" "Covid19" AND "Deep learning" AND "Chest X ray" OR "X ray" or "X ray Scan" "Covid19" AND "CNN" AND "Chest X ray" OR "X ray" or "X ray Scan" "Covid19" AND "Deep transfer learning" AND "Chest X ray" OR "X ray" or "X ray Scan"
Scopus	TITLE-ABS-KEY ("Covid 19" AND "Chest X ray" AND "deep learning" AND "Machine learning") (LIMIT-TO) (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020) AND (LIMIT-TO (DOCTYPE, "ar")) TITLE-ABS-KEY ("Covid 19" AND "CT scan" AND "deep learning" AND "machine learning") AND (LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020) AND (LIMIT-TO (DOCTYPE, "ar"))

Deep Learning and Deep Transfer Learning-Based Approaches

Ucar et al. [46] proposed a fine tuned deep learning model based on SqueezeNet and Bayesian optimization for the screening of COVID-19 patients. This Deep Bayes-SqueezeNet learning model takes chest X-ray images in order to diagnose COVID-19 disease. The proposed SqueezeNet is composed of 15 layers; 5 different layers as 2 convolution layers, 3 max pooling layers, 8 fire layers, 1 global average pooling layer, and 1 output layer softmax. This proposed model offered an accuracy of 100%, 98.04%, and 96.73% for the COVID-19, normal, and pneumonia cases. Hammoudi et al. [47] proposed a deep transfer learning-based model which is established on InceptionResNetV2 for the screening and diagnosis of COVID-19 patients. Their DenseNet169 model delivered approximately 96% average accuracy for the correct

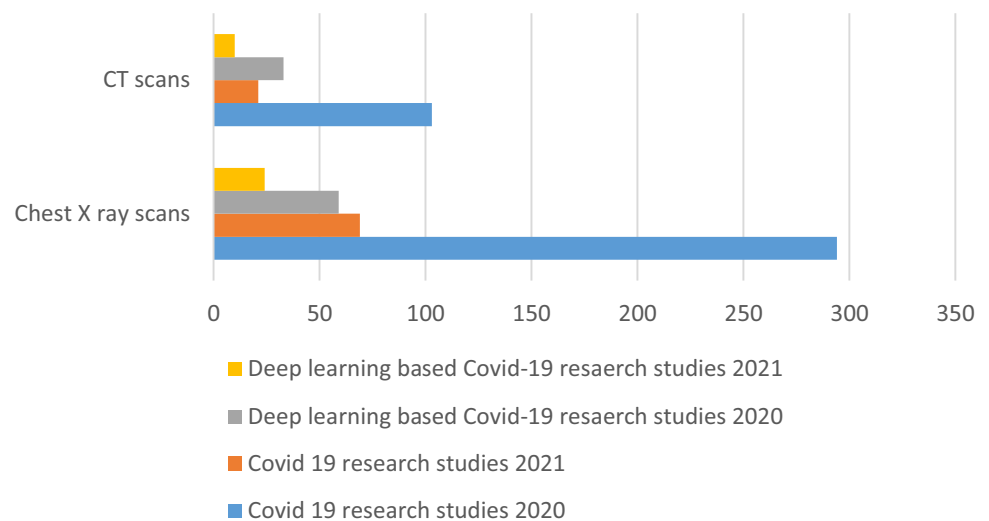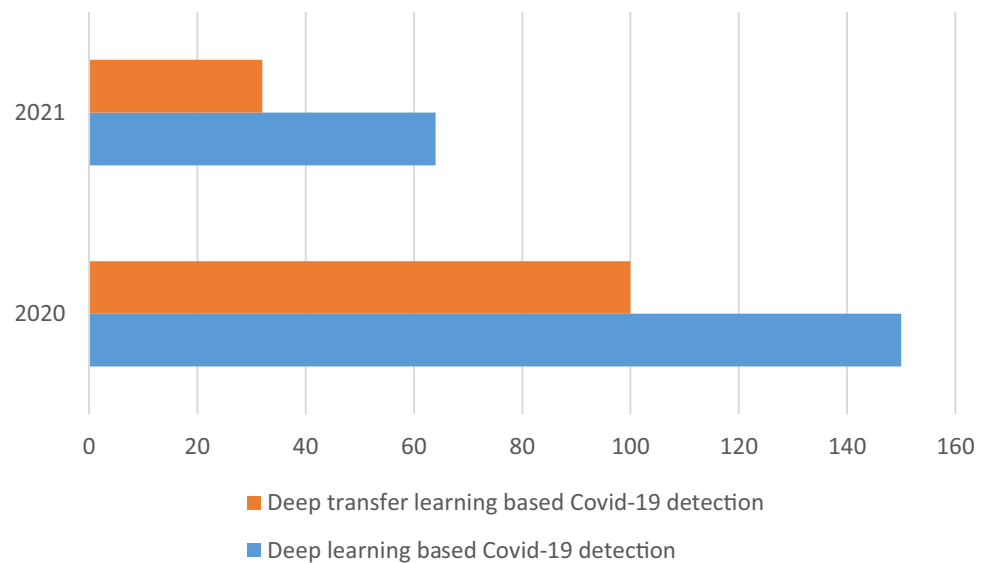**Fig. 3** CT scan and chest X-ray scans based COVID-19 research studies

Legend:
- Deep learning based Covid-19 resaerch studies 2021
- Deep learning based Covid-19 resaerch studies 2020
- Covid 19 research studies 2021
- Covid 19 research studies 2020

■ Deep transfer learning based Covid-19 detection

■ Deep learning based Covid-19 detection

classification of pneumonia cases using the chest X-ray imaging modality. Rajaraman et al. [48] proposed an iteratively pruned deep learning model for the detection of COVID-19 using the chest X-ray images and ImageNet models. The results give the accuracy of 99.01% and area under the curve = 99.72%. Also, the CXR images are taken for clear lung, bacterial pneumonia infections, and COVID-19 pneumonia infection manifesting at peripheral opacities in the left lung. Hall et al. [49] proposed a pre-trained CNN based on ResNet50 for screening of COVID-19 and pneumonia patients with tenfold cross validation. Their model achieved an overall accuracy of 89.2% and area under the curve was 95%. Their work focuses on CXRs which are simpler and cheaper to obtain but provide less information than CT. Rahimzadeh et al. [50] proposed a deep learning model based on Xception and ResNet50V2 for screening of COVID-19 patients. The proposed model performs the multiclass classification as normal cases, pneumonia, and COVID-19 cases. In their study both the Xception and ResNet50V2 are used for extracting deep features and then the softmax classifier performs the multiclass classification. Zhang et al. [51] proposed a deep

anomaly detection model for reliable and fast screening in order to identify COVID-19 from non-COVID-19 cases. This model is composed of three components, namely, a backbone network, a classification head, and an anomaly detection head. An 18-layer residual convolutional neural network pre-trained on the ImageNet dataset is used as the backbone network. Hemdan et al. [52] conducted a comparison study using the VGG19, DenseNet121, InceptionV3, ResNetV2, Inception-ResNet-V2, Xception, and MobileNetV2 DTL models for detection of COVID-19. The VGG19 and Dense CNN models showed good performances compared to other DTL models in their research study. Wang et al. [53] proposed a DL system consisting of three stages i.e. automatic lung segmentation, non-lung area suppression, and COVID-19 diagnostic and prognostic analysis. In this system, two DL networks were used initially, a DenseNet121-FPN for lung segmentation in chest CT image, and the proposed novel COVID-19Net for COVID-19 diagnostic and prognostic analysis. This COVID-19Net model used a DenseNet-like structure, consisting of four dense blocks, where each dense block had multiple stacks of convolution, batch normalization,
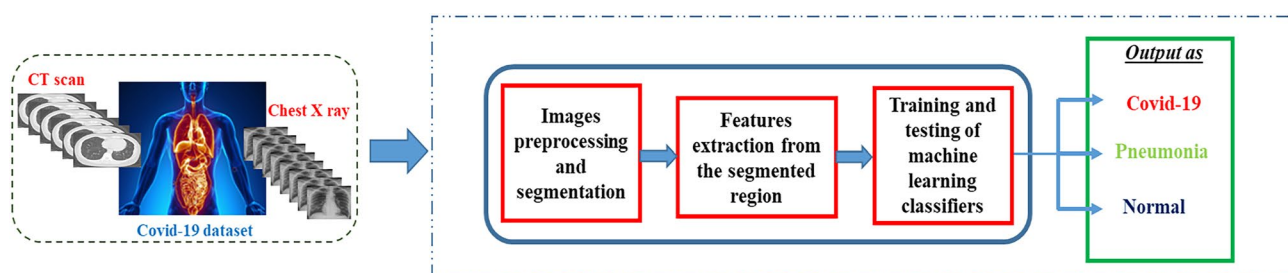

Fig. 5 General COVID-19 detection or classification approach based on machine learning
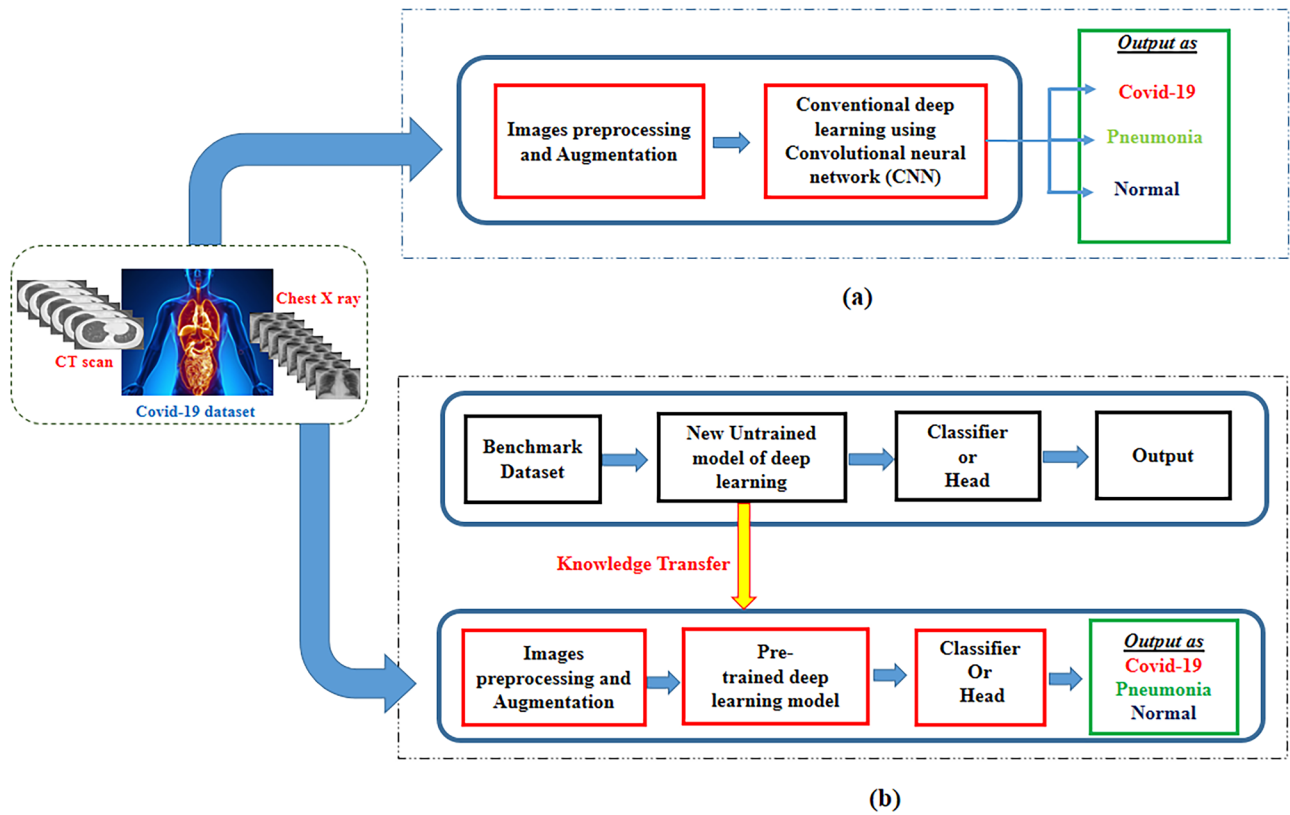
Fig. 6 General COVID-19 detection or classification approach based on **a** conventional deep learning using convolutional neural network, **b** deep transfer learning models

and ReLU activation layers. Each dense block uses a dense connection to contemplate multi-level image information. Zheng et al. [54] developed a weakly-supervised deep

learning-based software system using 3D CT volumes to detect COVID-19. In their system, the lung region was segmented using a pre-trained UNet and then the segmented
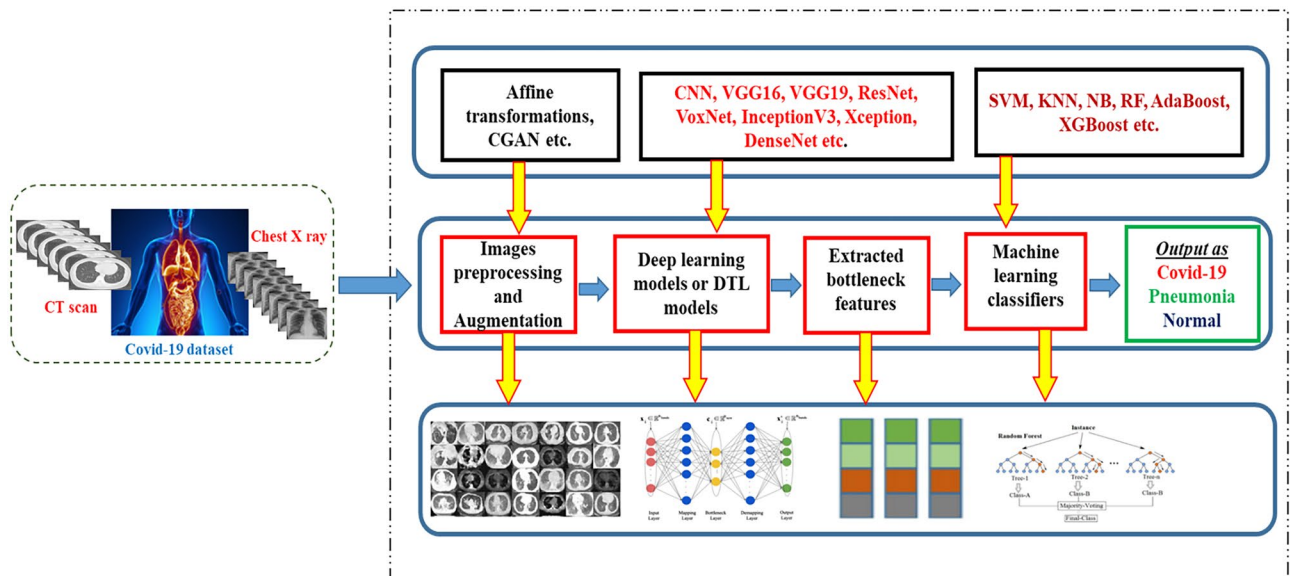

Fig. 7 An automated COVID-19 detection and classification approach based on Deep learning in conjunction with traditional machine learning classifiers also known as the hybrid models

3D lung region was fed into a 3D deep neural network to predict the probability of COVID-19 infection. Apostolopoulos et al. [55] proposed an automated detection system based on MobileNet V2. Different strategies were utilized in their study, such as transfer learning with off-the-shelf-feature extraction, transfer learning with fine tuning, and training from scratch. The training and evaluation procedure was performed with tenfold-cross-validation. Fu et al. [56] proposed a deep learning-based diagnostic tool using the ResNet50 architecture to perform multiclass classification into seven classes. The multiclass classification occurs for COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia, pulmonary tuberculosis, or and normal lung cases. Ardakani et al. [57] presented a comparison study using the DTL models like ResNet-101, AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, and Xception for detection of COVID-19 and Non-COVID-19. The best results were delivered by the ResNet-101 and Xception models. Their study compared the performance of radiologists in real-time with the performance of these ten DTL models for COVID-19 detection.

Rehman et al. [58] proposed an automated method for the diagnosis of COVID-19 positive cases. Their model tends to perform the multiclass classification differentiating a COVID-19 from viral, bacterial, and normal cases. Their research study compared the seven DTL pre-trained architectures of CNN which were: (1) AlexNet is composed of 5 convolutional layers and 3 fully connected layers. (2) VGG is composed of 16 convolutional layers and 3 fully connected layers. (3) SqueezeNet contains five modules and an expanded layer. (4) GoogleNet, composed of 9 inception models, 4 max-pooling layers, 2 convolutional layers, an average pooling layer, 2 normalization layers, 1 fully connected layer, and a linear layer. (5) Three variants of ResNet were used. ResNet18, composed of 5 convolution blocks, each containing 2 residual blocks. Each residual block contains 2 convolution layers. ResNet50 contains 5 residual blocks, each with a convolution and identity block. The convolution and identity blocks have 3 convolution layers. ResNet101 contains 3 convolutional, 3 residual blocks, and an identity block, (6) DenseNet contains 1×1 convolutional filters and max-pooling layers. (7) MobileNetv2 contains CNN layer, inverted residual, and linear bottleneck layer. Khalifa et al. [59] proposed a method for the detection of COVID-19 cases based on GAN (Generative Adversarial Network) with fine-tuned DTL models. They employed four types of DTL models, which were: (1) AlexNet, (2) SqueezeNet, (3) GoogleNet, (4) RestNet18 with 8, 18, 22, 18 layers respectively and these models are chosen

due to the less number of layers, so that the complexity, consumed memory, and time can be reduced. Loey et al. [60] proposed a model based on Generative Adversarial Network (GAN) and Deep Transfer Learning model to analyze various deep transfer learning models such as AlexNet, GoogleNet, and RestNet18 to detect COVID-19 disease. In their model GoogleNet achieved 100% testing accuracy and 99.9% validation accuracy. Then Shan et al. [61] proposed an accurate deep learning-based model for automatic segmentation and quantification of infection regions of COVID-19 from chest CT scans. The proposed model utilized VB-Net segmentation to clearly segment and quantify the infection area. The proposed model offers an accuracy of $91.6\% \pm 10\%$. Hu et al. [62], proposed an approach based on the customized CNN architecture for the detection of COVID-19 cases as well as for the quantification of infection region from the chest CT scans. The customized CNN architecture with five convolutional layers performs a multiclass classification as COVID-19, CAP (community-acquired pneumonia) and non-pneumonic to detect COVID-19 disease accurately. Wang et al. [63] proposed a model for the detection of COVID-19 disease using chest X-ray images. They used Deep learning tools like VGG-19, ResNet-50, and COVID-Net with the accuracy of 83.0%, 90.6%, and 93.3% respectively. Li et al. [64] proposed a model for the detection of COVID-19 using 3D deep learning framework based on CovNet. The CovNet framework consists of ResNet50 as the backbone using CT scan images as an input. They performed three-way classification between COVID-19, CAP (community-acquired pneumonia), and non-pneumonia patients. Minaee et al. [65] proposed a model for the detection of the novel coronavirus using chest X-ray images. Four DTL models, namely ResNet18, ResNet50, SqueezeNet, and DenseNet-121 performance, were compared on a very large size dataset in their study. Among these, the SqueezNet model offered the best result of 98% sensitivity and 92.9% specificity. Basu et al. [66] proposed a model for the detection of COVID-19 disease with the help of Domain Extension Transfer Learning (DETL) and Gradient Class Activation Map (Grad-CAM). Their study used pre-trained DTL models like AlexNet, VGGNet, and ResNet which offered an accuracy of 82.98%, 90.13%, and 85.98% respectively. The proposed model performs multiclass classification between normal, pneumonia, other disease, and COVID-19 cases. Khalifa et al. [67] explored a new dimension in the deep learning and deep transfer learning application for the COVID-19 detection. Their novel research study established on the concept of neutrosophic set along with the application of DTL models. In their study, CXR images available in the grayscale

domain are converted into the neutrosophic domain. The neutrosophic domain consists of three types of images: indeterminacy (I) images, true (T) images, and the falsity (F) images. Then, these neutrosophic images are used for the training of DTL models like AlexNet, GoogleNet, and ResNet18, which in turn perform the multiclass classification. The four-way classification into normal, bacterial pneumonia, viral pneumonia, and COVID-19 cases are done. Cohen et al. [68] proposed a model for severity score prediction of COVID-19 pneumonia using the CXR images. Such a tool can gauge the severity of COVID-19 lung infections. Their study used a DTL i.e. DenseNet model from the Torch X-Ray Vision Library. Their proposed model can predict geographic extent score and lung opacity score with 1.14 and 0.78 mean absolute error (MAE) respectively. Ying et al. [69], proposed a Detail Relation Extraction Network (DRE-Net)–based model to detect COVID-19 disease using chest CT scan images. Their proposed model performed the multiclass classification and its performance was compared with other DTL models like VGG16, DenseNet, and ResNet. The proposed DRE-Net model offered accuracy 94%.

Wang et al. [70] devised an alternate method for the diagnosis of COVID-19 cases, which was completely tested in a laboratory. Due to the challenges faced in the quality and availability of such laboratories in the infected areas, alternatives such as devising an artificial intelligence-based testing algorithm were proposed. This algorithm can assist the radiologist to easily differentiate between the COVID-19 positive cases and other viral pneumonias. It studied 453 enrolled CT images and used 217 as trained dataset and rest as validation set. The algorithm produced an accuracy of 82.9% in the internal validation and 73.1% in the external validation. Narin et al. [71] felt the need for an automatic COVID-19 case detection method to reduce the risk of spreading this pandemic disease at a widespread range. Three DTL models as ResNet50, InceptionV3, and Inception-ResNetV2 were proposed for detection of COVID cases using the chest X-ray images of suspected patients. The devised algorithm delivered the highest accuracy 98% with the ResNet50 model, InceptionV3, and Inception-ResNetV2 achieved 97% and 87% accuracy respectively. Jin et al. [72] proposed another deep learning-based AI system to increase the rate of diagnosis of COVID-19 disease for the welfare of society during this COVID-19 pandemic. It will enable timely detection of infected patients and help in controlling the growing rates of COVID-19 cases. The algorithm derived is a result of extensive statistical analysis of CT scan images. The analysis was done on nearly 10,000 CT volumes of community-acquired pneumonia (non-viral),

influenza-A/B, non-pneumonia, and COVID-19 suspected. Xu et al. [73] proposed a model to distinguish COVID-19 pneumonia from influenza-A viral pneumonia and healthy cases with pulmonary CT images using deep learning techniques. Their CNN model is accompanied with Noisy-OR Bayesian function to come up with an accuracy of 86.7% in testing of COVID-19 cases. Huang et al. [74] developed a deep learning-based algorithm which was focused on quantitative CT. It allows measuring the severity of COVID-19 and helps in studying the growth rate and opacity percentage of lungs within the patient body. The algorithm classifies patients between mild vs. moderate vs. severe vs. critical. All the results were cross-checked by two radiologists and the follow-up test conducted after the diagnosis of opacity percentage of the lungs. Farooq et al. [75] developed an automated approach for the detection and classification of COVID-19 cases by fine-tuning a pre-trained ResNet50 architecture named COVIDNet. The dataset used in their research study consisted of 5941 CXR images from 2839 different patients. The classification is done as normal, bacterial pneumonia, viral pneumonia, and COVID-19. It comes up with an accuracy of 96.23%. Authors now want the deduced algorithm to examine a large dataset and prove its reliability for the noble purpose. Chen et al. [76] devise a new model for the detection of COVID-19. Their study is based on high-resolution CT scan images of the suspected coronavirus pneumonia patients. The devised model is based on UNet + + for image segmentation and ResNet50 for the classification to deduce the results. The results were cross-checked by three radiologists and it is found that the time taken for testing the already evaluated images by radiologists is very less compared to evaluating new images. Asnaoui et al. [77] inspired by the achievements of the medical image analysis technique and motivated to publish a research based on the deep convolutional neural network (DCNN) architectures such as VGG16, VGG19, CNN, Inception_V3, Xception, Resnet50, Inception_Resnet_V2, DenseNet201, and MobileNet_V2. The results were classified in two parts as normal vs. pneumonia. To obtain the results, a total of 5856 images of chest X-ray and CT images were studied, of which 4273 were of pneumonic patients and the rest 1583 were of normal humans. The highest accuracy was achieved by Resnet50 and MobileNet_V2 architecture with 96.61% and 96.27% respectively. Chowdhury et al. [78] implemented and evaluated the eight different pre-trained models known as MobileNetv2, SqueezeNet, ResNet18, ResNet101, DenseNet201, CheXNet, Inceptionv3, and VGG19. The result was classified as normal vs. COVID-19 pneumonia vs. viral pneumonia. Chest X-ray images of 423 COVID-19 patients, 1485 viral pneumonia patients,

and 1579 normal patients were examined. DenseNet201 leads the results with the highest accuracy among other models with 99.70%. Apostolopoulos et al. [79] came up with a comparison study of various DTL models for the detection of COVID-19 cases. The models used were VGG19, MobileNet v2, Inception, Xception, and Inception ResNet v2. The highest three-class accuracy was achieved by VGG19 among all the models used. Moreover, the researchers took two datasets to devise the results of their study. Afshar et al. [80] understood that RT-PCR is a time consuming test, which is not desirable and includes too much physical contact with the COVID-19 patients. So, the authors collected the X-ray images from two different datasets and developed a capsule based framework named COVID-CAPS. The COVID-CAPS framework consists of 4 convolutional layers and 3 capsule layers. The result of the study was a binary classification into either COVID-positive patients or COVID-negative patients. The accuracy of the proposed work comes out to be 95.7% with sensitivity around 90% and specificity of about 95.8%. Butt et al. [81] realized the efficiency of artificial intelligence in diagnosing COVID cases. It is a clear fact that early detection of the infection will lead to a way of reducing mortality rates. It has been noted that radiographic patterns are far more fast and accurate in generating results when compared to RT-PCR detection of COVID-19 victims. Studies showed that the detection of different types of viral pneumonia becomes an easier task when diagnosed with the help of artificial intelligence. A sum of 618 CT images was used to process the result, which comes out to an accuracy of, specificity of, and sensitivity of about 99.6%, 92.2%, and 98.2% respectively. Ozturk et al. [82] proposed DarkNet model which was implemented with 17 convolutional layers to come up with accurate results. They succeeded in their task by attaining an accuracy of 98.08% in binary classification and 87.02% accuracy in multiclass classification.

Shah et al. [83] proposed CTnet-10 deep learning CNN–based model to classify CT scan images into COVID-19 and non-COVID-19. The CTnet-10 has 82.1% accuracy. They also observed that their model is faster compared to the RT-PCR method. They also verified DenseNet-169, VGG-16, ResNet-50, InceptionV3, and VGG-19. Among these, VGG-19 proved to be superior, having 94.52% accuracy. Javaheri et al. [84] have developed a model called CovidCT-Net using deep learning algorithms to do a binary classification into either COVID-19 and community-acquired pneumonia (CAP) from CT scans. The accuracy of CovidCTNet was 95%. The important facts about CovidCTNet are that it was designed to work with small and heterogeneous sample sizes irrespective of CT scanning hardware and it was open source. Wide pattern and imaging feature resemblance of COVID-19 and CAP challenged the algorithm training but achieved accuracy of CovidCTNet make it a tool to be adapted for clinical decision. Wang et al. [85] assessed a deep learning algorithm using CT images for screening COVID-19 patients throughout the influenza season. To validate their hypothesis, they used 1065 CT images, out which 740 were COVID-19 negative and 325 were COVID-19 positive. Their algorithm delivered 89.5% accuracy, 0.88 specificity, and 0.87 sensitivity.

Their future work will focus on linking hierarchical features of CT images to features of other factors like genetic, epidemiological, and clinical information for the purpose of multi-modeling analysis. This multi-modeling analysis will expedite enhanced diagnosis. Saad et al. [86] have used deep feature concatenation (DFC) mechanism in two ways. In one-way DFC does the linking of deep features extracted from X-ray and CT images through a CNN. In second-way DFC combines extracted features either from X-ray or CT scan using CNN architecture along with two pre-trained CNNs called ResNet and GoogleNet. Their proposed architecture has 3 deep layers to mitigate large time consumption issues. Their first way has delivered 96.13% accuracy, 94.37% precision, 97.04% recall, and an f_score of 95.69%. Their second way has delivered an accuracy of 98.9%, 93.6% precision; a recall of 98.5% and 98.29% f_score when using CT images but when X-ray images used, this second way has got 99.3% accuracy, 99.79% precision, 98.8% recall, and f_score of 99.3%. Serte et al. [87] proposed an AI system to determine COVID-19 from images of a patients' 3D CT volume. Their AI system employed Resnet-50 deep learning model in combination with majority voting to classify each 3D CT image into COVID-19 and normal CT image. Their AI system also used the ResNet-18 model together with majority voting to predict COVID-19 on a given patient's 3D CT image. The created ResNet-50 system attained 0.90 area under curve (AUC) and 96% accuracy compared to 0.67 AUC of 3D-ResNet50. The major asset of their work was fine-tuning and majority voting-based modeling.

Singh et al. [89] developed an ensemble model for automated COVID-19 prediction by ensembling deep transfer learning models like ResNet152V2, VGG16, and densely connected convolutional networks (DCCNs). They have used chest CT scanned images for the development of their model. Their ensemble model can do a 4-class classification, whereas most previous models can only do a binary or 3-class classification. They compared their model with 15 other models and demonstrated that their model outdoes prevailing models with respect to f-measure, AUC, specificity, sensitivity, and accuracy of 1.3274%, 1.8372%, 1.8382%, 1.283%, and 1.2738% respectively. The developed

ensemble model attained 99.2% accuracy on the training dataset. Kedia et al. [93] created CovNet-19, an ensemble deep convolutional neural network model using chest X-ray images to detect COVID-19. They performed a 3-class classification i.e. COVID-19, pneumonia, normal with an accuracy of 98.28%, 98.33% precision, 98.33% recall, 97.15% Matthews Correlation Coefficient (MCC) whereas accuracy of 99.71% and 99.26% MCC was delivered for binary class classification into Non-COVID-19 and COVID-19. F1 score was 99% for both 3-class and 2-class classification. Elgendi et al. [97] scrutinized 17 deep learning algorithms to figure out the impact of geometric augmentations for COVID-19 detection. Empirical analysis was done to measure the influence of augmentation with reference to accuracy, dataset variety, methodology of augmentation, and network size. Their results demonstrated that Matthews Correlation Coefficient (MCC) of all examined models improved after the removal of geometrical augmentation. They carried out this empirical analysis using MATLAB 2020a on a workstation having GPU NVIDIAGeForce RTX 2080Ti 11 GB, RAM 64 GB, and Intel ProcessorI9-9900 K @3.6 GHz. Ieracitano et al. [99] proposed a CAD system for differentiating portable CXR images of COVID-19 pneumonia patients from the Non-COVID-19 interstitial pneumonia patients in an accurate manner utilizing a local unbalanced dataset. This CAD system called CovNNet is a fuzzy enhanced deep learning-based framework. In this approach, CovNNet tends to extract the deep relevant features from the images which are the results of the combination of portable CXR images and fuzzy images. This CAD system achieved an encouraging accuracy of more than 80% over the local dataset. All these state-of-the-art approaches for the COVID-19 detection and classification based on the CT scans and chest X-ray images are summarized along with their respective future work with the help of Table 3:

Challenges and Limitations

The challenges and limitations in the deep learning-based COVID-19 detection or classification approaches utilizing CT scan and chest X-ray images are as follows:

1. Regulation: During any pandemic like COVID-19, the concerned authorities have to take a crucial role in framing policies and etiquette-like lockdown, social distancing in case of COVID-19. These regulations and etiquette can stimulate scientists, researchers, citizens, technological companies, and social organizations to curtail obstacles to the prevent spread of COVID-19.
2. Handiness of data: Application of DL in medical imaging requires large volumes of data for training of DL models. But in the case of COVID-19, availability of data is low. Also, checking candidness of data is difficult and requires expertise to interpret. So it will take some time to have befitting data to DL and thus to have widespread application of DL techniques in COVID-19 detection and classification.
3. Data privacy concerns: Privacy concerns are biggest hurdle in collection of data like medical images that is required for applications of AI like DL and ML for COVID-19. Unavailability of sufficient data may result in less accurate and questionable DL models.

Deep Learning in Conjunction with Traditional Machine Learning Classifiers and Machine Learning-Based Approaches

The conventional machine learning-based approaches involves three sub-stages i.e. segmentation, feature extraction followed by the training of machine learning classifiers with the aid of these extracted features from the segmented region. Hence, proper manual selection of all methods employed in these sub-stages is very important. The present research trend in this domain involves usage of particular deep learning architectures, especially for performing the segmentation as well as deep feature extraction in a complete automated manner. This practice of employing the various deep learning networks alongside traditional machine learning classifiers is rendering encouraging results and can be termed as *Deep learning in conjunction with traditional machine learning classifiers*. Tang et al. [100] proposed a chest CT images model based on Ground-Glass Opacity (GGO) regions and Random Forest (RF) model to assess severity in terms of severe and non-severe on COVID-19 patients which also based on quantitative measures. Using three-fold cross validation, it shows a 93.3% true-positive rate, 74.5% true-negative rate, 87.5% accuracy, and 91% AUC. The major resulting thing in GGO shows that the right lung is more affected to severity than the left lung. Barstugan et al. [101] proposed early phase detection of COVID-19 utilizing abdominal CT images, which are acquired from the hospitals in the Zhejiang region of China, using machine learning methods. There are different materials used for the statistical features of data set, such as visual dataset in different subsets in terms of non-infected and infected. The classification is done by support vector machine (SVM). There are different results of five subsets. Their study achieved 99.68% accuracy in tenfold cross-validation. The machine learning methods should be done on CT abdominal images, X-ray chest images, and blood test results. Sethy et al. [102] proposed an approach using deep learning-based methodology, which gives benefit to practitioners that are researching on

Table 3 The comparison among the state-of-the-art deep learning approaches for the COVID-19 detection

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass classification	Results	Dataset used (number of patient's data)	Future work
Ucar et al. (2020) [46]	Chest X-ray images	Bayes-SqueezeNet learning model	Multiclass classification as COVID-19 vs. normal vs. pneumonia	Accuracy = 98.26% Correctness = 98.26% Completeness = 98.26% Specificity = 99.13% F1 score = 98.25% Matthew Correlation Coefficient = 97.39%	Covid X dataset consist of total chest X-ray images of 1203 normal patients, 1591 pneumonia cases, and 45 COVID-19 patient cases	The proposed work is aimed to be made mobile compatible so that it can be used by the health care experts for the early screening
Hammoudi et al. (2020) [47]	Chest X-ray images	InceptionResNetV2 based deep learning model	Multiclass classification as COVID-19 vs. influenza vs. H1N1 vs. SARS vs. MERS	Accuracy = 92.8% Sensitivity = 99.3%	This dataset consist of 5,863 children X-Ray images	Future works depends on the models must be cross-checked by RT-PCR tests and clinical tests
Rajaraman et al. (2020) [48]	Chest X-rays	Modality-specific transfer learning and fine-tuning which includes VGG-16, VGG-19, InceptionV3, ResNet50, and DenseNet along with ensemble learning	Multiclass classification into COVID-19, viral pneumonia, and normal	Accuracy = 99.01% Area under the curve = 99.72%	Four publically available datasets are used in order to develop a dataset which are Pediatric CXR dataset, RSNA CXR dataset, Twitter COVID-19 CXR, and Montreal COVID-19 CXR dataset	Future studies will based on 3D CT scans, localization and detections of COVID-19
Hall et al. (2020) [49]	Chest X-ray images	Deep learning-based on ResNet50	Binary classification as COVID-19 vs. pneumonia cases	Accuracy = 89.2% AUC = 95%	Dataset of 135 chest X-rays of COVID-19 and 320 chest X-rays of viral and bacterial pneumonia	This work can be tested on large size dataset
Rahimzadeh et al. (2020) [50]	Chest X-ray images	Deep learning method as Xception and ResNet50V2 models	Multiclass classification as normal vs. pneumonia vs. COVID-19	For COVID-19: - Accuracy = 99.56% For overall classes: - Accuracy = 91.4%	Dataset consist of 180 COVID-19, 6054 pneumonia and 8851 normal CXR images	This work can be tested on large size datasets for the better accuracy
Zhang et al. (2020) [51]	Chest X-ray	Deep learning as deep anomaly detection model	Binary classification as COVID-19 vs. non-COVID-19	The sensitivity ranges from 72.00 to 96.00% and the specificity ranges from 97.97 to 70.65% depends on the threshold value	100 chest X-ray images of 70 patients confirmed with COVID-19 from the Github repository	To further reduce the false-negative rate and false-positive rate
Hemdan et al. (2020) [50]	Chest X-ray	Deep transfer learning models as VGG19, DenseNet121, InceptionV3, ResNetV2, Inception-ResNet-V2, Xceptio, and MobileNetV2	Binary classification as normal vs. COVID-19	The F1 score of VGG and dense CNN models are 89% and 91%	The dataset consist of CXR images of 25 normal cases and 25 COVID-19 positive images	This method can be modified to further grade the severity among the COVID-19 positive cases

The proposed approach updated version can be used along with smart devices in healthcare sector to classify COVID-19 positive cases |

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass classification	Results	Dataset used (number of patient's data)	Future work
Wang et al. (2020) [53]	Chest CT scan images	DenseNet121-FPN for lung segmentation and proposed COVID-19Net for classification	Multiclass classification into COVID-19, viral pneumonia, and other pneumonia	Accuracy = 85% Sensitivity = 79.35% Specificity = 71.43% AUC = 86%	A large size dataset consist of CT scan images of around 5372 patients	In future generative adversarial Network can be used, to convert CT images of different slice thickness into CT images with a unified slice thickness for the performance enhancement
Zheng et al. (2020) [54]	Chest CT scan images	Deep learning-based on 3D deep convolutional neural network	Binary classification	Accuracy = 90.1% Sensitivity = 90.7% Specificity = 91.7% AUC = 97.6%	Dataset consist of 630 CT scan images out of which 499 used for training and reaming 131 used for testing	Infection lung region segmentation can be improved and this proposed system can be evaluated on a large size dataset
Apostolopoulos et al. (2020) [55]	Chest X-ray images	MobileNet	Binary classification as COVID-19 vs. non-COVID-19	Accuracy = 99.18% Sensitivity = 97.36% Specificity = 99.42% Overall accuracy = 87.66%	A large size dataset of 3905 CXR images	This proposed approach can be enhance in terms of accuracy and determine the severity of COVID-19 into grades
Fu et al. (2020) [56]	Chest CT scan images	ResNet50 architecture	Multiclass classification as normal lung vs. COVID-19 pneumonia vs. non-COVID-19 viral pneumonia vs. bacterial pneumonia vs. and pulmonary tuberculosis	Accuracy = 98.8% Sensitivity = 98.2% Specificity = 98.9% PPV = 94.5% NPV = 99.7%	Dataset consist of 60,427 CT scan images collected from the Wuhan Jin Yin-Tan Hospital	Real-time testing required
Ardakani et al. (2020) [57]	CT Images	Ten DTL models like ResNet-101, AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, and Xception	Binary classification as COVID-19 vs. non-COVID-19	**ResNet-101:** Accuracy = 99.51% Sensitivity = 100% Specificity = 99.02% AUC = 99.4% **Xception:** Accuracy = 86.27% Sensitivity = 89.21% Specificity = 83.33% AUC = 87.3% **Performance of Radiologist:** Accuracy = 86.27% Sensitivity = 98.04% Specificity = 100% AUC = 87.3%	Dataset consist of CT scan images of 108 patients of COVID-19 and 86 patients viral pneumonia with diseases termed as non-COVID-19	Future work involves comparison of CAD system performance based on the DTL models with the radiologists in real-time

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass c classification	Results	Dataset used (number of patient's data)	Future work
Rehman et. al (2020) [58]	Chest X-ray images and CT scan	Pre-trained CNN networks AlexNet, VGG,SqueezeNet, GoogLeNet, MobileNet, ResNet with its variants (ResNet18, ResNet50, ResNet101) DenseNet	Binary Class Classification: Scenario A (COVID-19 and Healthy) Scenario B (COVID-19 and Bacterial pneumonia) Scenario C (COVID-19 and Viral pneumonia) Multiclass Classification: Scenario D (COVID-19, healthy and bacterial pneumonia Scenario E (COVID-19, healthy, bacterial pneumonia and Viral pneumonia)	Accuracies of Scenario A 1.AlexNet = 96.30% 2.SqueezNet = 98.15% 3.GoogleNet = 98.15% 4.VGG = 98.75% 5. MobileNet = 96.30% 6. ResNet50 = 98.75% 7. DenseNet = 98.75% Scenario B 1.AlexNet = 98.75% 2.SqueezNet = 98.75% 3.GoogleNet = 98.75% 4.VGG = 98.75% 5. MobileNet = 98.75% 6. ResNet50 = 98.75% 7. DenseNet = 98.75% Scenario C 1.AlexNet = 92.54% 2.SqueezNet = 98.51% 3.GoogleNet = 98.51% 4.VGG = 88.06% 5. MobileNet = 96.30% 6. ResNet50 = 98.75% 7. DenseNet = 97.01% Scenario D 1.AlexNet = 87.85% 2.SqueezNet = 94.39% 3.GoogleNet = 91.59% 4.VGG = 92.52% 5. MobileNet = 97.20% 6. ResNet50 = 92.52% 7. DenseNet = 93.46% Scenario E 1.AlexNet = 74.15% 2.SqueezNet = 70.07% 3.GoogleNet = 75.51 4.VGG = 63.95% 5. MobileNet = 80.95% 6. ResNet50 = 72.79% 7. DenseNet = 70.07%	Dataset consist of total 800 CT scan and CXR images out of which each class i.e. COVID-19, viral pneumonia, bacterial pneumonia, and normal cases has 200 images	-

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass classification	Results	Dataset used (number of patient's data)	Future work
Khalifa et al. (2020) [59]	Chest X-ray images	GAN (Generative Adversarial Network) with fine-tuned DTL Models like SqueezeNet AlexNet GoogleNet RestNet18	Binary classification as Normal and Pneumonia	Accuracy: AlexNet = 96.1% Squeezenet = 97.8% GoogleNet = 96.8% RestNet18 = 99%	Dataset consist of 5863 chest X-ray images of normal and pneumonic patients from Guangzhou Medical Center	Future work involves testing of this system on the much larger CXR and CT scan dataset
Loey et al. (2020) [60]	Chest X-ray images	Generative Adversarial Network with deep transfer learning models like AlexNet, GoogleNet, and RestNet18	Multiclass classification as COVID-19, bacterial pneumonia, viral pneumonia, and normal	Accuracy: four class classification - AlexNet = 66.67% GoogleNet = 80.56% RestNet18 = 69.46% Three class classification (COVID-19, normal, bacterial pneumonia) - AlexNet = 85.19% GoogleNet = 81.48% RestNet18 = 81.48% Two class classification (COVID-19, normal)- AlexNet = 100% GoogleNet = 100% RestNet18 = 100%	Dataset consist of 306 X-ray images of 4 categories (COVID-19, normal, bacterial pneumonia, and viral pneumonia)	The proposed model aims at applying the deep learning models with a larger dataset in the future
Shan et al. (2020) [61]	Chest CT scan	VB-Net neural network	Automatic and manual segmentation	First iteration Time = 31.1 ± 8.1 Accuracy = 85.1 ± 11.4% Number(images) = 36 Second iteration Time = 12 ± 2.9 Accuracy = 91.0 ± 9.6% Number(images) = 114 Third iteration Time = 4.7 ± 1.1 Accuracy = 91.6% ± 10.0% Number(images) = 249	Dataset consist of CT scans of 300 patients for validation and 249 patients CT images training	This work can be incorporated with other classification systems in order to developed a full scale CAD systems for the COVID-19 case detection in real-time

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass c classification	Results	Dataset used (number of patient's data)	Future work
Hu et al. (2020) [62]	Chest CT scans	Various deep transfer layers Conv3, Conv4, and Conv5 are used	Multiclass classification as COVID-19, community-acquired pneumonia (CAP), and non-pneumonic (NP)	Accuracy: Without NTS-NET- COVID-19=89.2% CAP=84.7% NP=88.3% With NTS-NET (Navigator-Teacher-Scrutinizer Network)- COVID-19=84.3% CAP=83.2% NP=80.1%	Total 450 CT Scans are used in which 150 each of COVID-19, CAP and NP and this data is extracted by three different institutions: MD Anderson Cancer Centre, Memorial Sloan-Kettering Cancer Centre, and the MAASTRO clinic, with 20 cases from each institution	The proposed model can be enhanced by deploying more advanced backbone architecture such as ResNet and Inception
Wang et al. (2020) [63]	Chest X-ray images	Deep transfer tools: VGG-19 ResNet-50 COVID-Net	Multiclass classification as normal, non- COVID-19 and COVID-19 patients	Accuracy of VGG-19=83.0% ResNet-50=90.6% COVID-Net=93.3%	Dataset consists of 358 X-Ray images from 266 COVID-19 patients, which were obtained from 5 different publicly available data repositories	The future aim of the proposed model is to improve sensitivity and PPV to COVID-19 and to extend COVID-Net to risk stratification for survival analysis, prediction risk status of patients, and predicting hospitalization duration
Li et al. (2020) [64]	CT Scan images	Deep learning model based on the CovNet	Multiclass classification COVID-19 CAP (community-acquired pneumonia) Non-pneumonic patients	COVID-19: Sensitivity=90 Specificity=96 AUC=0.96 P Value <0.001 CAP: Sensitivity=87 Specificity=92 AUC=0.95 P Value <0.001 Non-pneumonic: Sensitivity=94 Specificity=96 AUC=0.98 P Value <0.001	Dataset consist of total 4352 3D volumetric chest CT scans in which 1292 COVID-19, 1735 CAP and 1325 non-pneumonic CT scans	The future aim of the proposed model is to collect additional CT scans from different centers to evaluate its performance further

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass classification	Results	Dataset used (number of patient's data)	Future work
Minaee et al. (2020) [65]	Chest X-ray images	DTL models like ResNet18, ResNet50, SqueezeNet, DenseNet-121	Binary class classidication as COVID-19 and Non-COVID-19 cases	SqueezeNet offers the best results with Sensitiv-ity = 98% and Specificity = 92.9%	Dataset consist of total 5000 COVID X-Ray images out of which 2084 CXR are used for training and 3100 are used for testing. This dataset is publically avail-able at https://github.com/shervinmin/DeepCovid	The aim of the proposed model is to serve as a benchmark in the future
Basu et al. (2020) [66]	Chest X-ray images	Domain Extension Transfer Learning (DETL) and Gradi-ent Class Activation Map (Grad-CAM)	Multiclass i.e. four class clas-sification as Normal, Pneumonia, Other disease, and COVID-19	Accuracy: AlexNet = 82.98% VGGNet = 90.13% ResNet = 85.98%	Dataset consist of around 305 COVID-19 CXR images obtained from four open source databases	This proposed model is required to be evaluated and tested on large size dataset
Khalifa et al. (2021) [67]	Chest X-ray images	The concept of neutrosophic set along with the three DTL models i.e AlexNet, GoogleNet, and ResNet8 are used	Multiclass i.e. four class clas-sification as Normal, Pneumonia Bacte-rial, Pneumonia Viral and COVID-19 cases	With 90–10% training–testing split, an AlexNet delivers an highest accuracy of 87.1% using the indeterminacy (I) neutrosophic domain images	Dataset consist of total 306 CXR images in which 69 images of COVID-19, and 79 images each of Normal, Bacterial Pneumonia, and Viral pneumonia	Other complex DTL models like ResNet50, Inception etc. can be evaluated using the same concept over the large size CXR datasets
Cohen et al. (2020) [68]	Chest X-ray images	DenseNet model	Gauge the severity of COVID-19 lung infections	Geographic extent score (range 0–8) with 1.14 mean absolute error (MAE) and lung opac-ity score (range 0–6) with 0.78 MAE	Dataset consist of 94 poster-oanterior (PA) CXR images	This work can be extended using the CT scan images and to classify the COVID-19 cases
Ying et al. (2020) [69]	Chest CT scan images	Detail Relation Extraction Network(DRE-Net) and VGG16 DenseNet ResNet for comparison	Multiclass classification as COVID-19, Bacterial Pneu-monia, and healthy persons	Accuracy: VGG16 = 90% DenseNet = 92% ResNet = 92% DRE-Net = 94% Precision: VGG16 = 92% DenseNet = 85% ResNet = 96% DRE-Net = 96%	Local dataset consist of chest CT scan images of 88 patients diagnosed with COVID-19, 101 patients infected with bacteria pneumonia and 86 healthy people obtained from the hospitals of two provinces in China	This proposed model can be evaluated on the other bench-mark datasets of COVID-19 cases

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass classification	Results	Dataset used (number of patient's data)	Future work
Wang et al. (2020) [70]	CT images	Inception Network	Binary classification as Viral Pneumonia and COVID-19 cases	Internal Validation: Accuracy = 82.9% Specificity = 80.5% Sensitivity = 84% External Validation: Accuracy = 73.1% Specificity = 67% Sensitivity = 74%	Dataset consist of CT scan images of 99 people of viral pneumonia and COVID-19 cases	The work is now intended to link different factors like genetic, epidemiological with hierarchical features of CT images for enhanced disease diagnosis
Narin et al. (2020) [71]	Chest X-ray images	DTL pre-trained models like ResNet50, Inception V3, Inception-ResNetV2	Binary classification as COVID-19 and normal	Inception V3: Accuracy = 97% Specificity = 100% F1 score = 96% ResNet50: Accuracy = 98% Specificity = 100% F1 score = 98% Inception-ResNetV2: Accuracy = 87% Specificity = 90% F1 score = 86%	Dataset consist of 100 chest X-ray images consist of 50 normal and 50 COVID-19 patients	Other complex hybrid DTL models can be used in future and can be evaluated on large size datasets
Jin et al. (2020) [72]	Chest CT scan images	Deep convolutional neural network-based system	Multiclass classification as COVID-19 vs. influenza-A/B vs. non-viral community-acquired pneumonia (CAP) vs. non-pneumonia	AUC = 97.17% Sensitivity = 90.19%, and Specificity = 95.76%	Dataset consist of 10,250 CT scans from 7,917 subjects consisting of COVID-19, CAP, influenza, and non-pneumonia	In future proposed model can be trained and evaluate on the large dataset with linked CT and clinical information
Xu et al. (2020) [73]	CT images	3D-CNN model along with Noisy-OR Bayesian function	Multiclass classification as COVID-19 vs. influenza-A-viral-pneumonia vs. healthy cases	Accuracy = 86.7%	Dataset consist of 618 CT scan images out of which 219 COVID-19, 224 influenza-A-viral-pneumonia, and 175 healthy cases	The future work involves improving the segmentation and classification stage of this model further. At the same time evaluation of this algorithm on the larger dataset

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass classification	Results	Dataset used (number of patient's data)	Future work
Huang et al. (2020) [74]	Chest CT scan	Deep- learning-based quantitative CT	Multiclass classification as mild vs. moderate vs. severe vs. critical	The whole-lung opacification percentage significantly increased from baseline CT to first follow-up CT	Dataset consist of CT scans of 126 patients of COVID-19 positive cases	The future work involves improvement in processing because it still needs radiologist's supervision for final result
Farooq et al. (2020) [75]	Chest X-ray images	Fine-tune a pre-trained ResNet-50 architecture	Multiclass classification as normal vs. bacterial (bacterial pneumonia) vs. viral (viral pneumonia) vs. COVID-19	Accuracy = 96.23% Sensitivity: Normal = 96.58% Bacterial = 97.15% Viral = 93.96% COVID-19 = 100% F-1 Score: Normal = 97.84% Bacterial = 96.37% Viral = 93.33% COVID-19 = 100%	COVIDx dataset consist of 5941 CXR images from 2839 patients	The future work includes training of this algorithm with a larger dataset and testing it with general public with a larger cohort
Chen et al. (2020) [76]	Chest CT scan images	UNet + + is used for medical image segmentation, and then, ResNet-50 is employed for the classification	Binary class classification as COVID-19 and normal	Internal testing Accuracy = 95.24% Sensitivity = 100% Specificity = 93.55% PPV = 84.62% NPV = 100% External testing Accuracy = 96% Sensitivity = 98% Specificity = 94% PPV = 94.23% NPV = 97.92%	Large dataset consist of total 46,096 CT scan images from 106 Patients including 51 patient as COVID-19 positive and 55 controls	Authors want the model to be used in real-time for the detection of COVID-19 cases to observe the performance
Asnaoui et al. (2020) [77]	Chest X-Ray and CT scan images	The various DTL models like VGG16, VGG19, Inception_V3, Xception, Resnet50, Inception_Resnet_V2, DenseNet201, MobileNet_V2	Binary classification as normal vs. pneumonia	Accuracy: CNN = 84.18% VGG16 = 86.26% VGG19 = 85.94% Inception_V3 = 94.59% Xception = 83.14% DensNet201 = 93.66% MobileNet_V2 = 96.27% Inception_Resnet_V2 = 96.09% Resnet50 = 96.61%	Dataset consist of total 5856 images out of which 4273 are of pneumonia and 1583 are of normal patients	The work is intended to develop a full system for pneumonia diagnosis and improve the performance by using more dataset for diagnosis

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass classification	Results	Dataset used (number of patient's data)	Future work
Chowdhary et al. (2020) [78]	Chest X-Ray images	DTL models are MobileNetv2, SqueezeNet, ResNet18, ResNet101, DenseNet201, CheXNet, Inceptionv3, VGG19	Multiclass classification as normal vs. COVID-19 pneumonia vs. viral pneumonia	Accuracy: SqueezeNet = 99.4% MobileNetv2 = 99.65% ResNet18 = 99.6% InceptionV3 = 99.40% ResNet101 = 99.6% CheXNet = 99.69% DenseNet201 = 99.70% VGG19 = 99.60%	Dataset consist of total CXR images of 423 COVID-19, 1485 viral pneumonia patients, and 1579 normal	The study is now focused to evaluate large databases
Apostolopoulos et al. (2020) [79]	Chest X-ray images	DTL models like VGG19, MobileNet v2, Inception, Xception, Inception ResNet v2	Multiclass classification as normal vs. pneumonia vs. COVID-19 patients	Accuracy: VGG19 = 93.48% MobileNet v2 = 92.85% Inception = 92.5% Xception = 92.5% Inception ResNet v2 = 92.5%	Dataset 1: 1427 X-ray images including 224 images of COVID-19, 700 images of common bacterial pneumonia and 504 images of normal patients Dataset 2: 224 images of COVID-19 patients, 714 of confirmed bacterial and viral pneumonia and 504 healthy instances	Future work include distinguishing patients showing mild symptoms using these DTL model or hybrid models utilizing advanced medical imaging technology like CT scan images
Afshar et al. (2020) [80]	X-ray images	Capsule Network-based framework consist of several capsule and convolutional layers	Binary classification as either positive or negative cases	Accuracy = 95.7% Sensitivity = 90% Specificity = 95.8% Area under the curve (AUC) = 97%	Dataset consist of 94,323 chest X-ray images of common thorax diseases extracted from the NIH chest X-ray dataset including 112, 120 X-ray images for 14 thorax abnormalities	The researcher wishes to modify the architecture of COVID-CAPS and evaluate its performance on the newly available CXR and CT scan datasets
Butt et al. (2020) [81]	CT images	3D CNN model used with Noisy-OR Bayesian function	Multiclass classification as COVID-19 vs. influenza-A-viral-pneumonia vs. irrelevant-to-infection	AUC = 99.6% Sensitivity = 98.2% Specificity = 92.2%	A total of 618 transverse-section CT samples were collected to study consist of 219 COVID-19 patients and rest of normal people	The study tends work on more accuracy and sensitivity compared to the other study in the field
Ozturk et al. (2020) [82]	Chest X-ray images	Deep learning model known as DarkCovidNet-19 model	Binary classification as COVID vs. no-findings Multiclass classification as COVID vs. no-findings vs. pneumonia	Binary classification Accuracy = 98.08% Multiclass classification Accuracy = 87.02%	Dataset consist of 125 chest X-ray images of COVID-19 patients, 500 pneumonia patients and 500 normal	This study uses limited number of COVID-19 X-ray images and researchers want to study more such images to improve the efficiency of the model

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass c classification	Results	Dataset used (number of patient's data)	Future work
Shah et al. (2020) [83]	CT Scans	Deep learning CNN model called CTnet-10	Binary Classification: COVID-19 positive and COVID-19 negative	Proposed model CTnet-10 has 82.1% accuracy	An open-sourced dataset COVID-CT, which contains 349 COVID-19 CT images from 216 patients and 463 non-COVID-19 CT	-
Javaheri et al. (2021) [84]	CT scans	Deep learning model called CovidCTNet	Binary classification: COVID-19 or non-COVID-19 (CAP)	CovidCTNet has detection accuracy of 95% against 70% of radiologists, while the sensitivity was 93%	A dataset of 335 patients were used. Out of 335, 110 were having COVID-19 infection while rest 115 patients infected with CAP	Future works: (i) increase other samples as the current CT scans are mostly from Iranian patients, (ii) consideration of demographic details of patients like age, gender, and medical history
Wang et al. (2021) [85]	CT images	Deep transfer learning	Binary classification: COVID-19 and pneumonia	Their work had 89.5% accuracy, 0.88 specificity, 0.87 sensitivity	1065 CT images from Xian Jiaotong University First Affiliated Hospital (center 1), Nanchang University First Hospital (center 2), and Xian No.8 Hospital of Xian Medical College (center 3)	Their future work will focus on linking of hierarchical features of CT images to features of other factors like genetic, epidemiological, and clinical information for the purpose of multi-modeling analysis. This multi-modeling analysis will expedite enhanced diagnosis
Saad et al. (2021) [86]	X-ray as well as CT Images	deep feature concatenation DFC mechanism Deep Learning CNN	Binary Classification: COVID-19 positive and COVID-19 negative	DFC was used in two ways. The first way has delivered 96.13% accuracy of 96.13%, 94.37% precision, 97.04% recall and an f_score of 95.69%. The second way has delivered an accuracy of 98.9%, 9.36% precision, a recall of 98.5% and 98.29% f_score when using CT images but when X-ray images used, this second way has got 99.3% accuracy, 99.79% precision, 98.8% recall and f1_score of 99.3%	Dataset includes 2628 COVID-19 positive images and 1620 Non-COVID images	-

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass c classification	Results	Dataset used (number of patient's data)	Future work
Serte et al. (2021) [87]	CT volume (CT images and CT scans)	Deep learning ResNet-50 and ResNet-18 models	Binary classification: COVID-19 and normal	The prosed ResNet-50 system attained 0.90 AUC and 96% accuracy compared to 0.67 AUC of 3d-ResNet50	Mosmed-1110 [88] includes 1,110 3D CT scans of patients that were taken were obtained between 1st of March, 2020 and 25th of April, 2020 and provided by municipal hospitals in Moscow, Russia. The Mosmed-1110 dataset includes five categories of 3D CT volumes. These groups are named as CT0, CT1, CT2, CT3, and CT4	-
Singh et al. (2021) [89]	CT scanned images	Ensemble deep learning models DCCNS, ResNet152V2, VGG16	Multiclass (4-class) classification: COVID-19 positive, tuberculosis, pneumonia, and healthy	The created model outdoes prevailing models with respect to F-measure, AUC, specificity, sensitivity, accuracy 1.3274%, 1.8372%, 1.8382%, 1.283%, 1.27388% respectively. The developed ensemble model attains 99.2% accuracy on training dataset	4-class CT scanned images are collected from different sources like COVID-19, Pneumonia [90–92]	-

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass classification	Results	Dataset used (number of patient's data)	Future work
Kedia et al. (2020) [95]	Chest X–ray images	Ensemble deep convolution neural network called "CovNet-19"	Ternary classification (normal, pneumonia, COVID-19) as well as binary class classification (COVID-19 and non-COVID-19)	For 3-class classification, accuracy of 98.28%, 98.33% precision, 98.33% recall, 97.15 MCC whereas accuracy of 99.71% and 99.26% MCC was delivered for binary class classification. F1 score was 99% for both 3-class and 2-class classification	5484 chest x-ray images were collected from following five sources: 1. "COVID-19 Radiography Database" [94] from Kaggle. This dataset contained 1341 chest X-ray images of a healthy person, 2196 COVID-19 images and 1341 images of a pneumonia infection 2. "Chest X-ray images(Pneumonia)" [39]: Dataset from Kaggle contained a large number of X-ray images of Healthy and pneumonia infected patients. 1000images belonging to both classes were extracted from this dataset 3. "COVID-chest X-ray-dataset," [93] has a mix of chest X-ray and C.T. scan images of patients who are COVID-19 positive or infected by any other viral or bacterial pneumonia. From here, 457 chest X-ray Images of positive COVID-19 patients were taken 4. "COVID-19 chest X-ray dataset Initiative," [95], 50 X-ray im-ages of positive COVID-19 patients extracted from this dataset 5. "COVID-19 X-ray dataset," [96] from Kaggle, contributed 72 chest X-ray images of COVID-19 patients	More detailed analysis with more patient data. Considering patient's physiological and other characteristics can be used as input features to classification model Improving classification model by considering other similar diseases like SARS, MERS Fine tuning of DCNN Optimization of CovNet-19 so that it can be used on lower power devices like smart phones where camera may be to capture chest x-ray images for diagnosis

Table 3 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass c classification	Results	Dataset used (number of patient's data)	Future work
Elgendi et al. (2021) [97]	Chest X-ray images	Deep learning	Binary classification: COVID-19 and non-COVID-19	Their results demonstrated that Matthews Correlation Coefficient (MCC) of all examined models improved after the removal of geometrical augmentation	One public dataset and two local dataset used. Public dataset is "CoronaHack-chest X-ray dataset" [98]. First local dataset of 58 COVID-19 images are from Vancouver General Hospital (VGH), British Columbia, Canada. The second local dataset contains 374 coincident CXR and 366 PCR (178 male, 188 female) patient's data from Department of Radiology at Louisiana State University (LSU), USA	1. All combinations of augmentation methods were not used 2. Vast dataset containing healthy, viral pneumonia, bacterial pneumonia and COVID-19 samples provides the complete view 3. Segregation of X-ray images into PA vs. AP was not done 4. Quantification of effect of each geometrical transformation on different datasets
Ieracitano et al. (2022) [99]	Portable chest X-ray images	Deep learning along with fuzzy logic based system called as the CovNNet	Binary classification into COVID-19 pneumonia and non-COVID-19 interstitial pneumonias	Accuracy $=80.9 \pm 6.2\%$ Sensitivity $=82.5 \pm 11.9\%$ Specificity $=78.6 \pm 6.9\%$ Positive predicted value $=85.2 \pm 4.5$ Negative predicted value $=77.1 \pm 10.41$	An unbalanced local dataset consisting of total 121 portable CXR images out of which 57 belongs to a Non-COVID-19 interstitial pneumonias patients and rest 64 belongs to patients diagnosed with COVID-19 pneumonia	The accuracy can be further improved in the future This proposed approach can be trained and tested over the larger and linked global datasets

coronavirus patients. The models that are recommended are Resnet50 plus SVM, which achieved an accuracy of 95.38% for detecting COVID-19 positive patients. Their results were based on data which is available in the repository of GitHub, Kaggle, and Open-I as per their validated X-Ray images. Karawi et al. [103] proposed an approach based on machine learning techniques for analysis of chest CT scan images of COVID-19 patients. A frequency domain algorithm known as the Fast Fourier Transform (FFT)-Gabor scheme based on SVM model works in real-time and gets results with high accuracy along with low false-negative rate. This approach was trained on a dataset of 470 CT scan images in which 275 were positive cases and 195 were negative. Ozkaya et al. [104] proposed a hybrid model based on the SVM classifier for classification and DTL models like Resnet50, GoogleNet, and VGG-16 for deep feature extraction. Their proposed hybrid method shows high performance on both the datasets used in their research study. Alom et al. [105] proposed the multi-task deep learning model based on Inception Recurrent Residual Neural Network (IRRCNN) for COVID-19 classification and NABLA-N network models for infected lung region segmentation. These models were tested on X-ray, abdominal CT, and full body CT images. The results for X-Ray Images and CT Images had an accuracy of 86.67% and 98.78% respectively for COVID-19. Kumar et al. [106] proposed an intelligent system based on the ResNet152 DTL model for the deep feature extraction and machine learning classifiers like Logistic Regression (LR), k-Nearest Neighbour 26 (kNN 26), Decision Trees (DT), Random Forest (RF), Adaptive Boosting (AdaBoost), Naïve Bayes (NB), and XGBoost(XGB) for binary classification. Best results were delivered by the RF and XGBoost Predictive Classifiers. The above mentioned state-of-the-art approaches for the COVID-19 detection and classification are summarized along with their respective future work with the help of Table 4:

Challenges and Limitations

The challenges and limitations of machine learning and deep learning in conjunction with traditional machine learning classifiers approaches for the COVID-19 detection or classification utilizing CT scan and chest X-ray images are as follows:

- The accuracy and robustness of most of the traditional machine learning-based approaches depends on utilizing the accurate segmentation method followed by the efficient feature extraction methods. Which makes the proper selection of segmentation and feature extraction methods very important and thus affects the overall proposed approach for the COVID-19 detection.

- There is a need of properly annotated chest X-ray and CT scan datasets. These annotated datasets can be used to evaluate the segmentation accuracy and hence proved to be important for evaluating the performance of the proposed approach.
- Most of the traditional machine learning-based approaches lack experimentation with various segmentation methods and feature extraction methods. Such experimentation is mandatory to be able to propose an efficient COVID-19 detection approach.
- There is a scope for experimenting with various deep transfer learning models for performing the segmentation and deep feature extraction, as well as with various machine learning and ensemble learning classifiers for performing the classification of positive COVID-19 cases.

Majorly Used COVID-19 Chest X-Ray, CT Scan, and Ultrasound Image Dataset Description

In the present scenario, the propellant of modern computing, especially machine learning and deep learning, is training data. This training data is available in the form of datasets consisting of either medical images, histopathological images, biopsies images etc. All the deep learning and deep transfer learning-based approaches are totally depend on these training datasets. The COVID-19 detection approaches based on deep learning also require dataset of CT scan images, chest X-ray, statistics related to a country or a region, etc.; therefore, some of the majorly used open-source CT scan and chest X-ray dataset description are presented in Table 5.

Analysis and Evaluation

This section presents a brief analysis and evaluation of majorly used deep transfer learning (DTL) models like VGG16 [113], VGG19 [114], ResNet50 [115], and DenseNet [116] over the COVID-19 local CT scan dataset and global chest X-ray dataset. These four DTL models were initially fine-tuned and trained using the augmented local CT scan and chest X-ray dataset. The objective of this comparison is to illustrate how these commonly used DTL models perform on the local CT scan and global chest X-ray images COVID-19 datasets. The description of the two datasets used for the analysis is given below.

- Local COVID-19 CT scan dataset: An axial volumetric chest CT scans of COVID-19 positive patients and normal people are present in this dataset. These volumetric

Table 4 The comparison among the state of the art hybrid method-based approaches for the COVID-19 detection

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass classification	Results	Dataset used (number of patient data)	Future work
Tang et al. (2020) [100]	Chest CT images	Machine learning model having RF-based model with 63 quantitative features	Binary classification as severity and non-severity assessment	Accuracy = 87.5% True-positive rate = 93.3% True-negative rate = 74.5% AUC = 91%	Datasets of 176 patients in which 121 as non-severe and 55 are severe	In future, severity types will extend by collecting chest CT images from more patients through multi- center collaboration
Barstugan et al. (2020) [101]	Chest CT scans	Machine learning model having mean SVM classification performance	Binary classification as COVID-19 vs. pneumonia	Accuracy = 99.68%	Dataset consist of 150 CT abdominal images, of 53 infected cases	This method should be tested on another coronavirus CT image dataset
Sethy et al.(2020) [102]	Chest X-ray images	ResNet50 for deep feature extraction and SVM for binary classification	Binary classification as COVID-19 positive and COVID-19 negative	Accuracy = 95.38% FPR = 95.52% F1 = 91.41% MCC = 90.76%	Dataset consist of chest X-ray images of 25 COVID-19 positive patients and 25 normal people chest X-ray	More experimentation can be done with such types of hybrid models on the CT scan datasets also
Al-Karwai et al. (2020) [103]	Chest CT scans	FFT-Gabor scheme based on SVM model	Binary classification into COVID-19 positive and COVID-19 negative cases	Accuracy = 93% Sensitivity = 94% Specificity = 92%	470 CT scan images for training and 100 for testing	Will upgrade the results by conducting more prospective experiments with new samples and conduct similar investigations when lung ultrasound scans are available
Ozakaya et al. 2020 [104]	CT scan images	SVM classifier for binary classification and Resnet50, GoogleNet, VGG-16 DTL models for deep feature extraction	Binary classification as no finding patches vs. COVID-19	For Subset-1: - Accuracy = 95.60% Specificity = 93.33% Sensitivity = 95.60% Precision = 97.87% F1 score = 97.77% Matthews Correlation Coefficient = 91.29% For Subset-2: - Accuracy = 98.27% Specificity = 97.63% Sensitivity = 97.60% Precision = 97.63% F1 score = 98.28% Matthews Correlation Coefficient = 96.54%	3000 patch images are generated with the help of 150 CT scan images	In future, data augmentation techniques could be used along such hybrid models for the performance enhancement

Table 4 (continued)

Name of author and year	Modality used	Machine learning or deep learning model used	Binary or multiclass classification	Results	Dataset used (number of patient data)	Future work
Alom et al. 2020 [105]	X-Rays Images and CT images	The IRRCNN is used for binary classification and NABLA-N network model is used for infected region segmentation	Binary classification as COVID-19 vs. pneumonia	For X-ray images Accuracy = 84.67% For CT Images Accuracy = 97.78%	Dataset for IRRCNN model consist of 5,216 sample images and dataset for segmentation NABLA-N network consist 704 CXR images	More samples will be collected for COVID-19 detection which will develop a robust and more accurate system
Kumar et al. 2020 [106]	Chest X-Ray images	ResNet152 for deep feature extraction and ML classifiers for binary classification	Binary classification as COVID-19 vs. pneumonia	By RF classifier: Accuracy = 97.3% Sensitivity = 97.4% Specificity = 98.6% F1 score = 97.3% AUC = 99.7% **By XGBoost Classifiers: -** Accuracy = 97.7% Sensitivity = 97.7% Specificity = 98.8% F1 score = 97.7% AUC = 99.8%	Dataset of 5840 CXR images are used for training and testing of ResNet152 A dataset of size 2748 CXR images are used for the training and testing of ML classifiers	This proposed system can be evaluated on a large size dataset in future of both the CXR and CT scan images

Table 5 Majorly used open-source COVID-19 CT scan, chest X-ray, and ultrasound image dataset description

Name of dataset	Imaging modality	Size of dataset	Link
COVID-19 image data collection [107]	Chest X-ray images	468 COVID-19 positive images	https://github.com/ieee8023/covid-chestxray-dataset
COVID-CT-Dataset: A CT Scan Dataset about COVID-19 [108]	CT scan	349 CT images of COVID-19 from 216 patients	https://github.com/UCSD-AI4H/COVID-CT
COVID-19-CT-Seg-Benchmark	CT scan	525 CT images of COVID-19	https://gitee.com/junma11/COVID-19-CT-Seg-Benchmark
COVID-19 CT segmentation dataset	CT scan	Axial 100 CT scan of 40 patients in DICOM format	http://medicalsegmentation.com/covid19/
COVID-19 CT Segmentation dataset nr. 2	CT scan	829 slices out of which 373 are COVID-19 positive in in DICOM format	http://medicalsegmentation.com/covid19/
Coronacases Initiative	3D CT images	2623 CT scan images	https://coronacases.org
COVID-19 X-ray s	CT scan and chest X-rays scans	16 CT scan images and 79 chest X-ray images of COVID-19 positive	https://www.kaggle.com/andrewmvd/convid19-x-rays
COVID-19 CT Lung and Infection Segmentation Dataset [109]	CT scan	20 COVID-19 CT scans	https://zenodo.org/record/3757476
SIRM	CT scan	60 patients CT scan images	https://www.sirm.org/en/category/articles/covid-19-database/
Radiopaedia	CT scan and chest X-ray	101 COVID-19 patients CT scan and X-ray sequence	https://radiopaedia.org/articles/covid-19-3
Chest X-ray images (pneumonia)	Chest X-ray	5856 chest X-ray JPEG images	https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia
COVIDx V7A dataset	Chest X-ray	Total 15600 chest X-ray images out of whcih 1700 COVID-19 positive images	https://github.com/lindawangg/COVID-Net
COVIDx CT-2A [110]	CT scan	Total 194,922 CT scan images of 3745 patients	https://www.kaggle.com/hgunraj/covidxct?select=2A_images
COVIDx CT-2B [111]	CT scan	Total 201,103 CT scan images of 4501 patients	https://www.kaggle.com/hgunraj/covidxct?select=2A_images
COVID-19 Radiography Database	Chest X-ray	Total 1200 COVID-19 positive, 1341 normal, and 1345 viral pneumonia chest X-ray images	https://www.kaggle.com/tawsifurrahman/covid19-radiography-database?select=COVID-19+Radiography+Database
COVID-CT-MD [112]	CT scan	CT scans of 169 COVID-19 positive cases, 60 viral Pneumonia, and 76 healthy cases	https://figshare.com/s/c20215f3d42c98f09ad0
Extensive COVID-19 X-ray and CT chest image dataset	CT scan and chest X-ray	Total 17,099 X-ray and CT images out which 4044 chest X-ray COVID-19 positive images and 5427 CT scan COVID-19 positive images	https://data.mendeley.com/datasets/8h65ywd2jr/3
BIMCV-Covid 19+	CT scan and chest X-ray	Total of 1380 chest X-ray and 163 CT scan patient studies	https://osf.io/nh7g8/
MosMedData: COVID19_1000 Dataset	CT scan	Total 1000 sets of chest CT scans	https://mosmed.ai/en/
Pocovid-net	Ultrasound images	Total 1103 ultrasound images out of 654 COVID-19 positive, 172 healthy, and 277 viral pneumonia images	https://github.com/jannisborn/covid19_ultrasound

CT scans were obtained utilizing the Optima GE CT 660 machine installed at the MP MRI and CT scan center Jabalpur, Madhya Pradesh, India, under the supervision of head radiologist. The 64-slice version of Optima GE CT 660 is available in this center, making it well-suited for cardiac and coronary angiography applications. This

Table 6 The configuration parameters of VGG16, VGG19, ResNet50, and DenseNet121

DTL model parameters	VGG16	VGG19	DenseNet121	ResNet50
Input image size	224×224	224×224	224×224	224×224
Number of layers	16	19	121	50
Learning rate	0.0001	0.00001	0.01	0.001
Batch size	16	16	16	16
Number of epochs to converge	100	100	100	200
Momentum	0.9	0.9	0.9	0.9
Optimizer	Adam	Adam	SGD	SGD
Dropout rate	0.4	0.3	0.4	0.5

machine uses the Performix 40 tube (6.3 MHU) with a 40 mm V-Res detector. This Optima GE-CT660 acquires axial scans in sets of 2 through 64 contiguous images in one 360° rotation. For each rotation of the gantry, the Optima CT660 collects up to 64 rows of scan data. A total of 2080 CT scans were taken from 86 COVID-19 positive patients (mean age of 49.5 ± 19.1 years; range of 16–88 years, male 56, female 30) and 88 healthy people (mean age of 41.5 ± 16.8 years; range of 12–81 years, male 48, female 40). These cases were collected from July 2020 to January 2021. The main clinical symptoms in these patients were cough and fever. All the CT scan sequence are available in 16-bit grayscale DICOM format with 512*512 pixels resolution, which are converted into the PNG format.

- Global chest X-ray dataset: As the available COVID-19 datasets are of very limited size, so in order to make a decent size balanced dataset, the chest X-ray images of COVID-19 positive patients and healthy people are taken from the three different publicly available datasets. Around 500 COVID-19 chest X-ray images and 500 normal images were taken from the GitHub reposi-

tory by Dr. Joseph Cohen [96]. Then 220 COVID-19 positive images and 280 normal images were taken from the COVID-19 Radiography Database (COVID-19 Radiography Database 2020). Around 290 COVID-19 positive images and 280 normal images are taken from the IEEE8023/Covid Chest X-Ray Dataset [107]. This dataset consists of a total of 2070 chest X-ray images, which are further subdivided into the training and testing dataset.

All these CT scan and chest X-ray images are initially preprocessed and then augmented in order to create a large dataset for the training of these DTL models. As these medical images are obtained directly from diverse medical devices and may include artifacts and medical symbols, therefore, all these images are resized and cropped. The size of these CT scan and chest X-ray images is changed as per the input requirement of these DTL models. After pre-processing, an augmentation of the above two datasets are performed for the training of these DTL models in order to avoid the over-fitting. The augmentation strategies used in this section involve affine transformations composed of

Table 7 Performance of VGG16, VGG19, ResNet50, and InceptionV3 on the augmented local CT scan and global chest X-ray datasets

Classification rates	Classification rates formulas	VGG16		VGG19	
		Local CT scan	Global chest X-ray	Local CT scan	Global chest X-ray
Accuracy	(TP + TN) / (TP + TN + FP + FN)	95.75	96.25	96	97.95
Sensitivity	TP / (TP + FN)	95.68	96.36	96.12	96.43
Specificity	TN / (FP + TN)	95.8	96.7	95.9	94.09
Precision	TP / (TP + FP)	95	95.5	96	94
Negative predictive value	TN / (TN + FN)	94.5	95.5	94	95.5
False-positive rate	FP / (FP + TN)	5.13	7.28	4.08	5.91
False discovery rate	FP / (FP + TP)	5	7.5	4	6
False-negative rate	FN / (FN + TP)	7.32	4.64	5.88	4.57
F1 score	2TP / (2TP + FP + FN)	94.83	94.9	96.05	96.98

TP true positive, *TN* true negative, *FP* false positive, *FN* false negative

Table 8 Performance of ResNet50 and DenseNet121 on the augmented local CT scan and global chest X-ray datasets

Classification rates	ResNet 50		DenseNet121	
	Local CT scan	Global chest X-ray	Local CT scan	Global chest X-ray
Accuracy	92.75	94.5	94.25	94
Sensitivity	90.7	91.75	92.88	91.42
Specificity	91.8	89.32	91.64	91.58
Precision	92.5	91.9	92.5	91.5
Negative predictive value	91	93	93	94.5
False-positive rate	12.2	10.68	9.36	8.42
False discovery rate	12.5	11	9.5	8.5
False-negative rate	10.2	8.25	8.12	7.58
F1 score	91.61	92.36	92.18	92.96

vertical and horizontal flip (0% ± 10%), scaling (0% ± 20%), shearing (0° ± 10°), and rotation (0° ± 10°).

The algorithm for the analysis and evaluation is as follows:

Input COVID-19 CT scan and chest X-ray images or Normal CT scan or chest X-ray images.

Output The trained VGG16, VGG 19, ResNet50, and DenseNet models for the detection of COVID-19 positive cases.

Steps

- All the chest X-ray and CT scan images are preprocess for the elimination of artifacts, noise, and symbols.
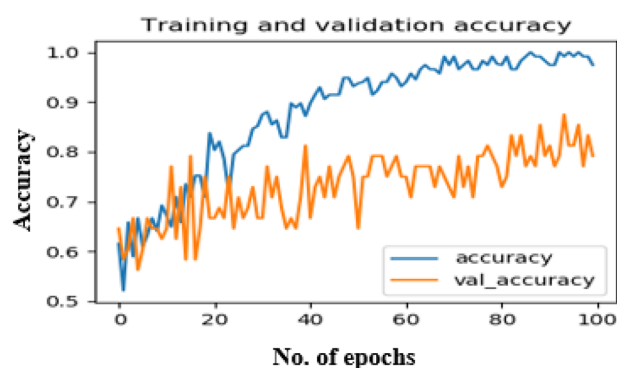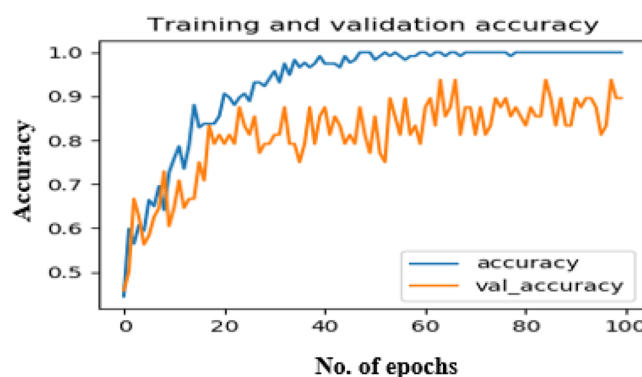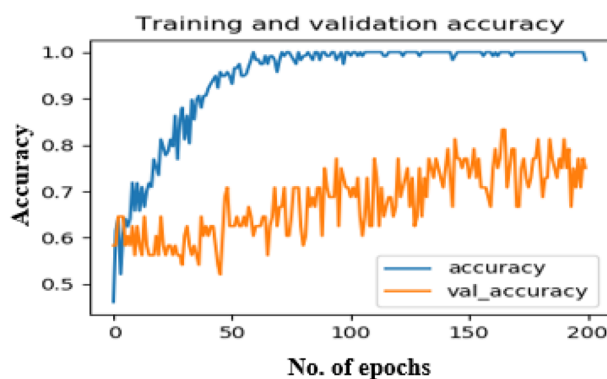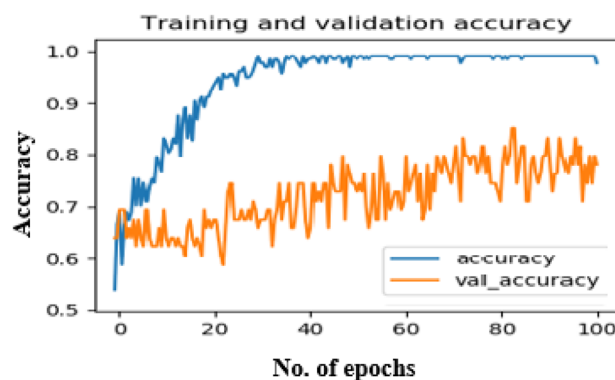
Fig. 8 The training and validation graphs of DTL models on Local CT scan dataset **a** VGG16, **b** VGG19, **c** ResNet50, and **d** DenseNet-121
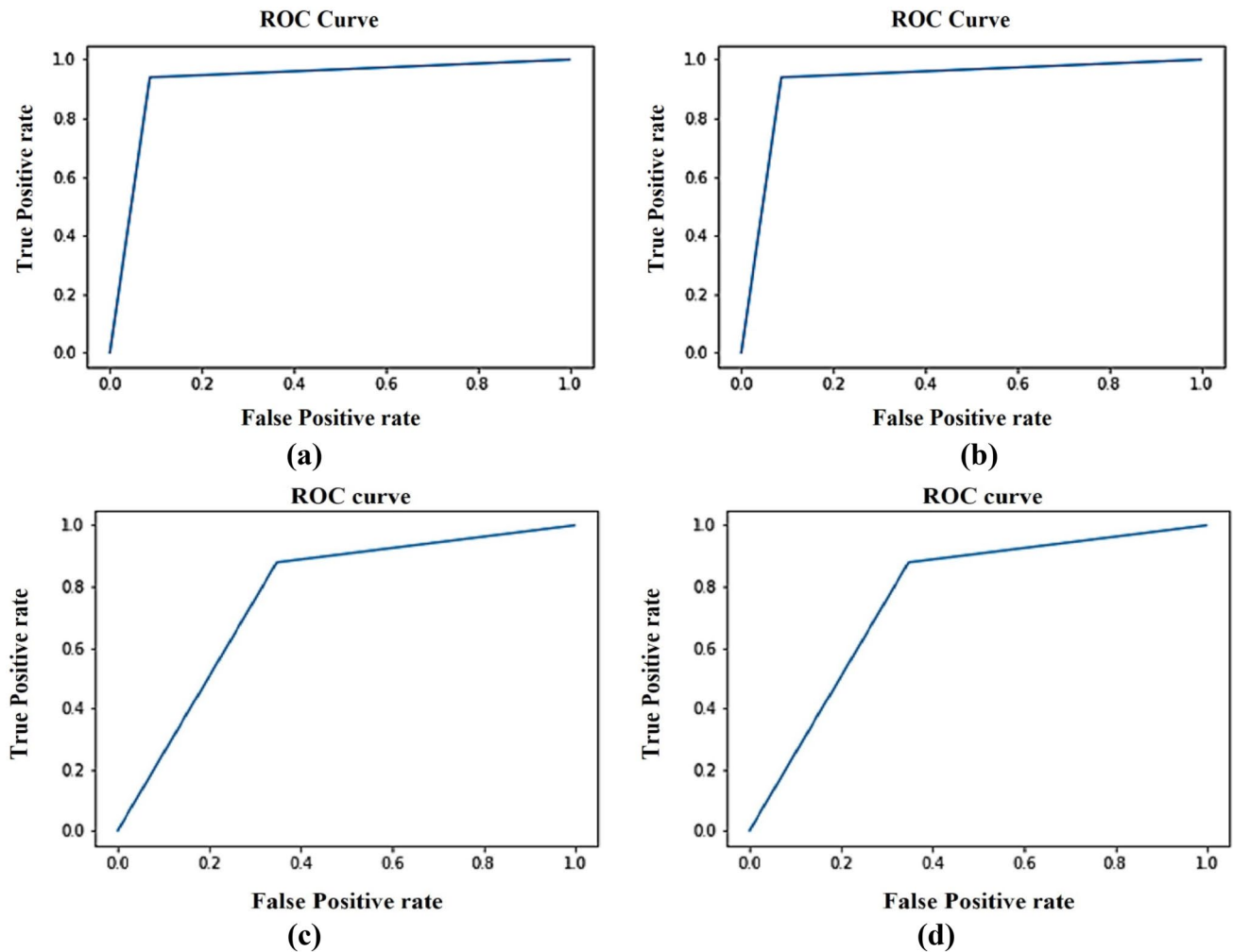
Fig. 9 The ROC curve of DTL models on Local CT scan dataset **a** VGG16, **b** VGG19, **c** ResNet50, and **d** DenseNet-121

- Utilizing the affine transformations as an augmentation method consist of rotation ($0° \pm 10°$), shearing ($0° \pm 10°$), vertical and horizontal flip ($0\% \pm 10\%$), and scaling ($0\% \pm 20\%$) of both the two datasets are done.
- Resize these CT scan and chest X-ray images to the size of 224-by-224-by 3 for the training of VGG16, VGG 19, DenseNet121, and ResNet50 DTL models.
- The fine tuning and training of these four DTL models over the augmented datasets.
- The VGG 16 and VGG19 models tends to converge at 100 epochs.
- The DenseNet121 and ResNet50 tends to converge at 200 epochs.
- Simulation and evaluation of these DTL models over the 20% augmented dataset which is reserved for the validation.

Initially, all the four DTL models are taken with similar settings, and then, in order to get the optimum performance from these DTL models, hyper parameter tuning is done during the training. The various combinations of the learning and dropout rate along with the two different optimizers were tried out in order to get the optimal configuration parameters of these four DTL models offering the best performance. The VGG16, VGG19, DenseNet-121, and ResNet50 DTL models' optimal configuration parameters are illustrated with the help of Table 6 after performing a number of experiments. All the four deep transfer learning models were trained and evaluated with different learning and dropout rates along with the two different types of optimizers, i.e. Adam and Stochastic gradient descent (SGD) [117] for the weights adjustment. Both the VGG16 and 19 models give best performance with the Adam. Similarly, the DenseNet 121 and ResNet50 models with SGD optimizer tend to give better performance. The number of epochs required to converge also varies from model to model. As the VGG 16, VGG 19, and DenseNet121 tend to converge at 100 epochs, and after that, their accuracies are not at all improving. Similarly, the ResNet 50 tends to converges at 200 epochs. The dropout method [118] is utilized in order to avoid the problem of over-fitting.
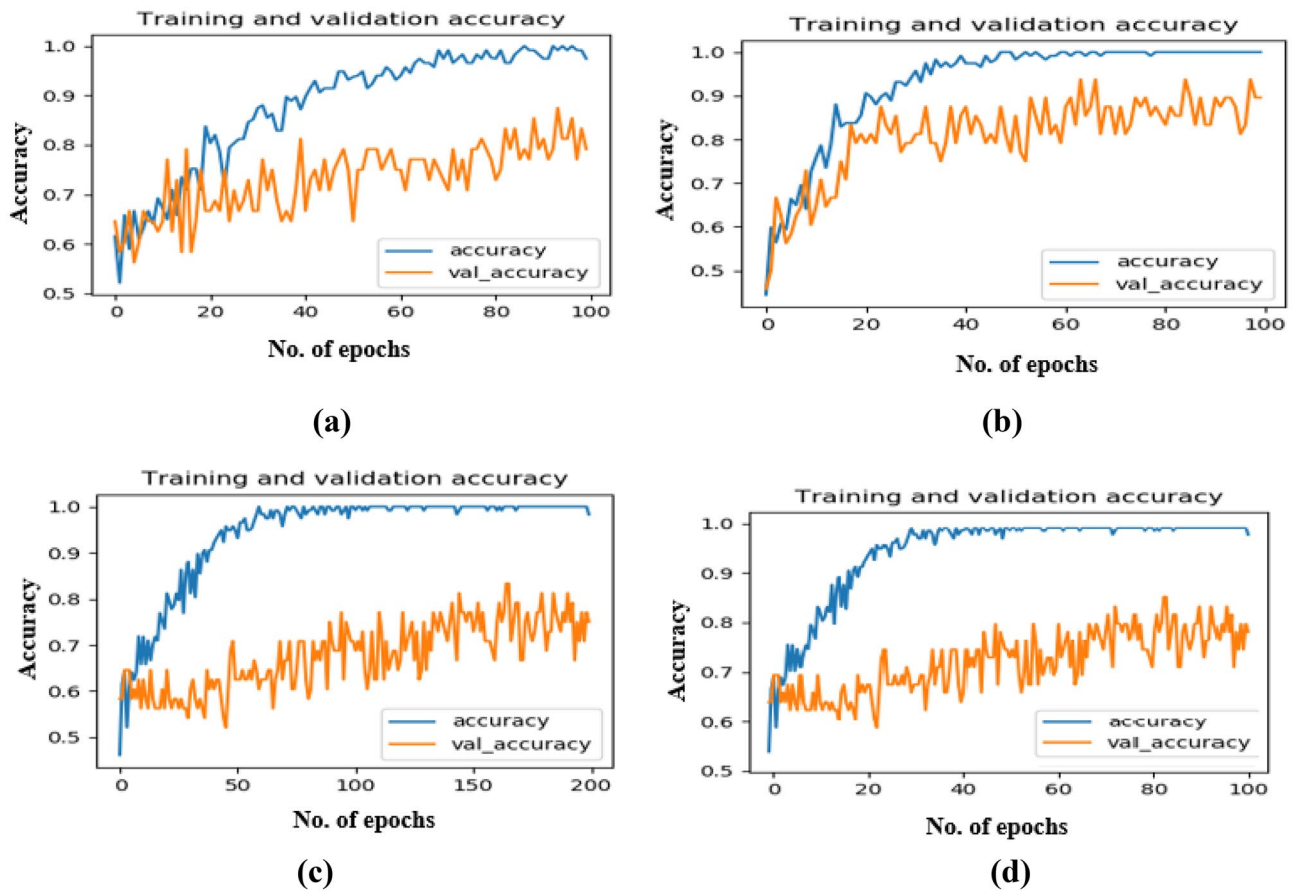
Fig. 10 The training and validation graphs of DTL models on global chest X-ray dataset **a** VGG16, **b** VGG19, **c** DenseNet-121, and **d** ResNet50

The training and validation ratio for the two augmented datasets are 80:20, which means 20% is used for validation and rest 80% for training. The performance of these four DTL models is illustrated with the aid of Tables 7 and 8 using the statistical parameters like accuracy, sensitivity, specificity, precision, and F1 score. The training and validation graphs, as well as the Receiver Operating Characteristic Curve (ROC) of all the four DTL models on the Local CT scan dataset, are presented with help of Figs. 8 and 9, whereas the training and validation graphs and the ROC of all the four DTL models on the global chest X-ray dataset are presented with the help of Figs. 10 and 11.

Now the computational and architectural complexity of these four VGG16, VGG19, DenseNet121, and ResNet50 models along with the average accuracy are also compared with the aid of Table 9. The architectural complexity is normally measured in terms of the number of learnable parameters, whereas the architectural complexity of these four models is expressed in terms of FLOPs (floating-point operations per second).

The classification performance of VGG19 deep transfer learning model on both the augmented datasets of COVID-19 is better in comparison to DenseNet121, VGG16, and ResNet50 DTL models. But considering the computational as well as architectural complexities, it is the VGG16 model offering the optimum computational and architectural complexities with decent classification performance as well.

As VGG16 delivers the best classification performance over both the chest X-ray and CT scan datasets. The Gradient weighted Class Activation Mapping (Grad-CAM) explainability technique [119] is used in order to visually interpret as well as to demonstrate the effectiveness of this DTL model. This Grad-CAM is applied to the last convolutional layer of our VGG19 model in order to verify and explain the output result delivered by the VGG19 as COVID-19 and normal case. Some of the CT scan and chest X-ray test case output results delivered by the VGG19 along with Grad-CAM are presented with the help of Fig. 12.
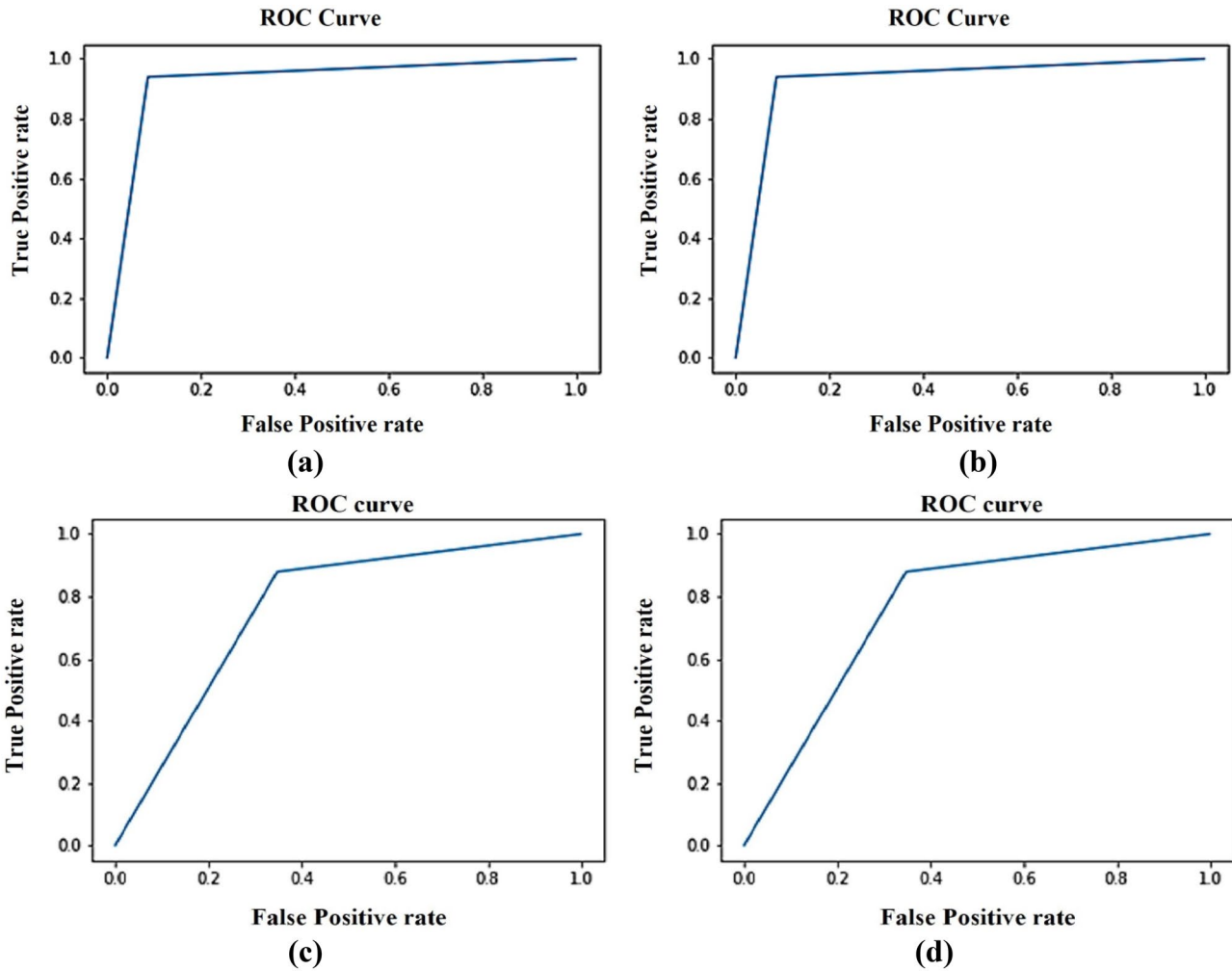
Fig. 11 The ROC curve of DTL models on global chest X-ray dataset **a** VGG16, **b** VGG19, **c** DenseNet-121, and **d** ResNet50

Table 9 Parameters, FLOPs, and testing accuracy comparison of the VGG16, VGG19, DenseNet121, and ResNet50 models on the augmented local CT scan and global chest X-ray datasets

Architectures (models)	Local CT scan			Global chest X-ray		
	Parameters (millions)	FLOPs (G)	Accuracy	Parameters (millions)	FLOPs (G)	Accuracy
VGG16	18.31	15.4	95.75	19.10	16.2	96.25
VGG19	21.2	18.10	96	22.14	19.28	97.95
DenseNet121	6.62	27.75	94.25	6.90	28.14	94
ResNet50	23.45	42.14	92.75	23.55	42.79	94.5

Fig. 12 VGG19 along with Grad-CAM visualization of some of the CT scan and chest X-ray test cases of COVID-19 positive patients
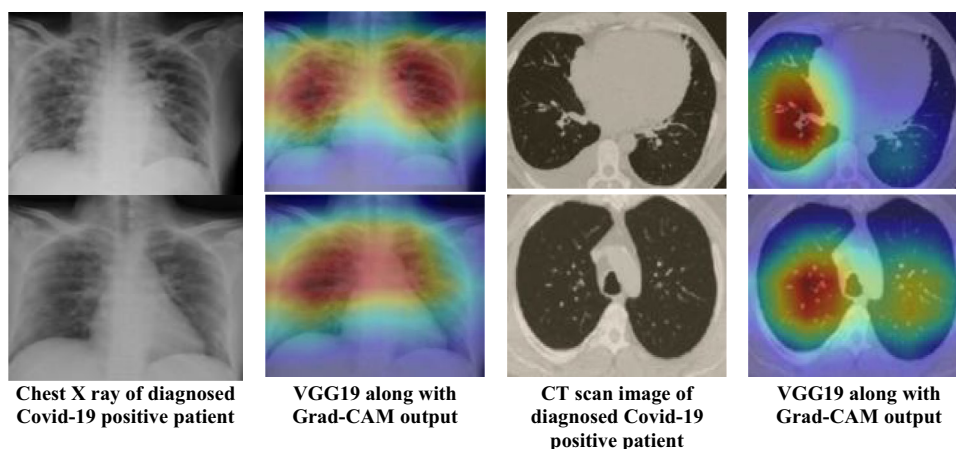
Chest X ray of diagnosed Covid-19 positive patient   **VGG19 along with Grad-CAM output**   **CT scan image of diagnosed Covid-19 positive patient**   **VGG19 along with Grad-CAM output**

Conclusion and Future Work

This methodical review presented a comprehensive analysis of the state-of-the-art deep and machine learning-based approaches for COVID-19 detection. A decent number of CT scan and chest X-ray datasets, which are available post-March 2020 were presented also in this study. Recent deep learning approaches utilizing chest X-ray images, CT scans, and ultrasound images certainly offer a low cost, rapid, automatic approach and do not require physical contact by medical staff for COVID-19 detection. This study discussed challenges and limitations also. Recently, some COVID-19 ultrasound scan datasets also became available for research. A good number of deep learning architectures are still left to be trained and tested on these datasets, which might offer more accurate results. Hence, further research studies should be conducted with objectives to test deep learning models on large size datasets of chest X-ray images, CT scans, and ultrasound images, and validate the results with radiologist's observations. This is obligatory to propose an acceptable real-time application for automatic detection of COVID-19 using imaging modalities. Deep learning approaches to detect COVID-19 could be improved, if more clinical information can be collected from images comprising multiple disease symptoms. Currently, major deep learning approaches focus only on the posterior-anterior (PA) view of X-rays. Hence, it cannot differentiate other views of X-rays such as anterior–posterior (AP), lateral, etc. Further research studies can consider these factors. Future deep learning models must seek to distinguish COVID-19 cases from other similar viral cases, e.g. SARS, MERS, and from varieties of common pneumonia.

Future research studies can primarily focus on development of hybrid models utilizing deep learning architectures for segmentation and feature extraction purpose along with machine learning classifiers for binary or multiclass COVID-19 classification, since these hybrid models does not require large size dataset. Deep learning approaches lack transparency and interpretability since it is impossible to determine which imaging features are being considered to determine the output. Even the heat-map that is used to visualize the essential regions in the scans cannot determine which unique features are used to establish the output. A substantial overlap exists between how the lung reacts to various offends and appearance of diseases in the lung that depend on host factors, e.g. age, drug reactivity, immune status, underlying comorbidities. Hence, multidisciplinary models may be required because no single method can differentiate all lung diseases form imaging appearance on chest X-rays and chest CT scans. Future deep learning models must also consider determining severity degree of COVID-19 besides detecting it in order to monitor and treat patients effectively.

Availability of Data and Material CT scan dataset can be provided on request, whereas the other chest X-ray dataset is publically available.

Code Availability The code will be provided on request.

Declarations

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

Consent to Participate This article does not contain any studies with human participants or animals performed by any of the authors.

Consent for Publication All the authors have given their consent.

Conflict of Interest The authors declare no competing interests.

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