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Supervised and weakly supervised deep learning models for COVID-19 CT diagnosis: A systematic review

Haseeb Hassan[a,b,c], Zhaoyu Ren[a], Chengmin Zhou[a], Muazzam A. Khan[d], Yi Pan[e], Jian Zhao[a], Bingding Huang[a,*]

[a] College of Big data and Internet, Shenzhen Technology University, Shenzhen, 518118, China
[b] Guangdong Key Laboratory for Biomedical Measurements and Ultrasound Imaging, School of Biomedical Engineering, Shenzhen University Health Science Center, Shenzhen, China
[c] College of Applied Sciences, Shenzhen University, Shenzhen, 518060, China
[d] Department of Computer Sciences, Quaid-i-Azam University, Islamabad, Pakistan
[e] Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, China

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ABSTRACT

Artificial intelligence (AI) and computer vision (CV) methods become reliable to extract features from radiological images, aiding COVID-19 diagnosis ahead of the pathogenic tests and saving critical time for disease management and control. Thus, this review article focuses on cascading numerous deep learning-based COVID-19 computerized tomography (CT) imaging diagnosis research, providing a baseline for future research. Compared to previous review articles on the topic, this study pigeon-holes the collected literature very differently (i.e., its multi-level arrangement). For this purpose, 71 relevant studies were found using a variety of trustworthy databases and search engines, including Google Scholar, IEEE Xplore, Web of Science, PubMed, Science Direct, and Scopus. We classify the selected literature in multi-level machine learning groups, such as supervised and weakly supervised learning. Our review article reveals that weak supervision has been adopted extensively for COVID-19 CT diagnosis compared to supervised learning. Weakly supervised (conventional transfer learning) techniques can be utilized effectively for real-time clinical practices by reusing the sophisticated features rather than over-parameterizing the standard models. Few-shot and self-supervised learning are the recent trends to address data scarcity and model efficacy. The deep learning (artificial intelligence) based models are mainly utilized for disease management and control. Therefore, it is more appropriate for readers to comprehend the related perceptive of deep learning approaches for the in-progress COVID-19 CT diagnosis research.

1. Introduction

The 2019 novel coronavirus disease (COVID-19) is a life-threatening and infectious disease with few therapeutic options. Coronavirus sickness can appear in various ways, from minor symptoms to serious illnesses. Fever, cough, shortness of breath, muscle ache, disorientation, headache, sore throat, rhinorrhea, nausea, and vomiting are common symptoms [1,2]. Pneumonia in both lungs, organ failure, respiratory failure, heart issues, acute renal injury, and bacterial infections are other consequences [3–7]. Early and accurate diagnosis of this disease is essential [8,9]. Diagnostic tests can be used for coronavirus infection, quarantine, and self-isolation. Several coronavirus disease (COVID19) tests, including diagnostic and antibody testing, are available [10]. Molecular testing, such as transcription-polymerase chain reaction (RT-PCR) and antigen tests, are examples of diagnostic assays. The antigen tests the virus's particular proteins while the RT-PCR detects the virus's genetic material [11,12].

The current gold standard for this disease is reverse transcription-polymerase chain reaction (RT-PCR) [13–20]. It is critical to assess the covenant's investigative accuracy in RT-PCR and antibody testing at various clinical stages. However, it takes many hours for the outcome to be released. Due to sample and laboratory mistakes, the RT-PCR test's sensitivity is also a concern [21–24]. According to Drame et al [25]., should RT-PCR be used to determine the viral load in the diagnosis of coronavirus disease 2019 (COVID19)? However, because of its sensitivity, the authors raised their reservations. Their sensitivity could be low as 38% [26]. Several other publications [27,28] also pointed to RT-PCR's poor performance in its sensitivity. Other limitations include sample

* Corresponding author.
E-mail addresses: zhaojian@sztu.edu.cn (J. Zhao), huangbingding@sztu.edu.cn (B. Huang).

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Abbreviations

ACC	Accuracy
SEN	Sensitivity
SPEC	Specificity
PRC	Precision
ILD	Interstitial Lung Disease
AUC	Area Under the Curve.
CAP	Community-Acquired Pneumonia
RC	Recall
ROI	Region of Interest
Mean IoU	Intersection Over Union
Mean IOU	mean Intersection Over Union
PPV	Positive Prediction Value
NPV	Negative Prediction Value
RVE	Relative Volume Error
HD	Hausdoff Distance
HD_{95}	95-th percentile of Hausdoff Distance
AA	Average Accuracy
CNN	Convolutional Neural Network
DSC	Dice Similarity Coefficient
MAE	Mean Absolute Error
NSD	Normalized Surface Dice
ASD	Average Symmetric Surface Distance
PO	Percentage of Opacity

collection limitations, transportation limitations, kit performance limitations, etc [2].

On the other hand, the antibody test searches for antibodies made by the immune system. Antibodies are not produced instantly by the immune system; they take days or weeks to develop. The antibody tests should not be cast-off to diagnose coronavirus disease (COVID-19) [10]. Therefore, different approaches for COVID-19 diagnosis are desperately needed by medical practitioners [29]. As a result, chest CT images along with artificial intelligence (AI) technology are considered and can be viewed as proof of concept from previous studies [13,27,29]. It aids in the early detection of disease, the speeding up of the treatment process, and the rapid isolation of patients.

So far, AI has been employed for disease and patient management, screening, monitoring, future outbreak forecasts, mortality risk, tracing the close contacts of COVID-19 suspects, producing medications and vaccines, and lowering the workload of healthcare personnel [30–32]. To diagnose and follow up COVID-19, radiological scans (X-Ray and chest CT) have also been considered, along with artificial intelligence's deep learning models. Several research studies [4,21,33-38] investigated COVID-19 from chest radiographs (X-Ray and chest CT images), implying that radiographic images are helpful for COVID-19 diagnosis.

However, chest radiographs (X-rays) have limited sensitivity for early diagnosis compared to CT images [34]. The CT images provide more information that manifests the multifocal consolidations and white lung representation in the later or severe stages [39]. Contrary to this, routine chest x-ray does not eliminate COVID-19 pneumonia very well because chest x-rays are complicated, and the COVID-19 pneumonia visibility could not be visible at early stages [40]. Therefore, several studies [2,41-50] suggested lung CT images' possible role in COVID diagnosing. This is because of the CT latent role in analyzing detecting complications and prognosis of coronavirus disease 2019 (COVID-19). Thus, it can be used as a precautionary measure, a standardized reporting system based on pulmonary findings, enriching the clinical utility.

It is important to emphasize that in asymptomatic cases, CT imaging diagnosis is not advised [51,52]. It could be beneficial for COVID-19 symptomatic patients (who have many pulmonary symptoms). For instance, an initial study revealed bilateral lung involvement and ground-glass opacities (GGO) in most hospitalized patients [13,53,54]. Vasculature enlargement, bilateral abnormalities, lower lobe involvement, and posterior predilection are other CT symptoms with a high incidence described in more than 70% of RT-PCR test–proven COVID-19 cases. Consolidation, linear opacity, septal thickening, crazy-paving pattern, air bronchogram, pleural thickening, halo sign, bronchiectasis, nodules, and bronchial wall thickening have all been described in 10%–70% of RT-PCR test–proven COVID-19 patients. CT manifestations with Low-Incidence have been reported to be uncommon in RT-PCR test–proven COVID-19 cases, including pleural effusion, lymphadenopathy, tree-in-bud sign, central lesion distribution, pericardial effusion, and cavitating lung lesions [39,41,52,55,56].

Deep learning approaches have been widely explored to diagnose COVID-19 based on CT images [57,58]. Several review articles on the subject had been published prior to our investigation, such as [59–66]. In [59], X-rays and computed tomography (CT) image-based studies were described in terms of image localization, segmentation, registration, and classification for COVID-19 diagnosis. Ghaderzadeh et al [60]. provided an overview of COVID-19 deep diagnosis models based on X-rays and CT modalities. In [61], the authors focused on summarizing and applying the state-of-the-art deep learning models for COVID-19 medical image processing. Samuel et al [62]. offered a review of COVID-19 diagnosis, medication, screening, and prediction strategies based on machine learning and artificial intelligence. Nguyen et al [63]. focused on COVID-19 medical image processing, data analytics, text mining, natural language processing, the Internet of Things (IoT), computational biology, and medicine. Hussain et al [62]. produced a list of the most cutting-edge AI applications for COVID-19 administrations. The research also classified many AI techniques utilized in clinical data analysis, such as neural systems, traditional SVM, and edge computing.

For COVID-19 classification task [67], Ozsahin et al [64]. classified thirty studies. COVID-19/normal, COVID-19/non-COVID-19, COVID-19/non-COVID-19 pneumonia, and COVID-19/non-COVID-19 severity were among the studies that were chosen. Shao et al [65]. researched the sensitivity and utility of chest CT scans for detecting COVID-19 and its potential surgical uses. The study acknowledged and addressed the sensitivity of CT for the diagnosis of COVID-19 positive cases, both symptomatic and asymptomatic. According to findings, CT sensitivity can be ranged from 57%–100% for symptomatic and 46%–100% for asymptomatic COVID-19 patients, whereas RT-PCR sensitivity ranges from 39%–89%. Recently, Islam et al [66]. have published a taxonomy of deep learning algorithms for CT and X-ray modalities. Their review highlighted the data partitioning techniques, various performance measures, and well-known data sets developed for COVID-19 diagnosis. Readers can learn and obtain a lot of knowledge from these review articles. However, these review articles do not adopt a systematic approach to categorize the COVID-19 CT literature, and numerous technical disciplines are ignored.

A review [68] published in the recent past explored the multi-level categorization of supervised and weakly supervised learning methods for medical image segmentation. Inspired by that, this review article aims to arrange the COVID-19 CT-based deep models into multi-level learning groups, i.e., supervised and weakly supervised learning. However, our review is different from that in many aspects. For instance, our topic is COVID-19 CT diagnosis, and for this purpose, we collect, classify, and analyze 71 primary and current studies. We provide a short description for each selected research and capture the most crucial information such as dataset information, adopted frameworks, and key results. Fig. 1. depicts the overall structure of our envisioned approach for the collected literature.

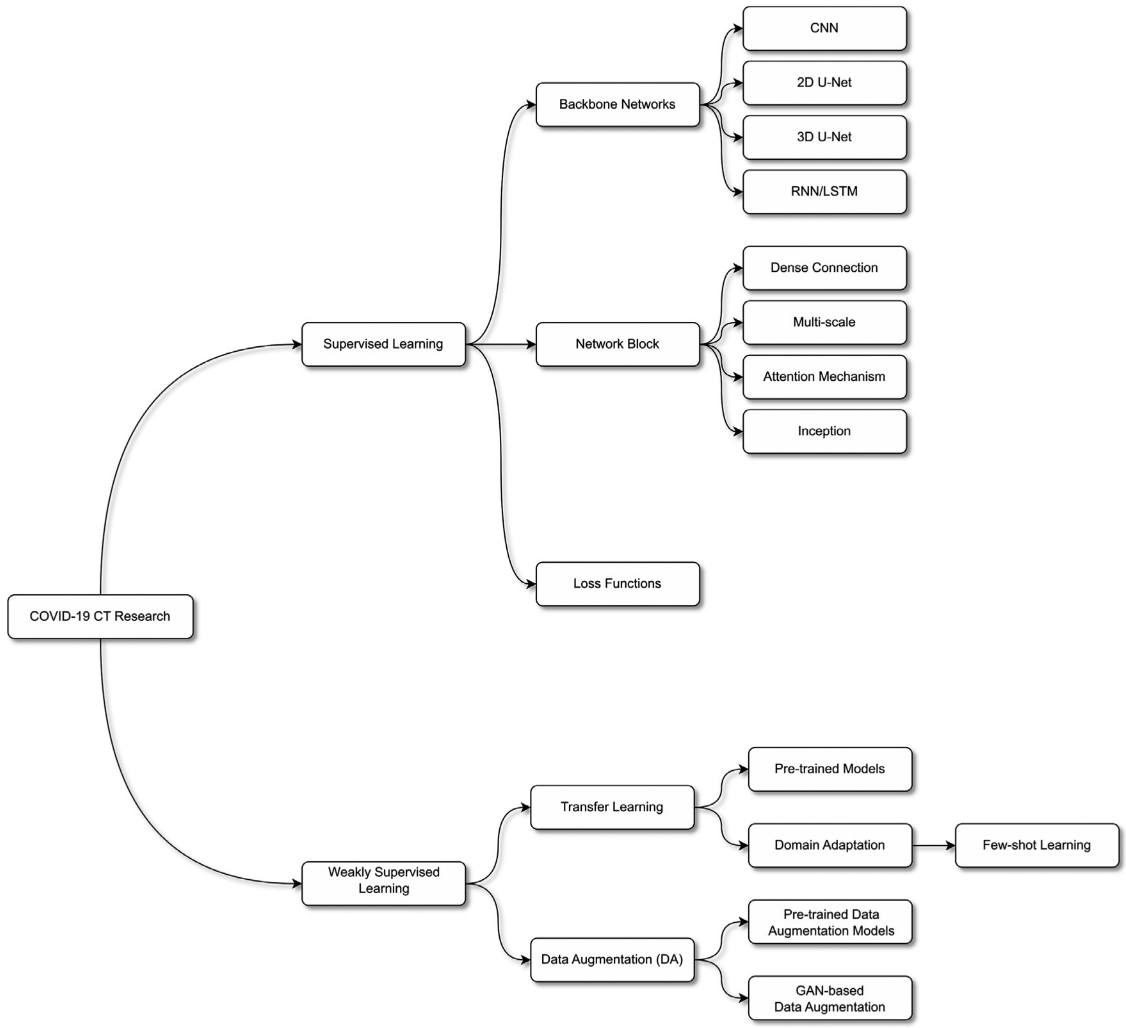

Fig. 1. Overview and arrangement of the collected literature based on supervised and weakly supervised learning.

Numerous COVID-19 CT diagnostic literature available and to include the relevant literature, we filter the unnecessary articles and consider their citations as a selection criterion, e.g., most of the included techniques are highly cited. Different reliable databases such as Google Scholar, IEEE Xplore, Web of Science, PubMed, Science Direct, and Scopus were used to obtain 71 pertinent studies on the given topic. We examine the selected approaches using backbone networks, network blocks, and loss functions for supervised learning. For weakly supervised learning, we analyze the collected literature using transfer learning and data augmentation techniques. Our review study is cascaded and aims to make it easier for researchers to find innovations to improve the accuracy of COVID-19 CT-based diagnosis. The other parts of this work are structured as follows. In Section 2, we examine the supervised learning-based literature. In Section 3, we group the collected literature based on weak supervision. Section 4. contains a discussion and future outlook on the provided issue.

2. COVID-19 CT diagnosis by supervised learning

Deep learning and machine learning are both subfields of artificial intelligence. Both can be divided into three types: supervised, weakly supervised, and unsupervised learning. Supervised learning enables us to acquire or generate data based on prior knowledge. In a supervised task, the data for training should be appropriately selected and handled. COVID-19 CT diagnosis widely utilizes supervised learning techniques, including network backbones, network blocks, and the design of loss functions. The following subsections categorize our collected literature accordingly.

2.1. Backbone networks

Backbone networks are used to describe feature extractor networks. These feature extractor networks calculate features from the input image, which are then upsampled using a simple decoder module to create the final feature maps. The previously proposed approaches utilized Convolutional Neural Networks (CNNs) [69], U-Net [70], UNet++ [71], 3DNet [72], VNet [73], and Recurrent Neural Network (RNN) architectures which are grouped in this category. To detect COVID-19 and community-acquired pneumonia, Li et al [74]. presented a supervised learning COVNet architecture based on the ResNet-50 [75]. The proposed model detected COVID-19 with 90% sensitivity and 96% specificity on an independent testing set. Serte et al [76]. also leverage the power of deep CNN model such as ResNet-50 by fusing image-level predictions to diagnose COVID-19. DeepPneumonia [77] was introduced to distinguish individuals with COVID-19 from bacterial pneumonia. ResNet-50 and the Feature Pyramid Network (FPN) [78] served as the foundation for their architecture. Singh et al [79]. proposed a CNN-based multi-objective differential evolution (MODE) framework to classify the COVID-19-infected patients as positive and negative infected.

Table 1
COVID-19 diagnosis techniques based on CNN backbone networks.

Source	Operations	No of CT Scans/Images/Slices/Patients	Adopted Framework	Results
Li et al [74].	COVID-19, CAP, and non-pneumonia classification	4356 chest CT exams from 3322 patients	ResNet-50	*For COVID-19* SEN: 90%, SPEC: 96%, AUC: 0.96 *For CAP* SEN:87%, SPEC:92%, AUC: 0.95 *For non-pneumonia* SEN:94, SPEC:96, AUC:0.98
Serte et al [76].	COVID-19 and normal CT volumes classification	80 normal CT scans and 19 COVID-19 CT scans	ResNet-50	AUC: 96%
DeepPneumonia [77]	Classification of COVID-19 infection and bacterial infection	COVID-19 88 chest CT scans	Resnet-50 and Feature Pyramid Network [78]	*On Diagnosis Dataset* RC:0.93, PRC:0.96, ACC:0.94 F1-score:0.94, AUC:0.99
Singh et al [79].	Classification of COVID-19 (+ve) and (-ve) infection	CT images adopted from [87]	Multi-Objective Differential Evolution (MODE)–based CNN	ACC: 93.5%, F-measure:89.9%
Xu et al [80].	Classification of COVID-19, IAVP, and healthy cases	618 CT Samples and (11,871 image patches)	Multiple CNN models	ACC:86.7%
Liang et al [81].	Classification between COVID-19 and CAP	2522 chest CT images	V-Net [73] and Deep forest model	ACC: 91.79%, SEN: 93.05%, SPEC: 89.95%, AUC: 96.35%, PRC: 93.10%, F1-score: 93.07%
Rahimzadeh et al [83].	Identification and classification of COVID-19 and normal patients	63,849 chest CT images	ResNet50V2 [84] and Feature Pyramid Network (FPN)	Accuracy: 98.49%
Jiantao et al [85].	Distinguishing COVID-19 from CAP	497 CT examinations	3D CNN	AUC: 0.70 with 99% CI (0.56–0.85)
Abdullah et al [86].	Classifying COVID and Non-COVID	349 CT images	Sequential CNN	ACC: 92.48 SEN: 94.17 SPEC: 89.58

To calculate the infection probability of COVID-19, Xu et al [80]. used various CNN models. The authors further classified COVID-19, non-COVID cases, and influenza-A viral pneumonia (IVAP). Sun et al [81]. anticipated technique targeted the deep high-level features. In their method, location-specific features were extracted from the chest CT image. After that, a deep forest model [82] is used to learn the latent high-level representations of extracted features. Finally, feature selection and classifier training are integrated adaptively into a cohesive framework for COVID-19 prediction. Rahimzadeh et al [83]. used ResNet50V2 [84] as a backbone and categorized input CT as COVID-19 or normal. Using a feature pyramid network (FPN), the proposed technique explored several resolutions of the input image [74], which greatly enhanced classification performance. In addition, Pu et al [85]. created multiple classifiers based on three-dimensional (3D) CNNs to distinguish COVID-19 from community-acquired pneumonia (CAP). According to the authors, compared to their proposed method, the radiologists' interpretation of CT scans has a low ability to identify between COVID19 and community-acquired pneumonia (CAP) cases. Another supervised-based technique [86] developed a sequential CNN to detect COVID-19 by analyzing the CT images. The model achieved an accuracy of 92.5%. Table 1 depicts the COVID-19 diagnosis techniques based on CNN backbone networks.

Apart from the CNNs, many COVID-19 CT diagnosis works relied on U-Net [70] and its variants, such as 3D U-Net [72], U-Net++, etc., as given in Table 2. U-Nets are faster to train and generate highly detailed segmentation maps using minimal trading samples [88]. Gozes et al [53]. proposed a technique using commercial software with trained U-Net, including a pre-trained model on some extensive CT data. The authors demonstrated that AI-based models could help COVID detection with high accuracy. Amine et al [89]. proposed a multitask deep learning method for COVID classification and segmentation. The proposed method used one encoder and two decoders for image reconstruction and infection segmentation. Their final step utilized fully connected layers to classify COVID and non-COVID. Pu et al [90]. adopted a U-Net-based framework to segment the lung infected regions followed by the identification process. Heatmaps were used to visualize and assess progression. Similarly, another U-Net-based framework [91] is proposed where lung spaces and COVID anomalies were segmented from chest CT scans.

Table 1. Table 4. Table 5. Table 7. Table 8.

Jun et al [93]. built a COVID-19 detection system on the top of U-Net++ [71]. ResNet-50 was used as the backbone of U-Net++. An external dataset containing 100 patients was used to evaluate the model's performance. The authors calculated five evaluating

Table 2
COVID-19 diagnosis techniques based on U-Net and its variants.

Source	Operations	No of CT Scans/Images/Slices/Patients	Adopted Framework	Results
Gozes et al [53].	Classification of COVID and non-COVID	Multiple international chest CT datasets (US-China)	RADLogics [92] (A commercial software) and U-Net	AUC: 0.99(95%CI: 0.989–1.00), SEN: 98.2%, SPEC: 92.2%
Amine et al [89].	COVID classification and COVID lesion segmentation	1044 chest CT images, 744 images, and 100 CT scans	U-Net	*For Segmentation* SEN: 20.2%, SPEC: 99.7%, ACC: 95.93 *For Classification* AUC:0.97, SEN: 0.96%, SPEC: 0.92%, ACC: 94.67%
Pu et al [90].	COVID identification and progression	120 and 72 CT scans were used	U-Net	SEN: 95% (CI 94–97%) SPEC: 84% (CI 81–86%)
Kuchana et al [91].	Lung spaces and COVID anomalies segmentation	20 chest CT scans and 929 slices	U-Net hyperparameters modification	F1-Score: 97.31% Mean IoU: 84.6%
Jun et al [93].	COVID-19 identification	46,096 Chest CT Images	U-Net++ and ResNet-50	*On External Dataset* SEN: 98%, SPEC: 94%, ACC: 96%, PPV: 94.23%, NPV: 97.92%
Ni et al [94].	COVID detection, voxel and pulmonary lobe segmentation.	19,291 CT scans	3D U-Net and MVP-Net [95]	*For lesion Detection* SEN: 1(95% CI 0.95,1.00) F1-measure: 0.97 *For lobe Segmentation* SEN: 0.96(95% CI 0.94, 0.98) F1-measure: 0.86
Shuo et al [96].	Segmentation and classification	CT data collection from five hospitals	*For Segmentation* (FCN-8 s), U-Net, V-Net and 3D U-Net++ *For Classification* ResNet-50, Inception networks, DPN-92, and Attention ResNet-50	*For 3D U-Net±+ and ResNet-50* AUC 0.991, SEN 0.974, SPEC: 0.922
Dominik et al [97].	Automated segmentation of COVID-19 infected regions	Chest CT dataset from Ma et al [98].	3D U-Net	DSC for lungs: 0.956 DSC for infection: 0.761

metrics: accuracy, sensitivity, specificity, positive prediction value (PPV), and negative prediction value (NPV). Ni et al [94]. presented a COVID detection technique where lesion detection and segmentation were conducted. The authors claimed that the algorithm's performance is better compared to radiologists. Jin et al [96]. designed a combination of segmentation and classification model. Segmentation was used for the lung lesion regions, followed by the classification technique to classify the lesion regions into COVID and non-COVID. For the segmentation task, several models were considered such as fully convolutional networks (FCN-8) [99], U-Net [70], V-Net [73] and 3D U-Net++ [71]. For classification task, the authors considered ResNet-50 [75], Inception networks [100–102] DPN-92 [103], and Attention ResNet-50 [104]. Dominik et al [97]. implemented a robust segmentation model for lungs and COVID-19 infected regions based on 3D U-Net architecture. The proposed method has comparatively better performance in terms of segmentation and improved medical image analysis with limited data.

As given in Table 3, some works used Recurrent Neural Networks (RNN) to detect and diagnose COVID-19. A recurrent Neural Network (RNN) is a class of artificial neural networks that allows temporal dynamic behavior. More simply, it allows previous outputs to be used as inputs while having hidden states. The Long Short-Term Memory (LSTM) [105] is one of the popular examples. Most of the RNN based techniques are utilized for the prediction [106–109] and spreading of COVID-19 disease. For instance, Yang et al [110]. incorporated the LSTM model with SIER [111] to predict COVID-19 in China. Many LSTM based techniques targeted the X-ray modality [112–114]. Some methods are data mining and prediction-based [109,115,116]. However, limited literature exists that utilizes CT imagery and the RNN models. For example, a DeepSense model (data mining-based hybrid model) [117] to diagnose the medical conditions of COVID patients. The developed model combined convolutional neural network (CNN) and recurrent neural network (RNN), which can extract and classify the related features of COVID-19 lesions from the lungs. Hassan et al [118]. presented technique extracted the relevant features with the Q-deformed entropy handcrafted features to diagnose COVID-19. They used LSTM network to precisely discriminate between COVID-19, pneumonia and healthy case.

2.2. Network function blocks

This section categorizes the collected literature based on dense connections, multi-scale, attention mechanism, and inception as provided in Table 4. A dense connection is used to design a special convolution neural network. Dense Convolutional Network (DenseNet) [122] connects each layer to another in a feed-forward fashion. Such types of convolutional neural networks also expanded for COVID detection. It can simultaneously extract the shal-

Table 3
COVID-19 diagnosis techniques based on Recurrent Neural Network (RNN).

Source	Operations	No of CT Scans/Images/Slices/Patients	Adopted Framework	Results
DeepSense model [117]	Extracting and classifying COVID-19 lung lesions	IEEE8023 [119], COVID-CT-Dataset [120], COVID-19 Open Research Dataset Challenge (CORD19) [121]	CNN and RNN	*On COVID-CT with 80% training data* ACC: 97.78%, F1-score: 92.14%, SEN: 97.55%, SPEC: 97.42%
Hasan et al [118].	Classification of Covid-19, Pneumonia and Healthy Lungs	Total 321 chest CT scans including 118 CT COVID-19 patients, 96 CT scans pneumonia, and 107 CT scans of healthy people	LSTM neural network classifier	ACC: 99.68%

Table 4
COVID-19 CT diagnosis based on dense connections, multi-scale, attention mechanism, and inception.

Source	Operations	No of CT Scans/Images/Slices/Patients	Adopted Framework	Results
Yang et al [123].	COVID and non-COVID classification	295 patient's chest CT Slices	DenseNet	*In the test set* AUC: 0.98, ACC:92%, SEN:97%, SPEC: 87% *Radiologist Performance* ACC:95%, SEN: 94%, SPEC:96%
Liu et al [124].	Classification of COVID and non-COVID-19	CT data from 920 COVID patients and 1370 from non-COVID pneumonia patients	modified DenseNet-264	AUC: 0.98, ACC: 94.3%
Yan [127]	Detection of COVID-19 and differentiating it from other CP	416 abnormal scans 412 non-COVID pneumonia scans, 412 pneumonia scans	MSCNN	SEN: 89.1%, SPEC: 85.7%
Qingsen et al [129].	Segmentation of chest CT images with COVID-19 infections	21,658 annotated chest CT images	Feature Variation FV and Progressive Atrous Spatial Pyramid Pooling (PASPP)	*For Lung* DSC: 0.987 *For COVID-19 Segmentation* DSC: 0.726
Mohamad et al [130].	COVID-19 detection	Total 2482 CT scan images 1252 COVID-19 patients' images and 1230 non-COVID-19 images	CNN, multi-scale features, and atrous convolution	ACC: 96.16%.
Ouyang et al [131].	Diagnosing COVID-19 from CAP	2186 CT scans for training 2796 CT scans for testing	3D CNN, Dual-Sampling Attention Network and VB-Net toolkit	AUC: 0.944, ACC:87.5%, SEN:86.9%, SPEC: 90.1%, F1-score: 82.0%
Bin et al [132].	Binary classification of COVID positive and negative	Chest CT dataset from [133]	Attention Mechanism	AUC: 94.0%, SEN: 88.8%, PRC:87.9%, F1-score:88.6%
Wang et al [93].	Identification of COVID-19 and ILD	936 normal CT scans. 2406 ILD CT scans 1315 COVID-19 CT scans	3D ResNets with prior attention	ACC:93.3%, SEN: 87.6%, SPEC: 95.5%
Zhao et al [134].	Segmentation of COVID-19 lung opacification	19 lung CT scans, 1117 segmented lung opacification and eight lung CT scans.	And spatial-wise attention module	DSC: 89.48%, SEN: 88.74%
Alom et al [135].	Identification of COVID-19 patients	420 CT samples collected from different sources	Modified Nabla-net and inception neural network	*For Chest CT* ACC: 98.78% *For X-ray* ACC: 84.67%

low features and inner representation of the image. For instance, Yang et al [123]. designed a DenseNet based model to classify images as COVID-19 or healthy. The proposed model has been evaluated in terms of sensitivity, specificity, and accuracy. Liu et al [124]. presented a modified DenseNet-264 model to screen and diagnose COVID-19 infected patients.

With the rapid development of deep learning, many architectures are designed, such as multi-scale information fusion [125,126]. Such architectures can effectively enhance the context information of networks and extract richer semantic information. However, such architectures cannot restore the loss of detailed information due to the pooling process. A method [127] used a multi-scale convolutional neural network (MSCNN) to diagnose COVID-19. The proposed model performed well on both slice level and scan level. The presented technique achieved promising COVID detection results.

Table 5
COVID-19 CT diagnosis based on improved or novel loss functions.

Source	Operations	No of CT Scans/Images/Slices/Patients	Adopted Framework	Results
Li et al [141].	Improving the discrimination and detection performance of COVID-19 images	COVID-CT-Dataset [120]	Stacked-autoencoders [31,32] and reconstruction of a loss function	AA: 94.7%, PRC: 96.54%, RC:94.1%, F1-Score: 94.8%
Tongxue et al [142].	Segmenting COVID-19 CT datasets	473 CT slices	U-Net and Attention Mechanism	SEN: 86.7%, SPEC: 99.3%
Saeedizadeh et al [143].	COVID-19 infected region segmentation and detection	Medseg Dataset [145]	U-Net and 2D total variation [134]	mIoU: 99%, Dice score: 86%
Wang [144]	COVID lesion segmentation	558 COVID-19 patients CT scans CNN	Dice loss, Mean Absolute Error (MAE) loss, and Self Ensembling CNNs [146,147]	Dice (%): 80.29±11.14, RVE (%): 17.72±23.40, HD_{95}(mm): 18.72±27.26

To overcome the loss of detailed information caused by pooling operation, Chen et al [128]. proposed the atrous spatial pyramid pooling module (ASPP) to improve image segmentation results. Such techniques are also extended for the COVID-19 detection and diagnosis. For instance, Qingsen et al [129]. proposed a COVIDSeg-Net to segment COVID-19 infection regions and the entire lung from chest CT images. The authors included a Feature Variation (FV) block to address the difficulty distinguishing COVID-19 pneumonia from the lung. The authors also introduced the Progressive Atrous Spatial Pyramid Pooling (PASPP), which progressively aggregated the information and obtained more useful contextual features. Another suggested technique by Mohamad et al [130]. employed the EfficientNet architecture as the backbone and applied several feature maps with varied scales to CT scans. Furthermore, the obtained multi-scale feature maps were used to atrous convolution at various rates to generate denser features, which aided the COVID-19 findings.

To diagnose COVID-19 from CT images, some recent works adopted the attention mechanism [136,137]. The attention mechanism is the notion or idea based on attaining focus, which pays greater attention to certain factors when processing the data. It is one of the most prominent ideas in the deep learning techniques even though this idea is also adopted for COVID-19 detection purposes. A method [131] introduced a dual-sampling attention network to diagnose COVID- 19 from CAP and utilized VB-Net toolkit segmentation [138] for pneumonia infection regions to ensure the predictions based on infected regions. Liu et al [132]. developed a lesion-attention deep neural network (LA-DNN) to predict COVID-19 positive or negative. Wang et al [93]. proposed a novel multitask prior-attention residual learning model to screen out COVID-19 and identify pneumonia types between COVID-19 and interstitial lung disease (ILD). The proposed model coupled two 3D-ResNets into a single model to perform the mentioned tasks. Another attention mechanism introduced a SCOAT-Net [134] framework, where a coarse-to-fine attention network is proposed for segmenting COVID-19 lung opacification from CT images. The method further involved embedding of spatial and channel-wise attention mechanism, which achieved comparatively a better performance.

Meanwhile, Inception [101] based methods are also introduced. The inception modules allow utilizing multiple types of filter sizes, instead of being restricted to a single filter size, in a single image block, which can be concatenated and passed onto the next layer. Alom et al [135]. proposed an inception-based method that targeted both the X-ray and CT imaging modalities for COVID-19 detection. The authors used an Inception Residual Recurrent Convolutional Neural Network methodology for COVID-19 detection. The proposed method further comprises COVID-19 infected regions segmentation inspired by Nabla-Net [139]. Note that most of the COVID-19 diagnostic models explored the networks with transfer learning strategy.

2.3. Loss functions

Apart from the backbone networks and function blocks, the selection of loss functions is also essential in improving network efficiency. Therefore, some works (organized in Table 5) also focused on improving COVID-19 CT diagnosis. Such types of networks could be helpful to avoid the class imbalance problem [140]. Li et al [141]. proposed a stacked auto-encoder detector model. Initially, four auto-encoders were built, followed by four auto-encoders and further connected with dense layer and softmax classifier. A new classification loss feature is created by superimposing a reconstruction loss to improve the model's detection accuracy. Another method [142] used U-Net based segmentation network by incorporating an attention system, including spatial and channel attention, into a U-Net architecture to capture rich contextual relationships for better feature representation. The proposed method introduced the focal Tversky loss to cope with minor lesion segmentation. Saeedizadeh et al [143]. trained an architecture similar to the U-Net model to detect ground glass regions. A regularization term to the loss function is used to promote connectivity of the segmentation map for COVID-19 pixels. The proposed model was named "TV-UNet" because it uses 2D-anisotropic total-variation. Wang et al [144]. developed a noise-robust Dice loss for robustness against noise and then COVID-19 pneumonia lesion segmentation network (COPLE-Net). Further, a teacher model, where the noise-resistant dice loss and COPLE-Net are combined in which the Exponential Moving Average (EMA) of a student model was used. The model had achieved better noise-robust loss functions, while their COPLE-Net technique achieved higher performance in terms of segmentation.

3. COVID-19 ct diagnosis by weakly supervised learning

Weakly supervised learning is another type of supervised learning which lies between both supervised and unsupervised learning. Supervised learning needs more annotative data to train and test the learning models. However, it isn't easy to collect or generate extensive scale data with more annotations in most cases. On the contrary, weakly supervised learning models require limited annotations, and most of the data remain unlabeled. Thus, recently it has been utilized extensively in medical imaging. Apart from its widespread applications in other areas of medical science, it has also been adopted for COVID-19 CT analysis.

For instance, an attention-based weakly supervised framework [148] is presented to diagnose COVID-19 and bacterial pneumonia. The proposed method achieved an overall accuracy of 98.6% and an AUC of 98.4%. Similarly, another attempt was made by Han et al [149]. with weak labels to achieve a more accurate and interpretable analysis of COVID-19 CT diagnosis. The proposed approach had a Cohen kappa score of 95.7%, an overall accuracy of 97.9%, and an AUC of 99.0%. In [150], a weakly supervised framework was developed for COVID-19 classification and lesion localization, where the pre-trained U-Net was used for the lung region segmentation. The infection probability was predicted based on the segmented 3D lung regions. The algorithm achieved a score of 0.959 ROC AUC and 0.976 PR AUC.

So basically, weak supervision is a branch of machine learning where noisy, limited, or imprecise sources provide supervision signals for labeling large amounts of training data in a supervised manner. Weak supervision can be further decomposed into transfer learning and data augmentation procedures. Thus, in the subsequent sections, we collected such COVID-19 CT diagnosis methods which adopted transfer learning and data augmentation techniques.

3.1. Transfer learning

Transfer learning is a method of reproposing a model or knowledge for another activity. In the framework of COVID-19 diagnosis, extensive research efforts have been done by employing transfer learning. However, the literature on transfer learning has undergone multiple revisions, and the terms associated with it have been used loosely and frequently interchangeably. Therefore, there are various types of transfer learning approaches, such as, in our case, domain adaptation. They are all linked in a few aspects and attempt to solve similar problems [151]. The remaining COVID-19 CT diagnosis literature is further organized into subsections based on pre-trained, few-shot learning, and domain adaptation.

3.1.1. Pre-trained models (conventional transfer learning)

In computer vision transfer learning is commonly expressed through pre-trained models. A pre-trained model has been trained on a big extensive benchmark dataset to address a problem comparable to the one we're working on. Due to the computational cost and complexity of training new models, importing and using such models from published literature (e.g., VGG, Inception, MobileNet). For example, Yu et al [152]. modified the GooLeNet, used the transfer learning strategy, and proposed a GoogLeNet-COD model. The authors suggested that the dropout layer and transitional layer are necessary for better computer-aided detection (CAD) system. In [153], a diagnosis method was proposed that initially extracted the region of interest (ROI) as input images for training and validation cohorts and then trained a modified inception network based on the extracted ROI images for further feature extraction. The proposed method reported accuracy, sensitivity, and specificity as primary evaluating metrics.

Wang et al [154]. proposed a two-step transfer learning prognostic model and claimed that their model could benefit medical resource optimization and COVID-19 prevention. The proposed system not only identified COVID-19 but also visualized the suspicious infected lung areas by using the heat maps. Aayush et al [155]. used the pre-trained neural networks to classify COVID positive and negative. The proposed model utilized pre-trained DenseNet-201 [122] for the classification task. Their results showed that DenseNet-201 has better performance compared with VGG [156], Inception ResNetX [101,157] and ResNet 152V2 [75]. Pathak et al [79]. built a COVID-19 positive/negative classification model based on ImageNet pre-trained ResNet-32 [75] version. The findings of their suggested method demonstrated that their transfer learning model could obtain superior classification accuracy than supervised learning-based models.

To categorize COVID-19 and non-COVID-19 classes, Ali et al [158]. employed the transfer learning approach using ten famous pre-trained convolutional neural networks: AlexNet [69], VGG-16 and VGG-19 [69], SqueezeNet [159], GoogleNet [101], MobileNet-V2 [160], ResNet-18, ResNet-50, ResNet-101, and Xception [161]. ResNet-101 and Xception had the best performance among all the networks. Xuehai et al [133]. created a model using the Self-Trans method. To limit the risk of overfitting to learn dominant and unbiased characteristics, the authors adopted self-supervised learning with a transfer learning strategy—the suggested framework classified chest CT as COVID-positive or COVID-negative. Furthermore, the authors poised a publicly accessible dataset containing hundreds of positive COVID-19 CT scans.

Kassania et al [162]. used state-of-the-art deep CNN descriptors to extract highly representative features from chest X-ray and CT images to differentiate between COVID-19 and healthy participants. Dilbag et al [163]. constructed a deep transfer learning model based on densely connected convolutional networks (DC-CNs), ResNet152V2, and VGG16 to categorize the suspected cases as COVID-19, TB, pneumonia, or healthy. Fu et al [164]. proposed a transfer learning strategy where they adopted ResNet-50 pre-trained weights on ImageNet and differentiated COVID-19 from other viral pneumonia.

Pham et al [165]. focused their research on using 16 pre-trained CNNs. In terms of accuracy, sensitivity, specificity, F1-score, and area under the curve, DenseNet-201 performed admirably. Their research showed that using transfer learning directly on the input slice yields better results than data augmentation-based training. Khan et al [166]. proposed optimized deep learning (DL) CT scheme to distinguish between COVID-19 infected and normal patients. In their proposed method, contrast enhancement was used to improve the quality of the original images. The pre-trained DenseNet-201 [122] classifier was then trained by adopting the transfer learning methodology Table 6. summarizes some conventional transfer learning methods proposed for COVID-19 CT analysis.

3. 1. 2 domain adaptation-based transfer learning methods

Domain adaptation is a subcategory of transfer and weakly supervised learning. The capacity to apply an algorithm trained in one or more "source domains" to a different (but related) "target domain" is known as domain adaptation. The source and target domains have the same feature space (but distinct distributions) in domain adaptation. However, transfer learning includes scenarios where the target domain's feature space differs from the source feature space or spaces [169–171]. The intuition behind this is that deep neural networks have a lot of capacity to learn representations from a single dataset, and some of that information can be reused for future tasks [172]. Such approaches could be adopted when there is a shortage of training data.

Similarly, in the case of COVID-19 CT diagnosis, the required training data scarcity has been addressed by the transfer learning domain adaptation strategy. For instance, COVID-DA is a domain adaptation method introduced by Zhang et al [173]. with only a few COVID-19 annotations. The suggested technique effectively diagnoses COVID-19. Chen et al [174]. also adopted a domain adaptation strategy to segment COVID-19 CT lung infections. The authors used limited real data without annotations and more annotated synthetic data to jointly train the U-Net segmen-

Table 6
COVID-19 diagnosis by conventional transfer learning pre-trained models.

Source	Operations	No of CT Scans/Images/Slices/Patients	Adopted Framework	Results
Shuai et al [153].	Classification of COVID-19 and typical pneumonia	1065 Chest CT images	Modified Inception Network	*Internal validation* Total ACC: 89.5% SPEC: 0.88, SEN: 0.87 *External testing dataset* Total ACC: 79.3% SPEC: 0.83, SEN: 0.67
Yu et al [152].	COVID-19 detection	148 chests CT images	GoogLeNet [94]	ACC:0.87, SPEC:0.84, SEN: 0.90
Wang et al [154].	Classifying COVID-19 from other types of pneumonia	A total of 5372 patients CT images including additional information	DenseNet121 [45] and FPN [76]	*For COVID-19* AUC: 0.87 *For Other Pneumonia* AUC: 0.88 *For Viral Pneumonia* AUC: 0.86
Aayush et al [155].	Classification of COVID (+ve) and COVID (-ve)	2492 CT scans, 68% for training, 17% for validation, and 15% for testing	Pre-trained DenseNet201	*On Test Set* AUC:0.97, ACC:0.998, SPEC:0.992, F1-score:0.998, RC:0.997, PRC:0.999
Pathak et al [79].	Classification of COVID +ve and COVID -ve	413 COVID +ve images 439 images of normal or pneumonia infected patients	Pre-trained ResNet-32	*On Test Set* ACC:0.93, SPE:0.95, SEN:0.91, PRC:0.95
Ali et al [158].	COVID-19 diagnosis And classification	1020 CT slices from 108 patients.	Ten pre-trained convolutional neural networks	*ResNet-101 Performance* AUC: 0.994, SEN: 100%, SPEC: 99.02%, ACC: 99.51% *Xception Performance* AUC: 0.994, SEN: 98.04%, SPEC: 100%, ACC: 99.02%
Xuehai et al [133].	COVID-19 diagnosis and construction of publicly available dataset	349 positive CT scans 397 negative CT scans	Train DenseNet-169 [122] by Self-Trans [167] method	*On Test Set* ACC:0.86, F1-score:0.85, AUC:0.94
Kassania et al [162].	To differentiate between COVID-19 and healthy participants	COVID-19 image data collection [119]	Pre-trained CNN models with machine learning classifiers	*Best Performer* DenseNet121 feature extractor with Bagging tree classifier achieved 99% classification accuracy
Singh et al [163].	Classification of COVID (+ve), pneumonia, and tuberculosis	2373 COVID, 2890 pneumonia infected, 3193 tuberculosis, and 3038 healthy images	VGG16, DenseNet201, and ResNet152V2	*On Test Set* AUC: 98.29%, ACC: 98.94%, SEN: 98.84%, SPEC: 98.83%, F1-score: 98.31%
Fu et al [164].	Detection and differentiating COVID-19 and other common infectious diseases	Private CT dataset	Pre-trained ResNet-50	*For the test dataset,* ACC: 98.8%, SEN: 98.2%, SPEC: 98.9%, PPV: 94.5%, NPV:99.5
Pham et al [165].	COVID–19 Classification	COVID-CT-Dataset [120]	16 pre-trained CNNs	DenseNet-201: ACC (%): 96.20 ± 4.95, SEN (%): 95.78 ± 5.27, SPEC (%): 96.67 ± 4.59, F1-score: 0.96 ± 0.05, AUC: 0.98 ± 0.03
Khan et al [166].	COVID-19 classification	Radiopaedia COVID-19 dataset [168]	Pretrained DenseNet-201 and contrast enhancement	Average classification ACC: 94.76%

tation network. The authors introduced conditional GAN for adversarial training to overcome the domain mismatch. The proposed network outperformed a few of the state-of-the-art methods significantly.

To address various infections and domain shift concerns in COVID-19 datasets, Jin et al [175]. presented a domain adaption-based self-correction model (DASC–Net). The proposed DASC–Net contained a novel attention and feature domain enhanced domain adaptation model (AFD-DA) to solve the domain shifts and a self-correction learning process to refine segmentation results. Compared to other state-of-the-art methods, the suggested method indicated that DASC–Net performance is quite promising. Li et al [176]. also solved the insufficient COVID-19 CT medical data problem by adopting the domain adaptation strategy and successfully detected the infected regions. The proposed model achieved better accuracy upon comparing with SOTA approaches. A few of the domain-adaptation inspired works are provided in Table 7.

3.1.2.1. Few-shot learning-based transfer learning models. Few-shot learning (FSL), also known as low-shot learning (LSL), is a machine

Table 7
Selective information from collected domain adaptation-based transfer learning methods.

Source	Operations	No of CT Scans/Images/Slices/Patients	Adopted Framework	Results
Zhang et al [173].	COVID-19 screening	A self-created COVID-DA dataset collected from different online sources	Transferring domain knowledge from a labeled source domain	F1-score: 92.98%, RC: 88.33%, PRC: 98.15%, AUC: 0.985%
Chen et al [174].	COVID-19 infection segmentation	Medseg dataset [145]	U-Net and conditional GAN	*For Infections* DICE: 86.15±0.29, SEN: 84.29±0.31, SPEC: 99.81±0.01 *For Lung* Dice: 96.13±0.07, SEN: 94.61±0.09, SPEC: 99.67±0.01
Jin et al [175].	COVID-19 infection segmentation	A dataset collected from three sources [98,145,177]	Segmentation, adversarial learning, and class activation map (CAM) [178]	COVID-19-T1 dataset Dice: 77%, SEN: 81.2%, SPEC: 98.0%
Li et al [176].	COVID-19 infection detection	300 slices from Zhongnan Hospital, Wuhan University and Medsegdataset [145]	Vanilla ResNet50, Network-in-Network (NIN) [179], Adversarial loss, and vanilla Faster R-CNN [180]	SEN:94.2%, SPE: 99.5%, ACC: 96.85%

Table 8
Important selective information from Few-shot learning-based transfer earning models.

Source	Operations	No of CT Scans/Images/Slices/Patients	Adopted Framework	Results
Yifan et al [181].	COVID-19 diagnosis	6000 source domains slices (synthetic data) and 60 target domain slices (real data). 600 real CT scans as test set.	Siamese network structure	ACC: 0.8040±0.0356 F1-score: 0.7998±0.038
Voulodimos [182]	COVID-19 infected area segmentation	Radiopaedia [168] and [98,187]	U-Net and on-line few-shot learning process	Few-shot U-Net (AUC): 0.968
Abdel et al [183].	COVID-19 infection segmentation	Medseg Dataset [145]	Encoder (using Res2Net module) [184] and Decoder Network	*On Test Set* DSC: 0.798, SEN: 0.803, SPE: 0.986, MAE: 0.065
Chen et al [185].	COVID-19 diagnosis	216 patients COVID (+ve) scans 171 persons have COVID (-ve) scans	Pre-trained encoder and self-supervised strategy	*On Test Set* ACC:0.868, PRC:0.883, AUC:0.931, RC:0.872

learning problem in which the training dataset contains just a tiny amount of data. This has been introduced to address the issue of domain adaptation with a limited number of training samples. Machine learning applications need extensive data and the common practice to feed as much data as the model can take. Feeding more data enables the model to predict better. Contrary to this, FSL seeks to create accurate machine learning models with fewer training data. Note that FSL has different variations and cases such as N-Shot Learning, One-Shot Learning, Zero-Shot Learning.

As medical CT datasets are limited for COVID-19 analysis. In order to tackle that, Yifan et al [181]. proposed a domain adaption-based COVID-19 CT diagnostic model on few-shot COVID-19 conditions. The authors utilized many synthetic COVID-19 CT images and adjusted the networks from the source domain (synthetic data) to the target domain (real data) with a cross-domain training mechanism. Voulodimos et al [182]. explored the efficacy of few-shot learning in U-Net architectures. Their experimental results indicated improved segmentation accuracy in identifying COVID-19 infected regions.

Abdel et al [183]. suggested another COVID-19 diagnosis technique based on few-shot segmentation. The primary goal of their research was to create accurate segmentation from a small set of annotated lung CT data. The proposed FSS architecture allowed learning from small support samples and improved query sample generalization. Furthermore, the Res2Net50-based encoder [184] allowed for better network convergence. Chen et al [185]. developed a few-shot learning approach for predicting COVID-19 CT analysis with minimum training. Initially, the instance discrimination task was carried out to test the model's ability to distinguish between two images, regardless of whether they are identical instances or not. They also avoided data augmentation by generating alternative views of the same images to supplement the same dataset. Finally, a self-supervised technique [186] based on momentum contrastive training was used to improve performance. The suggested model's efficacy was tested using two publicly available datasets. Table 8 depicts some of the COVID-19 CT diagnosis works based on Few-shot learning approch.

3.2. Data augmentation

Data augmentation is another type of weak supervision. It is also introduced to address the data scarcity problem. The data augmentation techniques could be further categorized into conventional data augmentation techniques and generative adversarial networks (GANs). This section organizes the COVID-19 CT diagnosis literature according to data augmentation with pre-trained models and data augmentation with GANs.

3.2.1. Data augmentation with pre-trained models

For COVID-19 CT analysis, several works adopted such approaches with pre-trained models to diagnose COVID-19. Silva et al

[188]. used data augmentation and transfer learning techniques to overcome data scarcity. Image rotation, zooming, and horizontal flipping were used as a data augmentation procedure. Horry et al [189]. performed a comparative study by adopting the transfer learning strategy with data augmentation. They optimized the VGG-19 model considering three different image modalities, including CT to COVID-19 against pneumonia or normal. In [190], a transfer learning-based DensNet-121 approach was adopted to identify COVID-19. In order to increase more training samples, a data augmentation-based procedure was applied. Ko et al [191]. performed classification on chest CT images to classify COVID-19 pneumonia, other pneumonia, and non-pneumonia. The proposed network applied two distinct forms of data augmentation: image rotation and zoom. It used transfer learning-based pre-trained convolutional neural network (CNN) models as a backbone where ResNet-50 achieved better predictions. Ahuja et al [192]. developed a three-phase COVID19-CT detection model with three stages. For data augmentation in Phase 1, stationary wavelets decomposition was used. For binary classification in Phase 2, a trained CNN model was used. Finally, defects in CT scan images were found in Phase 3. Zheng et al [193]. proposed a model that used the 3D CT volumes to detect COVID-19. A pre-trained U-Net is used to segment the lung region of each patient. The segmented 3D lung region was fed into a 3D deep neural network to predict the probability of COVID-19 infection. Data augmentation with random affine transformation and color jittering strategies were applied to avoid the overfitting problem. The proposed model identified COVID1–19 in a faster way.

Hu et al [194]. applied sixteen data augmentation operations to enrich the training set for the training phase. The authors used CNN with ShuffleNet-V2 as a backbone to efficiently distinguish the COVID-19 patients from non-infected or infected by other pneumonia (bacterial pneumonia or SARS). Hasan et al [195]. applied a newly adopted DenseNet-121 CNN with a data augmentation technique to classify and identify COVID-19 patients. The adopted DenseNet-121 CNN resulted in better COVID-19 predictions. Some authors [196] utilized ensemble transfer learning and fine-tuned a total of 15 pre-trained convolutional neural networks (CNNs) to detect COVID-19. Data augmentation was used during training to reduce the overfitting problem of deep CNN. A COVID-19 screening strategy based on transfer learning and data augmentation was also applied in a method [197]. The VGG-16 architecture has been fine-tuned and extracted features from CT scans. For feature selection, principal component analysis (PCA) was employed. Four distinct classifiers were employed for the final classification. Bagging ensemble using SVM achieved better classification results. Using less labeled data, Hu et al [198]. achieved a weakly supervised learning framework of COVID-19 classification and lesion localization. The suggested network considered data pre-and post-processing for lung segmentation. For lesion localization, the authors used multi-scale learning followed by weakly supervised learning. Bai et al [199]. adopted the pre-trained weights of EfficientNet with data augmentation technique and classified between COVID-19 and non–COVID-19 chest CT slices. The respective information for each selected article is provided in Table 9.

3.2.2. GAN based data augmentation methods

The fundamental reason for introducing GAN-based techniques is COVID-19 benchmark datasets scarcity. The primary goal is to collect feasible CT benchmark datasets and use traditional data augmentations with CGAN to generate new images to help COVID-19 identification. Such that, Loey et al [209]. induced a deep transfer learning (DTL) model to classify COVID-19. The authors composed a small dataset and enriched their collected dataset using classical data augmentation and CGAN. After that, a classifier was used to predict COVID/non-COVID as classification outcomes. Song et al [210]. introduced a representation learning technique based on a large-scale bi-directional generative adversarial network (BigBiGAN) architecture. The architecture was mainly designed to extract semantic features from the CT images. The semantic feature matrix was utilized as input for linear classifier construction. Sedik et al [211]. proposed bi-data-augmentation models to detect COVID-19 accurately. The purpose of the two data-augmentation models was to enhance the learnability of the Convolutional Neural Network (CNN) and the Convolutional Long Short-Term Memory (ConvLSTM) based deep learning models (DADLMs). The authors also used a data-augmentation-based strategy with CGAN. The proposed DALDLM model outperformed the data-augmented CGAN model in terms of the COVID-19 detection accuracy.

Mobiny et al [212]. created a Detail-Oriented Capsule Networks DECAPS framework by boosting the COVID-19 classification accuracy. The authors adopted conditional generative adversarial networks (GANs) based data augmentation procedure on dealing with data scarcity. Goel et al [213]. established a generative adversarial network (GAN) [214] and ResNet-50 based model to classify COVID-19 and non-COVID-19. The Whale Optimization Algorithm (WOA) [215] optimized GAN parameters and generated more CT images. In the final stage of the proposed model, the newly constructed images were further fed into ResNet-50 for diagnosis purposes. Ghassemi et al [216]. utilized a cyclic generative adversarial net (CycleGAN) as data augmentation and the transfer learning strategy. The proposed model achieved a high accuracy rate, i.e., 99.60% accuracy. The respective information about each selected article is given in Table 10.

4. Discussions and future perspectives

After extensive analysis of the COVID-19 CT diagnosis literature, it is evident that the supervised and weakly supervised deep learning models have been adopted extensively. Supervised learning has quite great benefits, but it is also challenging. For instance, supervised learning helps solve real-world problems, and for that, we need to choose lots of good examples from each class while training the classifier. However, it is not easy to have extensive and good data collection in hand for training. Classifying big data is another real challenge. Moreover, the comprehensive training data should be representative rather than non-representative, which could generalize the new cases and classes. Apart from these challenges, supervised learning requires a lot of computation time.

For artificial intelligence models (both machine and deep learning models), the data is the fuel: the more data, the more accuracy and reliability of the model. Many works either modified or retrained the deep learning models by adopting the supervised learning strategies and conducted their experiments. Similarly, numerous COVID research implemented the pre-trained models and transfer learning techniques (weakly supervised).

Initially, for COVID-19 diagnosis, these learning models were applied with limited CT datasets. Gradually, relatively large COVID-19 CT datasets [222–226] were introduced. Though, these datasets are still insufficient to solve the data scarcity problem. Therefore, weakly supervised learning techniques (especially conventional transfer learning) have been adopted extensively compared to supervised learning strategies. Along with these transfer learning techniques, many researchers used synthetic data procedures such as GANs and data augmentation to address the data scarcity. Similarly, some works in sections 3.1.2 and 3.1.2.1 adopted transfer learning data adaption and few-shot learning techniques to make the COVID-19 detection models more efficient. Despite an excellent performance, such strategies still don't provide closed-end solutions.

We may see a large number of conventional transfer learning research have good performance in test and validation phases, but

Table 9
COVID-19 CT data augmentation with pre-trained Models methods and their selective information.

Source	Operations	No of CT Scans/Images/Slices/Patients	Adopted Framework	Results
Silva et al [188].	COVID-19 detection	Datasets [120,200]	EfficientNet [201]	ACC: 87.6, F1-score: 86.19, AUC: 90.5
Horry et al [189].	COVID-19 detection	Multi-Modal datasets e.g., X-ray dataset [119], Chest CT dataset [202], and Ultrasound dataset [203]	CNN pre-trained model with data augmentation technique.	VGG19 model performed well and achieved a precision of up to 84% for CT
Li et al [190].	COVID-19 identification	349 CT images with clinical findings of 216 COVID-19 patient cases	Pre-trained DensNet-121	ACC: 0.87 and F1-score: 0.86,
Ko et al [191].	COVID-19 diagnosis	3993 chest CT images, comprises COVID-19, other pneumonia, and nonpneumonia disease from various sources	CNN pretrained Models VGG16 [156], ResNet-50 [75], Inception-v3 [100], and Xception [161] with data augmentation	*Results ResNet-50 as best performer* COVID-19 pneumonia ACC: 98.67% Other pneumonia ACC: 98.63% Nonpneumonia ACC: 100%
Ahuja et al [192].	COVID-19 detection with binary classification e.g., COVID and non-COVID	349 positive CT images and 397 CT images of non-COVID patients	ResNet18, ResNet50, ResNet-101, and Squeeze-Net [159]	*On Testing* ACC: 99.4%, SEN: 100%, SPE: 98.6%, AUC: 0.9965
Zheng et al [193].	COVID-19 detection	499 CT volumes for training 131 CT volumes for testing	Pre-trained U-Net, with random affine transformation and color jittering data augmentation techniques	ACC: 0.901, PPV: 0.840, and NPV:0.982
Hu et al [194].	Classification of COVID-19 positive and negative	521 COVID-19 and 397 healthy subjects	ShuffleNet V2 [204,205]	*On Test Set* AUC:0.969, SEN:0.902, SPE:0.916, ACC:0.912
Hassan et al [195].	COVID-19 Prediction	CT Dataset [206], Sao Paulo, Brazil	DenseNet-121	*Non-COVID* PRC:0.96, RC:0.85 *COVID-19* PRC: 0.84, RC: 0.95
Shalbaf et al [196].	COVID-19 detection	COVID-CT-dataset [202]	EfficientNets(B0-B5), NasNetLarge, NasNetMobile, InceptionV3, ResNet-50, SeResnet 50, Xception, DenseNet121, ResNext50 and Inception_resnet_v2	PRC: 0.857, RC: 0.854, and ACC: 0.85
Singh et al [197].	COVID-19 detection	Covid-19 image data collection [119], Covid-ct-dataset [120], and Italian Society of Medical and Interventional Radiology [207]	VGG16 architecture, principal component analysis (PCA), deep convolutional neural network (DCNN), extreme learning machine (ELM), online sequential ELM, bagging ensemble with support vector machine (SVM), and data augmentation techniques.	*Bagging ensemble with SVM* ACC: 95.7%, PRC: 95.8%, (AUC): 0.958, and an F1-score: 95.3%
Hu et al [198].	COVID-19 infection detection	Total 450 patient scans, 150 chest CT exams of COVID-19, CAP and NP patients with additional information, and Lung Segmentation dataset [208]	CNN and U-Net	*NP with AUC: of* 0.90±0.03 *CAP with AUC:* 0.86±0.03 *COVID-19 with* AUC: 0.92±0.02
Bai et al [199].	Classification of COVID and non–COVID	132,583 CT slices	EfficientNet B4 and Fully Connected Neural Network (FCNN)	*External Testing Dataset* ACC: 87%, SEN: 89% SPEC: 86% AUC: 0.90, PRC: 0.87

it may fail in practical clinical analysis. For instance, the most pre-trained weights are borrowed from ImageNet, where the images are common objects such as cars, airplanes, humans, buses, boats, etc. On the other hand, biomedical imaging data is quite different. It is also evident from recent research [227] that traditional transfer learning is over-hyped and not much that helpful for medical image processing. Therefore, transfer learning can be utilized effectively by reusing the sophisticated features rather than over-parameterizing the standard models.

Recently, the trend has been diverting towards few-shot and self-supervised learning to address data scarcity and model efficacy. Few-shot learning is a concept for learning a common representation for a wide range of tasks and then training task-specific classifiers on top of it. Compared with the few-shot learning, self-supervised learning can do tasks without labeled data. The self-supervised learning process is multi-layered like human cognition and can acquire more knowledge from fewer and simple data. Self-supervised learning is an emerging research area and relatively less explored in COVID-19 CT diagnosis. As a result, this paradigm has a lot of promise for clinical enterprises. It can also help with deep learning's most complex challenges, such as data/sample inefficiency and subsequent expensive training.

Current medical imaging research [228–231] has demonstrated the feasibility of self-supervised learning. In order to preserve

Table 10
Selective information from GAN-based data augmentation COVID-19 diagnosis methods.

Source	Operations	No of CT Scans/Images/Slices/Patients	Adopted Framework	Results
Loey et al [209].	COVID-19 detection	Utilized CGAN network and data augmentation to construct 4425 images for the training set and 418 for the validation set from the dataset [98]	Pre-trained CNNs (AlexNet, VGGNet16, VGGNet19, GoogleNet, and ResNet50)	ACC: 82.91%, SEN: 7.66%, SPE: 87.62%
Song et al [210].	COVID-19 diagnosis and classification	Chest CT data from 227 patients (106 COVID-19 positive patients and 121 non-COVID-19 patients)	BigBiGAN [217], additionally, support vector machine (SVM) and k-nearest neighbor (KNN) were used for comparison.	*BigBiGAN performance on Test set* AUC for test set: 0.972, SEN: 92%, SPEC: 91%. *SVM AUC for Test set: 0.531* *KNN AUC for Test set: 0.998*
Sedik et al [211].	COVID-19 Detection	500 Images and training set from [218]	CNN, ConvLSTM, and data augmentation (image transformations) along with GANs	*CNN1* *CGAN DADLM Performance* SEN: 100%, SPEC: 97.8%, PPV: 97.7%, NPV: 100%, and F1-Score: 99.0%
Mobiny et al [212].	COVID-19 classification	Covid-ct-dataset [120]	Capsule Networks (CapsNets) [219,220] and GAN [221]	*For Classification* PRC: 0.843, RC: 0.915, SPEC: 0.860, ACC: 0.876, F1-score: 0.871, AUC: 0.961
Goel et al [213].	COVID-19 screening and classification	1252 COVID-19 images 1230 non-COVID-19 images	Generative adversarial network (GAN) and ResNet-50	*On Test set* ACC: 99.2%, SEN: 99.78%, SPEC:97.78%, F1-score: 98.79%
Ghassemi et al [216].	COVID-19 diagnosis	1766 abnormal slices 1397 normal slices	several pre-trained CNN networks	ACC: 99.60%

more information, Zhuo et al [228]. presented Preservational Learning. Their study compared ImageNet pre-trained model with the pre-trained model on Luna [232], BraTS [233], and LiTS [234] and found that self-supervised training on related data sets can improve the performance of segmentation and detection models for medical imaging. In [229], a Swin UNETR structure was proposed with a hierarchical encoder by leveraging the self-supervised pre-training on CT modality and outperformed all the competitors on MSD and BTCV datasets. In [230], a self-supervised model for reconstructing and predicting geometric transformations was developed. Predictions based on geometric transformations have a greater influence on learning imaging features and have shown significant performance in predicting deviant scores in clinical brain CT data. Azizi et al [231]. introduced a novel Multi-Instance Contrastive Learning (MICLe) technique that combines several pictures of the underlying pathology of each patient case to create more informative positive pairs for self-supervised learning, increasing Top-1 accuracy by 6.7%.

Similarly, a few works [235–239] successfully induced the self-supervised intuition for COVID-19 diagnosis. Taking the above discussion into account, self-supervised learning has the protentional and can be applied successfully. For instance, combining the composition of data augmentations, introducing a learnable nonlinear transformation, and contrastive learning from larger batch sizes and more training steps can uplift the performance of a predictive model [167]. Likewise, the famous Momentum Contrast (MoCo) can be adapted to facilitate contrastive unsupervised learning [240]. Besides, the Masked autoencoders (MAE) introduced by He et al [241]. can be utilized to reconstruct the missing pixels and enable the model to learn richer semantic representations.

Another factor is evaluating the reliability and efficacy of intelligent diagnostics systems before their deployment into real-time practices; thus, uncertainty quantification [242] becomes essential [243–245]. This extra vision attempts to improve the overall trustworthiness of the systems so that clinicians and users can understand when and where they may trust the models' predictions [246]. In other words, the uncertainty quantification minimizes the poor generalization of a model in real-world clinical practice [247]. Consequently, accurate uncertainty estimations are required to improve the model's efficacy and apply it to the medical domain with trust and reliability. Therefore, to quantify the uncertainty of traditional deep learning methods, the Bayesian Deep Learning (BDL) methods can be a great solution [248]. Modeling uncertainty quantification not only improves the predictive performance but is also capable of detecting predictive failures [249].

5. Conclusion

Despite the current gold standard RT-PCR and other COVD-19 diagnosis tests, CT diagnosis by computer vision and artificial intelligence is an active area of research. Considerable research has been conducted, and many research articles cascaded that extensive spontaneous research works in the form of review articles by considering different aspects. Inspired by that, in this review article, we explored, arranged, and classified COVID-19 CT diagnosis research. For this purpose, we collected the relevant literature and categorized the collected techniques according to multi-level supervised and weakly supervised learning. Many works adopted the supervised schemes, such as network backbones and network block-based procedures.

On the other hand, due to the limitations of COVID-19 CT datasets, weakly supervised learning approaches gained much attention compared to supervised learning. To predict COVID-19, the pre-trained models with data-augmentation procedures are extensively adopted with traditional transfer learning. It is noted that recently, domain adaptation-based transfer learning methods have been introduced, which is helpful to alleviate data scarcity to some extent. However, limited attention has been given to self-supervised learning, which can do tasks without massive amount of labeled data. Therefore, self-supervised strategies could be another ultimate solution for COVID-19 CT analysis and dataset scarcity. Last but not least, uncertainty quantification procedures are also essential to evaluate the reliability of a diagnostic system before its deployment into clinical practices.

Declaration of Competing Interest

The authors declare no conflict of interest.

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