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Medical imaging and computational image analysis in COVID-19 diagnosis: A review

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ABSTRACT

Coronavirus disease (COVID-19) is an infectious disease caused by a newly discovered coronavirus. The disease presents with symptoms such as shortness of breath, fever, dry cough, and chronic fatigue, amongst others. The disease may be asymptomatic in some patients in the early stages, which can lead to increased transmission of the disease to others. This study attempts to review papers on the role of imaging and medical image computing in COVID-19 diagnosis. For this purpose, PubMed, Scopus and Google Scholar were searched to find related studies until the middle of 2021. The contribution of this study is four-fold: 1) to use as a tutorial of the field for both clinicians and technologists, 2) to comprehensively review the characteristics of COVID-19 as presented in medical images, 3) to examine automated artificial intelligence-based approaches for COVID-19 diagnosis, 4) to express the research limitations in this field and the methods used to overcome them. Using machine learning-based methods can diagnose the disease with high accuracy from medical images and reduce time, cost and error of diagnostic procedure. It is recommended to collect bulk imaging data from patients in the shortest possible time to improve the performance of COVID-19 automated diagnostic methods.

1. Introduction

Coronaviruses are a large family of viruses that cause disease in humans in the form of a common cold to more severe respiratory infections. An infectious disease caused by a newly discovered coronavirus, also known as COVID-19, is a disease that causes an acute respiratory syndrome, which can lead to the death of infected patients. The disease was first seen in December 2019 in Wuhan, China, and eventually became a global pandemic. According to the official statistics, the number of people infected with the disease had reached over 177 million worldwide, with over 3 million deaths until the middle of 2021 [1].

Patients have a variety of symptoms during the illness, including shortness of breath, fever, dry cough, and chronic fatigue. Sometimes the symptoms are so severe in patients they can be fatal. The leading cause of transmission is the contact of the person's hand with the contaminated surfaces and then touching the face. Despite many efforts by scientists, there is currently no definitive treatment for the disease. Therefore, the main advice to prevent infection is to observe personal hygiene by regularly washing hands, disinfecting surfaces and covering the airways with a mask [2].

CT imaging has been proposed as one way to diagnose the disease. A large number of studies have been published on the role of medical imaging in the diagnosis of this disease in the short time since the outbreak stage. Many researchers in medical image analysis are also seeking to provide artificial intelligence (AI) based solution for the automatic diagnosis of the disease based on medical images. This review provides a summary of peer-reviewed research articles, conference papers, case reports and letters to the journal editors related to the role of imaging and also peer-reviewed research articles and conference papers related to medical image analysis in COVID-19 to help other researchers in conducting their studies due to the importance of this disease and its destructive effects on societies. PubMed, Scopus and Google Scholar

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List of abbreviations

AI	Artificial Intelligence
COVID-19	Coronavirus disease 2019
CT	Computed Tomography
CXR	Chest X-ray
PCR	Polymerase Chain Reaction
RT-PCR	real-time Reverse transcription-PCR
NAAT	Nucleic acid amplification test
ESR	The European Society of Radiology
ESTI	The European Society of Thoracic Imaging
GGO	Ground-glass opacity
FDG	FluoroDeoxyGlucose
PET	Positron Emission Tomography
SPECT	Single-photon Emission Computed Tomography
MRI	Magnetic Resonance Imaging
CNN	Convolutional Neural Network
BCNN	Bayesian CNN
AE	Auto-encoder
GAN	Generative Adversarial Network
CGAN	Conditional GAN
SVM	Support Vector Machine
KNN	K-nearest Neighbours
MLP	Multi-layer Perceptron
GRU	Gated Recurrent Unit
ResExLBP	Residual Exemplar Local Binary Pattern
IRF	Iterative ReliefF
DT	Decision Tree
LD	Linear Discriminant
SD	Subspace Discriminant
AUC	Area Under the Curve
GLCM	Grey-Level Co-occurrence Matrix
GLDM	Gray Level Difference Method
LDP	Local Directional Pattern
GLRLM	Grey-Level Run Length Matrix
GLSZM	Grey-Level Size Zone Matrix
DWT	Discrete Wavelet Transform
RF	Random Forest
SNR	Signal-to-Noise Ratio
CNR	Contrast-to-Noise Ration
PPV	Positive Predictive Value
DECAPS	Detail-Oriented Capsule Networks
ICU	Intensive Care Unit
SMOTE	Synthetic Minority Over-Sampling Technique
FrMEMs	Fractional Multichannel Exponent Moments
MRFO	Manta-Ray Foraging Optimization
DE	Differential Evolution
HSGO	Hybrid Social Group Optimization

were searched for all outstanding peer-reviewed journal articles and the most cited articles, conference papers, case reports and letters to the journal editors that fulfil the following selection criteria until the middle of 2021:

- the role of all different medical imaging modalities in COVID-19 diagnosis;
- imaging findings related to COVID-19;
- advice and statements for using imaging in COVID-19 diagnosis;
- automated methods for detection and classification COVID-19 based on medical imaging data.

The rest of this review is structured as followed. Section 2 describes the contributions of the role of medical imaging in COVID-19 diagnosis. In this section, many articles, case reports, and letters to editors related to this field are reviewed so the reader can understand the main points of these articles and pick up with literature and critical contributions quickly. In section 3, articles related to automatic methods in the detection of COVID-19 based on AI techniques are reviewed. Finally, in section 4, this article concludes with a discussion and an outlook for future studies.

2. The role of imaging in COVID-19 diagnosis

There are several ways to detect COVID-19, including real-time reverse transcription-polymerase chain reaction (RT-PCR) and the nucleic acid amplification test (NAAT). Because often the test results may be negative despite having the person infected, and asymptomatic infections can spread the infection, there is a need for a more careful approach to diagnosis. Some studies and reports confirm that medical imaging can be an effective way to diagnose COVID-19 infection, even if the patient is asymptomatic. Therefore, where it is impossible to access the above tests, medical imaging can help diagnose the disease and prevent its spread in asymptomatic patients. In this section, we review studies that have been published on the role of medical imaging in the diagnosis of COVID-19. We summarise the most essential points of view of articles, including the features of the disease in medical images. The number of reviewed studies related to the diagnosis of COVID-19 based on imaging features in the mentioned period is 138, 19, 18, 7 and 3 for CT imaging, chest X-ray, ultrasound, ^{18}F-FDG PET/CT and other modalities, respectively.

The study of Revel et al. [3] provides advice from the European Society of Radiology (ESR) and the European Society of Thoracic Imaging (ESTI) about COVID-19 patients for radiology departments. In this study, the appropriate imaging technique for diagnosis and follow-up of COVID-19 patients is described. According to this study, chest radiography cannot be a useful modality in diagnosing COVID-19 pneumonia due to the lack of sensitivity in detecting GGO, which is the primary visual feature of COVID-19. Therefore, using chest radiography should be limited to the patient's follow-up and patients who cannot be CT scanned. Also, the use of chest ultrasound due to limitations such as the inability to differentiate viral and bacterial pneumonia cannot be a promising modality in the diagnosis of COVID-19. According to this recommendation, CT imaging has the necessary sensitivity in diagnosing the imaging characteristics of the disease in COVID-19 patients. This point can also be seen in the number of studies related to CT imaging's role in diagnosing COVID-19 than other modalities.

In the study of Rodrigues et al. [4], chest imaging findings were examined in the literature. Some pointed out that decisions should be made regarding determining medical imaging as a screening tool in patients with different severity of the disease. In the study of Nair et al. [5], the use of CT imaging in the diagnosis and management of COVID-19 disease in the UK was investigated by asking several questions and answering them. This study considers the results of CT imaging as a standard in the diagnosis of COVID-19 to be contradictory. As another example, in the study of Huang et al. [6], it is emphasised that CT imaging should not be recommended as a screening tool in the early diagnosis of COVID-19 due to two issues. The first is failure to prove that CT imaging can always succeed in diagnosing COVID-19, and the second is that overexposure of patients to radiation can have long-term adverse effects. Raptis et al. in their review study [7] concluded that the studies that have examined the role of CT imaging in the diagnosis and management of COVID-19 could not prove this role due to their limitations. Although some studies have debunked the role of medical imaging in the diagnosis of COVID-19, many studies have attempted to prove its importance by expressing the imaging features of the disease, and using

CT imaging is considered an effective solution in early diagnosis, severity assessment and patient management in the progression of COVID-19 [8–19].

In the study of Zhu et al. [20], 34 studies with 4121 COVID-19 patients have been systematically reviewed. The main features of CT in this study are ground-glass opacities (GGOs), air bronchogram sign, crazy-paving pattern, consolidation, pleural thickening, lymphadenopathy, and pleural effusion, respectively. Also, Lesion shapes are patchy, spider web sign, cord-like, and nodular. In the study of Li [21], the importance of using chest CT for the diagnosis and follow-up of COVID-19 patients has been investigated. CT features at different stages of the disease are different according to previous studies. Hani et al. [22], CT imaging has been cited as a critical complement in the diagnosis of COVID-19. CT features have been described as peripheral GGOs with multifocal distribution, and a progressive evolution towards organizing pneumonia patterns. According to a meta-analysis by Xu et al. [23], GGO and consolidation are the most common CT finding among the 16 studies reviewed. The results of this study indicate the high sensitivity of chest CT in the early detection of COVID-19. The results of a systematic review of 45 studies related to imaging manifestations of COVID-19 show that GGO with and without consolidation is the most common CT finding among 4410 adult patients with COVID-19 [24]. A study of radiographic findings in 240 COVID-19 patients with one of the highest statistical population of patients examined in chest radiographic modality, GGO and reticular alteration are the most important findings [25]. Besides, a meta-analysis of 33 studies with 1911 patients, including 934 patients with COVID-19, reported the main CT findings in these patients as GGO and consolidation [26].

In another systematic review study conducted by Bao et al. [27], 13 studies have been reviewed. CT characteristics have been listed as GGO, GGO with mixed consolidation, adjacent pleura thickening, interlobular septal thickening, air bronchograms, crazy-paving pattern, pleural effusion, bronchiectasis, pericardial effusion, and lymphadenopathy, respectively. The most anatomic distributions are bilateral lung infection and peripheral distribution. In the study by Salehi et al. [28], 30 studies consisting of 19 case series and 11 case reports with a total of 919 patients were systematically reviewed. CT findings are included GGO, bilateral involvement, peripheral distribution, and multilobar involvement. Other CT findings include interlobular septal thickening, bronchiectasis, pleural thickening, and subpleural involvement. Rarely found findings include pleural effusion, pericardial effusion, lymphadenopathy, cavitation, CT halo sign, and pneumothorax.

One of the areas in which medical imaging can help is the severity assessment of COVID-19. The severity assessment of COVID-19 can play an essential role in early management and treatment of patients. The disease's severity can be scored based on the type of imaging findings and the rate of progression of these findings. There are studies on how to score the severity of COVID-19 disease based on CT [29,30], CXR [31], and ultrasound [32] imaging findings. The study of Wasilewski et al. [33] has comprehensively examined different scoring systems in determining the severity of COVID-19 disease based on CT and CXR images. Based on previous studies, CT imaging can determine the severity of the disease with better sensitivity than other imaging modalities [34–37].

2.1. Computed Tomography

CT imaging has been widely used as a fundamental modality in the diagnosis of COVID-19 in the studies. High-resolution [38–43], low-dose [44,45], thin-section [46,47] and spiral [48] CT imaging are mentioned as a main modality in some of researches.

Some studies have shown that CT imaging is insufficient or incapable as a diagnostic modality for COVID-19 [49–51]. Some other studies show misdiagnosis in early-stage patients of COVID-19 [39], and propose the combination of CT imaging and clinical findings for better diagnosis of COVID-19 [52,53], especially in children [29,54,55]. A large number of studies have reported the importance of CT imaging in the diagnosis of COVID-19, and CT features related to the patients infected with COVID-19.

GGOs, patchy and wedge-shaped GGOs, consolidation, vascular enlargement and thickening, interlobular septal thickening, interstitial thickening, air bronchogram sign, fibrotic lesions, pleural effusion, crazy-paving pattern, linear and rounded opacities, reticulation, fine reticular opacity, subpleural and central lesions, irregular solid nodules, interstitial pulmonary oedema, halo sign, reversed-halo sign, architectural distortion, bronchial wall thickening, subpleural bands, traction bronchiectasis, intrathoracic lymph node enlargement, lymphadenopathy, thickening of the adjacent pleura, cystic changes, cord-like lesions, thickening of the bronchovascular bundles, pleural thickening, cavitation, tree-in-bud sign, interlobar fissure displacement, pericardial effusion, concomitant hydropericardium and/or hydrothorax, thickened lobular septum, thickened bronchial wall, vacuolar sign, bronchiolar dilatation, secondary tuberculosis, paving stone sign, pleural retraction sign, fine mesh shadow, pneumatocele, spider web sign, enlarged mediastinal nodes, underlying pulmonary emphysema, bullae of lung and obsolete tuberculosis and thickened leaflet interval are CT findings of patients with COVID-19 in the collected studies (Refer to Table 1).

Some studies have individually examined the characteristics of CT in children. A study by Li et al. [56], which was performed on five children, has found patchy GGOs as the main characteristic of CT in children with COVID-19 and believed that the abnormalities in CT images of children are similar but milder than those of adults. The study of Zhu et al. [57], which was performed on 44 younger (47.5 ± 8.7 y old) and 28 older patients (68.4 ± 6.0 y old) with COVID-19, despite the reporting of some similar CT features among younger and older patients, considers it more likely that extensive lung lobe involvement, subpleural line and pleural thickening will occur in older patients. The study of Feng et al. with 15 cases of paediatric patients diagnosed with COVID-19 [58], identified small nodular and speckled GGOs as the main features in CT images of these patients. Another study also described CT findings in children as milder than in adults [41]. In a study of nine children with COVID-19 aged 0–3 years by Zhou et al. [55], the CT findings are nodular lesions, patchy lesions, GGO with consolidation and halo sign noted to be milder than in adults. In their study, Liu et al. [29] believe that a history of exposure and clinical symptoms may be more useful in the screening of COVID-19 in children than CT imaging. Procalcitonin elevation and consolidation with surrounding halo signs are frequent in paediatric-patients than adults based on the study of Xia et al. [54].

Studies have also been performed in pregnant women with COVID-19. According to Wu et al. [45], the CT findings in pregnant women are similar to those in non-pregnant women. In the study by Liu et al. [29], consolidation has been described as a more common CT feature in pregnant women.

Table 1 is an overview of studies that have examined the role of CT imaging in the diagnosis of COVID-19. These studies have five or more cases of COVID-19, which are sorted based on the number of cases. CT and other related findings are summarised for each study. Table 2 deals with studies on CT imaging for COVID-19 diagnosis with less than five cases mostly written as a case report or letter to the editor. In these tables, to acquaint researchers with the studies conducted in this field, the number of cases, the features of COVID-19 infection in the studied images and the findings or essential points of these studies are summarised.

2.2. Chest X-Ray

Among the reviewed studies, 17 studies have focused on the signs of COVID-19 in CXR images. In the study of Jacobi et al. [59], which is a pictorial review, the possibility of using portable CXR imaging in the diagnosis of COVID-19 has been investigated due to its availability in most medical centres. Based on this research, CXR imaging also provides the ability to detect COVID-19. Zhang et al. have reported that the combination of clinical features and radiological findings can predict the severity of COVID-19 [53]. In their study [60], Wang et al. believe that

Table 1
Overview of studies on CT imaging that have five or more cases of COVID-19.

References	No. of cases	CT findings	Other findings
Ai et al. (2020) [129]	1014	GGOs, consolidation, reticulation/thickened interlobular septa and nodular lesions	Chest CT has a high sensitivity for the diagnosis of COVID-19.
Besutti et al. (2020) [130]	696	GGO and consolidation	CT showed a high positive predictive value and sensitivity for COVID-19 pneumonia compared with RT-PCR.
Zhang et al. (2020) [53]	645	GGOs and consolidation	Combing clinical features and radiographic scores can effectively predict severe/critical types.
Ling et al. (2020) [50]	295	Four patients with COVID-19 infection showed no clinical symptoms or abnormal chest CT images	The clinical symptoms and radiological abnormalities are not the essential components of COVID-19 infection.
Liu et al. (2020) [131]	276	GGO, consolidation, GGO with consolidation, nodule, patchy shadowing, lineal shadowing, air bronchogram sign, interlobular septal thickening, adjacent pleura thickening, crazy-paving pattern and bronchodilation	The common chest CT signs of COVID-19 pneumonia after exacerbation were ground glass opacity (GGO) with consolidation, bilateral distribution, and multifocal lesions.
Yang et al. (2020) [132]	273	GGOs, consolidation and linear opacities, solid nodules, fibrous stripes, chronic inflammatory manifestation, chronic bronchitis, emphysema, pericardial effusion, pleural effusion, bullae of lung and obsolete tuberculosis	Age, Monocyte-lymphocyte ratio, homocysteine and period from onset to admission could predict imaging progression on chest CT from COVID-19 patients.
Li et al. (2020) [133]	154 COVID-19 and 100 non-COVID-19	GGO and consolidation	A peripheral distribution, a lesion range > 10 cm, involvement of 5 lobes, presence of hilar and mediastinal lymph node enlargement, and no pleural effusion were significantly associated with COVID-19.
Colombi et al. (2020) [134]	236	Patchy GGO, diffuse GGO, GGO and consolidation, pleural effusion, mediastinal nodes enlargement, emphysema and pulmonary fibrosis	In patients with confirmed COVID-19 pneumonia, visual or software quantification the extent of CT lung abnormality were predictors of ICU admission or death.
Dai et al. (2020) [38]	234	Vascular enhancement sign, interlobular septal thickening, air bronchus sign, intralesional and/or perilesional bronchiectasis, pleural thickening, solid nodules, reticular/mosaic sign, interlobar fissure displacement, bronchial wall thickening, minor pleural effusion, pericardial effusion and	Chest High-resolution CT provided the distribution, shape, attenuation and extent of lung lesions, and some typical CT signs of COVID-19 pneumonia.

Table 1 (*continued*)

References	No. of cases	CT findings	Other findings
		mediastinal lymphadenopathy	
Bai et al. (2020) [135]	219	GGO, fine reticular opacity and vascular thickening	High specificity but moderate sensitivity in distinguishing COVID-19 from viral pneumonia on chest CT.
Liu et al. (2020) [136]	122 COVID-19 and 48 non-COVID-19	GGO, GGO with consolidation, consolidation, linear opacities, rounded opacities, crazy paving pattern, halo sign, nodules, tree-in-bud sign, air bronchogram, interlobular septal thickening, bronchiolar wall thickening, pleural effusion, pericardial effusion and lymphadenopathy	There are significant differences in the CT manifestations of patients with COVID-19 and influenza.
Caruso et al. (2020) [137]	158	GGO, subsegmental vessel enlargement, consolidation, lymphadenopathy, bronchiectasis, air bronchogram, pulmonary nodules surrounded by GGO, interlobular septal thickening, halo sign, pericardial effusion, pleural effusion and bronchial wall thickening	Chest CT sensitivity was high (97%) but with lower specificity (56%).
Fan et al. (2020) [138]	150	Ground-glass nodules, patchy GGO, consolidation, cord-like lesions, thickening of the bronchovascular bundles, pleural thickening, crazy-paving sign, air bronchogram sign, pleural effusion and enlarged lymph nodes	The main manifestations of initial chest CT in COVID-19 is GGOs, commonly involving single site in patients < 35 years old and multiple sites and extensive area in patients > 60 years old.
Yang et al. (2020) [51]	149	GGO, mixed GGOs and consolidation, consolidation, air bronchogram, centrilobular nodules, tree-in-bud, reticular pattern, subpleural linear opacity, bronchial dilatation, cystic change, lymphadenopathy and pleural effusion	Some patients with COVID-19 can present with normal chest findings.
Chen et al. (2020) [139]	70 COVID-19 and 66 non-COVID-19	Pure GGO, mixed GGO, consolidation, pleural traction sign, bronchial wall thickening, interlobular septal thickening, crazy paving, tree-in-bud, pleural effusions, pleural thickening and the offending vessel augmentation in lesions	The pneumonia patients with and without COVID-19 can be distinguished based on CT imaging and clinical records.
Li et al. (2020) [140]	131	GGOs, consolidation, nodule, interlobular septal thickening, vascular enlargement, air bronchogram, fibrosis, pleural thickening, hydrothorax and lymph node enlargement	The imaging pattern of multifocal peripheral ground glass or mixed consolidation is highly suspicious of COVID-19, that can quickly change over a short period.
	130	GGO, GGO with consolidation, vascular	COVID-19 imaging characteristic mainly

(*continued on next page*)

Table 1 (*continued*)

References	No. of cases	CT findings	Other findings
Wu et al. (2020) [141]		thickening, pleural parallel sign, intralobular septal thickening, halo sign, reversed-halo sign, pleural effusion and pneumatocele	has subpleural, centrilobular and diffused distribution. The first two distributions can overlap or progress to diffused distribution. In the later period, it was mainly manifested as organising pneumonia and fibrosis. The most valuable characteristic is the pleural parallel sign.
Wu et al. (2020) [142]	130	GGO, GGO with consolidation, parallel pleura sign, paving stone sign, air bronchogram, bronchiectasis, vascular thickening, halo sign, reversed-halo sign, pleural effusion and pneumonocele	GGO and consolidation are the most common CT signs of COVID-19.
Bernheim et al. (2020) [143]	121	GGOs, GGO with consolidation, consolidation, linear Opacities, rounded morphology of opacities, crazy paving pattern, reverse-halo sign, pleural effusion and underlying pulmonary emphysema	Recognising imaging patterns based on infection time course is paramount for helping to predict patient progression and potential complication development.
Zhang et al. (2020) [144]	120	GGOs, nodules, linear densities, consolidation, crazy paving, bronchiectasis, effusion, lymphadenopathy, air bronchograms, tree-in-bud sign and white lung	Using chest CT as the primary screening method in epidemic areas is recommended.
Hossain et al. (2020) [145]	119	GGOs, consolidation, crazy paving, pleural effusions, pleural thickening, bronchiectasis and air trapping	A significant proportion of patients who did not have the respiratory syndrome and underwent non-chest CT scans had evidence of COVID-19 on their CT scans.
Zhao et al. (2020) [146]	118	GGO, consolidation, centrilobular nodules, architectural distortion, bronchial wall thickening, reticulation, subpleural bands, traction bronchiectasis, vascular enlargement, intrathoracic lymph node enlargement and pleural effusions	The follow-up CT changes during the treatment could help evaluate the treatment response of patients.
Wang et al. (2020) [48]	114	GGO, consolidation and pleural effusion	Spiral CT can make an early diagnosis and for evaluation of progression, with a diagnostic sensitivity and accuracy better than that of nucleic acid detection.
Han et al. (2020) [147]	108	GGO, consolidation, GGO with consolidation, vascular thickening, crazy paving pattern, air bronchogram sign and halo sign	
Wang et al. (2020) [148]	13 COVID-19 and 92 non-COVID-19	GGO, consolidation, GGO with consolidation, air bronchogram and intralobular septal thickening	CT can be used with reasonable accuracy to distinguish influenza from COVID-19.
Zhao et al. (2020) [149]	101	GGOs, consolidation, mixed GGOs and consolidation, centrilobular nodules, architectural distortion, bronchial wall thickening, reticulation, subpleural bands, traction bronchiectasis, intrathoracic lymph node enlargement, vascular enlargement and pleural effusions	
Huang et al. (2020) [150]	100	GGO, consolidation, crazy-paving pattern, bronchiectasis, interlobular septal thickening and lymphadenopathy	The mechanism of CT features is explicable based on pathological findings.
Zhou et al. (2020) [151]	100	GGO, consolidation, GGO with consolidation, thickened interlobular and intralobular septum, crazy-paving, vacuolar sign, microvascular dilation, air bronchogram, subpleural transparent line, thickening of the pleura, pleural retraction, pleural effusion, subpleural line, bronchus distortion, fibrotic strips, lymphadenopathy, pneumothorax and pneumomediastinum	The main CT features of COVID-19 pneumonia mainly included GGO, GGO with consolidation, and GGO with reticular pattern.
Li et al. (2020) [152]	98	GGO, consolidation, vascular enlargement, interlobular septal thickening, air bronchogram and air trapping	Consolidations on CT images were more common in dead patients than in survival patients.
Wang et al. (2020) [153]	90	GGO, consolidation, crazy-paving pattern and pleural effusion	The extent of CT abnormalities progressed rapidly after symptom onset, peaked during illness days 6–11, and followed by persistence of high levels.
Xu et al. (2020) [154]	90	GGO, consolidation, crazy-paving pattern, interlobular septal thickening, linear opacities combined, air bronchogram sign, adjacent pleura thickening, pleural effusion, pericardial effusion and lymphadenopathy	
Liang et al. (2020) [155]	88	GGO, consolidation, linear opacities, discrete pulmonary nodules and cavitation	
Li et al. (2020) [34]	83	GGO, linear opacities, consolidation, interlobular septal thickening, crazy-paving pattern, spider web sign, bronchial wall thickening, subpleural curvilinear line, nodule, reticulation, lymph node	

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Table 1 (*continued*)

References	No. of cases	CT findings	Other findings
		enlargement, pleural effusion and pericardial effusion	
Shi et al. (2020) [52]	81	Bilateral, subpleural, GGOs with air bronchograms, ill-defined margins, and a slight predominance in the right lower lobe, irregular interlobular septal thickening, crazy-paving pattern, thickening of the adjacent pleura, nodules, cystic changes, bronchiectasis, pleural effusion, lymphadenopathy, consolidation patterns and reticular patterns	CT findings vary depending on the time interval between the onset of symptoms and the CT performing.
Wu et al. (2020) [156]	80	GGO, consolidation, interlobular septal thickening, crazy-paving pattern, spider web sign, subpleural line, bronchial wall thickening, lymph node enlargement, pericardial effusion and pleural effusion	
Li et al. (2020) [49]	78	GGOs, mixed GGOs, consolidation, interlobular septal thickening, air bronchograms, fibrotic lesions and pleural effusion	No centrilobular nodules or lymphadenopathy.
Liu et al. (2020) [35]	73	Unique GGOs, multiple GGOs, paving stone sign, consolidation, bronchial wall thickening, pleural effusion and thickening of lung texture	The size and CT abnormalities are related to disease severity.
Zhu et al. (2020) [57]	44 younger and 28 older	Pure ground-glass, GGO with consolidation, consolidation, reticular pattern or honeycombing, subpleural line, pleural thickening, pleural traction, pleural effusion, vacuolar sign, air bronchogram and vascular enlargement	Elderly and younger patients with COVID-19 have some similar CT features. However, older patients are more likely to have extensive lung lobe involvement, and subpleural line and pleural thickening.
Zhong et al. (2020) [157]	67	Solid plaque shadow, halo sign, fibrous strip shadow with ground-glass shadow and consolidation shadow	A solid shadow may predict severe and critical illness.
Pan et al. (2020) [42]	63	Patchy/punctate GGOs, GGOs, patchy consolidation, fibrous stripes and irregular solid nodules	
Zhou et al. (2020) [158]	62	GGO, consolidation, GGO with consolidation, nodule, rounded opacities, crazy-paving pattern, air bronchogram, halo sign, subpleural curvilinear line, thoracic lymphadenopathy, pleural effusion or thickening and pulmonary fibrosis	In patients with dyspno and respiratory distress, CT examination is very practical in the preclinical screening of patients with COVID-19.
Zhou et al. (2020) [159]	62	GGO, consolidation, GGO plus a reticular pattern, vacuolar sign, microvascular dilation sign, fibrotic streaks, subpleural line, subpleural transparent line, air bronchogram, bronchus distortion, thickening of pleura, pleural retraction sign and pleural effusion	GGO and a single lesion at the onset of COVID-19 pneumonia suggested that the disease was in its early phase. Pleural effusion might occur in the advanced phase.
Zhang et al. (2020) [160]	60	GGO, consolidation, linear opacities, crazy-paving pattern, air bronchogram, emphysema, fibrosis, calcification, pleural effusion and pericardial effusion	This study included critically ill COVID-19 patients with GGO, crazy-paving pattern and air bronchogram as the most common CT findings.
Liu et al. (2020) [29]	59	Pure GGO, GGO with consolidation, GGO with reticulation, consolidation and pleural effusion	Atypical clinical findings of pregnant women with COVID-19 could increase the difficulty in initial identification. Consolidation was common in the pregnant groups. The chest CT imaging features of children with COVID-19 pneumonia were non-specific. At the same time, the exposure history and clinical symptoms could be more helpful for the screening.
Meng et al. (2020) [161]	58	GGO with peripheral distribution and unilateral location, fine reticulation, subpleural curvilinear line, halo sign, air bronchogram, vascular enlargement and consolidation	CT scan has great value in the highly suspicious, asymptomatic cases with negative nucleic acid testing.
Lomoro et al. (2020) [66]	58	GGO, GGO with consolidation, crazy-paving patterns, fibrous stripes, subpleural lines, architectural distortion, air bronchogram sign, perilesional vascular thickening, scattered nodules, enlarged mediastinal lymph nodes and pleural effusion	
Fu et al. (2020) [162]	56	GGO, GGO with consolidation, consolidation, thickened small vessels within opacity, air bronchograms, interlobular septal thickening and crazy-paving pattern	CT plays a crucial role in early diagnosis and assessment of COVID-19 pneumonia progression.
Li and Xia (2020) [163]	53	GGOs and consolidation with or without vascular enlargement, interlobular septal thickening and air bronchogram sign	Low rate of misdiagnosis of COVID-19 in CT images.
Guan et al. (2020) [46]	53	GGO, crazy paving, consolidation, stripe, air bronchogram, pulmonary nodules and secondary tuberculosis	Identification of CT features of COVID-19 pneumonia provides timely diagnostic evidence.
	52	GGOs, patchy consolidation and sub-	The chest CT images of patients with COVID-

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Table 1 (*continued*)

References	No. of cases	CT findings	Other findings
Wang et al. (2020) [164]		consolidation, air bronchi sign, thickened leaflet interval and fibrous stripes	19 have specific characteristics with dynamic changes, which are of value for monitoring disease progress and clinical treatment.
Lin et al. (2021) [165]	52	GGO, consolidation, GGO with consolidation, mosaic attenuation, bronchial wall thickening, Centrilobular nodules, interlobular septal thickening, crazy paving pattern, air bronchogram and mucoid impaction	Most lesions in patients with COVID-19 pneumonia were located in the peripheral zone and close to the pleura, whereas influenza virus pneumonia was more prone to show mucoid impaction and pleural effusion.
Lyu et al. (2020) [36]	51	Consolidation, crazy-paving pattern and air bronchogram	Severity assessment of COVID-19 pneumonia based on chest CT would be feasible for critical cases.
Fang et al. (2020) [166]	51	GGOs, GGO with consolidation, consolidation and linear opacity	The sensitivity of CT for COVID-19 infection is 98% compared to RT-PCR sensitivity of 71%.
Xu et al. (2020) [167]	50	GGO, mixed GGOs and consolidation, consolidation, thickened intralobular septa, thickened interlobular septa, air bronchogram, pleural effusion and enlarged mediastinal nodes	Repeated CT scanning helps monitor disease progression and implement timely treatment.
Lei et al. (2020) [168]	49	GGOs, interstitial thickening, and consolidation, fibrosis, parenchymal band, traction bronchiectasis and irregular interfaces	
Yang et al. (2020) [169]	44	Pure GGOs, GGO with consolidation, GGO with interlobular septal thickening, consolidation, vessel expansion, air bronchogram, mediastinal lymphadenectasis and pleural effusion	The features of early-stage COVID-19 include GGO-based lesions with rare small size consolidation mainly distributed in the peripheral and posterior part of the lung.
Xiong et al. (2020) [43]	42	Single or multiple GGO, consolidation, interstitial thickening or reticulation, air bronchograms, pleural effusion and fibrous strips	
Long et al. (2020) [170]57	36	GGOs, GGO with consolidation, lymphadenopathy and pleural effusion	Patients with typical CT findings but negative RRT-PCR results should be isolated.
Chen et al. (2020) [171]	34	Pure GGO, GGO with reticular and/or interlobular septal thickening, GGO with consolidation, pleural effusion, pleural thickening and pericardial effusion	Chest CT is crucial for the early diagnosis of COVID-19, particularly for those patients with a negative RT-PCR.
Liu et al. (2020) [172]	33	Subpleural lesions, central lesions, ground-glass density shadow, consolidation, interstitial change and interlobular septal thickening	An important basis of CT images for early detection and disease monitoring.
Cheng et al. (2020) [173]	11 COVID-19 and 22 non-COVID-19	GGO, mixed GGO, consolidation, air bronchogram, centrilobular nodules, tree-in-bud sign, reticular pattern, subpleural linear opacity, bronchial dilatation and cystic change	findings of more extensive GGO than consolidation on chest CT scans obtained during the first week of illness were considered findings highly suspicious of COVID-19.
Zhou et al. (2020) [174]	29	GGO, GGO with consolidation, consolidation, interlobular septa thickening, parenchymal bands, air bronchogram, pleural thickening, architectural distortion and pleural effusion	Chest CT reflects the development of COVID-19 pneumonia.
Yuan et al. (2020) [175]	27	GGO, consolidation, GGO with consolidation, air bronchogram, Nodular opacities and pleural effusion	A simple CT scoring method was capable of predicting mortality.
Dane et al. (2020) [176]	23	GGO, ground-glass nodule, solid nodule, consolidation, halo sign and interstitial thickening	
Wu et al. (2020) [45]	23	GGO, patchy, wedge-shaped ground-glass shadows, intralobular interstitial thickening with consolidation, fibrous stripes and concomitant hydropericardium and/or hydrothorax	Radiological findings and clinical characteristics in pregnant women with COVID-19 were similar to those of non-pregnant women with COVID-19.
Himoto et al. (2020) [177]	21	Bilateral GGO, peripheral-predominant lesions without airway abnormalities, mediastinal lymphadenopathy and pleural effusion	Important supplemental role of CT imaging to triage and detect patients suspected COVID-19 pneumonia, before getting the results of RT-PCR.
Chung et al. (2020) [178]	21	GGOs, GGO with consolidation, consolidation, rounded morphology, linear opacities and crazy-paving pattern	
Pan et al. (2020) [179]	21	GGOs, crazy-paving pattern, inter- and intralobular septal thickening and consolidation	Chest CT signs of improvement began at approximately 14 days after the onset of initial symptoms.
Chen et al. (2021) [180]	21	GGO, consolidation with a subpleural distribution, air bronchogram, vascular enlargement, interlobular septal thickening and pleural effusions	Chest CT is important in the screening of patients in whom disease is clinically suspected, especially those who have negative initial RT-PCR results.
Xia et al. (2020) [54]	20	Consolidation with surrounding halo sign, GGOs, fine mesh shadow, tiny nodules, interlobular septal thickening, fibrosis lesions, air bronchogram signs and pleural thickening	Procalcitonin elevation and consolidation with surrounding halo signs were frequent in paediatric patients.
Zhu et al. (2020) [181]	7 patients with Heart failure and	GGO and thickening of the interlobular septum in both group. In heart	There are significant differences in chest CT features, such as

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Table 1 (*continued*)

References	No. of cases	CT findings	Other findings
	12 with COVID-19	failure group, the ratio of the expansion of small pulmonary veins was also higher.	enlargement of pulmonary veins, lesions distribution and morphology between heart failure and COVID-19.
Han et al. (2020) [47]	17	GGO, GGO with interlobular septal thickening, GGO with irregular linear opacities, consolidation, presence of nodule, enlarged pulmonary vessels, bronchiolar dilatation, crazy paving, air bronchogram, thickening of the adjacent pleura, interleaf fissure displacement, evidence of pulmonary fibrosis and pleural effusion	There is a synchronised improvement in both clinical and radiologic features in the 4th week.
Feng et al. (2020) [58]	15	Small nodular GGOs and speckled GGOs	Dynamic reexamination of chest CT and nucleic acid are essential in children.
Lei et al. (2020) [182]	14	Presence of nodular, GGO, bronchovascular enlarged, irregular linear appearances, consolidation pulmonary opacity and pleural effusion	
Zhu et al. (2020) [183]	14	GGOs, mixed GGO and consolidation, reticulation, crazy paving, cavitation and bronchiectasis	There is a need to develop a new detection technique.
Chate et al. (2020) [184]	12	GGOs, crazy-paving pattern, alveolar consolidation, reversed-halo sign and pleural effusion	
Agostini et al. (2020) [44]	10	GGOs, GGO with consolidation, linear opacities, rounded opacities, crazy-paving pattern, reverse-halo sign, bronchial wall thickening and bronchiectasis	Ultra-low-dose, dual-source, fast CT protocol provides highly diagnostic images for COVID-19 with potential for reduction in dose and motion artefacts.
Zhou et al. (2020) [55]	9	Nodular lesions, patchy lesions, GGO with consolidation and halo sign	Infants and young children with COVID-19 have mild clinical symptoms and imaging findings not as typical as those of adults.
Yoon et al. (2020) [68]	9	Pure GGO, mixed GGO and consolidation, consolidation, crazy-paving appearance and air bronchogram	
Iwasawa et al. (2020) [40]	6	GGOs, consolidation, linear opacities, reticulation and crazy-paving pattern	U-HRCT can evaluate not only the distribution and hallmarks of COVID-19 pneumonia but also visualise local lung volume loss.
Gao and Zhang (2020) [39]	6	GGOs, nodule, halo sign, thickened lobular septum, thickened bronchial wall, tree-in-bud sign, crazy-paving sign, proliferation and calcification	The imaging manifestations of early-stage COVID-19 are relatively mild, and the imaging findings of some patients are not typical, which can easily lead to missed diagnoses.
Zhu et al. (2020) [185]	6	GGO, GGO with consolidation, consolidation, reticulation, crazy paving and bronchiectasis	In the early-stage of the disease, the lesion can manifest as round nodular-like GGO in the central area of the lung lobe. The follow-up CT images showed the lesions are migratory manifested as the absorption of the primary lesions and the emergence of new lesions.
Li et al. (2020) [56]	5	Patchy GGOs	Similar but more modest lung abnormalities at CT of children compared to adults
Liu et al. (2020) [41]	5	GGOs with consolidation	The paediatric patients generally have milder CT findings than adults.
Lu and Pu (2020) [186]	5	Crazy-paving pattern, GGOs, septal line thickening, consolidation and thickened interlobular septa	
Xie et al. (2020) [187]	5	Multifocal GGO, parenchyma consolidation, mixed GGO and mixed consolidation	

since the diagnostic role of CT imaging has not been accurately proven, it is better to use a modality such as CXR with less radiation, especially for children.

One of the concerns of COVID-19 diagnosis based on CXR images is the sensitivity of this modality in detection. In a study by Smith et al. [61], the sensitivity for diagnosing COVID-19 based on CXR images collected from 366 patients was reported at 15.5%. Gatti et al. [62] believe that the sensitivity of this modality is low. The sensitivity is 61.1% for 260 patients. The sensitivity for diagnosing COVID-19 from reconstructed CXR from high-resolution CT images for 300 patients is 81.6%. This value is 95.2% for high-resolution CT images in the same study [63]. The sensitivity value in Cozzi et al. [64] is 68.1% for CXR images of 234 COVID-19 patients. However, the sensitivity of the COVID-19 diagnosis based on CXR images has been investigated between two groups of radiologists with different levels of experience. The results show 89% sensitivity for both groups of radiologists with more and less than ten years of work experience. Specificity is higher for the group of more experienced radiologists [65].

In the study of Lomoro et al. [66], which has been performed on 58 patients with COVID-19, CXR manifestations are consolidation and hazy increased opacity. In the study of Wong et al. [67], conducted with 64 patients with COVID-19, GGOs, consolidation and pleural effusion have been reported as CXR findings. The results of this study show bilateral lower zone consolidation, which peaked at 10–12 days from symptom onset. CXR findings also had sensitivity lower than initial RT-PCR testing. CXR manifestations are parenchymal abnormalities, consolidation, GGOs, single nodular opacity and patchy opacities in the study of Yoon et al. [68]. According to this study, a large proportion of patients with COVID-19 have normal CXR images. In a study with a high study population of 636 COVID-19 patients, the predominant findings are interstitial changes, GGO and consolidation. Based on the results of this study, effusions and lymphadenopathy are less common [69]. In another study of 350 COVID-19 patients, the findings of CXR images included consolidation opacities, reticular interstitial thickening, GGO,

Table 2
Overview of case reports and letters to the editors on CT imaging that have less than five cases of COVID-19.

Reference	Remarks
McGinnis et al. (2020) [188]	Asymptomatic COVID-19 was detected using CT imaging in a patient with recurrent non-small cell lung cancer.
Yan et al. (2020) [189]	Chest CT findings are important when there is a false-positive results for COVID-19.
Qi et al. (2020) [190]	CT imaging can play an important role in managing patients of COVID-19 for diagnosis and monitoring.
Zhang et al. (2020) [191]	CT imaging can be helpful for early detection of COVID-19 based on CT findings.
Tenda et al. (2020) [192]	Three patients with mild to moderate symptoms have been considered. They highly suggest the use of non-contrast chest CT for COVID-19 diagnosis in patients with moderate symptoms.
Erturk (2020) [193]	CT may help diagnose but not screening highly suspected cases.
Xu et al. (2020) [194]	Six patients from an extended family with COVID-19 have been investigated. It should be avoided to rely on CT for clinical diagnosis.
Liu et al. (2020) [195]	Chest CT has an indispensable role in early detection and diagnosis of COVID-19 infection, however, further investigation is needed.
Li et al. (2020) [196]	Repeated CT scanning could facilitate monitoring disease progression and implementing proper treatment.
Ufuk (2020) [197]	A patient with peripheral, multilobar areas of GGO sign in chest CT images and positive for COVID-19 has been presented.
Hamer et al. (2020) [198]	A positive case of COVID-19 and also a review of some studies in this field have been presented. CT morphology can be a support for COVID-19 diagnosis.
Kang et al. (2020) [199]	A low-dose scanning protocol has been presented that reduces the patient's dose to 1/8 to 1/9 of the standard dose without significant sacrifice of signal-to-noise (SNR) or contrast-to-noise (CNR) ratios.
Wang et al. (2020) [60]	The role of CT in the diagnosis of COVID-19 is not clear, so it is better to use alternative modalities such as Ultrasound or CXR due to lower radiation, especially for children.
Zou and Zhu (2020) [89]	A case with GGOs with areas of focal consolidation primarily in the right upper lobe and a focal opacity in the left upper and right middle lobes has been reported.
Dai et al. (2020) [200]	For patients with fever as the first symptom and with a history of exposure to COVID-19, chest CT examination should be performed soon.
Lin et al. (2020) [201]	Observe changes in CT images during the disease.
Lee et al. (2020) [202]	More research is needed into the correlation of CT findings with clinical severity and progression of COVID-19.
Kim (2020) [203]	Role of radiologists includes not only early detection of lung abnormality, but also suggestion of disease severity, potential progression to acute respiratory distress syndrome, and possible bacterial co-infection in hospitalised patients.
Zhang et al. (2020) [204]	One case of COVID-19 pneumonia showed multiple subpleural GGOs in bilateral lung, rapid progression, and it also accompanied nodular GGOs on chest CT.
Singh and Fratesi (2020) [205]	CT may expedite care in symptomatic patients with a negative or pending swab, and in those with worsening respiratory status or developing complications such as empyema or acute respiratory distress syndrome.
Tsou et al. (2020) [206]	In Singapore, the consensus of the infectious diseases experts is to rely on reverse transcriptase polymerase chain reaction (RT-PCR) for diagnosis rather than to use CT.
Vu et al. (2020) [207]	Patients not initially suspected of COVID-19 infection can be quarantined earlier to limit exposure to others using CT imaging features of COVID-19.
Çinkooğlu et al. (2020) [208]	Imaging plays a critical role in initial diagnosis and in assessment of disease severity and progression.
Asadollahi-Amin et al. (2020) [209]	A patient found to be positive COVID-19 after a CT scan performed for an unrelated condition revealed a lesion in the lung field compatible with COVID-19 infection.
Chen et al. (2020) [210]	Chest CT scan is the primary diagnostic approach for COVID-19 and its feature includes multiple, bilateral, patchy consolidation and GGO with subpleural distribution.
Hu et al. (2020) [211]	Two cases both demonstrated symptom relief but progression on CT, which indicates that clinical symptoms and imaging findings are inconsistent in early-stage of COVID-19 pneumonia.
Lim et al. (2020) [212]	This case series of three COVID-19 pneumonia patients highlights the variable chest CT features during the acute and convalescent phases. Chest CT is a highly sensitive tool for the delineation of the extent of lung disease. However, its use as a first-line diagnostic modality to replace RT-PCR is not guaranteed.
Ostad et al. (2020) [213]	Radiologists should know the possibility of artefacts when reporting the axial CT images with limited involvement, especially those cases with focal basal GGO, where linear atelectasis is also common. In such cases correlation with reformatted planes and utilising thin-section reconstructions are recommended to avoid misinterpretation.
Qanadli et al. (2020) [214]	Vascular findings convey both diagnostic and prognostic information and might contribute to disease diagnosis and patient management. The vascular congestion sign may help distinguish COVID-19 from community-acquired pneumonia.
Mungmungpuntipantip and Wiwanitkit (2020) [215]	Chest CT cannot discriminate early COVID-19 from other diseases.
Danrad et al. (2020) [216]	a case of positive lung ultra-sound findings consistent with COVID-19 in a woman with an initially negative RT-PCR result. We describe and illustrate early and advanced stage CT findings from patients with documented COVID-19 who have been admitted to University Medical Center in New Orleans, Louisiana. Early and advanced stage CT finding from patients with documented COVID-19 admitted to University medical center in New Orleans, Louisiana have been described.
Joob and Wiwanitkit (2020) [217]	If patients have underlying lung disease such as tuberculosis, atypical chest CT findings might be seen. Practitioners have to recognise the broad spectrum of possible CT findings in patients with COVID-19.
Li et al. (2020) [218]	Characteristic imaging changes were found with GGO, consolidation and septal thickening mainly distributed in peripheral and posterior area by thoracic CT scan in the three patients.
et al. (2020) [219]	A dynamic chest CT scan plays a significant role in the diagnosis and prognosis of COVID-19.
Li et al. (2020) [220]	CT plays a vital role in the diagnosis, staging, and monitoring of patients with COVID-19 pneumonia.
Lei et al. (2020) [221]	

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Table 2 (*continued*)

Reference	Remarks
	Knowing the corresponding CT feature of COVID-19 pneumonia at different stages, which could be helpful to precisely diagnose and understand CT characteristics of COVID-19.
Gross et al. (2020) [222]	CT may be a useful tool to evaluate the extent of the disease in severe cases, provide prognostic information and guide future treatment options.
Shi et al. (2020) [223]	COVID-19 pneumonia may present with atypical manifestations, such as haemoptysis and focal GGO with non-peripheral distribution, on initial CT scans.
Qu et al. (2020) [224]	This study is a report of manifestations of COVID-19 in a patient with lung adenocarcinoma.
An et al. (2020) [225]	Chest CT offers fast and convenient evaluation of patients with suspected COVID-19 pneumonia.
Wei et al. (2020) [226]	CT showed rapidly progressing peripheral consolidations and GGOs in both lungs of a 40-year-old female patient with COVID-19 pneumonia. After treatment, the lesions were almost absorbed leaving the fibrous lesions.
Fang et al. (2020) [227]	Under the circumstances, computed tomography imaging is not only useful for the detection, location of lesions but also helpful in evaluating the dynamic changes of patients with COVID-19. CT imaging can play a determinant role in clinical decision-making.
Duan and Qin (2020) [228]	At seven days, chest CT showed decreasing GGOs in a 46-year-old woman. At day 13 after admission, the GGOs in the right lung had resolved; the left GGOs showed partial resolution.
Shi et al. (2020) [229]	This study uses imaging data for patient's improvement monitoring in a case with COVID-19.
Fang et al. (2020) [230]	The authors report two cases of COVID-19 using CT imaging data.
Kanne (2020) [231]	In the correct clinical setting, bilateral GGOs or consolidation at chest imaging should prompt the radiologist to suggest COVID-19 as a possible diagnosis. A normal chest CT scan does not exclude the diagnosis of COVID-19 infection.
Adair and Ledermann (2020) [232]	This case report discusses the imaging findings of one of the first cases in the mid-western United States.
Burhan et al. (2020) [233]	The result may suggest that in an area with high number of COVID-19 case, CT Scan might be a better diagnostic tool compared to RT-PCR in diagnosing COVID-19.
Feng et al. (2020) [234]	It is challenging to distinguish COVID-19 pneumonia from other viral pneumonia on CT findings alone; however, the authors emphasise the utility of chest CT to detect early change of COVID-19 in cases which RT-PCR tests show negative results.
Hao and Li (2020) [235]	If patients have clinical symptoms, epidemiological characteristics, and chest CT imaging characteristics of viral pneumonia compatible with COVID-19 infection, we need to carefully consider the isolation and treatment of these patients even if the RT-PCR test is negative.
Yang and Yan (2020) [236]	A patient with RT-PCR-confirmed COVID-19 infection may have normal chest CT at admission.
Lei et al. (2020) [237]	The bilateralism of the peripheral lung opacities, without subpleural sparing, are common CT findings of COVID-19 pneumonia.

pulmonary nodules and pleural effusion in order of importance [70]. Table 3 summarizes the studies related to this section.

In summary, CXR imaging can be suitable for following up patients because its sensitivity is not sufficient to diagnose the disease, especially in its early stages. However, this modality can be used in cases where CT imaging is not possible for the patient.

2.3. Ultrasound

Some studies have suggested the use of lung ultrasound to detect COVID-19. In Lu et al. (2020) [71], lung ultrasound signs are interstitial pulmonary oedema and pulmonary consolidations. The study concluded that although the lung ultrasound diagnostic efficacy on the detection of COVID-19 in mild and moderate patients is relatively low, it is high in severe patients. 30 patients were examined in this study. In Lomoro et al. (2020) [66], lung ultrasound signs are B-lines patterns (focal, multifocal, and confluent) due to interlobular septal thickening or hazy opacities, subpleural consolidation, thickened pleural line, pleural effusion and mixed pattern with A- and B-lines based on information from 58 COVID-19 patients. In the study of Buda et al. [72], four patients of COVID-19 were examined by ultrasound. The features that appeared in the results include multifocal minor subpleural consolidations with C-line, Z-lines, segmental pleural irregularity, single focally located B-lines, the alveolar-interstitial syndrome (the white lung), the blurred pleural line, confluent B-lines and small consolidations. The lung ultrasound examinations of 20 patients in Peng et al. [73] show findings such as thickening of the pleural line, B-lines and consolidations with different patterns, and appearance of A-lines during the recovery phase. Based on Xing et al. [32] from a total of 36 ultrasound examinations,

Table 3
Overview of studies on CXR imaging and related findings.

References	No. of cases	Findings
Jacobi et al. (2020) [59]	–	Irregular, patchy, hazy, reticular and widespread GGOs
Lomoro et al. (2020) [66]	58	Consolidation and hazy increased opacity
Wong et al. (2020) [67]	64	GGOs, consolidation and pleural effusion
Zhang et al. (2020) [53]	645	GGOs and consolidation
Yoon et al. (2020) [68]	9	Parenchymal abnormalities, consolidation, GGOs, single nodular opacity and patchy opacities
Wang et al. (2020) [60]	–	It is better to use CXR due to lower radiation, especially for children.
Shi et al. (2020) [229]	1	This study uses imaging data for patient's improvement monitoring in a case with COVID-19.
Wu and Li (2020) [238]	229	In case of lack of access to CT imaging, mobile X-rays can be used for critically ill COVID-19 patients.
Vancheri et al. (2020) [25]	240	The most frequent lesions in COVID-19 patients are GGO and reticular alteration, while consolidation gradually increased over time.
Weinstock et al. (2020) [69]	636	Interstitial changes, GGO and consolidation
Yasin and Gouda (2020) [70]	350	consolidation opacities, reticular interstitial thickening, GGO, pulmonary nodules and pleural effusion
Smith et al. (2020) [61]	366	Bilateral patchy or confluent, bandlike GGO or consolidation
Rousan et al. (2020) [239]	88	The most common finding is peripheral GGO affecting the lower lobes.
Cozzi et al. (2020) [64]	234	Reticular–nodular opacities, GGO, consolidation, vascular congestion signs, cardiomegaly, nodules, pleural effusion and pneumothorax
Balbi et al. (2021) [240]	340	GGO, consolidation, GGO and consolidation, pleural effusion and nodules
Al-Smadi (2021) [241]	56	GGO, consolidation and mixed pattern

B-lines, consolidation and pleural line abnormalities are the main abnormal findings in the diagnosis of COVID-19. According to this study, ultrasound can be a promising modality in detecting and following up COVID-19 due to its radiation-free nature, flexibility and lower cost. Findings from lung ultrasound examinations of 10 patients with COVID-19 show glass rockets with or without the Birolleau variant, confluent B-lines, thick irregular pleural lines, and subpleural consolidations in most patients [74]. The main features observed in the lung ultrasound of 120 COVID-19 patients include patchy pleural thickening and patchy subpleural consolidations [75]. In the study population of 28 patients, ultrasound findings include B-lines, consolidation, and a thickened pleural line. Also, the predominant finding in severe and critical cases of the disease is pulmonary consolidations [76]. Besides, some studies proposed an acquisition protocol for using ultrasound in the detection of COVID-19 [77–79]. [80] also shows how ultrasound is performed in pregnant women with COVID-19.

In the study of Wang et al. [60], lung ultrasound is considered a suitable modality for the diagnosis of COVID-19 due to its non-radiation nature. Vetrugno et al. [81] also believe that lung ultrasound can show the severity and involvement of the lung in COVID-19. Although CT imaging seems to be promising for diagnosing COVID-19, lung ultrasound is also a suitable modality in certain conditions, such as pregnancy. According to claim [82], lung ultrasound in four pregnant women could detect COVID-19 and its main features are B-lines and irregular pleural lines. The study also states that ultrasound is a much more sensitive modality for detecting COVID-19 than CXR. Kalafat et al. (2020) [83] is a case report of positive lung ultrasound findings of COVID-19 in a pregnant woman with an initially negative RT-PCR result.

In summary, despite the advantages of ultrasound in the diagnosis of COVID-19, such as wide availability, portability, low cost, ease of use and safety, some disadvantages exist, including prolonged exposure of the operator to the patient, problems with contamination cleaning and less sensitivity than CT imaging [84,85].

2.4. ^{18}F-FDG PET/CT

Some studies have confirmed the role of this modality and its sensitivity to the detection of COVID-19. Based on Lutje et al. (2020) [86], this modality can play a complementary role in the management of COVID-19. It means this modality has the potential to diagnose COVID-19, and it can be used for estimating the extent to which organs are involved and determining the response to treatment in patients. Deng et al. [87] also highlighted the sensitivity of this modality in COVID-19 diagnosis and monitoring disease progression or the success rate of treatment. In a study by Qin et al. [88] that described the results of ^{18}F-FDG PET/CT for four patients, all patients had peripheral GGOs and consolidations in over two pulmonary lobes. According to this study, although it is impossible to use this modality widely, it has good potential in detecting the complex cases of COVID-19. Zou and Zhu [89] and Polverari et al. [90] are case reports in which imaging was performed with this modality. The imaging results revealed bilateral, diffuse, and intense FDG uptake in the lower lobes and less intense uptake in the remaining lobes.

However, there are also conflicting points about the effectiveness of this modality. Prolonged imaging may cause the disease to spread in imaging centres [91]. Also, due to the large number of COVID-19 patients, the ^{18}F-FDG PET/CT imaging capacity cannot cover this number of patients [92].

2.5. Other modalities

Some other studies have talked about other imaging modalities to detect COVID-19. Tulchinsky et al. [93] suggests that since CT-SPECT can diagnose COVID-19, nuclear medicine physicians should be familiar with the features of the disease in the images. The study of Poyiadji et al. [94] is a case report related to using MRI images to detect COVID-19–associated acute necrotising haemorrhagic encephalopathy. Acute necrotising encephalopathy is a rare complication of viral infections like influenza.

When the level of D-dimer increases during hospitalisation or sudden clinical deterioration, CT angiography can be a life-saving option for patients, as patients with COVID-19 may be associated with acute pulmonary embolism [95].

3. Automated image analysis methods for COVID-19 diagnosis

Due to challenges such as the unavailability of PCR testing in all centres of COVID-19 and the high false-negative rate of this test [96], which has been mentioned in many studies in this field, medical imaging for early detection of COVID-19 has received more attention. However, evaluating many of medical images in the epidemic situations will undoubtedly be a time-consuming and error-prone process. Therefore, given the advances in machine learning, more reliance on these techniques for the automatic diagnosis of COVID-19 based on medical images should be considered [97–99].

AI-based methods can provide automated tools for detecting COVID-19 [99]. The distinguishing features must first be extracted from the image to create automated diagnosis methods. The feature extraction process can either be based on handcrafted feature extraction methods or deep learning approaches [100]. Machine learning approaches can then be used for medical image classification, medical image segmentation, severity assessment of disease and other possible tasks based on extracted features.

This section presents an overview of automated methods in the diagnosis of COVID-19 based on medical imaging. We review the methods, the main contributions of the studies and the imaging datasets available in this field. We also discuss the performance of the methods.

3.1. Deep-learning-based approaches

With deep learning, many operations required to analyse images and extract features from images have become more manageable. Convolutional neural networks (CNNs) [101] have been widely used for image analysis, and this review cites several studies that use this approach to detect COVID-19 from CT or CXR images. A look at the famous CNN architectures shows that they all consist of three types of layers. These layers include convolutional, pooling, and fully-connected layers. Convolutional layers, which are based on the use of convolution kernels, are responsible for extracting features from images. Pooling layers reduce the resolution of feature maps based on operations such as average or max-pooling so that they can achieve shift-invariance. Fully-connected layers aim to perform classification based on obtained feature maps from previous layers. The reason for using multiple layers is that the kernels of the first convolutional layer are used to extract the low-level image features such as edges, and the subsequent convolutional layers extract the high-level features of the image. Softmax operation is usually used for the final classification, while other methods such as Support Vector Machine (SVM) can also be used for this purpose [102].

There is a need for large-scale data to take advantage of deep learning approaches, and some studies have collected data sets required to evaluate the automatic methods of detecting COVID-19 [103]. A comprehensive review study has been conducted to review and introduce the available COVID-19 datasets [104]. The European Institute for Biomedical Imaging Research has also compiled a list of open access COVID-19 imaging datasets for research purposes (https://www.eibir.org/covid-19-imaging-datasets/). Big datasets are not yet available for deep learning methods because it has not been long since the COVID-19 pandemic. Therefore, many studies have addressed the challenge of data scarcity using data augmentation [105] or transfer learning [106].

Transfer learning is a way in which knowledge gained from one domain can learn in another domain. It means it is possible to train a deep neural network and store the knowledge obtained on a domain where there is enough data and that knowledge can be used to train the network with little data from another domain. Two different strategies of transfer learning can be used for image classification. In one strategy, the pre-trained network can be used as a feature extractor, and in another strategy, the pre-trained network can be fine-tuned on images of COVID-19 patients. There are contradictory results regarding the use of these strategies, but in general, using transfer learning dramatically improves the classification accuracy. Using this method can sometimes even outperform human experts [107].

In the study of Varshni et al. [108], the use of pre-trained CNNs for feature extraction of CXR images along with different classifiers to distinguish between normal and abnormal images has been investigated for pneumonia detection. Some pre-trained CNN models including Xception [109], VGG16 and VGG-19 [110], ResNet-50 [111], DenseNet-121 and DenseNet-169 [112], and classifiers including Random Forest (RF), K-nearest neighbours (KNN), Naive Bayes and SVM have been evaluated in the study. Based on statistical results, the combination of DenseNet-169 for the feature extraction and SVM for the classification has been selected, and the accuracy of this proposed method is 80%. In the study of Narin et al. [113], transfer learning has been used on three deep CNNs including ResNet50, InceptionV3 and InceptionResNetV2. A total of 100 CXR images, including 50 images of patients with COVID-19 and 50 normal images, were used to learn the networks, and the results show a 98% accuracy of ResNet50 using 5-fold cross-validation. Another similar study [114], which used the transfer learning technique to diagnose COVID-19 automatically, evaluates seven deep convolutional neural networks. A 90% accuracy for VGG19 and DenseNet201 in a dataset, including 50 normal images and 25 images of COVID-19 patients, has been achieved. In the study of Ghoshal and Tucker [115], a pre-trained network called ResNet50V2 has been used. Dropweights based Bayesian CNN (BCNN) has also been used to estimate uncertainty in deep learning strategies to improve diagnostic performance. The study, with 5941 CXR images, including 68 images of patients with COVID-19, achieved an accuracy of about 89%.

Data augmentation is a way to address the problem of data limitation to avoid network overfitting. Data augmentation can be done with basic image processing techniques or deep learning approaches. The former includes geometric and lightning transformations, image mixing and filtering. Deep learning approaches include generative adversarial learning [105].

Loey et al. [116] have used conditional GAN (CGAN) for data augmentation, and this method has improved the performance of classification. The study of Apostolopoulos et al. [117] has used random rotation and random horizontal and vertical shift towards any direction for data augmentation. Data augmentation has been done in the study of Zheng et al. [118] using random affine transformation and colour jittering. The affine transformation comprised rotation, horizontal and vertical translations, scaling and shearing in the width dimension. The colour jittering adjusted brightness and contrast. Hu et al. [119] have augmented the data by cropping square patches at the centre of the input frames, rotation with a random angle, random horizontal reflection and contrast adjustment using randomly darkening or brightening.

Some studies have also tried to present a deep neural network architecture from scratch. In a study by Wang et al. [120], a deep convolutional neural network called COVID-NET is proposed to detect COVID-19 based on 13,975 collected CXR images. This study compared the results of the proposed method with the VGG-19 and ResNet-50, which shows that the accuracy of 93.3% for the proposed method is superior to the other methods. As another example, Oh et al. [121] identified COVID-19 in their study based on a patch-based CNN approach with a relatively small number of trainable parameters.

Table 4 summarizes the automated deep learning-based approaches for COVID-19 diagnosis.

3.2. Other approaches

Some studies use non-deep learning methods to detect COVID-19 automatically. Barstugan et al.'s study [122] used methods such as grey-level co-occurrence matrix (GLCM), local directional pattern (LDP), grey-level run length matrix (GLRLM), grey-level size zone matrix (GLSZM), and discrete wavelet transform (DWT) to extract the feature from 150 CT images. SVM has also been used for classification, and the results show a 99.68% accuracy of the classification using 10-fold cross-validation and GLSZM feature extraction method. In the study of Al-Karawi et al. [123], FFT-Gabor scheme and SVM have been used for feature extraction and classification respectively, with results showing a 95.37% accuracy rate among 275 positive COVID-19, and 195 negative patients. In Wei et al. [124], a texture analysis approach was proposed to diagnose the severity of COVID-19 disease in two categories, common and severe, using CT images. Features extracted from CT images include histogram features, grey-level co-occurrence matrix, grey-level size zone matrix (GLSZM), and grey-level run length matrix (GLRLM) features. The proposed method for the analysis of CT images of 60 common and 21 severe cases indicates an AUC of 0.93. In Study Khuzani et al. [125], similar methods were used to extract features from 420 CXR images. These methods include texture analysis, GLCM, grey level difference method (GLDM), FFT, and Wavelet transform. Multi-layer perceptron (MLP) was used to classify the data, and finally, the AUC value was reported to be around 0.91. In Tuncer et al. [126], other approaches such as residual exemplar local binary pattern (ResExLBP) have been used to generate features from 87 CXR images of COVID-19 patients. Iterative reliefF (IRF) has also been used to select the features. The classification of these features has been done using methods including decision tree (DT), linear discriminant (LD), SVM, KNN, and subspace discriminant (SD) methods that the 100% accuracy value has been reported for SVM. The methods of extracting and selecting the features in Ref. [127] are fractional multichannel exponent moments (FrMEMs) and manta-Ray foraging optimization (MRFO) based on differential evolution (DE), respectively. The accuracy is about 0.98 using KNN as a classifier. In Singh et al. [128], the hybrid social group optimization (HSGO) method was used to select the features, and several different classifiers were used for classification. SVM with 99.65% accuracy has been named as the best classifier.

4. Discussion

4.1. Overview

In this review study, many articles related to the role of medical imaging and automatic methods of medical image analysis in the diagnosis of COVID-19 were examined. Despite some articles that deny the role of medical imaging in the diagnosis and management of COVID-19, many studies have highlighted this role and examined the characteristics of the disease in medical images. Despite the sometimes contradictory results, a significant portion of the articles emphasises the use of medical images including CT, CXR, ultrasound, ^{18}F-FDG PET/CT and so on to diagnose COVID-19. The reasons for these studies are that the disease shows visible signs in medical images that can be used for early detection of COVID-19 in the lack of access to RT-PCR and other related methods.

Efforts have also been made to diagnose COVID-19 automatically from CT and CXR images using machine learning techniques. The wide range of machine learning methods, especially deep learning, can be used for COVID-19 diagnosis.

4.2. Key aspects of medical imaging for COVID-19 diagnosis

CT is the primary modality in early detection of COVID-19 because a significant portion of the reviewed studies, including 138 studies, examined the role of CT imaging. GGO and consolidation are the most

Table 4
Overview of deep learning approaches for automated COVID-19 diagnosis.

Reference	Task	Modality	Method	Total No. Of Images	No. Of Images From COVID-19 Cases	Accuracy (%)	Remarks
Wang and Wong (2020) [120]	Automatic COVID-19 diagnosis	CXR	CNN	13,975	358	93.3	COVID-Net has been proposed.
Narin et al. (2020) [113]	Automatic COVID-19 diagnosis	CXR	CNN	100	50	98	The pre-trained ResNet50 model provides the highest classification performance.
Hemdan et al. (2020) [114]	Automatic COVID-19 diagnosis	CXR	CNN	75	25	90	The VGG19 and DenseNet201 models showed a good and similar performance.
Ghoshal and Tucker (2020) [115]	Estimating uncertainty and interpretability in deep learning for COVID-19 diagnosis	CXR	BCNN	5941	68	89	Experiment has shown a strong correlation between model uncertainty and accuracy of prediction.
Apostolopoulos and Mpesiana (2020) [242]	Automatic COVID-19 diagnosis	CXR	CNN	1442	224	96.78	The MobileNet v2 effectively distinguished the COVID-19 cases from viral and bacterial pneumonia cases.
Apostolopoulos et al. (2020) [117]	Automatic classification of pulmonary diseases	CXR	CNN	3905	455	99.18	Mobile Net has been used for transfer learning.
Abbas et al. (2020) [243]	Automatic COVID-19 diagnosis	CXR	CNN	196	105	95.12	A deep CNN, called Decompose, Transfer, and Compose (DeTraC) has been validated.
Afshar et al. (2020) [244]	Automatic COVID-19 diagnosis	CXR	CNN	13,975	358	95.7	COVID-CAPS including several Capsule and convolutional layers has been proposed.
Chowdhury et al. (2020) [245]	Automatic COVID-19 diagnosis	CXR	CNN	2876	190	98.3	SqueezeNet outperforms AlexNet, ResNet18 and DenseNet201.
Oh et al. (2020) [121]	Automatic COVID-19 diagnosis	CXR	CNN	15,043	180	91.9	A patch-based deep neural network architecture that can be stably trained with small data set has been proposed.
Rajaraman et al. (2020) [246]	Automatic COVID-19 diagnosis	CXR	CNN	16,700	313	99.01	The best performing models are iteratively pruned to identify optimal number of neurons in the convolutional layers to reduce complexity and improve memory efficiency.
Luz et al. (2020) [247]	Automatic COVID-19 diagnosis	CXR	CNN	13,800	183	93.9	The proposed model has about 30 times parameters fewer than the baseline literature model, 28 and 5 times parameters fewer than the popular VGG16 and ResNet50 architectures, respectively.
Tartaglione et al. (2020) [248]	Automatic COVID-19 diagnosis	CXR	CNN	584	405	95	Possible obstacles in successfully training a deep model have been highlighted.
Hammoudi et al. (2020) [249]	Automatic COVID-19 diagnosis	CXR	CNN	5863	–	95.72	The DenseNet169 architecture has reached the best performance.
Khan et al. (2020) [250]	Automatic COVID-19 diagnosis	CXR	CNN	1300	284	89.5	CoroNet, a deep CNN based model, has been proposed.
Santosh et al. (2020) [251]	Automatic COVID-19 diagnosis	CXR	CNN	6756	73	99.96	The Truncated Inception Net deep learning model has been proposed.
Pereira et al. (2020) [252]	Automatic COVID-19 diagnosis	CXR	CNN	1144	90	–	A macro-avg F1-Score of 0.65 using a multi-class approach and an F1-Score of 0.89 for the COVID-19 identification in the hierarchical classification scenario have been achieved.
Murphy et al. (2020) [253]	Automatic COVID-19 diagnosis	CXR	CNN	25,146	416	–	An AUC of 0.81 has been achieved. The performance of an AI system in the detection of COVID-19 is comparable with that of six independent readers.
Ozturk et al. (2020) [254]	Automatic COVID-19 diagnosis	CXR	CNN	1127	127	98.08	The DarkCovidNet model has been proposed for binary and multi-class classification of COVID-19, no-Findings and pneumonia cases.
Togaçar et al. (2020) [255]	Automatic COVID-19 diagnosis	CXR	CNN	458	295	99.27	Features are extracted using deep learning architectures and classified by SVM.
Mahmud et al. (2020) [256]	Automatic COVID-19 diagnosis	CXR	CNN	6161	305	97.4	CovXNet architecture is proposed based on depthwise dilated convolutions.
Mahmoud et al. (2021) [257]	Automatic COVID-19 diagnosis	CXR	CNN	15,496	589	95.82	The CovidXrayNet model has been proposed for three-class classification.
Quan et al. (2021) [258]	Classification and segmentation of COVID-19 lesions	CXR	CNN	9432	781	90.7	The DenseCapsNet has been proposed.
Karakanis and Leontidis (2021) [259]	Automatic COVID-19 diagnosis	CXR	CNN and GAN	435	145	98.7	The GAN model has been used for data augmentation.
Jin et al. (2021) [260]	Automatic COVID-19 diagnosis	CXR	CNN	1743	543	98.64	A hybrid ensemble model, including a pre-trained AlexNet as feature extractor and an SVM classifier as the classifier, has been proposed.
Ahmad et al. (2021) [261]	Automatic COVID-19 diagnosis	CXR	CNN	4000	1000	98.45	Some of the existing CNN architectures with data augmentation have been used for COVID-19 diagnosis.
		CXR	CNN	11,106	5806	–	

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Table 4 (*continued*)

Reference	Task	Modality	Method	Total No. Of Images	No. Of Images From COVID-19 Cases	Accuracy (%)	Remarks
Zhang et al. (2021) [262]	Automatic COVID-19 diagnosis						An AUC of 0.92 has been achieved for CV19-Net deep neural network architecture. The results show that the proposed method works better in diagnosing COVID-19 than experienced thoracic radiologists.
Wehbe et al. (2021) [263]	Automatic COVID-19 diagnosis	CXR	CNN	14,002	5445	83	The DeepCOVID-XR architecture shows similar performance to experienced thoracic radiologists.
Keidar et al. (2021) [264]	Automatic COVID-19 diagnosis	CXR	CNN	2426	1289	90.3	Some pre-trained deep CNN architectures with data augmentation have been used.
Li et al. (2020) [265]	Automatic COVID-19 diagnosis	CT	CNN	4356	1296	–	An AUC of 0.96 for detecting COVID-19 has been achieved.
Huang et al. (2020) [266]	Evaluation of lung burden changes in patients with COVID-19	CT	CNN	126	126	–	A commercially available deep-learning-based tool has been used.
Zheng et al. (2020) [118]	Automatic COVID-19 diagnosis	CT	CNN	630	–	90.1	A pre-trained U-Net for lung segmentation and a 3D CNN architecture (DeCoVNet) have been used.
Chen et al. (2020) [267]	Automatic COVID-19 diagnosis	CT	CNN	35,355	20,886	95.24	U-NET++ has been used for retrospective and prospective COVID-19 dataset evaluation.
Hu et al. (2020) [119]	Automatic COVID-19 diagnosis	CT	CNN	450	150	96.2	A weakly-supervised deep learning framework for fast and fully-automated detection and classification of COVID-19 has been presented.
Loey et al. (2020) [116]	Automatic COVID-19 diagnosis	CT	CNN and CGAN	742	345	82.91	Data augmentations along with CGAN improve the performance of classification in AlexNet, VGGNet16, VGGNet19, GoogleNet, and ResNet50 deep transfer models.
Wu et al. (2020) [268]	Classification and Segmentation for COVID-19 diagnosis	CT	CNN	144,167	68,626	–	A Joint Classification and Segmentation (JCS) system obtains an average sensitivity of 95.0% and a specificity of 93.0% on the classification test set, and 78.3% Dice score on the segmentation test set.
Li et al. (2020) [269]	Automatic COVID-19 diagnosis	CT	CNN	4352	1292	–	The sensitivity and specificity for detecting COVID-19 are 90% and 96% respectively, with an AUC of 0.96.
Bai et al. (2020) [270]	Differentiating COVID-19 and other pneumonia	CT	CNN	132,583	–	96	Artificial intelligence improved radiologists' performance in distinguishing COVID-19 from other pneumonia.
Pu et al. (2020) [271]	Automatic COVID-19 diagnosis	CT	CNN	955	498	–	An AUC of 0.70 has been achieved.
Ni et al. (2020) [272]	Automatic COVID-19 diagnosis	CT	CNN	19,291	3854	94	The deep learning model improves diagnosis efficiency by shortening processing time.
Li et al. (2020) [273]	Segmentation of COVID-19 chest CT images	CT	CNN	558	558	–	The dice coefficient between the proposed method's segmentation and two experienced radiologists for the COVID-19-infected lung abnormalities is 0.74 and 0.76, respectively.
Ardakani et al. (2020) [274]	Automatic COVID-19 diagnosis	CT	CNN	1020	510	99.63	Different well-known CNN architectures were evaluated for COVID-19 diagnosis. ResNet-101 and Xception show the best performance.
Amyar et al. (2020) [275]	Classification and segmentation of COVID-19 lesions	CT	AE	1369	449	94.67	The dice coefficient of 88% was obtained using multi-task deep learning based model for image segmentation.
Serte and Demirel (2021) [276]	Automatic COVID-19 diagnosis	CT	CNN	7572	2496	98	The proposed method combined the ResNet-50 model and the majority voting with an AUC of 96% as the best result.
Arora et al. (2021) [277]	Automatic COVID-19 diagnosis	CT	CNN	3294	1601	100	Some of the pre-trained deep models have been evaluated for COVID-19 diagnosis using CT images.
Zhao et al. (2021) [278]	Segmentation of COVID-19 lesions	CT	CNN	2317	2317	–	A dilated dual attention U-Net based on the dual attention strategy and hybrid dilated convolutions has been proposed for COVID-19 lesion segmentation in CT images. A Dice score of 0.72 has been achieved.
Maghdid et al. (2020) [279]	Automatic COVID-19 diagnosis	CXR and CT	CNN	CXR: 170 CT: 361	CXR: 85 CT: 203	98	The utilised models can provide accuracy up to 98% via pre-trained AlexNet and 94.1% accuracy by using the modified CNN.
Jia et al. (2021) [280]	Automatic COVID-19 diagnosis	CXR and CT	CNN	CXR: 7592 CT: 104,009	CXR: 1770 CT: Not clear	CXR: 99.6 CT: 99.3	The modified MobileNet and ResNet have been proposed.
Chaudhary and Pachori (2021) [281]	Automatic COVID-19 diagnosis	CXR and CT	CNN	CXR: 1446 CT: 2481	CXR: 482 CT: 1252	CXR: 100 CT: 97.6	The combination of Fourier-Bessel series expansion-based image decomposition, different CNN architectures and various classifiers have been evaluated.

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Table 4 (*continued*)

Reference	Task	Modality	Method	Total No. Of Images	No. Of Images From COVID-19 Cases	Accuracy (%)	Remarks
Ibrahim et al. (2021) [282]	Automatic COVID-19 diagnosis	CXR and CT	CNN and GRU	33,676	4320	98.05	A multi-class classification method including VGG19 and some additional CNN layers shows the best performance.

common COVID-19 features in CT images based on the significant number of studies. The study of Ai et al. [129] with 1014 patients studied has the highest population compared to other studies. After that, Besutti et al. [130], Zhang et al. [53] and Ling et al. [50] studies are in the next ranks with 696, 645 and 295 patients, respectively. The number of patients in these studies shows there are limitations in terms of patient information. Therefore, more comprehensive studies are needed. There have also been studies on children and pregnant women. Given the conflicting results, more studies are needed in this respect. However, if we want to summarise, we can still acknowledge the constructive role of medical imaging in the diagnosis of COVID-19.

4.3. Key aspects of automatic AI-based COVID-19 diagnosis

Due to the growing potential of AI-based approaches for medical diagnosis and interventions, using these approaches to diagnose COVID-19 from medical images has received much attention. With deep learning, the accuracy of the proposed methods has also increased dramatically. To compare the studies conducted in this field, these studies have been summarised in terms of modality, methodology, accuracy and number of images used in Table 4. Summarised studies show an accuracy of over 80% in the diagnosis of COVID-19 based on deep learning methods. Therefore, this indicates the ability of deep learning methods in the analysis of medical images.

The main challenge in this area is the lack of big data for more accurate analysis. Although some studies have collected data, it is necessary to collect large dataset in this area due to using deep learning. However, the reviewed studies show the authors used approaches such as transfer learning and data augmentation to overcome this shortcoming. Fine-tuning of pre-trained neural networks for image classification can be an approach to network training with a small number of samples. Data augmentation using GANs or other image processing methods like image rotation and translation, lightning transformations, scaling and so on can also improve the learning and testing process by increasing the number of input images.

Although using deep neural networks has mostly been the basis for most articles in this field, hand-crafted feature extraction methods along with classification methods can also be evaluated for the COVID-19 diagnosis.

4.4. Outlook

In this study, two main issues related to COVID-19 were examined. First, the role of medical imaging in the COVID-19 diagnosis was investigated, and the details of the observed characteristics of this disease were listed based on different modalities. Second, AI-based automated methods for COVID-19 diagnosis in various images were reviewed to shed light on the importance of these techniques. This study could be useful for medical staff and technologists who want to get acquainted with the features of COVID-19 in medical images.

In future studies, it is possible to achieve more reliable results by collecting a much broader set of data from different medical centres and relying on approaches that simultaneously use multiple modalities and learning methods. Also, there is a need to develop an international protocol for using medical imaging to diagnose COVID-19 and its follow-up to control the destructive effects of medical imaging on patients, especially children and pregnant women.

Declaration of competing interest

There are no conflicts of interests to declare.

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