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A SURVEY OF AI IMAGING TECHNIQUES FOR COVID-19 DIAGNOSIS AND PROGNOSIS

Abstract

The Coronavirus Disease 2019 (COVID-19) has caused massive infections and death toll. Radiological imaging in chest such as computed tomography (CT) has been instrumental in the diagnosis and evaluation of the lung infection which is the common indication in COVID-19 infected patients. The technological advances in artificial intelligence (AI) furthermore increase the performance of imaging tools and support health professionals. CT, Positron Emission Tomography – CT (PET/CT), X-ray, Magnetic Resonance Imaging (MRI), and Lung Ultrasound (LUS) are used for diagnosis, treatment of COVID-19. Applying AI on image acquisition will help automate the process of scanning and providing protection to lab technicians. AI empowered models help radiologists and health experts in making better clinical decisions. We review AI-empowered medical imaging characteristics, image acquisition, computer-aided models that help in the COVID-19 diagnosis, management, and follow-up. Much emphasis is on CT and X-ray with integrated AI, as they are first choice in many hospitals.

1. INTRODUCTION

Towards the end of 2019, in early December, the outbreak of highly infectious disease is discovered. The disease named as coronavirus disease 2019 (COVID-19), is caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). This virus has affected almost all the countries and territories, resulting in 165 million cases, over three million deaths as of 21 May 2021. This disease has given rise to unparalleled health issues in the global community. On 11 March 2020, the World Health Organization (WHO) declared it as a pandemic. The representative characteristics of COVID-19 infected cases comprise of dry cough, fever, tiredness, headache, and a decrease in lymphocyte or white blood cell count. In serious conditions, the infection may lead to difficulty in breathing or shortness of breath, chest ache, loss of speech and/or movement, pneumonia, organ failure, and death (WHO, 2020).

WHO recommends Reverse Transcription-Polymerase Chain Reaction (RT-PCR) test for recognizing COVID-19 patients. This test is a labour-intensive and has to be performed in

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specialized laboratories. The RT-CPR test has low sensitivity as reported by Fang et al (Fang et al., 2009). The efficiency of the test depends on several factors, sample preparation, quality, availability, and stability of the detection kits. The RT-CPR test has low detection rates in the early stages. In many cases, the tests on alleged patients need to be repeated after some days before reaching a sanguine diagnosis. Radiological imaging is often used as an equivalent examination in COVID-19 diagnosis. The imaging analyses has played an indispensable part in the examination and treatment of corona disease and also in monitoring the development of diseases and assessing their therapeutic effectiveness (Ye, Zhang, Wang, Huang & Song, 2020), restraining the infection and combat COVID-19.

The roadmap of radiological imaging-based diagnosis includes three phases:

1. Pre-scan arrangement.
2. Image procurement.
3. Disease diagnosis.

In the first stage, the subjects are assisted by a laboratory technician to position on the table or bed of the imaging machine following the prescribed protocols. In the second stage, the radiological images are acquired. The scan ranges from top to base of the lung. From the procured data, the images are rebuilt and then transferred through Picture Archiving and Communication Systems (PACS) for eventual analysis.

Image processing techniques can be extensively administered in the medical field, for segmentation, image enhancement, and can assist in consequent diagnosis (Liu et al., 2018). Computer-Aided Diagnosis (CAD) systems are an indissoluble part of medical practice that helps radiologists diagnose efficiently. These CAD systems possess many benefits over the radiologists. These systems are adept at perceiving the elusive and fine vicissitudes that are impossible to be detected by the visual examination (Castellano, Bonilha, Li & Cendes, 2004). Radiological imaging is a significant tool that contributes to actively fight against COVID-19. AI-based procedures have been employed in innumerable situations like automated diagnoses and treatments. Several researchers are adopting AI and its subsets to find new medicines and remedies for the diseases. Multiple researchers affiliated with computer science are focusing on using medical image processing for identifying contagious patients. AI-assisted software may theoretically support less experienced practitioners triage patients by identifying vital chest regions (Wang & Wong, 2020). AI embedded with deep learning techniques of image analysis could be tailored to reinforce radiologists in analysing the data. AI solutions will analyse several cases simultaneously to detect lung anomalies in chest CT.

Because of the significance of AI in the whole spectrum of COVID-19, AI-enabled imaging-based analysis will encourage future potential uses and analytical studies. The reason for this study is to weigh the effect of the mentioned procedures and also recommend their use. This study concentrates on the advancements in artificial intelligence to tackle the coronavirus epidemic. Here we put forward radiological imaging systems for COVID-19. Finally, we provide a discussion on challenges and problems.

2. CONTACTLESS IMAGING PROCEDURE

SARS-CoV-2 is exceptionally infectious. This led to a precipitous rise in the percentage of affected patients. Because of the close proximity of health staff (doctors, technicians, nurses, etc.) with the patients, they are at risk of getting themselves infected. This pressurizes already overwhelmed health care institutions/systems. A world-wide deficit in Personal Protective Equipment (PPE) and various essentials is stressing the peril the health-care workers encounter as they nurse patients. There is an exigency of solutions so that hospitals and health-care systems can perform at their full efficiency.

2.1. Conventional imaging workflow

The traditional patient assessment involves several significant pre-scan events. These events involve physical contact between medical professionals and patients. These events involve leading the patients to the examination room, ensuring readiness for the scanning. To ensure optimal parameters for the scan, the technicians help position patients correctly.

It is necessary to exercise an automated and contactless acquisition of images to obviate perils of infection during this pandemic.

2.2. AI-enabled imaging procedure

Most current radiological imaging devices come furnished with cameras for patient monitoring. Throughout the COVID-19 pandemic, these devices allow patients to be screened contactless. The medical experts can now administer the scans while being physically far and safe from the chamber where the patient is contained. The patients are led to the inspection room and/or CT bed. The system ought to present visual prompts for assisting the patient and technician in appropriately preparing and positioning the patient correctly for scanning, taking images, and analysing them. Lab technicians must be personally in the operating room and use CT scanner panels for ISO-centring and orienting the patients. ISO-centring corresponds to the alignment of the subject's target body area in a way that the target body area centre overlaps with the centre of the ISO scanner for providing optimal image quality. Researchers found that the radiation amount can be whittled down with effective ISO-centring while the image retains the identical quality (Booij, Budde, Dijkshoorn & van Straten, 2019). By applying depth data to human mesh model which is premised on bodily keypoints that are detected from an RGB image, Singh et al (Singh et al., 2017) rebuilt 3D full mesh of the patients.

By acquiring the data using RGB, thermal cameras, Time-of-Flight (TOF), and pressure imaging, AI automates the process (Singh et al., 2017) of discerning the body shape and pose of the patient. By this, optimal parameters for the scan are determined.

3. AI-ASSISTED SEGMENTATION

Segmentation, repair, and image enhancement are essential steps in subsequent medical diagnosis (Liu et al., 2018). Segmentation facilitates the removal of irrelevant image segments which in turn aids the learning process in the detection of COVID-19. In radiological imaging, this process particularizes the Region of Interests (ROIs) like lungs, lesions, infected regions, tumours. The partitioned regions could facilitate the extraction of self-learned or handcrafted features for use in the diagnosis or other applications. Summarization of some of the segmentation works in COVID-19 and applications are done in this subsection.

3D images of high-quality for detecting COVID-19 are obtained from CT scans. Deep learning techniques are used to segment ROI in CTs. Some of the prevalent networks for segmentation in diagnosing COVID-19 are U-Net (Qi et al., 2001; Zheng et al., 2020), VB-Net (Shan et al., 2020), U-Net++ (Chen et al., 2020; S. Jin et al., 2020), V-Net (Milletari, Navab & Ahmadi, 2016), ResNet (He, Zhang, Ren & Sun, 2006).

3.1. Lung lesions segmentation

Generally lung-lesion-oriented methods is used for segmentation in COVID-19 identification. The lung-lesion-oriented methods are used to isolate lesions from the (Shan, 2020; Qi et al., 2001). The detection of lesions is a strenuous responsibility as the lesions may be small in a variety of forms. Lungs and lobes in the lungs are separated from X-ray or CT images using lung-region-oriented methods (Shan, 2020; S. Jin et al., 2020; Qi et al., 2001; Zheng et al., 2020). The reason behind this is, unabridged lung lobes are needed for radiologists to evaluate and compare lesion intensity with a mean density of adjoining organs.

Transformation in lesions of lungs is akin to the development of COVID-19. This is also exhibited in lung lesions on radiological imaging within 28 hours. In CT images, U-Net and its variations are used for segmenting lungs and its lesions, whereas ResNet and its variations (2D or 3D) are for classification

3.2. Segmentation methods

There are myriad techniques with various purposes for segmenting lungs (Milletari, Navab & Ahmadi, 2016; Zhou, Rahman Siddiquee, Tajbakhsh & Liang, 2018). Ronneberger (Ronneberger, Fischer & Brox, 2015) proposed a CNN technique with U-shaped architecture named as U-Net. U-Net has encoding and decoding paths for segmenting lung regions and COVID-19 lesions. This network is more suitable for segmentation in medical images as it can learn better semantics and contexture.

V-Net variant with residual block and optimized network with Dice loss is put forward by Milletari et al (Milletari, Navab & Ahmadi, 2016). A three-step AI technique (S. Jin et al., 2020) for lesion segmentation and classification of the lesion is developed. In the first step, using 3D U-Net extract lung regions. In the second step, explicit lesions were segmented. In the final step, identify lesions being positive or negative using a CNN-based classifier.

U-Net++ (Zhou, Rahman Siddiquee, Tajbakhsh & Liang, 2018), based on the U-Net model, is specifically designed for the segmentation of images in biomedicine. The U-Net++ model can identify the ROIs having lesions with the bounding boxes from CT image slices. Even though the network can ameliorate the execution of segmentation, its training is onerous. With this network, lesions can be discerned in COVID-19 diagnosis (Chen et al., 2020).

Training a comprehensive network for segmentation requires adequate labelled data. The exiguous training data in COVID-19 is due to manual, labour-intensive, and time-consuming delineation of lesions. Due to exiguous training data, weakly supervised approaches of machine learning are employed. An unsupervised method for producing pseudo-segmented image masks is proposed by Zheng et al (Zheng et al., 2020). From manually chronicled ROI, radiomic features are extracted. To diagnose the features that depict the relationship with COVID-19, Consensus clustering for unsupervised learning is used by S. Jin et al (S. Jin et al., 2020). The segmentation results of some of the best methods are shown in Fig. 1 (Q. Yan et al., 2020).

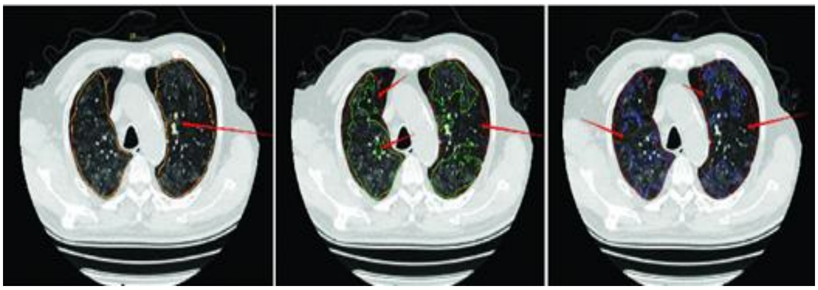

Fig. 1. Visual comparisons of COIVD-19 segmentation by some of the best AI methods testing data

Semi-supervised and unsupervised techniques are much sought as there is a deficiency of annotated medical images in lung segmentation.

4. AI-ASSISTED DIAGNOSIS FOR COVID-19

Patients suspicious of COVID-19 greatly need a prognosis and appropriate care. CT and X-ray scans are extensively carried out to furnish radiologists with evidence. Specialists take so much time to diagnose using Chest CT as they contain hundreds of slices. AI-based diagnosis is immensely needed as COVID-19 is a newly discovered disease and radiologists need to gain experience to accomplish high performance. In Tab. 2 we list some of the applications of modern technology in COVID-19 pandemic.

Segmentation (discussed in previous section) is used to pre-process images and here we list techniques that take segmentation results into diagnosis. These techniques can escalate efficiency and ease the pressure on radiologists by identifying the positive cases of COVID-19. The Tab. 1, lists some of the AI aided analysis of COVID-19.

Tab. 1. Summary of AI-assisted methods in Image segmentation in applications of COVID-19

S. No.	Literature	Procedure	AI Methods	Target Region	Application
1.	Wang et al. (S. Wang et al., 2020)	CT	CNN	Lung	Diagnosis
2.	Jin et al. (C. Jin et al., 2020)	CT	CNN	Lung Lesion	Diagnosis
3.	L. Wang et al. (Wang & Wong, 2020)	X-Ray	CNN	Lung	Diagnosis
4.	Narin et al. (Narin, Kaya & Pamuk, 2020)	X-Ray	ResNet50	Lung	Diagnosis
5.	Ghoshal et al. (Ghoshal & Tucker, 2020)	X-Ray	CNN	Lung	Diagnosis
6.	Zhang et al. (Zhang et al., 2020)	X-Ray	ResNet5	Lung	Diagnosis

Tab. 2. Modern Technology applications during the COVID-19 pandemic

S. No.	References	Applications	Description
1.	L.Wang et al. (L. Wang et al., 2020), Wang et al. (S. Wang et al., 2020)· Narin (Narin, Kaya & Pamuk, 2020)	diagnosis using radiological images	– Extracting radiological features using AI for accurate diagnosis of COVID-19. – Usage of CNN models, 3D deep learning models with more number of images can aid in early discovery of COVID-19. – COVID-Net, a variant of deep CNN system is applied on CT images and X-rays to detect COVID-19 cases. – COVNet, COVID-19 detection Neural Network is used to separate COVID from other types of Pneumonia.
2.	Wang et al. (Wang, Hu, Li, Zhang, Zhai & Yao, 2020)	disease tracking	– To estimate the count of infected and non-infected persons, Time-dependent susceptible-infected-recovered (SIR) model is used. – Applying GRU neural network with bidirectional and Attentional mechanisms (BI-AT-GRU) to categorize substantial breathing behaviors.
3.	Qi et al. (Qi et al., 2001), Yan et al. (L. Yan et al., 2020)	predicting the health status of patients	– Quantifying the risk of death using Supervised XGBoost model. – Predicting the days COVID-19 patients stay in the hospital, using ML-based radiomic models (CT).
4.	Richardson et al. (Richardson et al., 2020)	computational Medicines perspective	– Researchers at BenevolentAI found that blocking the way virus gets into the cell, is used to help prevent the infection.
5.	He et al. (He et al., 2006),	protein structure prsedictions	– For deeper image recognition, residual learning architecture is used. – To predict protein properties from its genetic sequence Critical Assessment of Techniques for Protein Structure Prediction (CASP) is used. – CNN is used for dense predictions.
6.	Zhavoronkov et al. (Zhavoronkov et al., 2020)	drug discovery	– To identify novel medicine compounds, AI is used.
7.	Maddah and Beigzadeh (Maddah & Beigzadeh, 2020), Nemati et al. (Nemati, Rahman, Nathan, Vatanparvar & Kuang, 2019)	social control and awareness	– For measuring infected people's temperature using smartphone thermometers. – By applying acoustic features to recorded audio, cough can be detected. – Classify white blood cell and chest X-ray images on a mobile phone.

4.1. X-ray screening for COVID-19

X-rays are the preferred way of radio imaging during the investigation of COVID-19 as it is cheap and easy compared to CT. But they are less sensitive compared to 3D CT images of the chest. Studies report that X-ray display normal in early and minimal infection (Wong et al., 2016). Abnormal chest x-rays are observed in 69% of patients at first admission and Sometime after hospitalization 80% of patients (Wong et al., 2016).

A ResNet based model to identify COVID-19 infected individuals and anomaly detection is put forward by Zhang et al (Zhang et al., 2020) and has AUC of 0.952. COVID-Net, a CNN variant to identify COVID-19 by employing X-ray images is put forward by L.Wang et al (Wang & Wong, 2020) and has obtained 83.5% test accuracy.

Several recent works use images from X-ray scan to distinguish between COVID-19 and healthy individuals and several kinds of pneumonia. These images are from online datasets with an inadequate quantity of COVID-19 images and these are inadequate to determine methodological robustness as the extent of subjects' severity is still uncertain. Future research may stress early detection of COVID-19. Comparisons of the normal person's X-ray images, with persons having COVID-19 and pneumonia in Fig. 2 (Rahimzadeh & Attar, 2020).

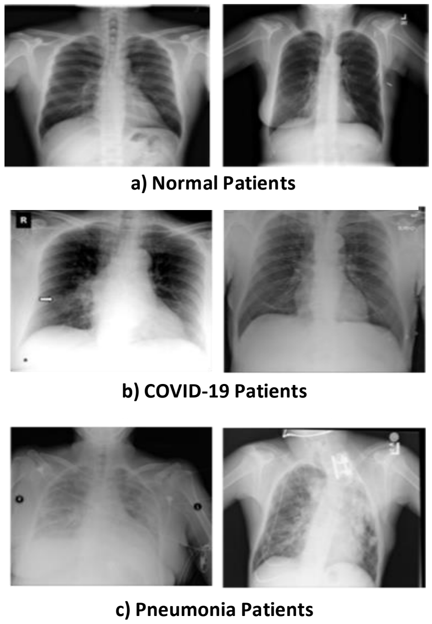

Fig. 2. Comparisons of a normal person with patients with COVID-19 and pneumonia

Most studies can distinguish COVID-19 from healthy patients and pneumonia subjects using X-ray images, though the severity is unknown. Future research can stress on the early detection of COVID-19.

4.2. COVID-19 CT screening and severity evaluation

4.2.1. CT characteristics of COVID-19

One salient feature to track COVID-19 is Ground-Glass Opacities (GGO). For the following characteristics (Guan et al., 2020; Bernheim et al., 2020; H. Shi et al., 2020; D. Wang et al., 2020) CT photographs of COVID-19 patients' chest may be analysed for: 1) appearance of GGO, 2) Consolidation existence, 3) lateralization of GGO and its consolidation, 4) count of impaired lobes with opacities, 5) Level of involvement of the individual lung lobes, along with the complete extent of the lung involvement is measured, 6) development of nodules, the existence of Pleural effusion, 7) detection of more than 10mm lymph nodes and airway abnormalities, 8) axial distribution and any underlying pulmonary disease. Such radiological observations provide considerable evidence in the COVID-19 assessment.

A more detailed description of the CT phases is done by Pan (Pan et al., 2020). He has split patients into four Phases, phase-1(0-4 days), phase-2 (5-8 days), phase-3 (9-13 days), and phase-4 (≥14 days) (Figure 3). In phase-1, people have GGO, consolidation, crazy-paving pattern are also identified. In phase-2, GGO had spread to other lobes, with extended consolidation and crazy-paving pattern. In phase-3, consolidation is the primary, with shrinkage in GGO, and crazy-paving patterns. In the phase-4, partial absorption of consolidation and with none of the crazy-paving pattern. 4 stages of Lung CT of patient recovered form COVID-19 is presented in Fig. 3 (Pan et al., 2020).

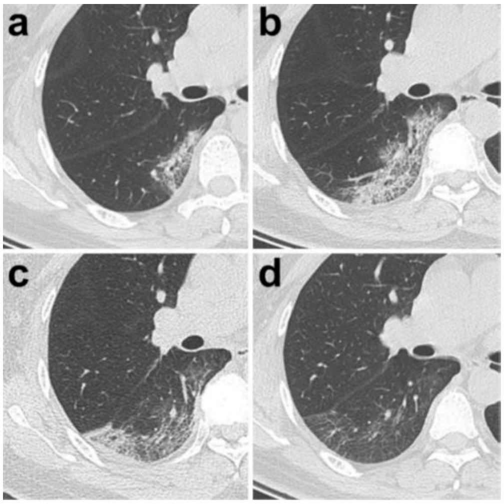

Fig. 3. 47-year old patient's CT findings in right lung: (a) at day 3, small GGO and partial consolidation; (b) 7th day, increased GGO with crazy-paving pattern and partial consolidation; (c) at day 11, a new region of subpleural consolidation and partial GGO; (d) 20th day, parenchymal bands and slight residual GGO

Bilateral patchy shadowing is among the most frequent radiological findings on chest CT (Guan et al., 2020). Wang *et al* (D. Wang et al., 2020) examined the proportion of bilateral engagement in COVID-19 infected patients. They found 100% involvement in people with COVID-19. Bilateral, consolidation of subsegmental areas, pulmonary fibrosis is standard discoveries in COVID-19 patients' chest CT.

Lesions with consolidation might also operate as a sign of disease advancement or disease severity (Song et al., 2020). The manifestation of multiple lesions is more likely than a single lesion in a preliminary CT scan of COVID-19.

4.2.2. Usage of CT features to discriminate COVID-19 against viral pneumonia

Viral pneumonia and COVID-19 have similar appearances and discerning their differences would facilitate the medical screening process. This discerning process of COVID-19 from other pneumonia using CT scans has gained attention. GGO and/or consolidation characteristics of COVID-19 and that of SARS, MERS is different from one another (Marinari, Danny & Miller, 2019). Patch and density increasing shadows are characteristics of viral pneumonia, whereas the presence of bilaterals and mottles are typical in COVID-19 and are represented in Fig. 4 (Zhao et al., 2020). COVID-19 victims display reverse halo, vascular thickening, reticular opacity, peripheral distribution (Bai et al., 2020).

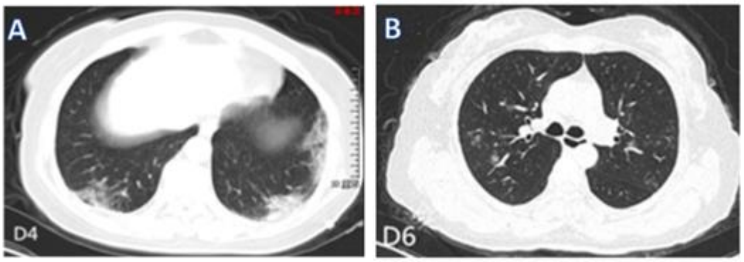

Fig. 4. (a) Characteristics of COVID-19, multiple mottles, and GGO; (b) Features of non-COVID-19 pneumonia, patchy and mottling shadows

4.2.3. CT features in asymptomatic COVID-19

A significant way of regulating the transmission of COVID-19 is testing asymptomatic patients and discovering their CT characteristics. All asymptomatic patients may not exhibit standard radiographic signs. Some preliminary RT-CPR outcomes were negative, while CT included GGO and/or consolidation. Ai et al (Ai et al., 2020) found GGO, bilateral lesions, and consolidations in CT of COVID-19 suspected patients who got negative in RT-CPR testing are shown in Fig. 5.

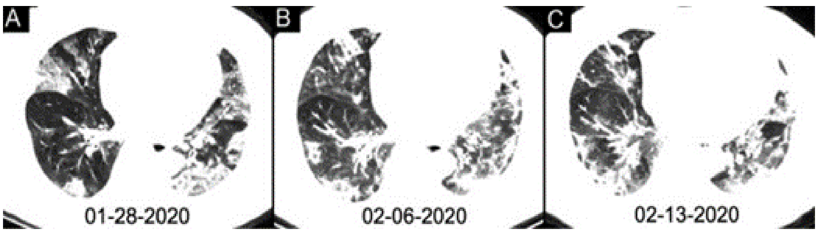

Fig. 5. Swab samples of 63 year old woman had negative results in RT-CPR – CT scans on bilateral lungs show mixed GGO and multifocal consolidation shadows over 16 days

All asymptomatic patients may not exhibit radiographic signs. This states that Typical CT signs are not present in all asymptomatic patients. Combination of RT-CPR and chest CT can detect asymptomatic COVID-19 patients.

4.2.4. CT features in asymptomatic COVID-19

The severity assessment is significant for laying out plans for treatment. Shi, Xia et al (F. Shi et al., 2020) adopted VB-Net to segment lungs into sub-regions like lobes. Based on these, infection volumes and ratios are computed and train an RF model. A quantitative assessment based deep-learning technique (W. Shi et al., 2020) is used to predict COVID-19 severity. This technique calculates the Mass of Infection (MOI) and the Percentage of Infection (POI). These have higher values in a severe group of patients. Clinical characteristics including age, C-Reactive Protein (CRP), Lactate dehydrogenase (LDH), CD4+ T helper cells count, combined with POI and MOI are fed to LASSO logistic regression model to identify the severity of patients. The prediction of COVID-19 is vitally important as it helps in treatment planning and assessment of ICU events.

4.3. Magnetic Resonance Imaging (MRI)

MRI is best suited for Imagining soft tissues and is also radiation free. As MRI is of excessive cost and has a long scanning period, it is not usually used for COVID-19. Diagnosis of COVID-19 in pregnant women and children can be done using MRI as it is radiation-free free (Liszewski, Görkem, Sodhi & Lee, 2017). Even though the SARS-CoV-2 is primarily spread in the lungs, the minimally invasive autopsy revealed infections in the heart, kidney, liver, and other body parts (Yao et al., 2020). SARS-CoV-2 enters lung cells via Angiotensin-Converting Enzyme 2 (ACE2) receptor and can spread to multiple organs. The patients having basic heart disease displayed a raise in ACE2 and have a greater risk of heart attacks and precarious conditions.

MRI provides excellent functional and visual information about soft organs. To understand the vulnerability of organs, the pathogenesis of COVID-19 could be understood.

4.4. Lung Ultrasound

Lung ultrasound (LUS) is portable, radiation-free, and non-invasive radiological imaging technique. LUS can be used for screening riskless patients, diagnosis in the emergency room, observing variations in pneumonia.

Ultrasonography of the lung does provide comparable results with that of chest CT for COVID-19-pneumonia diagnosis. Patients who are critically ill or need ventilation or admitted to ICU, LUS is an effective treatment. CT inspection is to be avoided for pregnant women suspicious of COVID-19, as radiation poses threat to the foetus. LUS (Moro et al., 2020) is recommended in these conditions and Fig. 6 displays the patterns of LUS in pregnant woman and suggestive COVID-19. LUS reduces the exposure between health care workers and patients.

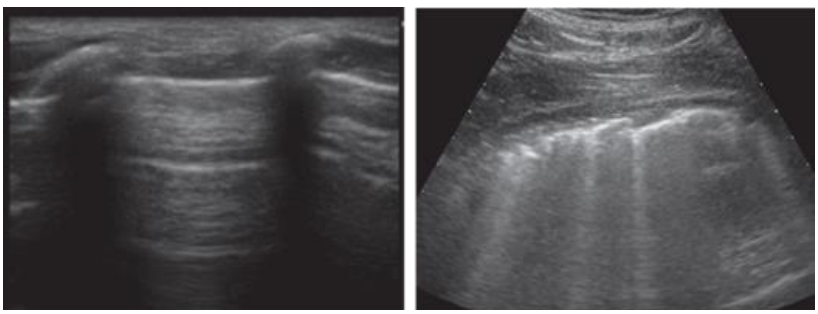

Fig. 6. Assessment and findings of LUS patterns in the pregnant women: (a) Regular A-lines and pleural lines indicate Normal Lungs, (b) Irregular pleural line and multiple B-lines indicates COVID-19

4.5. PET/CT

For analysing pulmonary and inflammatory diseases, monitoring the progress of diseases, invasive and sensitive imaging Positron Emission Tomography (PET) plays a vital role. Qin et al (Qin, Liu, Yen & Lan, 2020) advocate that during the initial period when the diagnosis is challenging, ^{18}F-FDG PET/CT can do supplementary diagnosis as displayed in Fig. 7. ^{18}F-FDG PET is a sophisticated test and has a lengthy testing time which could swell the disease transmission. They suggest more research is to be done to decide if ^{18}F-FDG PET/CT is applicable for diagnosing COVID-19.

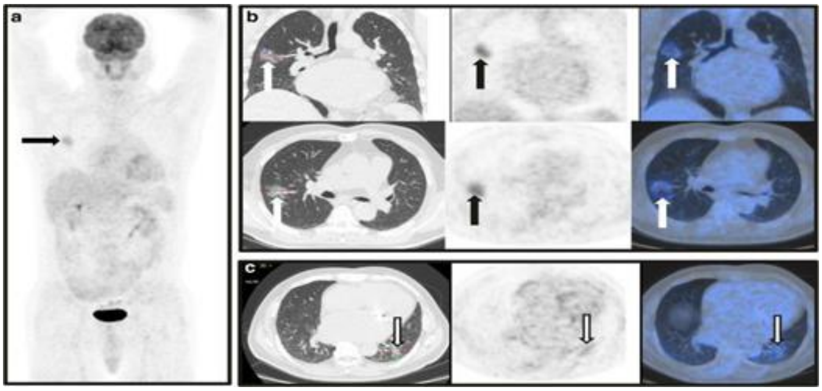

Fig. 7. (a), (b) Peripheral GGOs identified by ^{18}F-FDG PET/CT in the right lung and (c) Peripheral GGOs identified by ^{18}F-FDG PET/CT in the left lung

The ability, performance and value of X-ray, CT, MRI, LUS, PET/CT can be evaluated and compared for COVID-19 and pneumonia. Research can be done on their combinations and systematic studies of damage to the organs and mechanism of disease.

5. AI IN FOLLOW-UP STUDIES

The follow-ups subsequent to clinical treatment play a critical part in COVID-19 treatment. They evaluate the response and possible problems of patients after the treatment. Designing AI-empowered follow-up procedures for COVID-19 is strenuous and challenging. They are extremely limited follow-up studies for COVID-19 as current works are focused on pre-diagnosis of COVID-19. Researchers from Shanghai United Imaging Intelligence, use ML technique to determine and visualize the variations in clinical factors of patients. Clinical reports are generated automatically highlighting the changes as guidance for specialists for follow-ups. Quantification of lung infection reflects the development of COVID-19. It can be used in the follow-up research.

The research and works on the follow-up of COVID-19 are still in the initial phase. We are certain that previous work on segmentation, diagnosis, assessment can be helpful in building AI-enhanced COVID-19 follow-up studies.

6. DISCUSSION

The COVID-19 has emerged as a global threat and as a pandemic that affected over 48 million patients. Radiological imaging, in particular CT, have a crucial part in COVID 19 diagnosis and follow up. CT remains the key instrument for evaluating changes and the severity of lung lesions. The GGO and consolidations are the typical CT representation of COVID. A reduction in GGO and a rise in consolidation can be attributed with the progression of the disease. Variations occur in CT features including and not limited to GGO, crazy-paving, and reticular patterns. The clinical manifestations and therapeutic reaction can vary from patient to patient. Variations in lung lesions are associated with the development of COVID disease. Lung lesions are absorbed within 24–28 hours for COVID-19 patients with rapid progression, for patients with mild disease they absorbed after treatment, for critical patients the lesions may be irreversible. Additional research using larger sample sizes are required for providing further insights in evolution of GGO and lesions during and after the COVID-19 infection.

Ai et al (Ai et al., 2020), compared RT-CPR results and CT scans of 1,014 patients. CT scans have higher sensitivity than that of RT-CPR results. Chest CT results used RT-CPR results as a guideline and had 68% accuracy. Few COVID-19 patients display inflammatory changes on chest CT even though they got negative on nucleic acid tests. a lot of patients have no abnormal radiological findings (Guan et al., 2020). It is strongly recommended that the usage of chest CT, RT-PCR, and close monitoring validate and confirm the asymptomatic patients.

There's inadequate medical care in the world due to the pandemic COVID-19. Diagnosing and predicting the prognosis of individual patients is vital for managing COVID-19. AI coupled with radiological images can abet in the prognosis and diagnosis of COVID-19. Applying AI and its branches to COVID-19 research is just the prelude. More AI-enhanced technologies are expected to be incorporated into the image acquisition workflow to promote improved scanning efficiency and lower patient radiation dose. There have been studies of three forms of AI strategies. 1) Using AI to detect lesions to assist clinicians quickly screen for COVID-19, 2) use AI to diagnose CT images of whole or partial lungs, 3) Use AI to forecast other COVID-19 clinical results. Explainable Artificial Intelligence [XAI] having a finer localization map (Arrieta et al., 2020) may facilitate the use in clinical practice of diagnosis assisted with AI.

In the battle against COVID-19 deep learning has become the best strategy. Analysis of the whole lung provides comparable results that of segmented lung lesions. Datasets may be incomplete and inaccurate with a fewer number of samples and training algorithms on these datasets is a major challenge. It is costly and time-consuming to manually label the image data. Self-supervised, deep transfer learning, weakly supervised methods of deep learning can be used in these scenarios. Mobile based medical image diagnosis can be developed to identify COVID-19 in remote areas.

Follow-up studies are critical in evaluating and diagnosing COVID-19. The AI methodologies can be inspire follow-up studies. Combining data of COVID-19 patients from inside and outside the hospital for longer period of tracking the disease could benefit the follow-up procedure for COVID-19.

7. CONCLUSION

AI-enabled imaging techniques are very useful in COVID-19 combat. RT-CPR test is the best way for identifying the COVID-19. Imaging characteristics like GGOs, consolidations, pleural thickening, multiple mottling, and bilateral involvement in chest CT scans can help identify asymptomatic patients. X-rays and CT show the efficacy of AI-enhanced diagnostic imaging. For enhancing testing and diagnosis of COVID-19, RT-CPR, and medical imaging techniques can be combined. The usage of chest CT can counteract the low sensitivity of RT-CPR test and increases the accuracy and speed of COVID-19 diagnosis.

Follow-up reviews for COVID-19 are still inadequate and limited. Assessing the progressions of GGO, changes in lung lesions and consolidations can be observed with help of CT scans in early stages, advancement, treatment, and follow-up procedures of COVID-19. Combined usage of AI and radiological imaging can redress the drawbacks in traditional medical resources, help timely diagnosis, and COVID-19 prediction. We believe in AI for accurate and efficient diagnosis, review and follow-up of COVID-19.

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