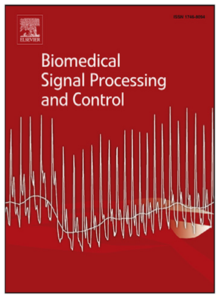
Journal Pre-proof



Automated diagnosis of COVID-19 using radiological modalities and Artificial Intelligence functionalities: A retrospective study based on chest HRCT database

Upasana Bhattacharjya, Kandarpa Kumar Sarma, Jyoti Prakash Medhi, Binoy Kumar Choudhury, Geetanjali Barman

PII: S1746-8094(22)00751-0
DOI: https://doi.org/10.1016/j.bspc.2022.104297
Reference: BSPC 104297

To appear in: *Biomedical Signal Processing and Control*

Received date : 3 June 2022
Revised date : 12 September 2022
Accepted date : 8 October 2022

Automated Diagnosis of COVID-19 Using Radiological Modalities and Artificial Intelligence Functionalities: A Retrospective study based on chest HRCT database

Abstract

(*Background and Objective*): The spread of coronavirus has been challenging for the healthcare system's proper management and diagnosis during the rapid spread and control of the infection. Real-time reverse transcription-polymerase chain reaction (RT-PCR), though considered the standard testing measure, has low sensitivity and is time-consuming, which restricts the fast screening of individuals. Therefore, computer tomography (CT) is used to complement the traditional approaches and provide fast and effective screening over other diagnostic methods. This work aims to appraise the importance of chest CT findings of COVID-19 and post-COVID in the diagnosis and prognosis of infected patients and to explore the ways and means to integrate CT findings for the development of advanced Artificial Intelligence (AI) tool-based predictive diagnostic techniques.
(*Methods*): The retrospective study includes a 188 patient database with COVID-19 infection confirmed by RT-PCR testing, including post-COVID patients. Patients underwent chest high-resolution computer tomography (HRCT), where the images were evaluated for common COVID-19 findings and involvement of the lung and its lobes based on the coverage region. The radiological modalities analyzed in this study may help the researchers in generating a predictive model based on AI tools for further classification with a high degree of reliability.
(*Results*): Mild to moderate ground glass opacities (GGO) with or without consolidation, crazy paving patterns, and halo signs were common COVID-19 related findings. A CT score is assigned to every patient based on the severity of lung lobe involvement.
(*Conclusion*): Typical multifocal, bilateral, and peripheral distributions of GGO are the main characteristics related to COVID-19 pneumonia. Chest HRCT can be considered a standard method for timely and efficient assessment of disease progression and management severity. With its fusion with AI tools, chest HRCT can be used as a one-stop platform for radiological investigation and automated diagnosis system.

Keywords: COVID-19, Ground glass opacities, Consolidation, Crazy –paving, Halo Sign, Machine Learning , Deep learning.

1. Introduction

With its emergence in late 2019, the persisting pandemic, namely the novel coronavirus (COVID-19), has drastically affected people across the globe. The outbreak of this deadly disease was caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The rapid transmission of this disease from human to human is phylogenetically close to bat SARS-like coronavirus with a separate monophyletic group [1]. The SARS-CoV-2 virus is a member of the human coronavirus (HCoV) family that affects the lower respiratory tract. Due to the high number of confirmed COVID-19 cases and no treatment for the infection, safety precautions are implemented worldwide, such as social isolation, the use of a mask to prevent the virus from entering the respiratory system, quarantine, and other containment measures, which are able to lower morbidity and mortality among highly susceptible individuals [2]. Still, studies reveal that, unlike the SARS-CoV and MERS-CoV viruses, the mortality rate is lower in the case of COVID-19 [3]. SARS-CoV-2 is largely spread through droplet inhalation, indirectly through contact with infected fomites, and through airborne inhalation of bioaerosols that are suspended in the air. The symptoms of COVID-19 are inconsistent, but common symptoms include fever, difficulty in breathing, cough, fatigue, loss of smell, taste, and headache [4]. These symptoms may occur between one to fourteen days if exposed to the virus. An infected person may experience a few of these symptoms, and it may last for a minimum of seven days. If the severity of symptoms continues for more than seven days, then there are chances that the patient may include symptoms like dyspnea, hypoxia, and the involvement of 50% of the lung. Considering the impact factors and statistics, studies disclose that COVID-19 is a severe case of pneumonia that affects the lungs. Such symptomatic patients are easy to identify and take corrective measures for. But the situation worsens when the patient is asymptomatic COVID-19 positive. Even though they often go unnoticed, these people may be contagious and help SARS-CoV-2 spread to healthy people. Despite the fact that such patients are responsible for fewer secondary infections than symptomatic cases, asymptomatic COVID-19 subjects can still spread SARS-CoV-2 to other people. It is noteworthy that asymptomatic COVID-19 cases have viral loads that are equal to or higher than symptomatic cases [5]. Asymptomatology and high viremia can thus coexist and represent a significant risk factor for the spread of COVID-19 infection [6]. Because they don't exhibit symptoms that would make one wonder if they have COVID-19. Several variants of SARS-CoV-2 have been brought into focus by the World Health Organization (WHO), designated as the Alpha, Beta, Gamma, Delta, and Omicron variants [7]. With their potential for rising transmission and virulence, these variants have contributed to the persistence of this pandemic. The SARS-CoV-2 Delta strain was discovered in India in late 2020 and has since been discovered in almost 60 other countries [5][6]. A higher rate of transmission is possible in Delta compared to other SARS-CoV-2 variations. Testing and the infected patients' record study revealed that the Delta variation may result in more serious lung deformities, leading to death in extreme cases. While mass vaccination campaigns are currently just getting started, several medications have shown in vitro activity against SARS-CoV-2 or potential clinical benefits. Early identification and appropriate treatment of immunologic complications can reduce morbidity and mortality in patients with COVID-19 infection. The COVID-19 vaccination was first administered in India on January 16, 2021. India had provided more than 2.04 billion doses of currently recognized vaccinations as of August 29, 2022, including the first, second, and booster doses. In India, 86.87% of the eligible population (12+) is fully vaccinated, and 94.48% of the eligible population (12+) has received at least one shot [*https://vaccinate-india.in/dashboard*].

It is also true that contaminated vaccine recipients may conveniently show only moderate symptoms, stay asymptomatic, or otherwise go unreported. When significant viral loads are proven, vaccine recipients may spread the infection even more subtly. This is due to the possibility that participants in the COVID-19 mass vaccination campaign would neglect their need to maintain social distance. Therefore, it's crucial to consistently follow hygiene practices including hand washing, face mask use, and other public health safety precautions, such as social isolation. Additionally, it is important to promote the proper use of personal protection equipment, such as surgical masks and filtering face pieces, in high-risk settings, including crowded areas, public transportation, and indoor establishments like schools or hospitals. Additionally, it is important to improve occupational health safety practices, such as health surveillance, screening, testing mainly self-testing with antigen tests, and contact tracing activities [4]-[10].

The reverse transcription-polymerase chain reaction (RT-PCR) is considered the primary diagnostic test for COVID-19, which can analyze thousands of samples in a single day and has a testing sensitivity of 95%. Thus, the RT-PCR technique is regarded as the gold standard for both qualitative and quantitative viral nucleic acid detection. The lesser sensitivity in the RT-PCR method demonstrates various analytical issues, including human mistakes, testing outside the diagnostic window, active viral recombination, and insufficiently validated assays, which compromise the diagnostic accuracy [2][11][12]. The viral loads in throat swabs are most substantial when the virus first manifests, and the virus may start to shed two to three days prior to the beginning of symptoms, making presymptomatic or asymptomatic transmission easier. Therefore, instead of considering it as a diagnostic standard, we may consider RT-PCR as the primary detection measure. As lung involvement is a part of coronavirus infection, the physicians suggest chest computer tomography (CT) as a mandate for the proper diagnosis and prognosis of COVID-19 in its early detection due to its high sensitivity (60%-98%), of a viral lung [11]-[13]. Although chest CT imaging is not considered a standard screening test protocol for COVID-19, it is beneficial for people with mild symptoms or asymptomatic ones or those with a negative RT-PCR experiencing mild symptoms or chest anomalies, or unexplained lung pathology. Nevertheless, chest CT also, proves to be helpful for recovered cases of COVID-19 (post-COVID). Other imaging techniques like X-ray and ultrasound also help to evaluate the disease progression, but diagnosis with chest CT is preferred due to its three-dimensional pulmonary view and versatility [14].

Decision making with the detection of chest CT is typically based on several parameters such as whether the patient is RT-PCR positive, whether the patient has post-COVID symptoms or any other disease with overlapping distortion in the chest/lung. Moreover, diagnosis with the help of chest CT sounds advantageous in both alternative diagnosis, prognosis, and figuring out complications in COVID-19, reducing the rate of severity and mortality in cases [15]. While monitoring these parameters in manual and traditional way,in many cases it is time consuming, tedious and repetative. Machine Learning (ML) and Deep Learning (DL) tools may provide a helping hand to the physicians so as to increase the screening rate [16]-[19]. The automated ML and DL algorithms can be used in biomedical platforms and can be used as AI-based tools to design predictive models. These models, deployed on a computer system, learn to detect, classify, or diagnose the CT images. The AI-aided predective diagnostic tool may be configured to avoid the tedious and repetative task of manually evaluating each CT image of COVID patients. Whereas AI enables the computer to understand from a large set of databases, to identify or classify diseased cases, a proper methodology to configure the system is required to design and deploy it. In a previous work [20] on methods for COVID-19 detection, the authors have reviewed the current ongoing research with the reported databases. In that work, the authors compared various algorithms and schemes for classification, based on the reported findings. As a summary of that paper, in a nutshell, engineers need to use the signal processing on these CT scan images with ML and DL tools to help the physicians screen at a faster rate [21]. In this direction, the first criteria is to understand the CT scan images and their findings so that they can be incorporated into the algorithms for better identification and classification of diseased cases. Studies have brought into focus several initial chest CT findings in COVID-19 positive cases, which include peripheral ground-glass opacity (GGO), consolidation, GGO with consolidation, and crazy pavings [11][23]-[25]. The later stage of the disease shows less common findings such as bronchiectasis, septal and pleural thickening, and subpleural involvement. These findings are expected in COVID-infected lungs and other viral infections or diseases. A patient with RT-PCR positive and the above-mentioned findings is considered for COVID-19 infected cases.

Therefore, this study aims to understand the CT image find-

Table 1: CO-RADS level of suspicion for COVID infection [22]

CORADS	Class	CT Findings
CO-RADS 1	Nil	Healthy or Non-infectious anomalies
CO-RADS-2	Minimal	Infectious non-COVID anomalies
CO-RADS-3	intermediary	May be infectious with COVID-19, status unclear
CO-RADS-4	Moderate	Infectious with COVID-19 suspicion
CO-RADS-5	Severe	COVID-19 typical
CO-RADS-6	RT-PCR +	

ings so that they can be incorporated into algorithms of ML and DL with a focus on (a) the role of chest HRCT in the diagnosis and prognosis of COVID-19, (b) significant radiological findings, and (c) its severity based on CT score. Further, in this research work, we characterized HRCT findings in 188 patients, presenting a retrospective study on the collected database from Marwari Hospitals, Guwahati, Assam, India. The findings of the database have been compiled in association with a team of radiologists from the Dr. Bhubaneswar Borooah Cancer Institute (BBCI). This study aims to appraise the usefulness of the spectrum of HRCT chest findings on COVID-19 cases and estimate the infection's severity, to rule out the findings for further processing, and explore the possibility of incorporating different AI tools for the design of a predictive diagnostic framework for fast confirmatory screening of COVID-infected patients.

2. Chest CT and Significance of Radiological Modalities

In this section, we highlight the importance of chest CT and the significance of radiological diagnostic aids in combating COVID-19 infections.

2.1. Importance of Chest CT in COVID-19 and its protocol

Chest CT plays a significant role in the automatic diagnosis and prognosis of lung disease detection. Chest CT is advised on the third day of the symptomatic patients of COVID-19. As per record, 56% of cases imaged during the initial two days with the above-mentioned COVID symptoms may show normal lung findings [27]. Moreover, chest CT is a well-chosen diagnosis technique for cases with negative RT-PCR reports but having mild to severe COVID-19 symptoms. Radiological findings in chest CT are beneficial for analyzing the seriousness of the confirmed cases. At the early stage of the disease, about 15-50% of cases have shown normal lung [22]. Considering the chest CT limitations and cost, it is not recommended as a regular screening test for COVID-19. Therefore, cases with false-negative RT-PCR and normal CT scan reports may result in isolation. Again, the chest CT findings of COVID-19 are incomprehensible to other viral infections like influenza, adenovirus, pertussis, swine flu, rhinovirus, etc. Hence, it may mislead the proper diagnosis of infected cases. Another restriction on performing CT is that it should be done after procuring every suspected individual and is time-consuming. Besides, chest CT is useful in suspected COVID cases with negative RT-PCR and normal chest X-ray (CXR) even though the person has a high suspicious index and suffers from mild-to-severe respiratory symptoms. The COVID-19 Reporting and Data System (CO-RADS) developed by the Dutch Radiological Society has become a reliable and convenient assessment scheme for radiologists to classify further COVID-19 based on the CT findings [28]. The CO-RADS shows a five-point assessment scale representing the suspicious COVID cases with pulmonary chest CT involvement, as shown in Table 1. Also, chest CT plays a crucial role in post-COVID diagnosis and prognosis periods where a patient recovering from COVID infection persists with impaired lung dysfunction. In such cases, chest CT puts forward a helping hand in differentiating the post-COVID infection (lung fibrosis) sequence from other lung diseases.

People of any age can get infected with this virus. So, keeping this in consideration, chest CT is always suggested to be done using a low radiation dose [29]. Using a low radiation dose helps reduce the radiation burden as the infected patient may need to undergo a sequence of CT follow-ups. With the continuity of COVID from the past two years worldwide, all medical personalities must know the usefulness of CT in proper management and detection of COVID suspected, infected, and recovered cases to contribute to this disease's diagnosis and prognosis care [30].

2.2. Significant radiological findings

Lung:. The lung is a spongy, air-filled, pyramid-shaped organ connected to the trachea by the right and bronchi on the left [31]. Thin tissue layers called pleura cover the lung cavity. The right lung is shorter and broader than the left lung, which occupies a smaller area than the right lung. Both the lungs are separated into lobes by fissures. The right lung consists of superior, middle, and inferior lobes, while the left lung involves only superior and inferior lobes. Three regions can be mentioned to study the lung findings: the central region, placed on the interior boundary of the lung; the peripheral region, which includes the area between the central and the outline of the whole lung; and the basal region, the inferior lobes [32]. Figure 1 shows these anatomies.

Lung findings:. Several studies have reported a wide variety of chest CT findings in the detection of COVID-19 [24][27][30]. However, the main CT findings include ground-glass opacity (GGO), consolidation, GGO with consolidation, and crazy paving. The GGO may be bilateral and multilobar with a peripheral, central, and basal distribution, mainly in the lower lobes and less visible in the upper and middle lobes [Figure

Table 2: CT Score severity [26]

Percentage (%) involvement of the five lobes	CT scale	Severity
0% lung involvement	0	None
Less than 5% lung involvement	1	Minimal
Above 5% upto 25% lung involvement	2	Mild
Above 25% upto 50% lung involvement	3	Moderate
Above 50% upto 75% lung involvement	4	Severe
Above 75% lung involvement.	5	Extensive

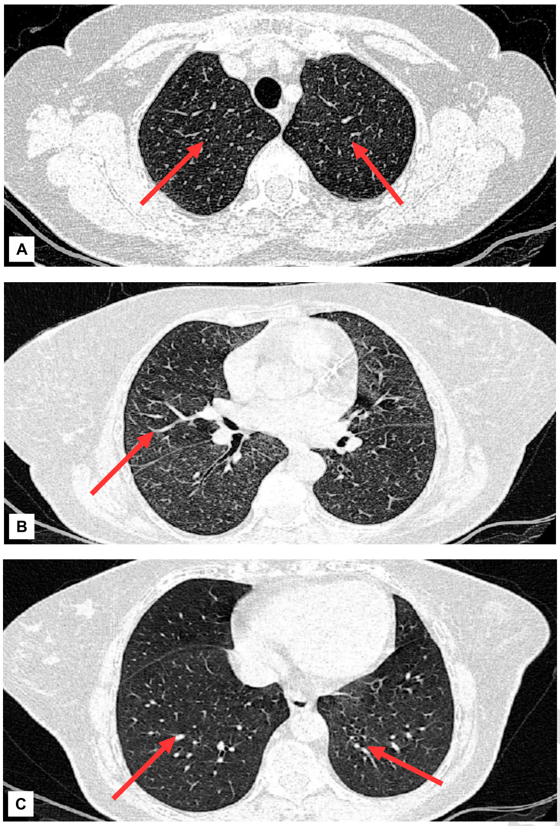


Figure 1: Axial HRCT images of lungs showing normal lobar anatomy of bilateral lungs. (A) shows bilateral upper lobe (B) shows the right middle lobe (C) shows bilateral lower lobe.

2(a)]. GGO are hazy areas in the lungs, primarily oval, rounded, lobulated or polygonal in structure [33]. These hazy areas are the increased lung opacities through which structures of the bronchus and vessels may be seen. The next stage of GGO is consolidation, where an area of compressible lung tissue is filled with liquid instead of air [Figure 2(b)]. The presence of GGO is mainly seen in younger cases or during early detection. Consolidation or mixed GGO with consolidation may be seen in the late phase of the disease or elderly patients [Figure 2(c)]. Gradually, the appearance of GGO decreases when the severity of the infection decreases. Similarly, the consolidation lesions increase progressively and remain stable for 6–13 days [11][34][35]. The later stage of the disease may show a crazy-paving pattern, an illusion of GGO with superimposed intralobular and interlobular septal thickening [36] [Figure 2(d)].

Other findings include a halo sign lesion which is rounded in structure. A halo sign is a rounded consolidation surrounded by ground-glass [Figure 2(e)] [37]. Moreover, vascular dilatation (widening of the vessels), fibrosis, traction bronchiectasis, subpleural bands, and architectural distortion are some less common findings mainly seen during the later progression of the infection or the post-COVID phase.

2.3. Severity based on CT score:

COVID-19 infected patients have a variable infection rate where the severity of the infection ranges from mild with less than 10% of lung parenchyma involvement to severe infection comprising of white lung on CT [Figure 2(f)]. The severity of the disease correlates with the involvement of the lung in HRCT, which can be estimated visually. The prior concern regarding the use of chest CT scan imaging was to appraise the spectrum of imaging findings and to recognize the different typical, atypical, and indeterminate CT patterns for COVID-19 as mentioned in the previous subsection.

The pulmonary involvement of COVID-19 related anomalies from thin-section CT images can be standardized and communicated using the 25-point severity score or CT severity score for COVID-19. Without any additional tools, radiologists can use this scoring technique, which is fairly reproducible. Based on an approximation of the pulmonary affected areas, the COVID-19 lung alterations and involvement are scored using the CT severity score index [38]-[40]. As per the information, it is evident that the combination of individual lobe scores, from negative to maximum lung involvement, 0 to 25, gives the total CT score (over 75% involvement of five lobes).

In our work, we have considered the 25-point severity score [26], where the severity of the disease is visually assessed by experienced radiologists. The involvement of all the five lobes is categorized on a five-point scale as given in Table 2. As per this scoring system for each of the 5 lobes (Right lung: Upper, Middle, Lower lobe; and Left lung: Upper, Lower lobe) is awarded a CT score from $0-5$ depending on how much of the lobe is affected. Score 0 for 0% involvement of the lobe; score 1, corresponding $< 5\%$ involvement; score 2, for 5–25% involvement ; score 3 for 26–50% involvement; score 4 to 51–75% involvement, and finally score 5 for $> 75\%$ involvements of the lobe. The total CT score is calculated as the sum of the individual scores of the five lobes, corresponding from 0 (no involvement) to 25 (maximum involvement) across the lung lobes.

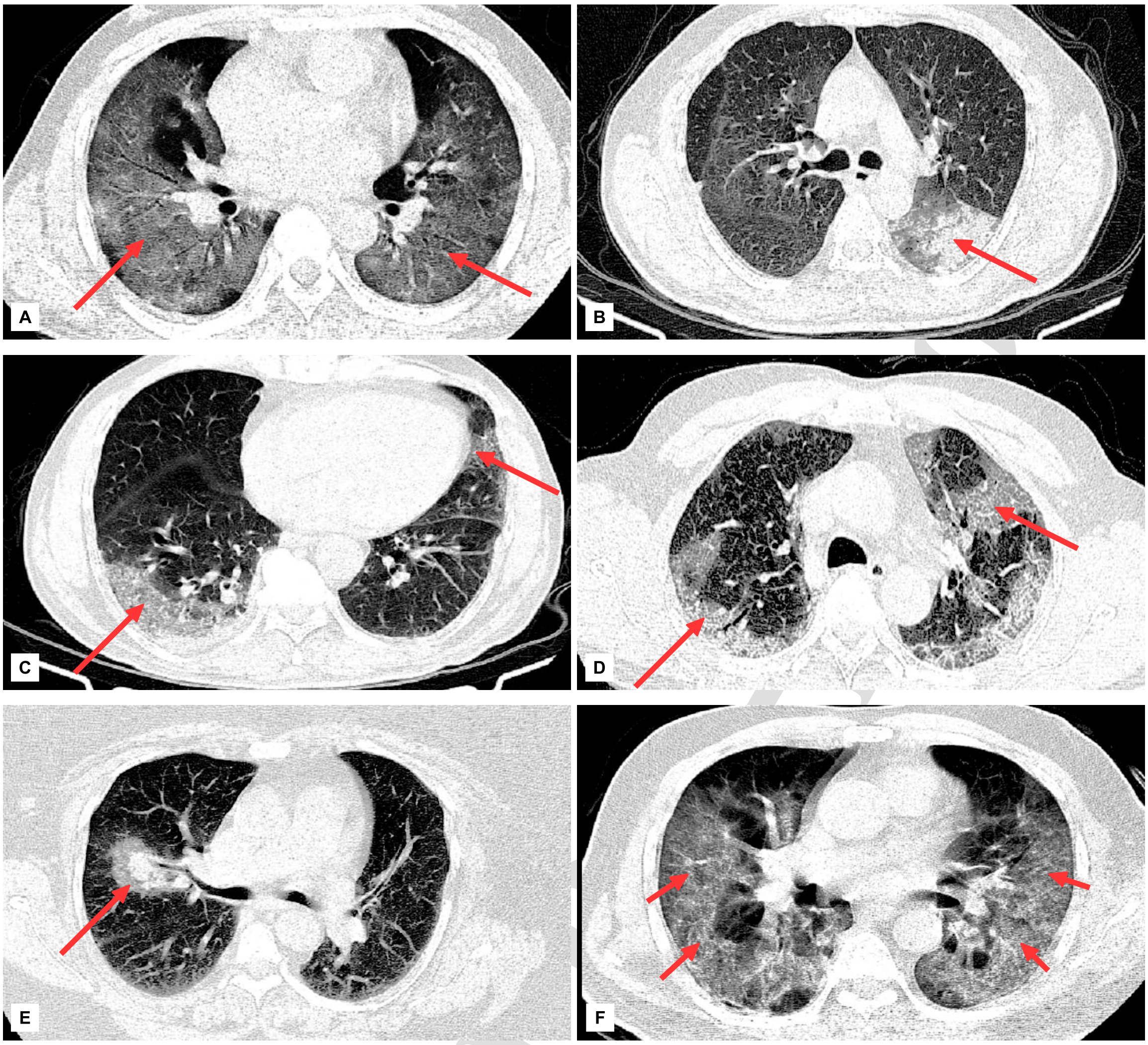


Figure 2: Radiological findings: (A) Axial HRCT of a COVID positive 40 years male showing GGO in bilateral lungs (arrows). (B) Axial HRCT of a COVID positive 45 years male shows an area of consolidation in the left lower lobe (arrow). (C) Axial HRCT of a COVID positive 70 years male showing GGO with consolidation in the right lower lobe (arrow) and a scattered area of GGO in the inferior lingular segment of the left lung (arrow). (D) Axial HRCT of a COVID positive 65 years male shows multifocal areas of GGO with interstitial thickening suggestive of crazy paving in the upper lobes of bilateral lungs (arrows). (E) Axial HRCT of a COVID positive 65 years female showing a nodular opacity with perilesional GGO suggestive of halo sign in right upper lobe (arrow). (F) ”white lung” appearance of a COVID positive 62 years male with respiratory distress showing severe GGO(arrows) involving 75% of the bilateral lungs.

3. Materials and methods

The section details the data acquisition procedure, the criteria of the included and excluded data, imaging technique and interpretation, and the de-identification process.

3.1. Data acquisition procedure

The database used for this study was obtained from Marwari Hospitals, Guwahati, Assam, India recorded from May 2021 to February 2022. The patient’s identity was kept confidential adhering to the ethical guidelines. The present study is purely retrospective and was carried out on 188 patient databases. The acquired dataset consists of imaging findings inclusive of:

- GGO with minimal to moderate hazy opacity.
- Consolidation pattern.
- GGO with consolidation.
- Crazy Paving patterns.
- GGO with crazy paving.
- Halo sign.

3.2. Criteria of the included and excluded data

All the cases used for this study were diagnosed with COVID-19, detected by the RT-PCR method tested in the hospital, and had undergone HRCT with the proper consent of doctors and laboratory technicians. The subjects used in this study had a few common clinical symptoms: loss of smell and appetite; a severe cold and cough; sore throat; anxiety; and breathing difficulties. Few patients have a history of COVID as per hospital records. Among different age groups of 188 patients,

Table 3: Age distribution of COVID and post-COVID cases

PARTICULARS	COVID				POST COVID			
	MALE		FEMALE		MALE		FEMALE	
	COUNT	% COUNT	COUNT	% COUNT	COUNT	% COUNT	COUNT	% COUNT
AGE UPTO 30 YR	8	05.5	11	07.5	2	04.8	5	11.9
AGE 30 YR TO 60 YR	40	27.4	34	23.3	7	16.7	8	19.0
AGE 60 YR TO 90 YR	35	24.0	17	11.6	8	19.0	12	28.6
AGE ABOVE 90 YR	1	00.7	0	00.0	0	00.0	0	00.0
TOTAL NO. OF CASES	84	57.5	62	42.5	17	40.5	25	59.5

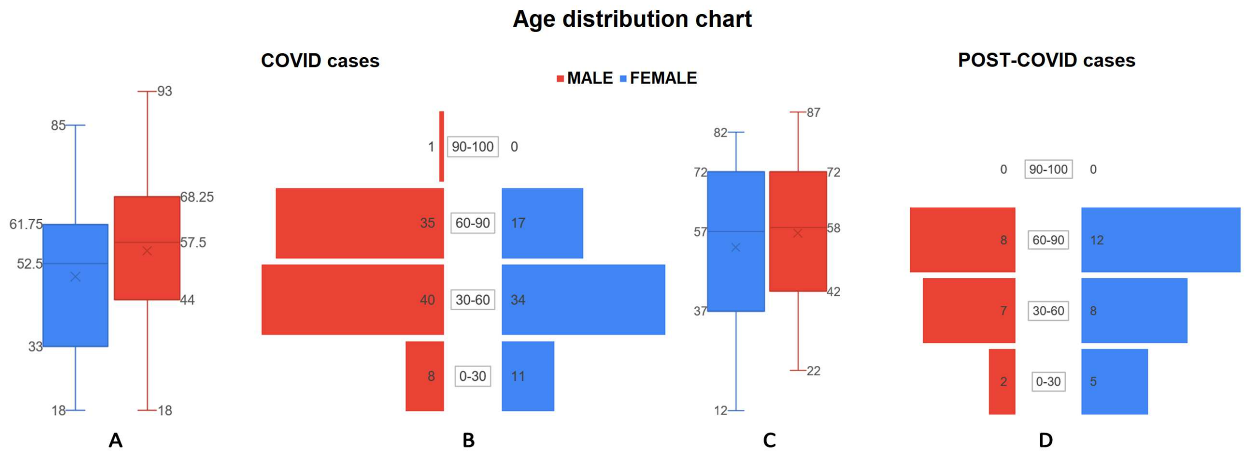


Figure 3: Chart showing the inception of COVID-19 with respect to age distribution and gender: (A) Box plot for male and female COVID-infected cases; (B) Butterfly plot showing patient distribution by age category; (C) Corresponding box plot for post-COVID cases; (D) Corresponding butterfly plot for post-COVID cases.

inclusive of both male and female sex, 144 patients are RT-PCR positive, with a true negative of two patients. The remaining 42 patients are post-COVID cases. This study excludes pregnant women and patients on ventilator support.

3.3. Imaging technique and interpretation

All HRCTs have been carried out using SOMATOM go. Here, a 32-slice CT scanner by Siemens Healthineers has been used. Standard CT scan protocols have been applied with a topogram of 512 cm with 120 kV and 35 mA ratings. The lung images have been obtained in an axial window and reconstructed into 1.5mm thin slices. Finally, all the HRCT images acquired are saved in the Digital Imaging and Communications in Medicine (DICOM) format, which further helps in the re-evaluation process. Two radiologists with 33 and 10 years of experience have reviewed the findings using the DICOM software. All the images have been viewed in both lung and mediastinal windows. We have evaluated our study using a few parameters, considering the HRCT findings as mentioned above. Laterality of lung involvement, lobar involvement and region of coverage of lungs, and CT Score Severity Grading are the parameters used to diagnose the extent of infection taking place in the lung as found in the COVID samples.

3.4. De-identification process

Keeping in view the privacy of the patients, we have de-identified all the CT studies using the DICOM software. Every name, patient ID, and centre-related information has been removed for further statistical characteristics calculation of the dataset.

4. Data statistics and interpretation results

CT scan images are extensively used as diagnostic aids for the treatment of COVID-19 infected patients. From the collected images, we have obtained the annotation and data classification based on the statistics for the mentioned retrospective study. This section highlights the statistics of the data, truly based on retrospective study to incorporate its applicability for the development of ML and DL algorithms, which are to be used as AI tools to create predictive models based on pure database patterns acquired from CT scanners. At the end of this section, a discussion based on the statistical analysis and a few of the limitations of the available data is brought to the fore.

The allocation based on age group and gender for both COVID and post-COVID is shown in Table 3 and Figure 3. Among the COVID positive cases, 57.5% are male, and 42.5% are female patients. The distribution of patients is shown in the box plot of Figure 3(A) separately for males and females. As per age groups, referring to the plot shown in Figure 3(B) the highest number of sufferers were 30–60 years old, with 27.4% male and 23.3% female. The next group is 60–90 years old, with 24% male and 11% female. The minor sufferer group belongs to the age group of 30 years (05.5% male and 07.5% female). We also have one patient (male) belonging to the age group of 90. The CT scan of this case is shown in Figure 4.

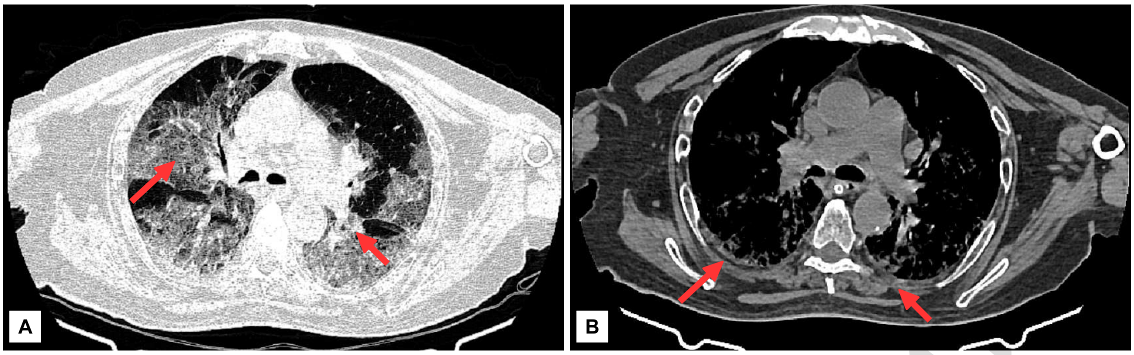


Figure 4: Axial HRCT of a 93-year-old COVID positive man shows (A) extensive GGO in the bilateral lung with small areas of consolidation (arrow). (B) The mediastinal window shows minimal bilateral pleural effusion in the same patient(arrow). The HRCT was obtained 12 days after the infection with a low oxygen level and high fever symptoms.

Table 4: Laterality of lung involvement of COVID and post-COVID cases

PARTICULARS	POSITIVE COUNT	POSITIVE % COUNT	NEGATIVE COUNT	NEGATIVE % COUNT
Bilateral lung involvement of COVID and post-COVID	82	43.6	106	56.4
Laterality of RIGHT lung involvement of COVID and post-COVID	92	48.9	96	51.1
Laterality of LEFT lung involvement of COVID and post-COVID	95	50.5	93	49.5

Table 5: Lobar involvement of lungs of COVID and post-COVID

Distribution of lobes of lung of COVID and post-COVID		NO	UPPER MIDDLE LOWER	UPPER LOWER	LOWER MIDDLE	UPPER	MIDDLE	LOWER
RIGHT LUNG	COUNT	96.0	54.0	04.0	06.0	05.0	07.0	16.0
	% COUNT	51.1	28.7	02.1	03.2	02.7	03.7	08.5
LEFT LUNG	COUNT	93.0	00.0	65.0	00.0	05.0	00.0	25.0
	% COUNT	49.5	00.0	34.6	00.0	02.7	00.0	13.3

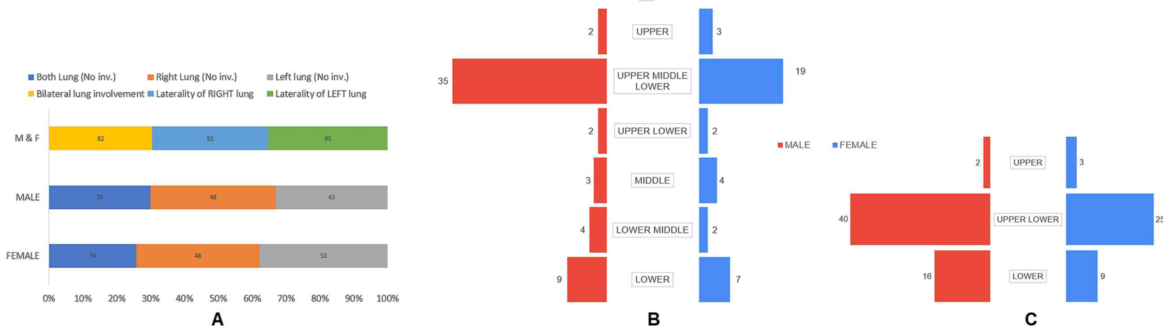


Figure 5: Chart showing HRCT findings for lung involvement of COVID and post-COVID cases with respect to gender: (A) A bar diagram depicting the patient count for lung involvement in both the right and left lungs; (B) a butterfly plot depicting lobar involvement of the right lung in both male and female patients; and (c) a corresponding butterfly plot depicting lobar involvement of the left lung.

Table 6: Region of coverage of COVID and post-COVID cases

REGION OF COVERAGE	POSITIVE COUNT	POSITIVE % COUNT	NEGATIVE COUNT	NEGATIVE % COUNT
CENTRAL	30	16.0	158	84.0
PERIPHERAL	92	48.9	96	51.1
BASAL	92	48.9	96	51.1

Similarly, in 42 post-COVID cases, 40.5% belonged to male patients and 59.5% to female patients. The box plot in Figure 3(C) shows the corresponding distribution. As seen from the butterfly plot Figure 3(D), the highest post-COVID cases be-

Table 7: HRCT findings

HRCT findings in COVID and post-COVID case	MALE		FEMALE	
	COUNT	% COUNT	COUNT	% COUNT
Minimal Ground Glass Opacities	07.0	06.9	01.0	01.1
Ground Glass Opacities	40.0	39.6	34.0	39.1
Consolidation	25.0	24.8	16.0	18.4
Ground Glass Opacities with consolidation	15.0	14.9	06.0	06.9
Crazy Paving	06.0	05.9	01.0	01.1
Ground Glass Opacities with crazy paving	05.0	05.0	00.0	00.0
Halo sign	02.0	02.0	03.0	03.4
Nil parameter findings cases	40.0	39.6	44.0	50.6
One parameter findings cases	30.0	29.7	28.0	32.2
Two parameter findings cases	25.0	24.8	12.0	13.8
Three parameter findings cases	04.0	04.0	03.0	03.4
Four parameter findings cases	02.0	02.0	00.0	00.0
Five parameter findings cases	00.0	00.0	00.0	00.0
Six parameter findings cases	00.0	00.0	00.0	00.0
Seven parameter findings cases	00.0	00.0	00.0	00.0

long to the age group of 60-90 years, with 19% male and 28% female, followed by 30-60 years, 16.7% male and 19% female, and the rest belonging to the age group of 30 years, with 4.8% male and 11.9% female.

Hence, from the available database, we may conclude that the highest number of COVID-infected patients belong to the age group of 30–60 years, with a high prevalence among male patients. The post-COVID cases show a high rate in the age group of 60–90 years old, with more female cases.

HRCT of the COVID symptomatic patients has been performed between the 4^{th} to 14^{th} days of infection for the 146 COVID cases. The 42 post-COVID cases underwent the scan due to breathing difficulties, low oxygen saturation (SPO_2), palpitation, weakness with body ache after testing RT-PCR negative post-infection. Out of 188 cases, it was found that 43.6% of them had bilateral lung involvement, while 48.9% had involvement in the right lung and 50.5% had involvement in the left lung; the details are given in Table 4 and Figure 5.

As observed from Table 5, and Figure 5 (c) both upper and lower lobes (65%, with 50% to 25% male female ratio) of the left lung were the most commonly involved, followed by the right upper, middle, and lower lobes (54%, with 35% to 19% male female ratio), referring to Figure 5 (b). Next in the count is the left lower lobe (25%, 16 : 9) and the right lower lobe (16%, 9 : 7). Considering the regions as shown in Table 6, 48.9% of the cases had findings in both peripheral and basal regions of both the right and left lung, followed by 16% in the central region.

In this study, it is noticeable that 44 female cases (50.6%) had a normal HRCT scan with the absence of all the parameters taken into consideration, followed by 40 male cases (39.6%). The most common finding is the presence of multifocal, bilateral, peripheral GGO, which is significantly found in 40 male patients (39.6%) and 34 female patients (39.1%), followed by 7 (06.9%) male and 1 (01.1%) female with minimal opacities. The HRCT performed on the cases mentioned, with minimal to severe GGO was done approximately between the 4^{th} to 12^{th} days from being infected with the virus. The next common finding that was seen in 25 male (24.8%) and 16 female (18.4%) patients is the presence of consolidation. GGO with consolidation was present in 15 male (14.9%) and 6 female (06.9%) patients. A crazy-paving pattern was found in 6 male (05.9%) patients and 1 female (01.1%). GGO with the presence of a crazy-paving pattern was found only in 5 male patients (05.0%). A halo sign has been seen in 2 (02.0%) male and 3 (03.4%) female patients. None of the cases had all the seven parameter findings. Maximum cases had only one parameter finding (either the presence of GGO or consolidation or GGO with consolidation or GGO with crazy paving patterns), followed by a minimum of four to three-parameter findings [Table 7]

The CT score is done visually based on the severity of the disease [Table 8 and Figure 6]. A total of 85 patients with

Table 8: CT Score Severity Grading

CT score	Patient Count
0	85
1 - 5	40
6 - 10	37
11 - 15	19
16 - 20	6
21 - 24	1

COVID and post-COVID infection have no lung involvement. The highest CT severity is assigned to 1 patient with a CT value ranging between 20-25 with bilateral lung involvement, involving all the lobes [shown in Figure 2 (a)]. 40 patients had CT scores between 1 and 5, where the cases showed bilateral lung involvement in a few cases and involvement of either one lung in a few cases with the presence of minimal to moderate peripheral GGO, GGO with consolidation, and halo sign [refer Figure 7 for an example]. 37 patients showed CT severity ranging between 6-10, showing patches of consolidation, consolidation with the presence of GGO, and a few crazy paving patterns in less than 10 patients, for example as shown in Figure 8. 19 pa-

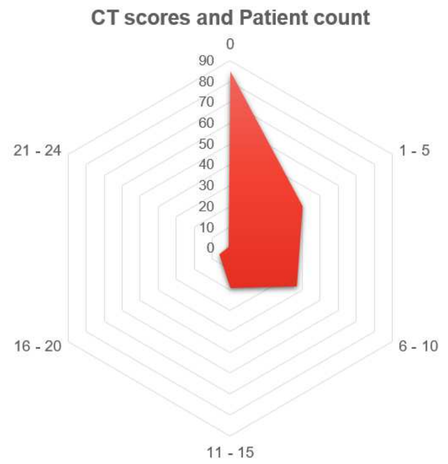


Figure 6: Scatter plot shows the CT Score Severity Grading with respect to CT score division and corresponding patient count.

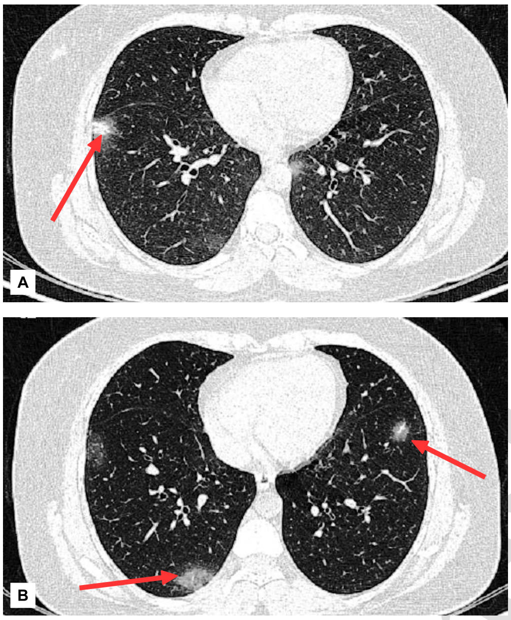


Figure 7: COVID positive 41 years female, scan done on 7th day from infection: (A) axial HRCT showing the occurrence of a nodular opacity with surrounding GGO (arrow), and (B) scattered areas of GGO's in both lower lobes (arrows).

tients had CT severity between 11-15, involving both lungs with moderate GGO and consolidation, as shown in Figure 9 as an example, followed by 6 patients whose CT severity ranged between 16-20 showing bilateral peripheral GGO with interstitial thickening, GGO's with consolidation, and bilateral pleural effusion [refer Figure 10 for an example]. Several chest HRCTs reported in our study with symptoms of chest pain, pounding heartbeat, shortness of breath and fatigue were found to have opacities parallel to the pleura [as an example refer Figure 11], fibrosis along with bronchiectasis as shown in Figure 12, interstitial thickening and subpleural band [Figure 13 for reference]. The evidence of the prior information on HRCT con-

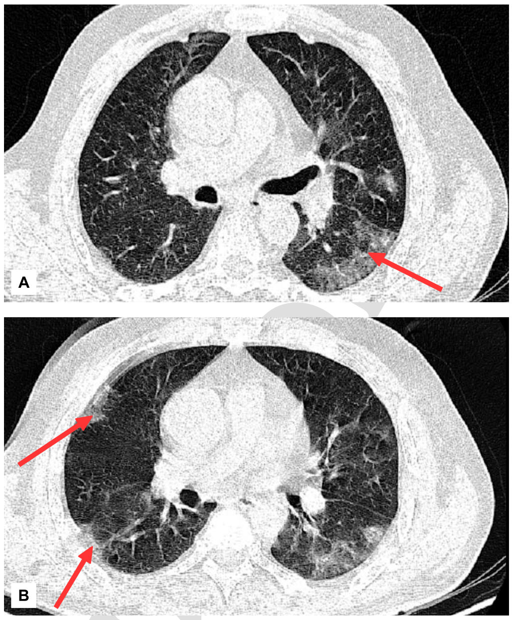


Figure 8: COVID positive 65 years male, scan done on 9th day from infection: (A) axial HRCT showing patchy GGO with crazy-paving pattern in left lower lobe (arrow), (B) GGO with consolidation in the right middle and lower lobes (arrows).

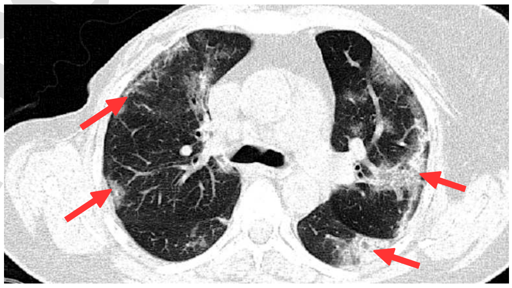


Figure 9: COVID positive 52 years female on the 9th day of infection: axial HRCT shows the occurrence of GGO in bilateral, peripheral areas in the upper lobe and patchy areas of consolidation in left upper and lower lobes (arrows).

firms the presence of the virus in earlier months, along with some pre-existing diseases. However, a few cases with post-COVID symptoms did not show any findings on HRCT done 2 months prior to the infection. These few cases may have other pre-existing diseases due to which they might experience the above-stated post-COVID symptoms.

5. Discussions

As per the statistics of North-East India collected during the pandemic stage, thousands of new COVID-19 cases were registered on a daily basis. The gold standard for COVID identification, the RT-PCR test, is efficient, but it shows true negatives and therefore fails to be 100% accurate. Moreover, the case becomes more challenging for asymptomatic patients. As a secondary measure, CT-scans are advised, but generally patients

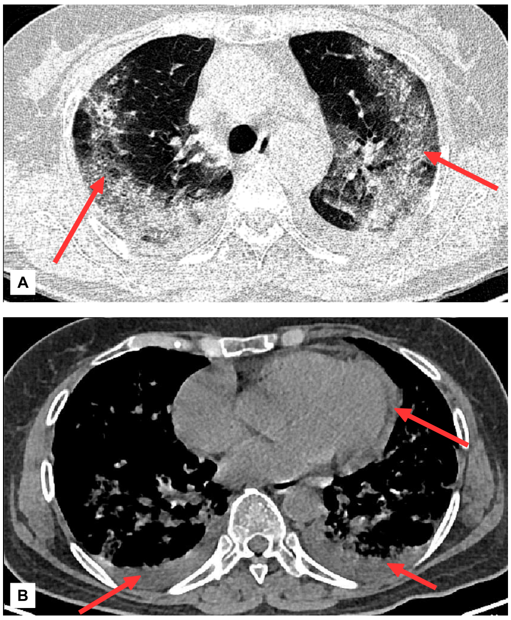


Figure 10: COVID positive 54 years female on the 13^{th} day of infection: (A) axial HRCT shows the occurrence of GGO and consolidation in bilateral upper lobes in the peripheral region (arrow). (B) The mediastinal window shows moderate pleural effusion bilaterally and mild pericardial effusion (arrows).

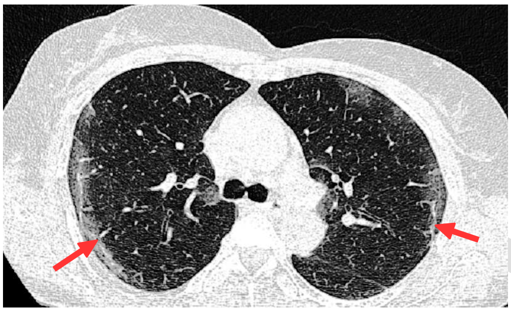


Figure 11: 56 years old female with a history of COVID shows thin linear opacities parallel to the pleura in bilateral upper lobes, representing a subpleural band and adjacent GGO (arrows). She tested positive for COVID two months ago and had persistent shortness of breath. The HRCT was done when she tested negative two months post-COVID.

show less interest unless they are suffering from symptoms related to lung disorders. Also, the lung anomalies start at a later stage of COVID inception and when not treated in time, lead to total lung dysfunction and finally death. During the second wave of COVID, the post-COVID anomalies have increased the number of death counts.

As already mentioned, we have collected CT-scans of a total of 188 COVID positive patients. However, as far as the accuracy of the corresponding RT-PCR report is concerned, we have found two HRCT cases that show that they belong to COVID positive patients but were actually evaluated as RT-PCR negative. The CT scan of these two cases is shown in Figure 14 which clearly signifies the presence of COVID. The database statistics showed more infections in the age group of 30–60, with a higher rate of male patients. This demography may vary

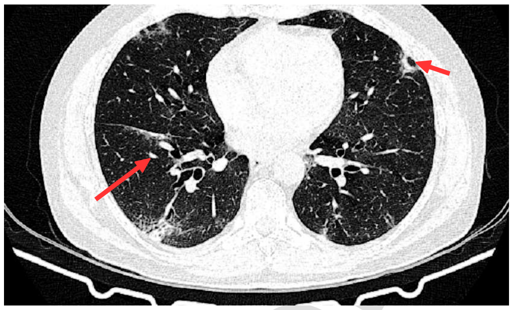


Figure 12: 58 years old man was discharged from the hospital after testing negative with the help of supportive therapy. He had symptoms of chest pain, fever, and breathing difficulties. HRCT done after one week shows fibrosis and bronchiectasis in the right lower lobe (arrow) and a small fibrotic opacity in the left upper lobe (arrow).

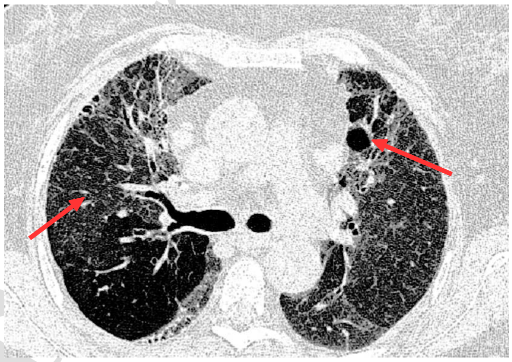


Figure 13: 58 years female with symptoms of low oxygen level, breathing difficulties and cough showed evidence of fibrosis, interstitial thickening, subpleural cyst and bronchiectasis in bilateral upper lobes and interstitial thickening right lower lobe (arrow). She was admitted to the hospital due to a rapid drop in oxygen levels after two weeks of testing RT-PCR negative.

depending on location and populations, but there is a probability match of the statistics with those recorded in other parts of India [7][41]. Next, as per the HRCT findings on lung involvement, the pattern is similar in both genders with more effect on the upper-middle-lower lobes in the right and upper-lower in the left lung, respectively. As per the study findings, out of a total of 188 cases, 40 (39.6%) male and 44 (50.6%) female patients showed normal HRCT with zero findings with respect to GGO and consolidation. Thus, CT-scans can't be used as a standalone measure for screening and RT-PCR will continue to be the gold standard for mass identification. But the point to be noted is that for the RT-PCR positive cases or post-COVID, CT-scans are mandatory. These studies were also reported in previous literature [11][24][41][42], but the main objective of this work is to understand the HRCT findings useful to apply image processing tools and for automated AI algorithms to classify and grade COVID-19 severity from the samples.

Considering the versatility of the disease, the detection process based on radiological findings has many shortcomings despite its wide applications in diagnostic centers. Correspondingly, researchers related to the medical and computer fields use AI tools such as ML and DL models for analyzing these ra-

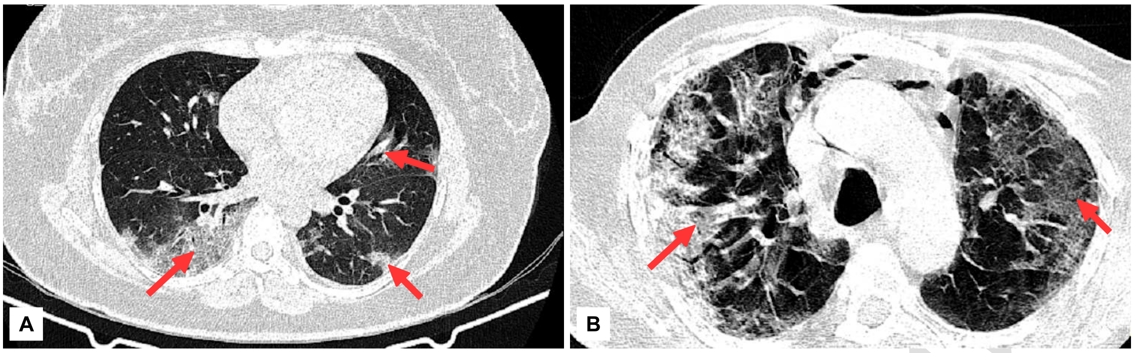


Figure 14: True negative in RT-PCR and corresponding CT scans; (A) Axial HRCT of a 36-year-old female COVID negative patient showing crazy paving and consolidation in the right peripheral and basal area (arrow), and patchy areas of consolidation are seen in the left lower lobe lingular segment (arrow). This patient had symptoms of high fever, headache, and sore throat, which resulted in RT-PCR being negative during testing. The patient underwent HRCT due to non-recovery from the symptoms, which resulted in the findings mentioned above suggestive of COVID positive. (B) axial HRCT of a 62-year-old man with symptoms of COVID infection resulting in breathing difficulties. The patient tested RT-PCR negative, but HRCT showed areas of consolidation in the right lung and GGO's in the left lung in peripheral locations (arrows).

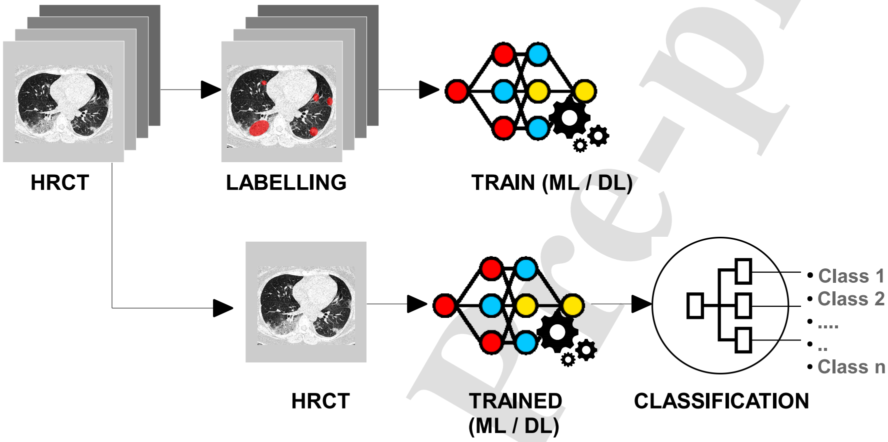


Figure 15: Block diagram of ML-DL model for automated classification of COVID-19

diological findings. There were many systematic reviews which showed that ML and DL algorithms can be used for various disease detection and diagnosis processes [21],[43]-[45]. These algorithms have proven themselves to be efficient in the detection and classification of various diseases from different types of databases [46][47]. Using different DL algorithms, studies have embarked on the identification and differential diagnosis of COVID-19. The DL-based architecture in the field of COVID-19 based on radiological findings helps to reduce false-positive and negative errors in the analysis of the disease, providing a fast and safe diagnosis system for patients. Figure 15 provides an overview of a predictive model for the detection and diagnosis of COVID-19 using radiological modalities. Various studies reviewed that DL based detection for COVID diagnosis is classified into two categories: pre-trained models with deep transfer learning (DTL) and customized DL [20]. Pre-trained models use trained data in areas that have similarity with the content of the application. Pre-trained models with DTL provide the facility to accelerate convergence with network generalization other than the general training models, which requires more computation time. On the other hand, custom based DL techniques have specific applications and deal with feasible architecture development, which gives accurate performance due to their consistency. The custom networks use specific DL algorithms or hybridization of DL techniques with other fields of application like AI, such as data mining, ML, etc. [48]. Various popular architectures such as AlexNet, GoogleNet, MobileNetv2, Inception, InceptionV3, Xception, VGG-16, VGG-19, ResNet, ResNet18, ResNet50, ResNet101, Inception ResNetV2, DenseNet201, XceptionNet, CCSHNet, FGCNet are used in both of these models [49]-[60]. Responses reported on these architectures by state-of-the art methods are reproduced in Figure 16 where pre-trained model comparison is based on its sensitivity of detection, where-as the customized methods are categorized as per its accuracy of detection [49]-[70].

As per the literature, although efficient algorithms have been proposed in this area, there are certain limitations to these studies. As reported in our previous publication of COVID-19 review [71] there are two fold shortcomings, which includes, (*i*) improper database and (*ii*) limited database. Due to the noisy, incomplete, and unmarked data, issues like redundancy, spar-

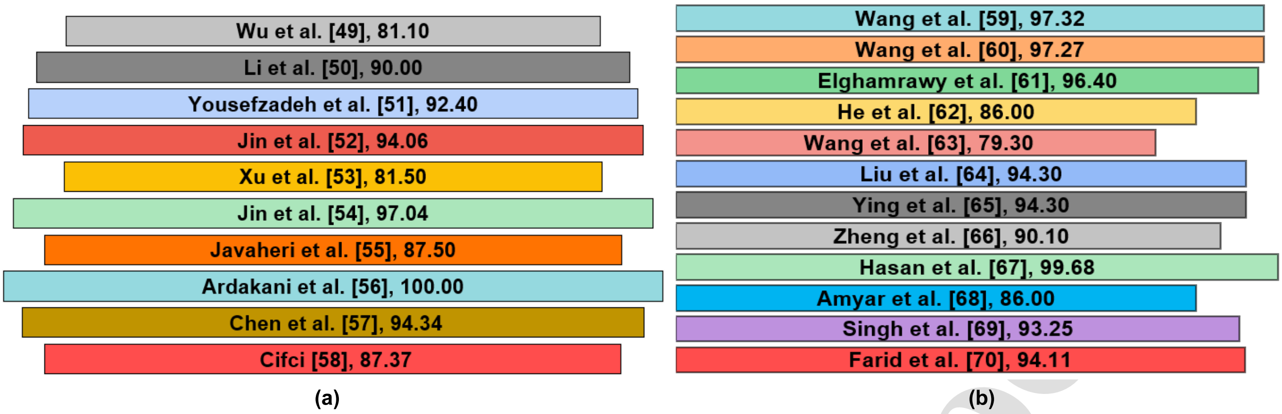


Figure 16: Comparison of state-of-the art DL algorithms for detection of COVID-19 using HRCT images based on, (a) Sensitivity of Pre-trained models, and (b) Accuracy of Customized models.

sity, and non-availability of values are encountered during the training of classification modules. Again, the unavailability of accessible implies the application of limited local databases, which are very minimal compared to the actual patient data. This leads to underfit or overfit problems while applying DL. Apart from this, with the unavailability of standard databases, it becomes hard to calculate the proper efficiency. Hence, considering these factors and the modality under consideration, we would like to continue our work in the direction of automation of CT-scan grading using ML and DL tools, to increase the sensitivity and specificity of detection.

Limitations:. There are a few limitations encountered during this work. Since the study is retrospective, and all the cases diagnosed are COVID-infected, it cannot be used to evaluate the exact sensitivity and specificity of COVID-19 HRCTs. RT-PCR and HRCT cannot be compared for COVID detection. For instance, all the post-COVID subjects considered in this study are not RT-PCR positive. These patients underwent HRCT due to post-COVID symptoms as mentioned in hospital records and clinical results. Again, the slices and lobes reviewed during the study depended on regions with distinctive COVID findings; some subjects had pre-existing lung disorders, resulting in subjective findings, which put hindrances during the study. A few low-quality HRCT scans showed mild motion artefacts that may be due to shortness of breath (dyspnea) experienced by the patients. Apart from these, there are certain other associated infections/diseases which worsen the COVID-19 patient's condition. Some of them are bacterial or fungal co-infections, with mucormycosis being the most common. Mucormycosis is a common side effect of corticosteriods that are prescribed for severe COVID-19. At mucormycosis the patient's immune system weakens and blood sugar level increases, and it becomes life threatening for the diabetic patients [72]. As per the International Diabetes Federation, India being the hub of diabetes, the appearance of mucormycosis is common for most of the databases under consideration. But this information was not available in the current CT scan reports of Marwary Hospitals and therefore not considered in this work.

To summarize, we may say that, with considerable evidence, chest HRCT proves itself to be an essential module for diagnosis, prognosis, and follow-up for individuals with COVID infection. All the patients confirmed with COVID-19 have the same imaging patterns, which may be helpful for the radiologist for early detection and estimating the severity of the disease. We have performed this study as a familiarization step to HRCT findings of COVID and post-COVID so that it may help the research community to explore possibilities for analysis or prognosis of this challenging disease of the current epoch.

6. Conclusion

The HRCT findings of the chest play an essential role for radiologists in adequately diagnosing the COVID-19 infection. Mass screening by chest HRCT is a must, along with RT-PCR tests, to rule out better disease management. The presence of common imaging patterns of bilateral, peripheral, multifocal GGO, consolidation, and GGO with consolidation, in the initial phase of the infected cases, may help in the early detection of the disease. Asymmetrical and bilateral distribution of opacities of lungs is considered a benchmark for radiologists to detect COVID-19 pneumonia.

The current retrospective study analyses the clinical characteristics and outcomes of 188 patients with COVID-19 and post-COVID infections. It identifies six HRCT findings based on age, gender, laterality of lung involvement, lobe involvement of lungs, region of coverage and lastly, CT severity score for proper assessment of the severity of the disease progression. The strength of this study is to assist researchers in exploring the radiological imaging patterns or findings of COVID-19 to develop knowledge-based systems using AI tools for detecting and diagnosing COVID-19. At the same time, it will be helpful for radiologists and medical institutes as an additional tool for the early detection of the disease. In the near future, we will analyze these findings for implementing AI tools to propose a novel automated algorithm for detecting and grading COVID-19.

Although HRCT outperforms the RT-PCR tests as a mass screening tool, for the time being, RT-PCR is regarded as the primary gold standard test as being cost-effective and able to detect subclinical cases due to the rising number of infections in the community level transmission.

7. Acknowledgment

We would like to acknowledge Marwari Hospitals, Guwahati, Assam, India, for providing and allowing the use of COVID-19 database comprising 188 cases, for this study.

References

[1] W. Zhao, Z. Zhong, X. Xie, Q. Yu, J. Liu, et al., Relation between chest ct findings and clinical conditions of coronavirus disease (covid-19) pneumonia: a multicenter study, AJR Am J Roentgenol 214 (5) (2020) 1072–1077.

[2] G. Nucera, F. Chirico, V. Raffaelli, P. Marino, Current challenges in covid-19 diagnosis: a narrative review and implications for clinical practice, Italian Journal of Medicine 15 (3) (2021).

[3] C. Wang, P. W. Horby, F. G. Hayden, G. F. Gao, A novel coronavirus outbreak of global health concern, The lancet 395 (10223) (2020) 470–473.

[4] P. Afshar, S. Heidarian, N. Enshaei, F. Naderkhani, M. J. Rafiee, A. Oikonomou, F. B. Fard, K. Samimi, K. N. Plataniotis, A. Mohammadi, Covid-ct-md, covid-19 computed tomography scan dataset applicable in machine learning and deep learning, Scientific Data 8 (1) (2021) 1–8.

[5] I. Hasanoglu, G. Korukluoglu, D. Asilturk, Y. Cosgun, A. K. Kalem, A. B. Altas, B. Kayaaslan, F. Eser, E. A. Kuzucu, R. Guner, Higher viral loads in asymptomatic covid-19 patients might be the invisible part of the iceberg, Infection 49 (1) (2021) 117–126.

[6] F. Chirico, G. Nucera, O. Ilesanmi, A. Afolabi, M. Pruc, L. Szarpak, Identifying asymptomatic cases during the mass covid-19 vaccination campaign: insights and implications for policy makers, Future Virology 17 (3) (2022) 141–144.

[7] WHO, Tracking SARS-CoV-2 variants : (May 2022). [link].
URL https://www.who.int/coronavirus/variant

[8] F. W. Peacock, T. Dzieciatkowski, F. Chirico, L. Szarpak, Self-testing with antigen tests as a method for reduction sars-cov-2, The American Journal of Emergency Medicine 53 (2022) 274.

[9] F. Chirico, G. Nucera, N. Magnavita, Estimating case fatality ratio during covid-19 epidemics: Pitfalls and alternatives, The Journal Of Infection In Developing Countries 14 (05) (2020) 438–439.

[10] F. Chirico, G. Nucera, N. Magnavita, Hospital infection and covid-19: Do not put all your eggs on the "swab" tests, Infection Control & Hospital Epidemiology 42 (3) (2021) 372–373.

[11] J. Li, R. Yan, Y. Zhai, X. Qi, J. Lei, Chest ct findings in patients with coronavirus disease 2019 (covid-19): a comprehensive review, Diagnostic and Interventional Radiology 27 (5) (2021) 621.

[12] T. Ai, Z. Yang, H. Hou, C. Zhan, C. Chen, W. Lv, Q. Tao, Z. Sun, L. Xia, Correlation of chest ct and rt-pcr testing for coronavirus disease 2019 (covid-19) in china: a report of 1014 cases, Radiology 296 (2) (2020) E32–E40.

[13] M.-Y. Ng, E. Y. Lee, J. Yang, F. Yang, X. Li, H. Wang, M. M.-s. Lui, C. S.-Y. Lo, B. Leung, P.-L. Khong, et al., Imaging profile of the covid-19 infection: radiologic findings and literature review, Radiology: Cardiothoracic Imaging 2 (1) (2020) e200034.

[14] H. Kim, H. Hong, S. H. Yoon, Diagnostic performance of ct and reverse transcriptase polymerase chain reaction for coronavirus disease 2019: a meta-analysis, Radiology 296 (3) (2020) E145–E155.

[15] M. Barstugan, U. Ozkaya, S. Ozturk, Coronavirus (covid-19) classification using ct images by machine learning methods, arXiv preprint arXiv:2003.09424 (2020).

[16] A. B. Salem Salamh, A. A. Salamah, H. I. Akyüz, A study of a new technique of the ct scan view and disease classification protocol based on level challenges in cases of coronavirus disease, Radiology Research and Practice 2021 (2021).

[17] A. Mashraqi, H. Halawani, T. Alelyani, M. Mashraqi, M. Makkawi, S. Alasmari, A. Shaikh, A. Alshehri, Prediction model of adverse effects on liver functions of covid-19 icu patients, Journal of Healthcare Engineering 2022 (2022).

[18] R. Abou Ghayda, K. H. Lee, J. S. Kim, S. Lee, S. H. Hong, K. S. Kim, K. E. Kim, J. Seok, H. Kim, J. Seo, et al., Chest ct abnormalities in covid-19: a systematic review, International journal of medical sciences 18 (15) (2021) 3395.

[19] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, U. R. Acharya, Automated detection of covid-19 cases using deep neural networks with x-ray images, Computers in biology and medicine 121 (2020) 103792.

[20] M. Gupta, G. Chaudhary, V. H. C. de Albuquerque, Smart Healthcare Monitoring Using IoT with 5G: Challenges, Directions, and Future Predictions, CRC Press, 2021.

[21] M. Ghaderzadeh, F. Asadi, Deep learning in the detection and diagnosis of covid-19 using radiology modalities: a systematic review, Journal of healthcare engineering 2021 (2021).

[22] M. Garg, N. Prabhakar, A. S. Bhalla, A. Irodi, I. Sehgal, U. Debi, V. Suri, R. Agarwal, L. N. Yaddanapudi, G. D. Puri, et al., Computed tomography chest in covid-19: When & why?, The Indian Journal of Medical Research 153 (1-2) (2021) 86.

[23] C. Hani, N. H. Trieu, I. Saab, S. Dangeard, S. Bennani, G. Chassagnon, M.-P. Revel, Covid-19 pneumonia: a review of typical ct findings and differential diagnosis, Diagnostic and interventional imaging 101 (5) (2020) 263–268.

[24] T. C. Kwee, R. M. Kwee, Chest ct in covid-19: what the radiologist needs to know, Radiographics 40 (7) (2020) 1848–1865.

[25] Z. Cheng, Y. Lu, Q. Cao, L. Qin, Z. Pan, F. Yan, W. Yang, Clinical features and chest ct manifestations of coronavirus disease 2019 (covid-19) in a single-center study in shanghai, china, American Journal of Roentgenology 215 (1) (2020) 121–126.

[26] M. Abdel-Tawab, M. A. A. Basha, I. A. Mohamed, H. M. Ibrahim, A simple chest ct score for assessing the severity of pulmonary involvement in covid-19, Egyptian Journal of Radiology and Nuclear Medicine 52 (1) (2021) 1–10.

[27] A. Bernheim, X. Mei, M. Huang, Y. Yang, Z. A. Fayad, N. Zhang, K. Diao, B. Lin, X. Zhu, K. Li, et al., Chest ct findings in coronavirus disease-19 (covid-19): relationship to duration of infection, Radiology (2020) 200463.

[28] M. Prokop, W. Van Everdingen, T. van Rees Vellinga, H. Quarles van Ufford, L. Stöger, L. Beenen, B. Geurts, H. Gietema, J. Krdzalic, C. Schaefer-Prokop, et al., Co-rads: a categorical ct assessment scheme for patients suspected of having covid-19—definition and evaluation, Radiology 296 (2) (2020) E97–E104.

[29] Z. Kang, X. Li, S. Zhou, Recommendation of low-dose ct in the detection and management of covid-2019, European radiology 30 (8) (2020) 4356–4357.

[30] S. Salehi, A. Abedi, S. Balakrishnan, A. Gholamrezanezhad, et al., Coronavirus disease 2019 (covid-19): a systematic review of imaging findings in 919 patients, Ajr Am J Roentgenol 215 (1) (2020) 87–93.

[31] Human Anatomy, Lungs : (May 2022). [link].
URL https://www.webmd.com/lung/picture-of-the-lungs

[32] Physiopedia, Lung Anatomy : (May 2022). [link].
URL https://www.physio-pedia.com

[33] M. Infante, R. Lutman, S. Imparato, M. Di Rocco, G. Ceresoli, V. Torri, E. Morenghi, F. Minuti, S. Cavuto, E. Bottoni, et al., Differential diagnosis and management of focal ground-glass opacities, European Respiratory Journal 33 (4) (2009) 821–827.

[34] D. M. Hansell, A. A. Bankier, H. MacMahon, T. C. McLoud, N. L. Muller, J. Remy, et al., Fleischner society: glossary of terms for thoracic imaging, Radiology 246 (3) (2008) 697.

[35] Predible, Suthirth Vaidya: (september 2022). [link].
URL https://medium.com/predible/covid19-severity-scoring-from-ct-primer-for-radiologists-930536dfade5

[36] W. De Wever, J. Meersschaert, J. Coolen, E. Verbeken, J. A. Verschakelen, The crazy-paving pattern: a radiological-pathological correlation, Insights into imaging 2 (2) (2011) 117–132.

[37] M. Agrò, N. Flor, Single, unilateral halo sign in covid-19 pneumonia, Clinical Imaging 73 (2021) 117.

[38] Radiology, Radiology assistant : (May 2022). [link].

URL https://radiologyassistant.nl/chest/covid-19/covid19-imaging-findings-chest-ct-ct-involvement-score

[39] M. Chung, A. Bernheim, X. Mei, N. Zhang, M. Huang, X. Zeng, J. Cui, W. Xu, Y. Yang, Z. A. Fayad, et al., Ct imaging features of 2019 novel coronavirus (2019-ncov), Radiology (2020).

[40] A. M. Al-Mosawe, N. A. H. Fayadh, et al., Spectrum of ct appearance and ct severity index of covid-19 pulmonary infection in correlation with age, sex, and pcr test: an iraqi experience, Egyptian Journal of Radiology and Nuclear Medicine 52 (1) (2021) 1–7.

[41] S. A. Shah, M. I. Gajbhiye, A. S. Saibannawar, M. S. Kulkarni, U. D. Misal, D. I. Gajbhiye, Retrospective analysis of chest hrct findings in coronavirus disease pandemic (covid-19)-an early experience, Indian Journal of Radiology and Imaging 31 (S 01) (2021) S101–S109.

[42] A. Oulefki, S. Agaian, T. Trongtirakul, A. K. Laouar, Automatic covid-19 lung infected region segmentation and measurement using ct-scans images, Pattern recognition 114 (2021) 107747.

[43] R. Mahmoudi, N. Benameur, R. Mabrouk, M. A. Mohammed, B. Garcia-Zapirain, M. H. Bedoui, A deep learning-based diagnosis system for covid-19 detection and pneumonia screening using ct imaging, Applied Sciences 12 (10) (2022) 4825.

[44] S. Shamim, M. J. Awan, A. Mohd Zain, U. Naseem, M. A. Mohammed, B. Garcia-Zapirain, Automatic covid-19 lung infection segmentation through modified unet model, Journal of Healthcare Engineering 2022 (2022).

[45] H. Hu, L. Shen, Q. Guan, X. Li, Q. Zhou, S. Ruan, Deep co-supervision and attention fusion strategy for automatic covid-19 lung infection segmentation on ct images, Pattern Recognition 124 (2022) 108452.

[46] A. Khan, R. Garner, M. L. Rocca, S. Salehi, D. Duncan, A novel threshold-based segmentation method for quantification of covid-19 lung abnormalities, Signal, Image and Video Processing (2022) 1–8.

[47] L. Fan, J. Shi, N. Shi, W. Tu, Y. Bian, X. Zhou, Y. Guan, Y. Shi, S. Liu, Artificial intelligence-based evaluation of infectious disease imaging: A covid-19 perspective, in: Artificial Intelligence in Cardiothoracic Imaging, Springer, 2022, pp. 447–457.

[48] M. M. Islam, F. Karray, R. Alhajj, J. Zeng, A review on deep learning techniques for the diagnosis of novel coronavirus (covid-19), Ieee Access 9 (2021) 30551–30572.

[49] X. Wu, H. Hui, M. Niu, L. Li, L. Wang, B. He, X. Yang, L. Li, H. Li, J. Tian, et al., Deep learning-based multi-view fusion model for screening 2019 novel coronavirus pneumonia: a multicentre study, European Journal of Radiology 128 (2020) 109041.

[50] L. Li, L. Qin, Z. Xu, Y. Yin, X. Wang, B. Kong, J. Bai, Y. Lu, Z. Fang, Q. Song, et al., Artificial intelligence distinguishes covid-19 from community acquired pneumonia on chest ct, Radiology (2020).

[51] M. Yousefzadeh, P. Esfahanian, S. M. S. Movahed, S. Gorgin, D. Rahmati, A. Abedini, S. A. Nadji, S. Haseli, M. Bakhshayesh Karam, A. Kiani, et al., ai-corona: Radiologist-assistant deep learning framework for covid-19 diagnosis in chest ct scans, PloS one 16 (5) (2021) e0250952.

[52] C. Jin, W. Chen, Y. Cao, Z. Xu, Z. Tan, X. Zhang, L. Deng, C. Zheng, J. Zhou, H. Shi, et al., Development and evaluation of an artificial intelligence system for covid-19 diagnosis, Nature communications 11 (1) (2020) 1–14.

[53] X. Xu, X. Jiang, C. Ma, P. Du, X. Li, S. Lv, L. Yu, Q. Ni, Y. Chen, J. Su, et al., A deep learning system to screen novel coronavirus disease 2019 pneumonia, Engineering 6 (10) (2020) 1122–1129.

[54] S. Jin, B. Wang, H. Xu, C. Luo, L. Wei, W. Zhao, X. Hou, W. Ma, Z. Xu, Z. Zheng, et al., Ai-assisted ct imaging analysis for covid-19 screening: Building and deploying a medical ai system in four weeks, MedRxiv (2020).

[55] T. Javaheri, M. Homayounfar, Z. Amoozgar, R. Reiazi, F. Homayounieh, E. Abbas, A. Laali, A. R. Radmard, M. H. Gharib, S. A. J. Mousavi, et al., Covidctnet: An open-source deep learning approach to identify covid-19 using ct image, arXiv preprint arXiv:2005.03059 (2020).

[56] A. A. Ardakani, A. R. Kanafi, U. R. Acharya, N. Khadem, A. Mohammadi, Application of deep learning technique to manage covid-19 in routine clinical practice using ct images: Results of 10 convolutional neural networks, Computers in biology and medicine 121 (2020) 103795.

[57] J. Chen, L. Wu, J. Zhang, L. Zhang, D. Gong, Y. Zhao, Q. Chen, S. Huang, M. Yang, X. Yang, et al., Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography, Scientific reports 10 (1) (2020) 1–11.

[58] M. A. Cifci, Deep learning model for diagnosis of corona virus disease from ct images, Int. J. Sci. Eng. Res 11 (4) (2020) 273–278.

[59] S.-H. Wang, D. R. Nayak, D. S. Guttery, X. Zhang, Y.-D. Zhang, Covid-19 classification by ccshnet with deep fusion using transfer learning and discriminant correlation analysis, Information Fusion 68 (2021) 131–148.

[60] S.-H. Wang, V. V. Govindaraj, J. M. Górriz, X. Zhang, Y.-D. Zhang, Covid-19 classification by fgcnet with deep feature fusion from graph convolutional network and convolutional neural network, Information Fusion 67 (2021) 208–229.

[61] S. Elghamrawy, A. E. Hassanien, Diagnosis and prediction model for covid-19 patient's response to treatment based on convolutional neural networks and whale optimization algorithm using ct images, MedRxiv (2020).

[62] X. He, X. Yang, S. Zhang, J. Zhao, Y. Zhang, E. Xing, P. Xie, Sample-efficient deep learning for covid-19 diagnosis based on ct scans, medrxiv (2020).

[63] S. Wang, B. Kang, J. Ma, X. Zeng, M. Xiao, J. Guo, M. Cai, J. Yang, Y. Li, X. Meng, et al., A deep learning algorithm using ct images to screen for corona virus disease (covid-19). medrxiv, Preprint at https://www. medrxiv. org/content/10.1101/2020.02 14 (2020) v5.

[64] B. Liu, P. Liu, L. Dai, Y. Yang, P. Xie, Y. Tan, J. Du, W. Shan, C. Zhao, Q. Zhong, et al., Assisting scalable diagnosis automatically via ct images in the combat against covid-19, Scientific reports 11 (1) (2021) 1–8.

[65] Y. Song, S. Zheng, L. Li, X. Zhang, X. Zhang, Z. Huang, J. Chen, R. Wang, H. Zhao, Y. Chong, et al., Deep learning enables accurate diagnosis of novel coronavirus (covid-19) with ct images, IEEE/ACM transactions on computational biology and bioinformatics 18 (6) (2021) 2775–2780.

[66] C. Zheng, X. Deng, Q. Fu, Q. Zhou, J. Feng, H. Ma, W. Liu, X. Wang, Deep learning-based detection for covid-19 from chest ct using weak label. medrxiv 2020, preprint [https://doi. org/10.1101/2020.03.12.20027185] (2020).

[67] A. M. Hasan, M. M. Al-Jawad, H. A. Jalab, H. Shaiba, R. W. Ibrahim, A. R. AL-Shamasneh, Classification of covid-19 coronavirus, pneumonia and healthy lungs in ct scans using q-deformed entropy and deep learning features, Entropy 22 (5) (2020) 517.

[68] A. Amyar, R. Modzelewski, H. Li, S. Ruan, Multi-task deep learning based ct imaging analysis for covid-19 pneumonia: Classification and segmentation, Computers in Biology and Medicine 126 (2020) 104037.

[69] D. Singh, V. Kumar, M. Kaur, et al., Classification of covid-19 patients from chest ct images using multi-objective differential evolution–based convolutional neural networks, European Journal of Clinical Microbiology & Infectious Diseases 39 (7) (2020) 1379–1389.

[70] A. A. Farid, G. I. Selim, H. A. A. Khater, A novel approach of ct images feature analysis and prediction to screen for corona virus disease (covid-19) (2020).

[71] U. Bhattacharjya, K. K. Sarma, Existing methods and emerging trends for novel coronavirus (covid-19) detection using residual network (resnet): A review on deep learning analysis, Smart Healthcare Monitoring Using IoT with 5G (2021) 131–147.

[72] L. Szarpak, F. Chirico, M. Pruc, L. Szarpak, T. Dzieciatkowski, Z. Rafique, Mucormycosis—a serious threat in the covid-19 pandemic?, Journal of infection 83 (2) (2021) 237–279.

Highlights:

- The role of chest CT in diagnostic decision making.
- The typical initial CT findings in COVID-19.
- Chest CT imaging importance in diagnostic work-up and management in patients with COVID-19.
- Retrospective study of collected 188 cases of HRCT images.
- Application of deep learning in the field of COVID-19 radiological imaging

Automated Diagnosis of COVID-19 Using Radiological Modalities and Artificial Intelligence Functionalities: A Retrospective study based on chest HRCT database

Upasana Bhattacharjya[1], Kandarpa Kumar Sarma[2], Jyoti Prakash Medhi[3], Binoy Kumar Choudhury[4] Geetanjali Barman[5]

Address for correspondence:

[1,2,3]Department of Electronics and Communication Engineering Gauhati University, Guwahati Guwahati-781014, Assam, India Ph: +91-9854994832

[4,5] Department of Radio Diagnosis and Imaging, Dr. Bhubaneswar Borooah Cancer Institute, Guwahati, Assam

Email IDs:

[1] *upasanabhatta@gauhati.ac.in; upasana.b90@gmail.com*

[2] *kandarpaks@gauhati.ac.in*

[3] *jpmedhi@gauhati.ac.in*

[4] *bkchoudhury@gmail.com*

[5] *drgeetanjalibarman@gmail.com*

Authors' contribution(s) to the submitted manuscript are attributed as below.

UPASANA BHATTACHARJYA

Conceptualization, Data curation, Project administration, Formal analysis, Resources, Writing – original draft

KANDARPA KUMAR SARMA

Validation, Supervision – review & editing

JYOTI PRAKASH MEDHI

Conceptualization, Investigation, Project administration, Resources, Data curation, Supervision, Review & editing,

BINOY KUMAR CHOUDHURY

Investigation, Data analysis, Project administration, review & editing, Supervision

GEETANJALI BARMAN

Conceptualization, Data analysis, Resources, Writing – original draft, review & editing

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

MARWARI HOSPITALS

Ref: MH/HR/M.F-19/95 / 22-23/ 418

September 06, 2022

WITHOUT ANY PREJUDICE

TO WHOM IT MAY CONCERN

This is to certify that Ms. Upasana Bhattacharjya, research scholar from Gauhati University, Department of Electronics and Communication Engineering has taken data from the hospital which contains HRCT Images and corresponding RT-PCR test information regarding her ongoing research on biomedical images related to automatic diagnosis of COVID-19.

Please note, we have no objection in using these data for research purpose only by adhering to the ethical guidelines and also these data do not contain any biological sample.

Yours faithfully,
For, Marwari Hospitals,
(A unit of Shree Marwari Databya Aushadhalaya)

(Rohit Updhayay)
Hospital Superintendent

A unit of **Shree Marwari Databya Aushadhalaya**
Sati Jaimati Road, Athgaon, Guwahati-781008, 0361-2602738 / 2739, 2541201 / 1202
www.marwarihospitals.com, email : info@marwarihospitals.com