Computational Modelling and Imaging for SARS-CoV-2 and COVID-19

EDITED BY

S. Prabha • P. Karthikeyan
K. Kamalanand • N. Selvaganesan

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Contents

Preface ix
Editors xi
Contributors xiii

Chapter 1 Artificial Intelligence Based COVID-19 Detection using Medical Imaging Methods: A Review 1

M Murugappan, Ali K Bourisly, Palani Thanaraj Krishnan, Vasanthan Maruthapillai, and Hariharan Muthusamy

1.1 Introduction 1
1.1.1 Statistics 2
1.1.2 Clinical Symptoms, Manifestations and their Effects 3
1.2 Diagnosis Methods and Need for an AI-based Solution 4
1.3 Artificial Intelligence Methods 6
1.4 Datasets 9
1.5 Related Research 9
1.5.1 CT Scan Images based COVID-19 Detection using AI Methods 9
1.5.2 X-ray Images based COVID-19 Detection using AI Methods 14
1.6 Conclusion 18
References 19

Chapter 2 Review on Imaging Features for COVID-19 23

D. Chitradevi and S. Prabha

2.1 Introduction 23
2.2 Review of Literature 26
2.3 Diagnosis 27
2.3.1 RT-PCR Test 28
2.3.2 Chest Radiography 29
2.3.3 PET/CT 30
2.3.4 Magnetic Resonance Imaging (MRI) 30
2.3.5 Ultrasonography 31
2.3.6 Chest Computed Tomography (CT) 31
2.4 Prevention Mechanisms 36
2.5 Discussion 39
2.6 Conclusion 40
References 40

Chapter 3 Investigation of COVID-19 Chest X-ray Images using Texture Features – A Comprehensive Approach ... 45

J. Thamil Selvi, K. Subhashini, and M. Methini

3.1 Introduction ... 45
3.2 Methodology ... 46
3.2.1 Database ... 46
3.2.2 Materials and Methods ... 46
3.3 Results and Discussion ... 49
3.4 Conclusion ... 56
References ... 56

Chapter 4 Efficient Diagnosis using Chest CT in COVID-19: A Review ... 59

J. Sivakamasundari and K. Venkatesh

4.1 Introduction ... 59
4.2 Clinical Evaluations ... 60
4.3 Image Interpretations ... 61
4.4 Conclusion ... 69
References ... 69

Chapter 5 Automatic Mask Detection and Social Distance Alerting Based on a Deep-Learning Computer Vision Algorithm ... 73

N. Vinoth, A. Ganesh Ram, M. Vijayakarthick, and S. Meyyappan

5.1 Introduction ... 73
5.2 Convolutional Neural Network ... 76
5.3 Region Proposal based Framework ... 77
5.4 Bounding Box Regression Principle ... 80
5.5 Proposal Layer ... 80
5.6 Faster RCNN Training ... 82
5.7 Need of GPU Cloud ... 84
5.8 Tensorflow Object Detection (TFOD) ... 86
5.9 Configuration Steps for Tensor Flow Object Detection ... 87
5.10 Results and Analysis ... 87
5.11 Conclusion and Future Scope ... 90
References ... 91

Chapter 6 Review of effective Mathematical Modelling of Coronavirus Epidemic and Effect of Drone Disinfection 95

Agnishwar Jayaprakash, R. Nithya, and M. Kayalvizhi

6.1 Introduction 95
6.2 Methodology 97
6.3 Thermal Imaging 103
6.4 Broadcasting Information 103
6.5 Delivery of Essentials 104
6.6 Patrolling 104
6.7 Disinfection 104
6.8 Results and Discussion 104
6.9 Conclusion 107
References 107

Chapter 7 ANFIS Algorithm based Modeling and Forecasting of the COVID-19 Epidemic: A Case Study in Tamil Nadu, India 111

M. Vijayakarthick, E. Sivaraman, S. Meyyappan, and N. Vinoth

7.1 Introduction 111
7.2 Computational Methumaods 112
7.3 Mathematical Modeling of COVID-19 Pandemic 113
7.4 Adaptive Neuro Fuzzy Inference System (ANFIS) 114
7.5 Forward Modeling of COVID-19 using ANFIS 115
7.6 Simulation Study of ANFIS Models for Epidemic Cases in the State of Tamil nadu, India 119
7.7 The Prediction of Tamil nadu Province Epidemic 121
7.7.1 Epidemic Transmission 121
7.7.2 Active Cases 122
7.7.3 Fatality Rate 122
7.8 Conclusion 122
References 123

Chapter 8 Prediction and Analysis of SARS-CoV-2 (COVID-19) Epidemic in India using LSTM Network 125

A. Ganesh Ram, S. Prabha, and M. Vijayakarthick

8.1 Introduction 125
8.2 Data Source 126
8.3 Current Scenario of SARS-CoV-2 (COVID-19) in India ... 126
8.4 Study Daily Infection and Death Rates in State 127
8.5 Methods-LSTM Network Model Using Python 130
8.6 LSTM Network Implementation 133

8.7 Moving Average ... 139
8.8 Results and Discussion ... 141
8.9 Conclusion ... 142
References ... 142

Index ... 145

Preface

SARS-CoV-2 is a highly contagious RNA virus that was first identified in Wuhan, China. As of 8th March 2021, the COVID-19 epidemic has affected 219 countries worldwide, with a total of 117,446,648 infected individuals and 2,605,302 reported deaths throughout the globe. The World Health Organization (WHO) has declared COVID-19 a pandemic and at present several countries are going through a second wave. Since COVID-19 infection leads to symptoms ranging from mild to severe, and the transmission rate (R0) of the epidemic ranges from 1.5 to 3.5, this infection has a high impact on public health. Further, the incubation period of COVID-19 infection falls between 2 to 14 days, during which the SARS-CoV-2 is contagious, but the infected individuals do not display any symptoms. Hence, it is highly important to offer timely research and information of various aspects of SARS-CoV-2 and the COVID-19 epidemic. This edited book is an effort to highlight the computational and mathematical tools for computer-assisted analysis of the SARS-CoV-2 infection. This book entitled "Computational Modelling and Imaging for SARS-CoV-2 and COVID-19" covers a variety of topics on the imaging aspects of COVID-19 detection and staging of the infection, and progression modelling of the epidemic using machine learning and analyzing the effect of interventions on the epidemic.

This book is organized into eight chapters. The first chapter, entitled "Artificial-Intelligence-Based COVID-19 Detection using Medical-Imaging Methods: A Review", authored by Murugappan et al., provides a general introduction to the COVID-19 epidemic and offers several artificial-intelligence-based schemes for detection using radiographic images. The second chapter, entitled "Review of Imaging Features for COVID-19", authored by Chitradevi and Prabha, presents a review of imaging features of different modalities, namely, Radiography, Positron Tomography, Ultrasonography, Magnetic Resonance Imaging and Computed Tomography, and their application in analysis of the SARS-CoV-2 infection. The third chapter, entitled "Investigation of COVID-19 Chest X-ray Images Using Texture Features – A Comprehensive approach", authored by Thamil Selvi et al., presents an attempt to investigate normal and COVID-19-positive chest X-ray images using texture features. The fourth chapter, entitled "Efficient Diagnosis using Chest CT in COVID-19: A Review", authored by Sivakamasundari and Venkatesh, offers a review of the techniques for analysis of COVID-19 infection in chest CT images, since they offer a better tool for analysing the complications of COVID-19 infection.

Since it is well established that the use of surgical masks and N95 masks can slow down the transmission of the COVID-19 epidemic, the fifth chapter, entitled "Automatic Mask Detection and Social Distance Alerting Based on a Deep- Learning Computer-Vision Algorithm", authored by Vinoth et al., presents an approach based on a deep-learning algorithm to detect people with and without a mask, along with the social distancing protocol in public places.

The sixth chapter, entitled "Review of Effective Mathematical Modelling of Coronavirus Epidemic and the Effect of Drone Disinfection", authored by Jayaprakash et al., analyses the effect of intervention strategies on the COVID-19 epidemic using a mathematical-modelling approach. The seventh chapter, entitled "ANFIS Algorithm-Based Modeling and Forecasting of the COVID-19 Epidemic: A Case Study in Tamil Nadu, India", authored by Vijayakarthick et al., presents an ANFIS model for predicting the progression of the epidemic in terms of both active cases and deaths. The final chapter, entitled "Prediction and Analysis of SARS-CoV-2 (COVID-19) Epidemic in India using an LSTM Network", authored by Ganesh Ram et al., proposes an LSTM network and moving average technique for predicting the confirmed, active and deceased cases in India.

This book aims to offer timely literature on computational/imaging aspects of the SARS-CoV-2 infection. We thank Dr. Marc Gutierrez, Editor, and Dr. Nick Mould, Editorial Assistant, CRC press, for their continuous support from the initial stage to final publication. We hope that this book is interesting and informative to its users.

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1 Artificial Intelligence Based COVID-19 Detection using Medical Imaging Methods: A Review

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1.1 INTRODUCTION

The novel coronavirus was first found in Wuhan, China, on Dec 2019, and was spread over 218 countries/territories by 26 October 2020, with nearly 43 million people infected and around 1 million deaths worldwide (Europa Data 2020). Now, the novel coronavirus infection is officially referred to as COVID-19 disease. The coronavirus that causes this disease is the Severe Acute Respiratory Syndrome (SARS-CoV-2), an RNA-type virus which is a challenge to the scientific community as it is difficult to characterize. COVID-19 is a deadly virus. It enters the human body through droplets and close contact, starts changing its genetic code and rapidly spreads among organs, specifically the lungs, over a short period. Some of the most challenging factors behind COVID-19 are: (i) it does not have any standard genetic code to describe its behaviour; (ii) symptoms of this virus differ from person to person based on their antibody behaviour; and (iii) symptoms and effects of this virus are not always immmediatly apparent. Because of the above characteristics, vaccine development for COVID-19 is more challenging. Researchers are developing several vaccines for testing. Furthermore, this virus spreads among humans through respiratory droplets and close contact; it stays alive in the air for more than 3 hours. COVID-19 is a lower-respiratory-tract infection which is different from the common cold, an upper-respiratory-tract infection. Moreover, COVID-19 can cause severe breathing problems and pneumonia.

1.1.1 Statistics

The World Health Organization (WHO) declared the COVID-19 a pandemic disease in February 2020 (another name for COVID-19 is Severe Acute Respiratory Syndrome coronavirus-2 or SARS – CoV-2) (WHO-Coronavirus 2020, Stoecklin et al. 2020). There are 218 countries/regions affected by COVID-19. According to recent statistics from Johns Hopkins University (JHU), there are 43,009,98 confirmed cases in the world and total mortalities due to COVID-19 increased to 1,153,861 as of 26 October 2020 (Europa Data 2020, Corona eGov Kuwait COVID-19 Updates 2020, COVID-19 Alibabacloud 2020). A statistical report states that nearly 95%of infected patients survive the disease, while 5% become seriously or critically ill (NGC-Coronavirus 2020). Countries like the USA, India, Brazil, Russia and Argentina have the most confirmed cases of COVID-19. Table 1.1 reports the top 5 worst-affected countries by number of confirmed cases, new cases and death reported in the last 24 hours and total deaths (NIH harnesses AI 2020).

TABLE 1.1
Top 5 worst-affected countries due to COVID-19*

Country	Confirmed Cases	Cases Newly Reported in Last 24 hr	Deaths Newly Reported in Last 24 hr	Total Deaths	Transmission Classification
USA	8,403,121	82,630	943	222,507	Community
India	7,864,811	50,129	578	118,534	Cluster of cases
Brazil	5,353,656	30,026	571	156,471	Community
Russia	1,513,877	16,710	229	26,050	Cluster of cases
Argentina	1,069,368	15,718	381	28,338	Community transmission

Notes:
* https://covid19.who.int/ [Accessed on 26/10/2020]

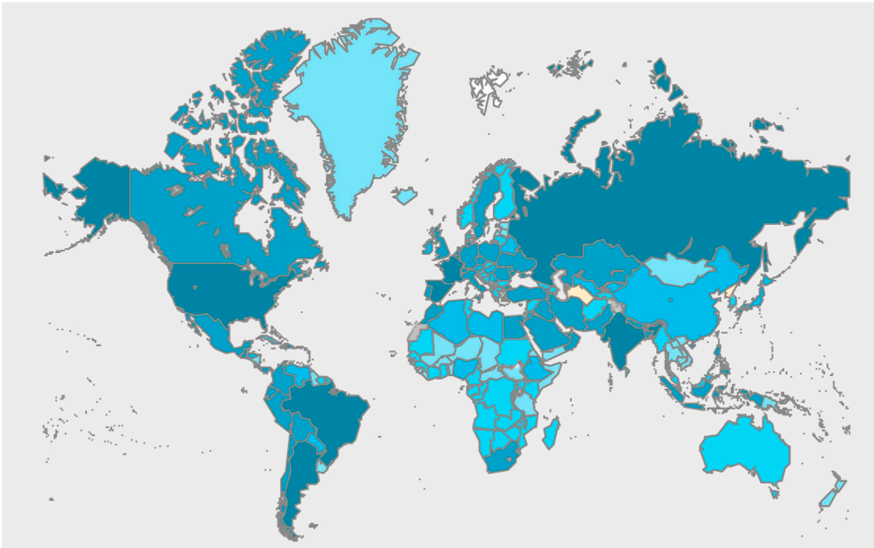

FIGURE 1.1 Choropleth map of the world (total number of confirmed cases of COVID-19).

Figure 1.1 shows the choropleth map of the world (confirmed cases of COVID-19 and total deaths) accessed on 26 October 2020. From Figure 1.1, it is observed how the novel coronavirus is spreading around the globe; more than 218 countries or regions are affected by the deadly novel coronavirus (WHO Coronavirus Dashboard 2020). The USA, India, Brazil, Russia and Argentina have the most confirmed cases of COVID-19, represented in Figure.1.1 in dark blue. From Figure 1.2, it can be noted that the rapid spread of COVID-19 virus has resulted in a massive increase of deaths. A maximum number of deaths has been reported in the USA, Brazil, Argentina, Spain, the UK, Italy, Mexico and France due to COVID-19.

1.1.2 Clinical Symptoms, Manifestations and their Effects

The COVID-19 virus has symptoms similar to other coronaviruses, such as Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS) (WHO-Coronavirus 2020, Huang et al. 2020, Chowdary et al. 2020). Current clinical manifestations of COVID-19 can include: (i) fever; (ii) breathing trouble; (iii) pneumonia; (iv) reduced white blood cell count (WBC); (vi) rapid increase in erythrocyte sedimentation rate (ESR); and (vii) reduced lymphocyte count. Clinical symptoms of COVID-19 have been classified into four different stages: mild; moderate; severe; and critical (Worldmeters-Coronavirus 2020). According to a recent study, most COVID-19 patients have mild symptoms. The signs of a mild infection include fever, cough, dyspnea, respiratory symptoms (i.e., breathing difficulties or short breath), muscle ache, diarrhoea, and headache (WHO-Coronavirus 2020). The signs of moderate infection include high fever and

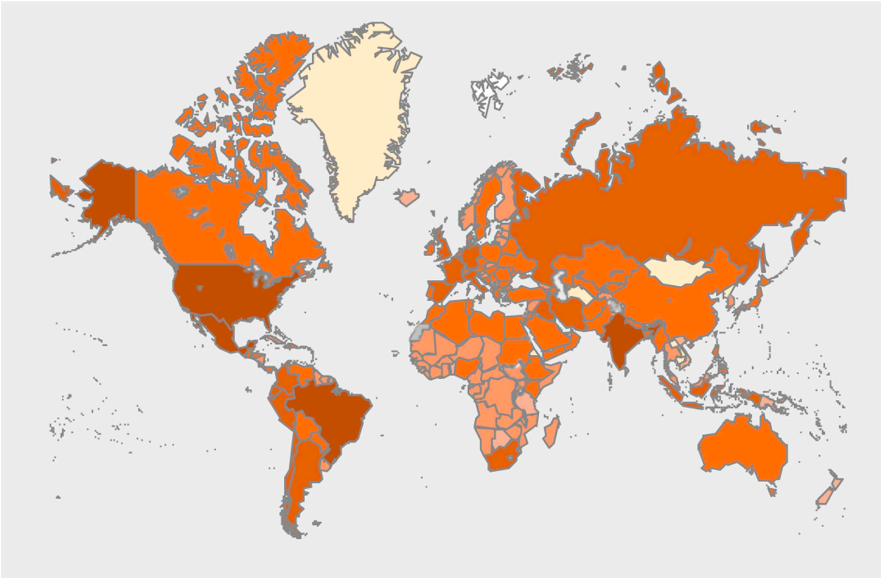

FIGURE 1.2 Choropleth map of the world (total number of deaths of COVID-19).

pneumonia symptoms. Respiratory distress (Respiration rate ≥ 30 times/min) and oxygen saturation ≤ 93% in a resting state are the most common signs of severe infection. However, respiratory failure, septic shock, multi-organ failure, Severe Acute Respiratory Syndrome (SARS), and death are signs of the critical stage (Mahase 2020, Wang et al. 2020b).

The most common effects of COVID-19 are respiratory problems due to viral infection of the lungs. This virus goes inside the human body through the oral pathway, and starts changing its genetic code over the infection's duration. It then creates ground-glass opacities (GGO), multiple ground-glass opacities (MGGO), and lesions, which infiltrate the lungs, and enlarge the lymph nodes (Guardian:COVID-19 2020, Itnonline:COVID-19 2020, European Lung 2020). The effects of COVID-19 are quite similar to other viruses, such as SARS and MERS, and it is highly challenging to differentiate pneumonia due to COVID-19. According to a recent report of researchers from China, those with A + blood and those older than 55 are profoundly affected by COVID-19 over the world. Besides, patients with a history of chronic disease are more easily affected by COVID-19, compared to healthy individuals.

1.2 DIAGNOSIS METHODS AND NEED FOR AN AI-BASED SOLUTION

Currently, COVID-19 has been conclusively diagnosed through molecular tests ((polymerase chain reaction (PCR) and real-time reverse transcription-polymerase chain reaction test (RT-PCR)) with a high success rate. However, due to limited facilities to perform molecular or rapid antigen tests (RAT), most countries require more than 48 hours to disclose results of the COVID-19 diagnosis. The present clinical procedure to detect COVID-19 is minimally invasive at best, but requires more facilities, trained human resources (epidemiologist or virologist), and time.

Diagnosis of COVID-19 relies on the following criteria: (a) clinical symptoms; (b) clinical imaging (i.e., Computed Tomography (CT) and general X-Ray images); (c) nucleic acid test/pathogenic testing; (d) close contact history; (e) contact history with patients with fever; (f) clustering occurrence; and (g) epidemiological history (Sana et al. 2020, Radiology assistant 2020). The standard test recommended by the WHO to diagnose COVID-19 is the Nucleic Acid Amplification Test (NAAT) and RT-PCR (Hao & Li 2020, EUA-COVID-19 2020). Sudden increase in levels of C-reactive protein and ESR is used as an additional tool for diagnosing COVID-19. Significant limitations of RT-PCR testing are: (a) many countries do not have abundant access to sophisticated labs and appropriate laboratory tools to perform this test; (b) the test is supposed to be repeated 2 to 3 times to validate the accuracy of results; (c) limited access to virologists and epidemiologists in many countries slows down the diagnosis process; (d) turnaround time to get the results of RT-PCR can be up to 72 hours for one sample; (e) testing is expensive and could not be afforded by developing countries; and (f) finally, it is minimally invasive (Soon et al. 2020). The above limitations of RT-PCR are also valid for the NAAT test; however, if the viral load is low while testing, the NAAT test results will be negative (Ying et al. 2020). All the above issues significantly delay the diagnosis process. Early isolation stops the spread and allows treatment to start early.

Because of the limitations of RT-PCR and NAAT mentioned above, clinical imaging methods also play a vital role in diagnosis in countries where conventional methods are inaccessible. As of early Feb 2020, many countries do not have the facilities to perform RT-PCR tests utilizing radio-imaging methods as first-line tools to diagnose COVID-19. Some of the most common clinical imaging tools used for COVID-19 diagnosis are ultrasound images, chest Computed Tomography (CT) scanning, and chest X-Ray (). These imaging methods are mostly found in hospitals, they are affordable, give accurate results as compared to RT-PCT in a short period. They also offer faster response time and are non-invasive. X-Ray images are mostly used for clinical diagnoses such as bone fractures, bone relocation, tumour identification, lung infections, and pneumonia. In the case of X-Ray imaging, the significant advantages are that it is convenient, economic and available in all hospitals and clinics. Several research works have used chest x-ray (CXR) images to develop an intelligent COVID-19 diagnosis system using AI methods (Feng et al. 2020, Ozturk et al. 2020, Abbas et al. 2020, Khan et al. 2020, Sethy et al. 2020, Mukherjee et al. 2020, Ucar et al. 2020, Kumar et al. 2020, Afshar et al. 2020, Farooq et al. 2020, Basu et al. 2020, Chowdhury et al. 2020, Li et al. 2020a, Narin et al. 2020, Mahdy et al. 2020). However, X-Ray images are not suitable for analyzing ground-glass opacities, crazy paving patterns, or multiple ground-glass opacities due to its low image resolution. The above indications are more prevalent in COVID-19 pneumonia compared to other viral pneumonia. Hence, significant preprocessing methods are required to improve image contrast for better clinical diagnosis. Compared to X-Ray images, a CT scan is mostly used for investigating the soft structure of the active body, and it gives clear, high-resolution images of soft tissues and organs (Li et al. 2020, Ho et al. 2020). Hence, most of the earlier works and physicians preferred to use CT scan images compared to X-Ray images in the clinical diagnosis of COVID-19 (Wei-cai et al. 2020, Shuai et al. 2020, Ran et al. 2020, Lu et al. 2020, Ophir et al. 2020, Lin et al. 2020, Wang et al. 2020, Singh et al. 2020, Abdullah et al. 2020, Li et al. 2020, Xu et al. 2020, Chen et al. 2020, Elghamrawy et al. 2020, Shan et al. 2020, He et al. 2020, Amyar et al. 2020). Collective findings from chest CT scan images are categorized into five different stages in COVID-19 detection: (i) Ultra-early (No pneumonia symptoms, CT scan images may show single or multiple GGO, air bronchogram after 1-2 weeks of infection); (ii) Early (single or multiple GGO and interlobar septal thickening); (iii) Rapid progression (large, light consolidative opacities, and air bronchogram); (iv) Consolidation (reduction in density and size of consolidative opacities); and finally (v) Dissipation, with death resulting from organ failure (Ran et al. 2020). This classification is performed by investigating the morphological features of GGO and lesions, such as size, density, area, depth, and location in the lung region. It is also important to note that access to CT imaging may be a challenge compared to RT-PCR and NAAT, as it requires patients to enter a hospital, and these imaging modalities are also limited. It is more challenging to deploy on mobile bases. Hence, most investigators are interested in carrying out an investigative study to develop an intelligent COVID-19 diagnosis system to aid in classification of COVID-19 patients. This is done by observing respiratory symptoms, which may go unnoticed by fatigued radiologists. It also helps in automation so that clinicians can free up time to focus on other clinical issues and administration during COVID-19.

To circumvent these issues of conventional COVID-19 detection methods, researchers started developing artificial-intelligence-based clinical diagnosis systems for speeding up the early detection of COVID-19. Perhaps imaging could aid in screening or accelerate the speed of diagnosis, especially with shortages of RT-PCR. Hence, most of the recent works in the literature aim to design and develop an AI-based algorithm using medical-imaging methods to detect COVID-19 in such a way to help doctors to diagnose COVID-19 patients. This will also help them decide what to do next, depending on the output of the algorithm, help automate the diagnosis/prognosis of COVID-19 patients to help doctors determine the severity of COVID-19 and tell them how to proceed for patients. Consequently, doctors' time will be saved as the algorithm will automate a process that can be very time-consuming.

1.3 ARTIFICIAL INTELLIGENCE METHODS

Artificial-Intelligence-based (AI-based) clinical diagnosis systems are prevalent in many healthcare systems; they have resulted in paradigm shifts over recent years in healthcare delivery. The power of AI-based systems is that they produce accurate and reliable diagnosis results in a short period without fatigue. Also, AI systems are used to improve the workflow of a healthcare system by reducing the burden on human resources. In the case of COVID-19 detection, AI systems have been used to detect lesions and ground-glass opacities (GGO) in the CT scan images, which is faster compared to a manual clinical specialist diagnosis, thereby saving time of clinical specialists/physicians and significantly aiding them in the sometimes lengthy process of manually reading images one by one to identify high-risk cases. It also may significantly reduce patient time in the hospital, which poses a severe risk of spreading the virus (McCall 2020, Ali et al. 2020). Figure 1.2 illustrates the methodologies developed for the diagnosis of COVID infection from radiographic images (CT/X-ray) using various machine-learning and deep- learning methods (Figure 1.3).

Extracting COVID-19-related features from chest CT scan is highly complex, challenging, and time-consuming; a simple calculation may not work well with the CT scan image data and needs many repetitions for decision making. Therefore, machine-learning methods have been applied to COVID-19 detection using chest CT scan images (Shuai et al. 2020, Lu et al. 2020, Ophir et al. 2020, Lin et al. 2020). Machine learning is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns, and make decisions with minimal human intervention; this method automates analytical model building. Machine learning has been used as a decision-making algorithm for unknown chest CT scan images based on a set of training data, and past studies have implemented machine learning on COVID-19 detection using chest CT scan images (Ali et al. 2020). In recent years, the revolution in neural networks, primarily Deep Learning (DL), has attracted several researchers in developing an intelligent clinical diagnosis system using medical images. Deep-learning architecture has several hidden layers, and each layer can extract information from input data to model the behaviour of the data. Graphical Processing Units (GPU) are used to implement the DL models to discover intricate patterns in the data, since the model needs to process a massive amount of data and demands more computational power for processing data in multiple levels (layers). Therefore, DNNs can extract features that generalize well for unseen scenarios and samples. Besides, DNNs offer a better temporal and spatial resolution to analyze signals compared to conventional machine-learning methods (lin et al. 2020).

The performance of machine-learning and deep-learning algorithms predominantly depends on network hyper-parameters. Because tuning of these network parameters helps the network better to understand the characteristics or patterns of input samples, some of the most common hyper-parameters used in DL models for possible tuning are: (i) a total number of hidden layers; (ii) a maximum number of fully connected layers; (iii) type of activation function in the output layer; (iv) number of training epochs; (v) type of optimization function; (vi) a maximum number of convolutional layers; (vii) batch size; (viii) dropout rate; and (ix) learning rate. These hyper-parameters learn in an iterative fashion using stochastic gradient descent and its variations. Deep-learning techniques, on the other hand, utilize multi-stage hierarchical techniques in which the features are learned directly from the raw signal values, then combined with those extracted from other layers and directly fed to the classifier. Therefore, in addition to providing an algorithm which can be trained directly from the chest CT scan images to labels (COVID-19 or normal or other pneumonia), the features learned in the intermediate stages are designed specifically for the target task.

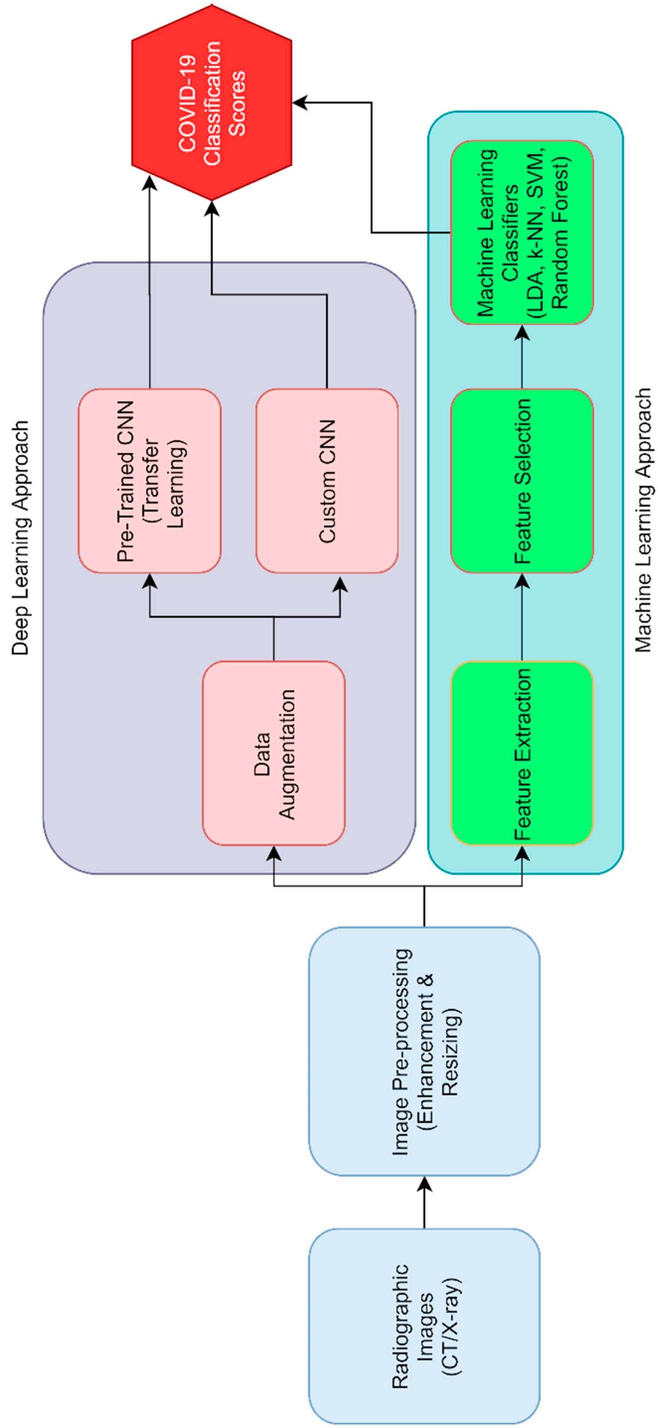

FIGURE 1.3 AI-based COVID-19 disease diagnosis from radiographic-input images of test subjects.

1.4 DATASETS

Image data acquisition is an essential step to design and develop AI-based methods for COVID-19 detection. Lung infection or pneumonia is the most common complication of COVID-19. Chest X-ray and CT are widely-accepted imaging modalities for the diagnosis of lung diseases. Large public CT or X-ray datasets are available for lung diseases. However, the number of CT or X-ray datasets available for the development of AI methods for COVID-19 applications is minimal. Most of the published works so far have used medical images from different websites, and some of the works have used their self-collected images. Table 1.2 reports available datasets from different websites (normal, COVID-19 and other pneumonia) in terms of modality used, number of subjects available. its sources and existing deep-learning models available on websites.

Several deep-learning architectures are deployed for the detection of COVID-19; some of those developed by researchers are listed in Table 1.2. Images used in many of the research works published in the literature were taken from the following two websites

i. https://github.com/ieee8023/covid-chestxray-dataset (Chest X-ray images)
ii. https://github.com/UCSD-AI4H/COVID-CT (Chest CT images)

1.5 RELATED RESEARCH

In recent days, researchers started focusing on developing clinical diagnostic tools for early detection of COVID-19 using pathogenic testing, clinical imaging methods, and artificial intelligence to combat the virus. The symptoms and causes of COVID-19 are highly similar to SARS and MERS. In a recent study (Melina et al. 2020), researchers investigated three different types of viruses (SARS, MERS, and COVID-19), their clinical symptoms, and their characteristics. Early detection of COVID-19 and quarantining of the suspects are the most critical actions against COVID-19 to stop spreading the virus and save millions of lives. To date, there is no vaccine or medication invented by scientists or researchers in the world. Due to the limitations of pathogenic testing, clinicians may prefer to detect COVID-19 through clinical imaging methods as the first-line tool for diagnosis (Ho et al. 2020). Among clinical imaging methods, medical images are providing more meaningful information about virus infection and are used more frequently for analyzing disease progression, compared to other imaging methods. Specifically, the performance of chest X-Rays and CT images-based COVID-19 detection system achieved higher sensitivity than RT-PCR tests (Ho et al. 2020). Thereby, medical images are considered promising, accurate, fast, and economical methods of screening and testing COVID-19.

1.5.1 CT Scan Images based COVID-19 Detection using AI Methods

Modified Inception Transfer Learning (MITL) was used to classify COVID-19 or other viral pneumonia using Region of Interest (ROI) features in (Shuai et al. 2020).

TABLE 1.2
Datasets and deep-learning models available

S.No	Modality	Number of Subjects/Images	Reference
1	Chest X-ray	• 219- COVID-19 positive images • 1341 normal images • 1345 viral pneumonia images	https://www.kaggle.com/tawsifurrahman/covid19-radiography-database
2	Chest X-ray	• 115 – COVID-19 positive images	https://www.sirm.org/category/senza-categoria/covid-19/
3	Chest X-ray	• 542-COVID-19 images from 262 people from 26 countries	https://github.com/ieee8023/covid-chestxray-dataset
4	Chest X-ray	• 8066 normal images • 5538 non-COVID19 pneumonia images • 358 COVID19 images from 266 COVID-19 patient	https://github.com/lindawangg/covid-net
5	Chest X-ray	CZI 1236 recordsPMC 27337bioRxiv 566medRxiv 361	https://www.kaggle.com/allen-institute-for-ai/CORD-19-research-challenge?select=metadata.readme
6	Chest X-ray	**Testing:** • 234 normal images • 390 pneumonia images **Training:** • 1341 normal images • 3875 pneumonia images **Validation:** • 8 normal images • 8 pneumonia images	https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia?
7	Chest X-ray	• 7470 – normal chest X-ray images	https://medpix.nlm.nih.gov/home
8	Chest CT	• 349 COVID-19 from 216 patients • 397 non-COVID19 images	https://github.com/UCSD-AI4H/COVID-CT
9	Chest CT	• 50 lung CT images	http://www.via.cornell.edu/databases/lungdb.html

Deep-learning models

S.No	Modality	Name of the deep-learning models	Reference
1	Chest X-ray	COVID-RENet, PyTorch based implementation (Custom VGG model)	https://github.com/m-mohsin-zafar/
2	Chest X-ray	DeTrac- Deep CNN approach, called Decompose, Transfer, and Compose.	https://github.com/asmaa4may/DeTrac_covid19
3	Chest CT	ConvNet-PyTorch based implementation	https://github.com/bkong999/covnet
4	Chest X-ray	DarkCOVIDNet- Binary Class and Three class implementation	https://github.com/muhammedtalo/covid-19

Morphological features such as multiple ground-glass opacities, pseudo cavity, and enlarged lymph nodes from CT scan images are extracted using preprocessing and used as input for training the deep neural network. Maximum classification rates of 89.5% and 79.3%, sensitivity of 88%, and 83%, and specificity of 87%, and 67% are achieved on validation and external dataset, respectively. They used 1065 CT scan images from 219 subjects (COVID-19: 79, and other pneumonia: 180) for developing the deep-learning model for COVID-19 classification.

CT scan images are handy to identify the progression of GGO and mGGO in COVID-19 suspects over a time. Thereby, it provides a way of identifying different stages of COVID-19. The different stages of COVID-19 infections are classified based on the level of severity in the CT scan images. The amount of severity is calculated based on the number of multiple ground-glass opacities in both lungs. These chest CT severity scores are beneficial for clinicians to discover the different stages of COVID-19, such as mild, moderate, severethan classifying COVID-19 or normal (Ran et al. 2020). The researchers used the transfer-learning property a in Convolutional Neural Network (CNN) to classify the input sample into two classes: COVID-19 positive and other viral pneumonia. They achieved a maximum accuracy of 89.5%. The same algorithm gives 79.3% accuracy while testing with the external dataset.

However, researchers have classified the stages of COVID-19 into four: mild; moderate; severe; and critical using serial chest CT scan images and deep-learning models to achieve a maximum mean classification rate of 84.81% in (Lu et al. 2020). A Convolutional Neural Network (CNN) with U-Net architecture is used to differentiate among the four different stages of COVID-19 based on a percentage of opacification score from the segmented chest CT scan images. The two lung regions and five lobes of lung regions are extracted from 126 subjects' CT scans and a group of radiologists. A Likert scale is used to derive the percentage of opacification and group the subjects according to stage.

In another study, researchers utilized ultrasound to observe imaging manifestations of COVID-19 (Yi et al. 2020). They investigated ultrasound images of 20 patients who suffered from mild symptoms; results confirmed that ultrasound sound images captured from posterior and inferior areas of the lung indicate viral infection compared to normal lung images. However, this method may not be useful for diagnosing COVID-19 patients with moderate, severe, or critical symptoms (Lung ultrasound, 2020).

RADLogics brand has developed an intelligent Artificial Intelligence Powered System for detecting COVID-19 using CT scan images; this achieved a maximum sensitivity of 98.2% and specificity of 92.2% when testing the system with 157 patients. This AI system is currently deployed in hospitals in China, Italy, and Russia for combating COVID-19 (Ophir et al. 2020). In Lin et al. (2020), researchers developed a deep-learning network called COVNet as a screening tool for COVID-19 detection. The network utilized visual features from chest CT scan images of COVID-19 pneumonia and non-pneumonia to develop a robust model. The model achieved a maximum sensitivity of 87% and 90% for COVID-19 and other pneumonia detection, respectively. Using AI to develop a frontline tool to assist specialists in diagnosing COVID-19 could save millions of lives. However, developing an intelligent AI-based system requires high-quality clinical data for accurate detection. To develop an intelligent system, the diagnosis system should be trained with a large number of input samples of different types to effectively model the system for better prediction or detection (McCall 2020). Alibaba Research Academy has developed its automated clinical diagnosis system for COVID-19 using artificial intelligence methods, achieved a maximum accuracy of 96% and diagnosed more than 30,000 cases in 26 hospitals in China (Ali et al. 2020).

Wang et al. have developed a fully functional deep-learning model for COVID-19 detection using a large number of chest CT scan images collected from six regional cities in the Republic of China (Wang et al. 2020). A total of 5,372 subjects' chest CT scan images (COVID-19: 1,266 subjects, CT-EGFR (epidermal growth factor receptor): 4106 subjects). Two deep-learning networks, namely, DenseNet-121 and COVID-19Net, are used for extracting the lung area from CT scan, and COVID diagnostics, respectively. Here, two transfer-learning algorithms are used to extract 64-dimensional deep-learning features from DenseNET and combined with clinical features (sex, age, and comorbidity) to develop a multivariate Cox Proportional Hazard (CPH) model to predict chances of the patient needing a long hospital stay to recover. The performances of deep-neural networks are assessed through the Area Under Curve (AUC), and the maximum value of AUC achieved for training, and testing is 0.90, and 0.86, respectively. Besides, the researchers used deep-learning visualization algorithms to identify the most common lung region affected by COVID-19 patients.

The first work on COVID-19 detection by using CNN and conventional machine-learning methods such as Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) is reported in (Singh et al. 2020). The researchers used multiple objective differential evaluation (MODE) to tune the hyperparameters of CNN (batch size, kernel function, epoch, activation function, hidden neurons and convolution filter size and number). The proposed system can classify the severity of the COVID-19 suspects into four different levels: mild; moderate; severe; and critical) and achieved a higher mean classification rate of 93.5% in MODE-CNN compared to conventional CNN (93%), ANFIS (92.1%), and ANN (90.2%).

In Abdullah et al. (2020) the researchers used four image filtering methods such as MPEG7 Histogram filter, Gabor filter, Pyramid of Rotation-Invariant Local Binary Pattern Histograms Image Filter, Fuzzy 64-bin Histogram Image Filter to choose the most selective regions from chest CT scan images of COVID-19 and Severe Acute Respiratory Symptoms (SARS). The proposed work utilizes a limited number of samples (COVID-19: 51 images; SARS: 51 images) to differentiate between COVID-19 or SARS using conventional machine-learning and deep-learning methods. These features are fed into Genetic Algorithm (GA) to find an optimized feature and classified as COVID-19 or SARS using four classifiers: Support Vector Machine (SVM); Naïve Bayes (NB); CNN; and Random Forest (RF)). Maximum mean accuracy of 96.11% is achieved using the RF classifier compared to CNN (94.11%), SVM (86.27%), and NB (86.35%).

Li et al. have used a large number of CT scan images of COVID-19 ($n = 1296$), Community-Acquired Pneumonia ($n = 1735$) and non-pneumonia ($n = 1325$) from

3,322 subjects (male: 1,838, female: 1,484) from six different cities in China to develop an intelligent COVID-19 detection system using a deep-neural network (Li et al. 2020). The U-Net segmentation method is used to preprocess and extract the lung region from the CT scan and to train the CNN. The proposed model achieved a maximum sensitivity of 90% and sensitivity of 96% in detecting COVID-19 and 87% and 90% as sensitivity and specificity of Community Acquired Pneumonia (CAP). Though the system has been trained with larger data, still it does not utilize clinical features to improve robustness.

In Xu (2020), using a 3D-CNN deep neural network, researchers put chest CT scan images into three classes: COVID-19; Influenza-A-viral pneumonia; and healthy. The 3D-CNN model was used to extract multiple cubes from two lung regions based on a location-attention mechanism. Finally, the Bayesian function is used to compute overall infection probability of the chest CT-scan image. The V-Net backbone Inception ResNet (VNET-IR-RPN) model is used to segment the centre image from the input image; data expansion mechanisms (clipping, up-down flipping, and mirroring) are used to increase the larger number of samples of equal size for classification over three types. Finally, classification is performed by using two types of CNN models based on traditional ResNet network architecture, such as ResNet50 and ResNet with Location Attention Mechanism. Finally, the ResNet with location attention mechanism model outperformed the ResNet architecture, giving a maximum mean accuracy of 86.7% for three classes.

In Chen et al. (2020), researchers developed an AI-based COVID-19 diagnosis tool using cloud-based open-access platforms, chest CT scan images and a deep-learning network. The model was developed in such a way that the input CT image is analyzed to find the activation map related to COVID-19 symptoms. It predicted the region in lungs, filtered out unnecessary fields from chest CT scan images, divided the image into four quadrants and analyzed the three consecutive CT images to find lesions. The model was developed and analyzed with retrospective and prospective COVID-19 subjects along with clinical features. The UNet++ model was used for segmenting the infected region in the lungs by searching for ground-glass opacities, and diminutive nodules.

An Artificial Intelligence-inspired Model for COVID-19 Diagnosis and Prediction for Patient Response to Treatment (AIMDP) is proposed in (Elghamrawy et al. 2020). The model has two essential modules; firstly, the diagnosis module, which utilizes a CNN network to process chest CT scan images and diagnose COVID-19. Here, the whale optimization algorithm is used to select the most prominent features of chest CT scan images (such as ground-glass opacity and crazy paving patterns) then feed them into the CNN for COVID-19 detection. The second is the prediction module; in this module, clinical features (sex, age, infection stage, respiratory failure, multi-organ failure and treatment regimens) predict patient response to the given treatment. The conventional ML algorithms such as Support Vector Machine (SVM), Naïve Bayes (NB) classifier, and Discriminant Analysis (DA) methods are used for COVID-19 classification. Noise is filtered from non-lung regions in CT scans and converted into grey-scale images, followed by normalization for reducing the computational complexity of the proposed diagnosis model. Finally, the SVM classifier outperforms NB and

DA classifiers by giving a maximum mean classification rate of 97.14%, compared to 95.99% and 94.71%, respectively.

Researchers used 3-D CNN that combines V-Net architecture with a bottle-neck structure to enhance the quality of chest CT scan images for COVID-19 detection (Shan et al. 2020). Because the raw chest CT scan images usually have low contrast, it is challenging to locate the GGO or mGGO in the scan images. Besides, they used the human-in-the-loop strategy (HITL) to reduce the requirement of a radiologist in locating the infected regions in the lung CT scan images to train the proposed model. They divided the training images into a set of batches; the first batch gets feedback from the radiologist on locating the infected regions in the lung. After that, these images are used to train the model, which will automatically locate the infected regions in the second batch. Here, the radiologist corrects any misinterpretations of the model. It is the first work in COVID-19 detection which utilizes HITL model to develop an intelligent system using chest CT scan images. Two performance measures such as dice- similarity coefficient (DSC), and Pearson correlation coefficient (PCC) are used to classify the COVID-19 subjects into three classes: mild; moderate; and severe. Here DSC is used to measure the percentage of different opinions in detecting infection regions identified by the radiologists and the automated method of detection using a deep-learning model. The POC is used to identify the percentage of lung region infected due to COVID-19, compared to normal lung region. The average value of DSC and POI over three cases are 91.6% and 86.7%, respectively.

He et al. developed an intelligent COVID-19 detection tool using Self-Trans network and chest CT scan images (He et al. 2020). 397 chest CT scans of normal subjects and 349 of COVID-19 patients are used to train, validate and test the system using a transfer-learning approach in different deep-learning architectures, such as VGG16, ResNet18, ResNet50, DenseNet-121, DenseNEt-169, EfficientNet-b0, and EfficientNet-b1. The maximum mean accuracy, Area Under Curve (AUC) and Fl score, of 86%, 0.94 and 0.85, respectively, are achieved using a Self-Trans network with DenseNet-169.

In Amyar et al. (2020), researchers employed Multi-Task Learning (MTL) in a deep-learning network for smaller size chest CT scan images to detect COVID-19. They performed the three tasks in MTL such as classification (COVID19 vs Non-COVID19), lesion segmentation using U-Net, and Image reconstruction. They utilized three international standard databases in their work. The system used for COVID-19 detection involves preprocessing (resize and intensity normalization), segmentation (lesion detection), and classification using a deep-learning network with MTL method. The proposed MTL work with an input image size of 256×256 achieved a maximum mean accuracy of 86%, sensitivity of 94%, specificity of 79% and area under the curve (AUC) of 0.93.

1.5.2 X-Ray Images based COVID-19 Detection using AI Methods

X-ray based COVID-19 detection systems are more popular compared to CT scan images due to cheaper cost, lower radiation, easier operation and less harm (www.siim.org). A group of researchers investigated three different types of deep-

Artificial Intelligence Based COVID-19 Detection using Medical Imaging Methods: A Review

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Automatic Mask Detection and Social Distance Alerting Based on a Deep-Learning Computer Vision Algorithm

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Review of Effective Mathematical Modelling of Coronavirus Epidemic and Effect of drone Disinfection

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ANFIS Algorithm-based Modeling and Forecasting of the COVID-19 Epidemic: A Case Study in Tamil Nadu, India

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