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Chaos, Solitons and Fractals 141 (2020) 110337

Contents lists available at ScienceDirect

Chaos, Solitons and Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

journal homepage: www.elsevier.com/locate/chaos

Review

A survey on artificial intelligence approaches in supporting frontline workers and decision makers for the COVID-19 pandemic

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ARTICLE INFO

Article history:
Received 21 August 2020
Accepted 1 October 2020
Available online 10 October 2020

Keywords:
Artificial intelligence
Computer-aided diagnosis
Deep learning
Machine learning
Infectious diseases
COVID-19
SARS-CoV-2

ABSTRACT

While the world has experience with many different types of infectious diseases, the current crisis related to the spread of COVID-19 has challenged epidemiologists and public health experts alike, leading to a rapid search for, and development of, new and innovative solutions to combat its spread. The transmission of this virus has infected more than 18.92 million people as of August 6, 2020, with over half a million deaths across the globe; the World Health Organization (WHO) has declared this a global pandemic. A multidisciplinary approach needs to be followed for diagnosis, treatment and tracking, especially between medical and computer sciences, so, a common ground is available to facilitate the research work at a faster pace. With this in mind, this survey paper aimed to explore and understand how and which different technological tools and techniques have been used within the context of COVID-19. The primary contribution of this paper is in its collation of the current state-of-the-art technological approaches applied to the context of COVID-19, and doing this in a holistic way, covering multiple disciplines and different perspectives. The analysis is widened by investigating Artificial Intelligence (AI) approaches for the diagnosis, anticipate infection and mortality rate by tracing contacts and targeted drug designing. Moreover, the impact of different kinds of medical data used in diagnosis, prognosis and pandemic analysis is also provided. This review paper covers both medical and technological perspectives to facilitate the virologists, AI researchers and policymakers while in combating the COVID-19 outbreak.

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1. Introduction

Coronaviruses are a large family of viruses that can cause severe illness to human beings [1]. Whilst we as humans do have experience with some coronaviruses, the current pandemic has been caused by a novel zoonotic disease [2]. Novel here means that humans have not yet been exposed to this virus, whereas zoonotic means it spread from animals to humans [3]. Due to the novelty of the virus, it appears to be the case that humans do not have any innate level of immunity, which would, in the case of exposure to other viruses, help lessen the spread and the effect. Viruses, especially novel viruses, have the potential to develop either into local epidemics, or more widespread pandemics [4]. For the purpose of this paper, a pandemic can be understood as an outbreak of any infectious disease that tremendously increases mortality and morbidity rate over the wider geographical region, whereas, an epidemic means an occurrence of disease spans over a passage of time in a limited area [5].

Pandemics and epidemics are not anything strange for the world, in just the more recent past, the Severe Acute Respiratory Syndrome (SARS) epidemic virus infected 8096 humans and caused the deaths of more than 770 persons, whereas the smallpox pandemic has infected millions of individuals and caused more than 500 million death world-wide throughout its existence [6]. The most severe viruses over the past century as well as their associated epidemics and pandemics are listed in Table 1.

SARS-CoV-2, the virus that is responsible for COVID-19 (this is the name of the disease), belongs to a large family of viruses that frequently causes severe respiratory symptoms [17]. In 2002 SARS-CoV, a predecessor to the current pandemic-causing virus be-

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https://doi.org/10.1016/j.chaos.2020.110337
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Table 1
Deadliest Viruses Over Last Century.

Year	Name	Spread by	Signs and Symptoms	Peak Pandemic Time period	Infected persons	Death toll/Fatality Rate (%)	Majorly Hit Areas	Ref
1918	Influenza (Spanish flu)	Contact with infected person	Fever, fatigue and chill	1918	500M	50 – 100M	Worldwide	[7]
1920	Rabies	Bite or scratch from rabid animal	Fever and tingling sensation around the wound. Fatal inflammation of the brain	1920	29 M every year	59,000/year	India and Africa	[8]
1920	HIV	Receiving unsafe injections, or blood transfusions	Influenza-like illness, swollen lymph nodes	1981 – Present (1997 Peak)	75M	32M	Worldwide	[9]
–	Smallpox	Contact with infected person	Scars and often blindness	Unknown – 1979		300 M (in 20th century)	Worldwide	[6]
1950s	Hantavirus	Exposure to droppings of infected rodents	Fever, vomiting, abdominal pain and coughing	1950, 1993	300,000/year	30% – 50%	Korea, USA and China	[10]
1950	Dengue	Mosquitoes bite	Abdominal pain, fever, bleeding gum and vomiting	1950 – Present	100 M – 400 M every year	2.5%	Philippines, Thailand and subtropical regions	[11]
1967	Marburg virus	Contact with blood, body fluid or infected tissue	Fever, myalgia, and maculopapular rash	1967 – 1968, 1998 – 2000, 2004 - 2005	466	24% - 88%	Germany, Serbia, Congo, Angola and Uganda	[12]
1973	Rotavirus	Fecal-oral route	Diarrheal, dry mouth and fussiness	2003, 2013	–	200,000 – 500,000/year	Worldwide	[13]
1976	Ebola virus	Contact with blood, broken skin, or mucous membranes	Fever, fatigue, muscle pain, Headache, sore throat, vomiting, rash	2014 - 2016	31,095	12,950	Sudan and Congo and West Africa	[14]
2002	SARS-CoV	Contact with infected person	Fever, chills, body aches and pneumonia	2002 – 2004	8096	Over 770 (9.63%)	Worldwide	[15]
2012	MERS-CoV	Contact with infected person	Respiratory problems, fever, cough	2012	2494	858	Middle East countries	[15]
2019	SARS-CoV-2	Contact with infected person	Fever, dry cough, tiredness, and loss of taste	2019 - Present	18.92M	710,916 (till August 6th, 2020)	First China, then worldwide	[16]

gan to spread; this virus was discovered in Guangdong, China. In 2012 another coronavirus (MERS-CoV) outbreak began in the Middle East, which caused a severe respiratory disease now known as Middle East Respiratory Syndrome [18]. This virus caused 858 deaths and infected 2494 humans. Now the world is grappling with another coronavirus which seems to have begun its spread in December 2019, though this is still disputed. COVID-19 is an infectious disease that spreads in humans mainly through direct or indirect contact with an infected person, respiratory droplets produced when an already infected human sneezes or talks, or aerosolized droplets (airborne transmission) [19]. The early symptoms include dry coughing, highly persistent fever, and respiratory difficulties which may lead to multiple organ failure or acute respiratory distress; in severe cases, death may also occur [20, 21].

As this pathogen is easily spread and grows exponentially and sustainably between humans, the manpower to combat this is limited. To put this another way, there is only a finite number of doctors, health care workers, and contact tracers and when the pandemic is at peak levels there may not be enough capacity to fully manage the pandemic. Thus, to this end, there is a distinct need for tools that can help improve these specialists' ability to do their job. This can include the development of contact tracing applications, statistical dashboards and visualizations, machine learning models, or other sorts of AI-based tools.

To tackle the pandemic of COVID-19, scientists and medical experts are trying to come up with state-of-the-art solution to control the spread, identify infected patients, monitor virus growth and develop vaccines. Many researchers are working with computer-based diagnosis techniques using clinical blood samples, radiography images, and respiratory-related datasets. AI and machine learning techniques are helping medical personnel in monitoring, analysis and prediction of various critical applications such as survival mortality assessment, forecasting models, virions sequence formation and drug discovery models.

In order to help stop the pandemic, the early detection of positive cases is crucial as it facilitates the containment and isolation of the virus, thus reducing its spread. Currently, the standard procedure followed for identification of COVID-19 positive cases is performed by Reverse-Transcription Polymerase Chain Reaction (RT-PCR) [22]. To further improve and hasten the early detection process, there is room for the development of new and innovative tools that may improve the early detection and tracking of the virus [23, 24].

As there is a clear need for these innovative technical solutions, there has, logically, been a large amount of rapid-paced development of these tools. However, due to the speed and number of these developments, it is easy to become overwhelmed, thus limiting the ability to critically examine, explore, and understand what a given solution does, how it performs, and whether or not it may or may not be beneficial. Thus, with this in mind, the main objective of this comprehensive review is to provide an in-depth account of COVID-19 and various advancements in AI techniques that have been currently developed to help manage or combat COVID-19.

2. Methodology

The review was conducted between July and August 2020, using the keywords "COVID-19" AND (*combined with one of the following*: "AI", "Machine Learning", "Deep Learning") as well as "COVID-19" AND "AI" AND (*combined with one of the following*: "Clinical Blood Samples", "Forecasting Models", "Drug Discovery Models"). This approach is, admittedly, broad, but allowed for a large number of relevant papers to be identified. Additionally, due to the nature of this study being a relatively new research subject, pre-print papers (such as those submitted to arxiv) were not precluded. As recommended by [25], we selected Google Scholar as our electronic bibliographic databases to remove any kind of biasness for any specific scientific publisher. We then excluded papers not written in English, duplicates, guest editorials, poster sessions, and blogs. Once the papers were identified, they were analyzed and grouped based on their aims and approaches.

2.1. Scope of the survey and contributions

Based on this conducted study, it is hoped that this paper will serve as a common ground for both medical experts and computer scientists to better understand the current state-of-the-art associated with COVID-19 and technological innovation. Although the research community has collected and shared adequate amount of information in the last few months, this review paper covered both medical and technological perspectives to facilitate the virologists, AI researchers and policymakers while in combating the COVID-19 outbreak. Due to a lack of in-depth understanding about COVID-19, numerous experts and hobbyists have taken advantage of different technological tools, such as open government data, big data, artificial intelligence (AI), etc. to help combat or understand the virus. A multidisciplinary approach needs to be followed for diagnosis, treatment and tracking, especially between medical and computer sciences, so, a common ground is available to facilitate the research work at a faster pace. This is interesting as COVID-19 is the first wide-spread global pandemic where these technological tools have been available, and accessible to such an extent that any stakeholder could, in theory, participate in the development of potential solutions.

With this in mind, the main contributions of this study are as follows:

- Detailed history, characteristics, taxonomy, symptoms, behavior, and patterns of COVID-19 are outlined.
- Presentation and discussion of AI (both traditional ML and advanced DL) approaches applied to COVID-19 in a variety of aspects and domains.
- Description of major COVID-19 diagnosis techniques using clinical blood samples, radiography images, respiratory-related data for various critical applications such as survival mortality assessment, forecasting models, virions sequence formation and drug discovery models.
- A detailed discussion on issues, challenges, and recommendations to tackle the pandemic through AI and timely facilitate effective decision making is presented.

In order to meet these objectives, the rest of the paper is organized as follows. Section 2 lays out the historical overview, origin and means of transmission, and global dispersion of the virus. Section 3 highlights the novel AI techniques that have been applied to COVID-19, and furthermore, it explores non-applied, but potentially useful, AI-based applications for vaccine discovery, mortality and survival rate prediction, and outbreak forecasting. Section 4 discusses the challenges in COVID-19 research. Finally, the review is concluded in Section 5 by presenting a summarized overview of the conducted studies.

3. Origin and overview of SARS-CoV-2

The type of coronaviruses that cause infections in humans belongs to a subfamily called *Coronavirinae* which is part of a larger *Coronaviridae* family. The coronavirus family is a very large family that is comprised of several viruses, such as Middle East Respiratory Syndrome virus (MERS-CoV), Severe Acute Respiratory Syndrome (SARS-CoV), and COVID-19 (SARS-CoV-2) [26].

The name *Corona* comes from the fact that the viral particle has spike-like projections or structures on its outer layer that can be seen under a scanning electron microscope. The RNA of coronaviruses is single-stranded, positive sense, has a diameter of around 80 to 120 nm and a nucleic acid length from 26 to 32 kbs [27]. They are classified under four variants or genera entitled as alpha (α), beta (β), gamma (γ) and delta (δ) [27]. It has been observed that mammals typically get infected by the α- and β-CoV while the other two (γ- and δ-CoV) mostly infect birds. From the α-CoV group, HCoV-NL63 and HCoV-229E have been found to affect humans, normally causing a mild respiratory illness, similar to the common cold. From the β-Cov group, SARS-CoV and MERS-CoV both tend to cause moderate to severe respiratory illnesses with a higher morbidity and mortality rate [28, 29].

The most recent addition to the coronaviruses is that of SARS-CoV-2, which became known in late 2019 after a number of a-typically presenting pneumonia cases were identified in Wuhan China; it was initially speculated that these cases might originate from the Huanan Seafood market [30]. The hallmark sign of many of the cases was the development of certain symptoms including dry cough with fever, breathing difficulty and a-typical presentation of pneumonia. On January 7th 2020, after a thorough analysis of the samples taken from nasopharyngeal swabs (collecting a clinical test sample of nasal secretions from the back of the nose and throat), the United States - Center for Disease Control (U.S. CDC) stated publicly that this disease appeared to be caused by the novel coronavirus [31]. After this, the International Committee on Taxonomy of Viruses (ICTV) named it the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) [17], whereas the disease itself is named COVID-19.

In early 2020, due to the pervasive spread of COVID-19 around the globe, the WHO declared it a Public Health Emergency of International Concern (PHEIC) on 30th January 2020 after cases were reported in 18 different countries worldwide [32]. On the 11th of March 2020 the WHO upgraded the threat, declaring COVID-19 a global pandemic and a serious hazard to public health after a sharp incline in the number of cases reported outside of China [33].

Among the 213 different countries, so far, the USA has seen the highest number of cases and fatalities, though other countries such as Brazil, India, Russia, South Africa, Mexico, Peru, Chile, Colombia, Spain, Iran, UK, Saudi Arabia, Pakistan, and Bangladesh have also registered a high number of cases; Fig. 1 shows the top 15 countries for coronavirus infections and deaths – based on the latest WHO situation reports [34]. The disease itself is so pervasive due to the ease with which it is able to transmit itself, via small respiratory droplets (such as those created when talking, sneezing, coughing, and breathing) and has a higher level of danger to a person's health due to the current absence of targeted pharmaceutical solutions such as vaccines or antiviral drugs.

4. AI-Based approaches for COVID-19

Pandemics are an ever-present threat to human society, health, and wellbeing and, therefore, attention must be dedicated to understanding how they occur, how they can be prevented, and how we can strategically mitigate the negative effects they cause. The current pandemic associated with COVID-19 is unique in that it represents the first and largest pandemic in modern times where

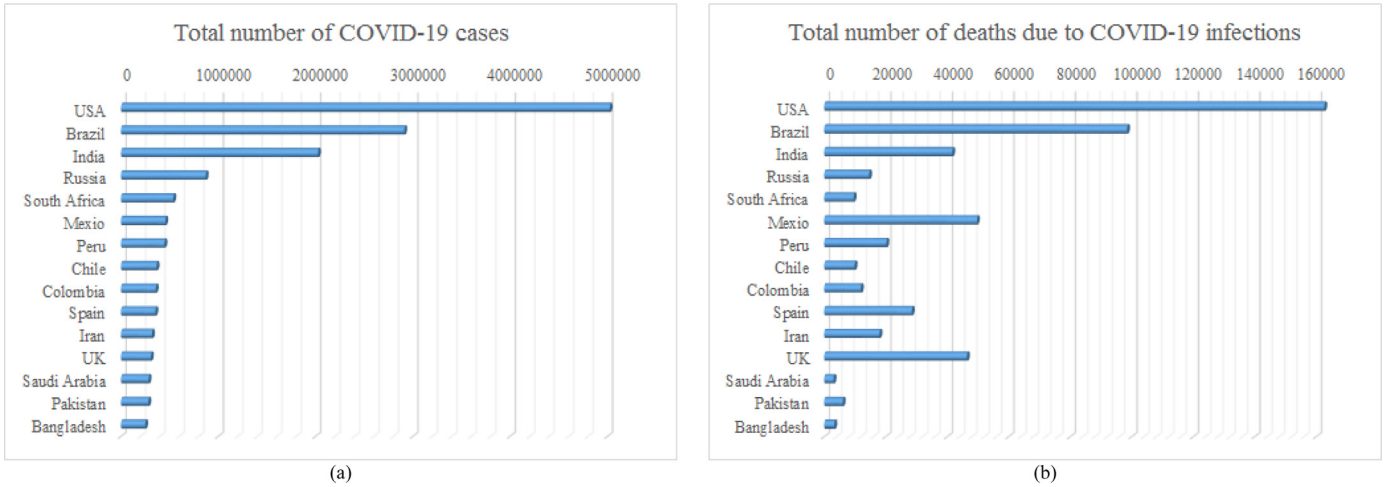

Fig. 1. COVID-19 transmission pattern in top 15 countries (August 6, 2020), (a) total number of COVID-19 infections, (b) total number of deaths due to COVID-19 infection.

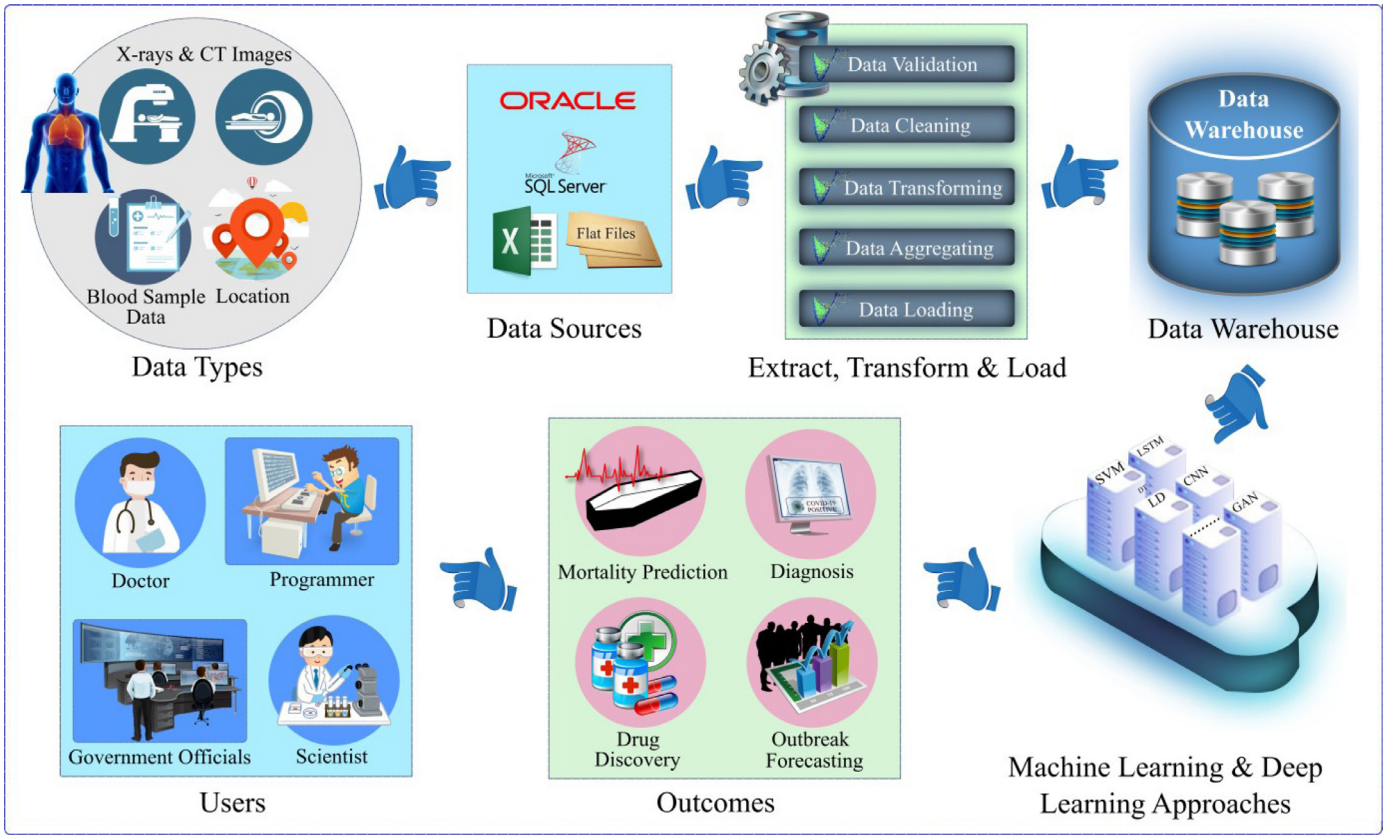

Fig. 2. Illustration of an AI-based solution for diagnosis, forecasting and mitigation of COVID-19.

new technological solutions, e.g. AI, are not only applicable to the pandemic, but able to be created by a large group of stakeholders from scientists to doctors to AI-hobbyists alike. As the pandemic has caused great disruption to normal day-to-day operations and created a sense of unknown amongst the public, many motivated scientists and citizens have tried to assist in the COVID-19 response by developing their own unique AI-based tools to solve a large number of problems, in a variety of applied domains, such as: COIVD-19 disease detection and classification, mortality rate prediction and severity assessment, outbreak forecasting and tracking, biological insight of SARS-Cov-2 strain, and drug discovery.

In order to explore the different approaches that are currently being developed and trialed, this section presents a selection of the different ways in which AI-based solutions have been applied to the COVID-19 pandemic. In order to provide a visual representation of how an AI-based COVID-19 system may work, a generic model has been created in Fig. 2. The system can process various types of raw data including images, blood samples, crowed sourced data, even GPS information for tracking positive cases, etc., which can be stored in a repository. Data mining techniques are usually applied to clean the raw data that is and then stored in a database for further processing and retrieval. ML and DL methods can be

Table 2
Machine Learning-Empowered COVID-19 Diagnostic Tools Using Radiography Images.

Ref	Year	Model/Method Names	Task	Data Type	Classes	Acc	P	Sn	Sp	F1-score
[38]	May 2020	Deep learning models (MobileNetV2, SqueezeNet) with Social Mimic Optimization method and SVM classifier	COVID-19 detection	X-ray images	99.27 (CP)	98.89 (CP)	98.33 (CP)	99.63 (CP)	98.58 (CP)	–
[39]	April 2020	SVM with Multi-Level Thresholding	COVID-19 detection	X-ray images	2	97.48	–	95.76	99.70	–
[35]	April 2020	SVM using ResNet50's deep features	Detection of COVID-19	X-ray images	3	95.33	–	95.33	–	95.34
[40]	April 2020	ResNet152 model with SMOTE, and Random Forest and XGBoost classifiers	COVID-19 screening from healthy and other pneumonia cases	X-ray images	3	97.70	–	97.7	98.8	97.7
[41]	May 2020	Clus-HMC framework and conventional ML algorithms (SVM, DT, MLP, kNN) and RF)	COIVD-19 identification in hierarchical and multi-class scenario	X-ray images	7	–	–	–	89.0	–
[42]	May 2020	Residual Exempler Local Binary Pattern (ResExLBP) based on iterative Relief (IRF) feature selection and ML classifiers (DT, linear discriminant, SVM, kNN, and subspace discriminant (SD))	COVID-19 Diagnosis.	X-ray images	2	99.69	–	98.85	100.0	–
[43]	July 2020	Five ML-based approaches (Decision Tree, Ensemble, kNN, 3-naïve Bayes, and SVM)	Discriminate COVID-19 from other pneumonia patients	CT images	2	91.94	90.63	93.54	90.32	
[44]	April 2020	Fast Fourier Transform (FFT)-Gabor scheme with SVM classifier	Identifying COVID-19 positive cases from radiography images dataset	CT Images	2	95.37	–	95.99	94.76	–
[45]	April 2020	CNN-based transfer learning Fusion and Ranking techniques (VGG-16, GoogleNet and ResNet50) along with SVM classifier	COVID-19 classification	CT images	2	98.27	97.63	98.93	97.60	98.28
[46]	March 2020	SVM with statistical feature extraction techniques (GLCM, LDP, GLRLM, GLSZM, DWT)	COVID-19 classification using segmented patches and feature extraction	CT images	2	97.71	99.62	97.56	99.68	98.58
[36]	March 2020	Infection Size Adaptive Random Forest method (iSARF) with DT other ML techniques (LR, SVM, NN, SARF)	COVID-19 classification from community acquired pneumonia by acquiring lungs and infection fields segmentation	CT images	2	87.90		90.70	83.30	–

Acc = Accuracy, P = Precision, R = Recall, Sn = Sensitivity, Sp = Specificity, AUC = Area under Curve, CP = Values specifically pertaining to COVID-19 class classification.

applied to this data for better visualization, diagnosis, and forecasting, which can help the end-users making better decisions and taking actions to mitigate the disease.

4.1. COVID-19 diagnosis using radiography images

Early diagnosis of COVID-19 is important to ensure better outcomes for those who have been infected. At the beginning of the pandemic, due to the sense of the unknown that surrounded the new disease, one way that was being used to diagnose patients was via radiographic imagery (such as CT scans or X-Rays) of the lungs.

4.1.1. ML-BASED techniques and applications

Several experts have extensively applied various ML algorithms and approaches to COVID-19 radiographic imagery, such as Sethy et al. [35] who presented a COVID-19 diagnostic tool for the medical practitioner based on a Support Vector Machine (SVM) model. In this three-class problem, thirteen various pre-trained Convolutional Neural Network (CNN) models such as AlexNet, VGG16, VGG19, etc. extracted deep features from 381 chest X-ray (CXR) images, out of which 127 images belonged to COVID-19 infected patients, 127 images to other viral/bacterial pneumonia and 127 normal patients CXR. Finally, the SVM model was used to classify COVID-19 patients using extracted deep features. The comparative analysis in the study showed that ResNet50 plus SVM secured an average classification accuracy of 95.33% in 20 independent executions when the data was split into an 80:20 ratio of training and testing sets. Shi et al. [36] also proposed a model for assisting in the diagnosis of COVID-19 with a model called infection Size Aware Random Forest (iSARF). The proposed framework processed CT images of 1027 community-acquired pneumonia (CAP) patients and 1658 COVID-19 infected patients to obtain infections and lung fields' segmentation using a modified version of V-net [37] (VB-Net). It identified the infected lesion size in each segmented lung and categorized it into four groups. Later, a Random Forest (RF) model was used for the final diagnosis in each group. From the experimental results, it was noted that the model provided an accuracy of 87.9%, a specificity of 83.3% and 90.7% sensitivity under 5-fold cross-validation to avoid any biasness in experimental tests. Other models that were identified from the literature review are expressed in Table 2.

4.1.2. DL-BASED techniques and applications

There has also been a large number of DL-based approaches proposed to identify COVID-19 from radiographic imagery in the

literature. For example, Brunese et al. [47] exploited the transfer learning technique and fine-tuned DL-based modified Visual Geometry Group (VGG-16) model. The proposed framework was divided into 2 models that considered 6523 chest X-rays (2753 belongs to patients with pulmonary diseases, 250 of COVID-19 infected patients, while 3520 related to healthy patients). The first model discriminates between healthy and pulmonary diseases patients, while the second model classifies the chest X-ray (CXR) of pulmonary disease patient as COVID-19 or other pneumonia. In the end, if a CXR is classified as COVID-19, the framework provides a visualization of the CXR highlighting the potentially SARS-CoV-2 infected area.

From the experimental data, it was observed that the discriminatory model (model 1) achieved accuracy, sensitivity, specificity and f-measure of 96%, 96%, 98% and 94% respectively, whereas the disease classification model (model 2) yielded an accuracy of 98%, sensitivity of 87%, specificity of 94%, and an f-measure of 89%.

Similarly, to identify SARS-CoV-2 infected cases from CXR images, various CNN frameworks such as VGG19, MobileNet v2, Inception, Xception, and Inception ResNet v2 have been evaluated using transfer learning by Apostolopoulos and Mpesiana [48]. From their conclusion, it was observed that MobileNet v2 outperformed the other tested state-of-the-art architectures by securing 99.10% sensitivity, 97.09% specificity, 97.40% accuracy on the two-class problem and 92.85% accuracy on the three-class problem. In that paper, the models were trained and evaluated on a dataset of 1427 CXR images that constitutes 700 images of bacterial pneumonia infected patients, 224 images of COVID-19 infected cases, and 504 belonging to normal patients. MobileNet v2 also performed well yielding a sensitivity, specificity, two-class problem accuracy, and three-class problem accuracy of 98.66%, 96.46%, 96.78% and 94.72%. For this model, the dataset was composed of 714 viral pneumonia CXRs images, 224 COVID-19 cases images, and 504 normal patients CXRs.

Jaiswal et al. [49] applied the deep transfer learning (DTL) technique with the pre-trained DenseNet201 model on chest CT images. In this study, a total of 1262 chest CT images related to SARS-CoV-2 positive cases and 1230 CT images of other patients were utilized and diversified using data augmentation technique to train and test the pre-trained DenseNet201 with additional CNN structure. The proposed tool achieved better performance on the testing set in terms of accuracy, precision, recall, f-measure and specificity of 96.25%, 96.29%, 96.29%, 96.29% and 96.21% respectively.

Xu et al. [50] developed a 3D CNN-based DL model to differentiate COVID-19 infected cases from influenza-A caused viral pneumonia (IAVP) and healthy person's by using a dataset consisting of 618 CT samples (224 IAVP CT images, 219 samples from 110 COVID-19 infected patients, and 175 healthy cases instances) from three Chinese hospitals. The images were segmented and features were extracted using ResNet. Later, the location-attention classification model classified the segmented CT images with an overall accuracy of 86.7%.

Other identified DL-based methods and approaches are highlighted in Table 3. COVID-19 DIAGNOSIS USING CLINICAL BLOOD SAMPLES DATA

Many developing countries and rural areas may not have X-rays or CT scan machines readily available; therefore, researchers have also practiced ML and DL approaches on clinical blood reports to segregate COVID-19 patients. A COVID-19 positive cases predictor based on five distinct ML approaches (namely gradient boosting trees, logistic regression, random forest, neural networks, and SVM) were evaluated by Batista et al. [109]. In this study, blood sample data of 235 adult patients was collected from a hospital in Brazil, out of which 102 patients were confirmed to be COVID-19 positive. The collected dataset was divided into a 70:30 ratio for training and testing and the models were tested under 10-fold cross-validation. Each sample had 15 features including red blood cells, red cell distribution width (RDW), c-reactive protein (CPR), basophils, lymphocytes, leukocytes, platelets, mean corpuscular volume (MCV), eosinophils, hemoglobin, mean corpuscular hemoglobin, monocytes, mean corpuscular hemoglobin concentration, gender and age. From the findings, it was observed that the SVM model produced satisfactory results similar to other state-of-the-art techniques. For the same dataset it achieved an accuracy of 84.7%, sensitivity of 67.7%, specificity of 85.0%, F1-score of 72.4%. Moreover, the SVM approach also exhibited a positive predicted value (PPV), negative predicted value (NPV) and brier score of 77.8%, 77.3% and 16.0% respectively.

Table 4 illustrates other identified COVID-19 detection applications based on ML approaches that use blood sample data.

4.2. COVID-19 diagnosis using respiratory and coughing wave data

Another type of COVID-19 diagnostic tool that has been developed is related to respiratory wave data, such as developed in Wang et al. [114]. In this paper, the authors proposed a respiratory pattern classification model that was based on a novel GRU neural network [115], which extends GRU networks with bidirectional and attentional mechanisms (BI-AT-GRU) by using time-series real-world and stimulated respiratory data. The model detects and distinguishes the Tachypnea respiratory pattern, a more rapid respiration symptom that occurs in COVID-19 infected patients, from 6 other viral infection patterns. A novel Respiratory Stimulated Model (RSM) was used to generate stimulated breathing patterns to fill the scarce real-world data. The trained model was evaluated on real-world data captured by a depth camera. The proposed BI-AT-GRU model resulted in precision, recall, f1-score, and accuracy of 94.4%, 95.1%, 94.8% and 94.5% respectively.

Table 5 lists the other identified COVID-19 AI-based applications that utilize respiratory or coughing data.

4.3. DISEASE severity and survival-mortality assessment models

Outside of just diagnosis of COVID-19, AI-based tools have also been applied to identifying the severity of the disease in a patient, as well as to develop and optimize treatment strategies. For example, in order to attempt to help to reduce the mortality of COVID-19, and to optimize potential treatment strategies, a novel DL-based framework, combined with a multivariate logistic regression model, was proposed by Bai et al. [119]. Multi-layer perceptron (MLP) was used to convert each statistical sample containing 75 clinical data characteristics to a 40-dimensional feature vector. The proposed model was then evaluated using a dataset of 133 patients and achieved an overall accuracy of 89.1% and 95.4% AUC under 5-fold cross-validation repeated 5 times. The researchers found six key risk factors (age, lymphocyte, comorbid with hypertension, albumin, hypersensitive C-reactive protein level, and progressive consolidation in CT images) plus fibrosis in CT as a predictive factor for malignant progression.

Albahri et al. [120] also proposed an ML-based rescue framework that was combined with a novel multi-criteria decision-making (MCDM) model to identify and prioritize severely infected COVID-19 patients who are most suitable for relevant convalescent plasma (CP) transfusion.

Chen et al. [121] developed a fatality rate predictive model for severe SARS-CoV-2 patients based on five distinct ML approaches, namely: elastic net, bagged flexible discriminant analysis (bagged-FDA), logistic regression, random forest and partial least squares regression. The model used data of 183 severely infected COVID-19 patients, out of which 115 survived and found four key features and clinical pointers (age, D-dimer level, lymphocyte count, and high-sensitivity C-reactive protein level) for survival/mortality

Table 3
Deep Learning-Empowered COVID-19 Diagnostic Tools Using Radiography Images.

Ref	Year	Model/Method Names	Task	Data Type	Classes	Acc	P	Sn	Sp	F1-score
[49]	July 2020	DenseNet201 based transfer learning and CNN	Detection and diagnosis of COVID-19	CT images	2	96.25	96.29	96.29	96.21	96.29
[51]	July 2020	Customized CNN-based ResNet50	COVID-19 detection from multiclass	CT images	3	91.0	–	92.1	90.29	–
[52]	June 2020	Deep CNN-based network	COVID-19 detection from multiclass	CT images	4	–	–	90.19	95.76	–
[53]	June 2020	COVID-19Net and DenseNet121-FPN	COVID-19 prognostic and diagnostic analysis	CT images	2	78.32	–	80.39	76.61	77.0
				External Validation. set 2	2	80.12	–	79.35	81.16	82.02
[50]	June 2020	3D DL model	Early stage COVID-19 classification from other viral pneumonia and healthy cases	CT images	3	86.70	86.80	86.6	–	86.7
[54]	June 2020	Contrastive self-supervised learning (CSSL) fine-tuned ImageNet-pretrained model (DenseNet169, ResNet50)	COVID-19 classification	CT images	2	89.10	–	–	–	89.60
[55]	May 2020	3D CNN-based network	COVID-19 diagnosis using chest CT infiltrative biomarkers	CT images	2	70.0	–	–	–	–
[56]	May 2020	GAN, ResNet-32 and variant of 3D U-Net architectures	Effect of synthetic data enhancement on COVID-19 classification	CT Images	–	–	–	–	–	–
[57]	May 2020	CNN and MLP (SVM and Random Forest) based model	COVID-19 diagnosis	CT images + clinical data	2	83.5	81.9	84.3	82.8	–
[58]	May 2020	Transfer learning ResNet-32 based Deep CNN model	COVID-19 classification	CT images	2	93.02	95.19	91.48	94.78	–
[59]	May 2020	Various DL-based segmentation models (U-net, DRUNET, FCN, SegNet & DeepLabv3) and 3D ResNet-18 classification model	Diagnosis, severity and prognosis prediction of COVID-19 among other pneumonia. Later tested on external validation set	CT images with metadata	3	92.49	–	94.93	91.13	–
[60]	April 2020	Multitask deep learning model (Encoder, 2 decoders, MLP, and CNN)	COVID-19 classification and segmentation	CT images	4	86.0	–	94.0	79.0	–
[61]	April 2020	EfficientNet B4 with Fully-connected NN	Develop and evaluate AI network for COVID-19 classification from other pneumonia	CT images	2	96.0		95.0	96.0	–
				External dataset		87.0		89.0	86.0	
[62]	April 2020	3D DL models	COVID-19 detection, and infected region identification.	CT images	3	86.70	86.87	98.20	92.20	86.70
[63]	April; 2020	CNN-based Deep learning networks (Inception-V4 and AlexNet)	Diagnosis and prognosis of COVID-19 case	CT images	2	94.74	–	87.37	87.45	–
[64]	April 2020	Multi-objective differential evolution-based CNN	COVID-19 patients' classification and disease evaluation	CT images	2	93.50	–	91.00	91.00	89.90
[65]	April 2020	Modified Deep Transfer Learning based Inception model	Diagnosis of COVID-19 by extracting graphical features from CT images. Later tested on external validation set	CT images	2	89.50		88.00	87.00	77.00
				External dataset		79.3		83.0	67.0	63.0
[66]	March 2020	Composite hybrid feature extraction (CHFS) based Stack Hybrid Classification (SHC) composed of CNN and ML models (SVM, RF)	Predicting recurrences in no recurrence COVID-19 and SARs cases	CT images	2	96.07	96.10	96.10		96.10
[67]	March; 2020	ResNet-50	Classification of COVID-19 from other viral and infectious diseases	CT images	5	98.80 (CP)	94.50 (CP)	98.20 (CP)	98.90 (CP)	–
[68]	March 2020	Variants of DL models (Segmentation; 3D U-Net++, U-Net, FCN-8 s, V-Net. Classification; Inception networks, ResNet-50 and DPN-92)	COVID-19 detection	CT images	2	–	–	97.40	92.20	–

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Table 3 (*continued*)

Ref	Year	Model/Method Names	Task	Data Type	Classes	Acc	P	Sn	Sp	F1-score
[69]	March 2020	Deep Learning based COVNet	COVID-19 detection from community acquired non-pneumonia and pneumonia lungs CT images	CT images	3	–	–	90.0 (CP)	96.0 (CP)	–
[70]	March 2020	Weakly supervised pre-trained 2D UNet-based 3D deep CNN called DeCoVNet	Rapid diagnostic tool for COVID-19 detection using 3D CT images	CT images	2	90.10	84.0	90.70	91.10	–
[71]	Feb;2020	DL-based Details Relation Extraction NN (DRE-Net)	Online and fast diagnosis of COVID-19 from bacterial pneumonia cases using 3D CT images	CT images	2	94.0	96.0	93.0	–	94.0
[72]	July 2020	CNN-based Deep Convolutional CAPSNET	COVID-19 diagnosis	X-ray images	2	97.23	97.08	97.42	97.04	97.24
					3	84.22	84.61	84.22	91.79	84.21
[73]	July 2002	DL-based 2D curvelet transform-CSSA-EfficientNet-B0	COVID-19 detection	X-ray images	3	99.69	99.62	99.44	99.81	99.53
[74]	July 2020	Deep transfer learning-based customized CNN model	COVID-19 detection	X-ray images	2	97.40	–	97.09	97.29	96.96
[75]	July 2020	CNN-based Confidence-aware anomaly detection (CAAD) model with EfficientNet	Anomaly detection and classification of viral pneumonia from non-viral pneumonia	X-ray images	2	72.77	–	71.70	73.83	–
[76]	June 2020	DL-based CNN Truncated Inception Net	COVID-19 cases detection	X-ray images	2	98.77	99.0	95.0	99.0	97.0
[77]	June 2020	Deep CNN based Inception V3 model	COVID-19 classification using transfer learning and data augmentation	X-ray images	3	98.0	–	–	–	–
[47]	June 2020	VGG-16	Pneumonia detection, COVID-19 identification and localization	X-ray images	3	97.0	–	92.0	96.0	92.0
[78]	June 2020	Various pre-trained DL techniques (AlexNet, DenseNet201, RestNet18, and Deep CNN Sgdm-SqueezNet)	COVID-19 detection using image augmentation	X-ray images	2	98.3	100.0	96.7	100	98.3
					3	98.3	100.0	96.7	99	98.3
[79]	June 2020	Pretrained Xception-based Deep CNN CoroNet	COVID-19 detection	X-ray images	2	99.0	98.3	99.3	98.6	98.5
					3	95.0	95.0	96.9	97.5	95.6
					4	89.6	90.0	89.9	96.4	89.8
[80]	June 2020	Transferable multi-receptive feature optimizer with Deep CNN-based CovXNet	COVID-19 detection with other pneumonias	X-ray images	2	98.1	98.0	98.5	97.9	98.3
					3	95.1	94.9	96.1	94.3	95.5
					4	91.70	92.90	92.10	93.60	92.60
[81]	June 2020	Customized CNN and pre-trained ImageNet models (VGG16, VGG-19, Inception-V3, etc.)	COVID-19 screening by learning modality-specific features	X-ray images	3	99.01	99.01	99.01	–	99.01
[82]	May 2020	CNN-based MobileNet v2	Extracting COVID–19 Biomarkers and classification of pulmonary diseases	X-ray images	2	99.18	–	97.36	99.42	–
					7	87.66				
[83]	May 2020	Concatenated Xception and ResNet50V2 Networks	COVID-19 cases identification from normal and other pneumonia infected patients' X-rays	X-ray images	3	91.4	72.8	87.3	94.2	–
[84]	May 2020	Weakly labeled data augmentation with different deep learning models	COVID-19 detection	X-ray images	2	99.26	–	–	–	–
[85]	May 2020	Modified InceptionV3 model	COVID-19 screening	X-ray images	4	76	–	93.0	91.8	–
[86]	May 2020	CNN-based COVID-Net	COVID-19 classification from normal and other pneumonia cases	X-ray images	3	93.30	98.90	91.0	–	–
[87]	April 2020	CNN-based COVID-CAPS	COVID-19 identification	X-ray images	5	98.30	–	80.0	98.60	–
[88]	April 2020	Resnet50 and VGG16 plus Customized CNN	Diagnosing COVID-19	X-rays images	2	91.24	–	78.79	93.12	–

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Table 3 (*continued*)

Ref	Year	Model/Method Names	Task	Data Type	Classes	Acc	P	Sn	Sp	F1-score
[89]	April 2020	Tailored CNN models (ResNet34, ResNet50, DenseNet169, VGG-19, Inception ResNetV2, and RNN-LSTM architectures)	COVID-19 screening, detection and infection evaluation	X-ray images	3	84	–	–	–	–
[90]	April 2020	ResNet-50	COVID-19 diagnosis from viral pneumonia	X-ray images	4	99.0	99.0	99.80	–	99.80
[91]	April 2020	GAN with fine-tuned deep transfer models (AlexNet, GoogLeNet, Squeeznet and ResNet18)	Effects of data augmentation on COVID-19 detection from x-rays images dataset	X-ray images	2	99.00	98.97	98.97	–	98.97
[92]	April 2020	Light weight Deep Neural Network (DenseNet-121, SqueezeNet, MobileNetV2)	On-device COVID-19 screening using X-rays and noisy snapshots of chest x-rays	X-rays Noisy snapshots	2	89.7	–	–	–	–
				X-ray images	2	93.50	–	–	–	–
[93]	April 2020	GAN with deep transfer models (Alexnet, Googlenet, and Restnet18)	COVID-19 detection	X-ray images	2	100	100	100	–	100
					3	85.2	85.2	85.2	–	85.2
					4	80.6	84.2	80.6	–	82.3
[94]	April 2020	Shallow light-weight CNN-tailored model	COVID-19 screening	X-ray images	2	96.92	100	94.20	100	97.01
[95]	April 2020	CNN-based DarkCovidNet model	COVID-19 classification	X-ray images	3	98.08	98.03	95.13	95.30	96.51
[96]	April 2020	Fine-tuned Deep Bayes-SqueezeNet-based COVIDiagnosis-Net	COVID-19 Diagnosis using augmented dataset	X-ray images	3	98.26	–	–	99.13	98.25
[97]	March 2020	CNN-based Decompose, Transfer, and Compose (DeTraC) model	COVID-19 disease recognition from other pneumonia cases	X-ray images	3	95.12	–	97.91	91.87	–
[48]	March 2020	Transfer learning based CNN models (VGG19, MobileNet v2, Inception, Xception, Inception ResNet v2)	COVID-19 detection	X-ray images	2	96.78	–	98.66	96.46	–
[98]	March 2020	Deep CNN-based COVID-ResNet	COVID-19 Classification from other pneumonia cases	X-ray images	4	96.23	96.86	96.92	–	96.89
[99]	March 2020	Drop-weights based Bayesian CNN network (BCNN)	Improving classification accuracy for COVID-19 diagnosis from other bacterial, viral pneumonia and healthy cases	X-ray images	4	89.82	–	–	–	–
[100]	March 2020	CNN-based COVIDX-Net includes seven different architectures (VGG19, DenseNet121, InceptionV3, ResNetV2, Inception-ResNetV2, Xeption, MobileNet2)	To diagnose COVID-19 in X-ray images	X-ray images	2	90.00	83	100	–	91.00
[101]	March 2020	CNN-based three different models (ResNet50, InceptionV3 and Inception-ResNetV2)	COVID-19 detection	X-ray images	2	98.0	100	96.0	100	98.0
[102]	July 2020	GAN with CNN and ConvLSTM-based deep learning models	COVID-19 infection detection	X-ray and CT images	2	99.0	97.7	100	97.8	99.0
[103]	June 2020	Fine-tuned DL networks (ResNet, Inception-v3, Inception ResNet-v2, DenseNet169, and NASNetLarge)	COVID-19 classification	X-ray and CT images	2	98.0	88.0	90.0	95.0	89.0
					3	96.0	93.0	90.0	94.0	91.0
[104]	May 2020	Commercialized deep learning-based CAD system	COVID-19 infected patient identification	X-ray images	2	–	–	68.8	66.7	–
				CT images	2	–	–	81.5	72.3	
[105]	May 2020	Seven deep learning models (VGG16, VGG19, DenseNet201, Inception_ResNet_V2, Inception_V3, Resnet50, and MobileNet_V2)	COVID-19 detection and classification	X-ray & CT images	3	92.60	93.85	82.80	97.37	87.98

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Table 3 (*continued*)

Ref	Year	Model/Method Names	Task	Data Type	Classes	Acc	P	Sn	Sp	F1-score
[106]	April 2020	Multi-task DL methods; NABLA-N (for region segmentation) and Inception Residual Recurrent Convolutional Neural Network	Identification of COVID-19 patients and infected region localization	X-ray images	2	84.67				
				CT images	2	98.78	–	–	–	–
[107]	April 2020	Seven pre-trained architectures of CNN (AlexNet, SqueezeNet, GoogleNet, VGG-16, MobileNetV2, ResNet18, ResNet50, DesnseNet201)	Diagnosing COVID-19 disease from normal and other viral and bacterial pneumonia cases	X-ray and CT images	2	98.75	96.43	100	97.50	98.18
					3	97.20	97.67	97.50	98.51	97.50
					4	80.95	82.52	82.20	93.48	82.23
[108]	March 2020	CNN and Pre-trained AlexNet	COVID-19 Diagnosis	X-ray images	2	98.0	–	100.0	96.0	–
				CT images	2	94.1	–	90.0	100.0	–

Acc = Accuracy, *P* = Precision, *R* = Recall, Sn = Sensitivity, Sp = Specificity, AUC = Area under Curve, CP = Values specifically pertaining to COVID-19 class classification.

Table 4
Machine Learning-Empowered COVID-19 Diagnostic Applications Using Clinical Blood Samples Data.

Ref	Year	Model/Method Names	Task	Data Type	Classes	Acc	P	Sn	Sp	F1-score
[110]	July 2020	Random Forest and other ML models (Decision Tree, Extremely Randomized Trees, kNN, Logistic Regression, Naïve Bayes, and SVM)	Diagnosis of COVID-19 from routine blood exams' hematochemical values	Text	2	82.0	83.0	92.0	65.0	–
[111]	July 2020	Gradient Boosted Decision Tree and other ML models (Decision Tress, Logistic Regression, and Random Forest)	COVD-19 diagnosis using 27 routine laboratory tests	Text	2	–	–	76.1	80.8	–
[112]	June 2020	Supervised ML-based models (Adaboost, Decision Tree, Logistic Regression, Multinomial Naïve Bayes, Random Forest, Stochastic Gradient Boosting, and SVM) with Term Frequency/Inverse Document Frequency feature engineering	COVID-19 classification from other viral pneumonia using clinical reports	Text	4	96.2	94.0	96.0	–	95.0
[109]	April 2020	SVM and other ML models (Random Forest, LR etc.)	Diagnosis of COVID-19	Text	2	84.7	77.8	67.70	85.0	72.4
[113]	March 2020	Random Forest	COVID-19 Identification using clinical blood test data, each with 49 parameters. Later, tested on external validation set	Text	4	95.95		95.12	96.97	–

Acc = Accuracy, *P* = Precision, *R* = Recall, Sn = Sensitivity, Sp = Specificity, AUC = Area under Curve.

assessment. Moreover, the developed models were evaluated on an external validation set that consisted of 64 severe COVID-19 confirmed cases, out of which 33 were survivals. The experimental results concluded that the logistic regression model was to be preferred over other ML models due to its high interpretability and simplicity; it obtained sensitivity, specificity and AUC of 89.2%, 68.7% and 89.5% respectively.

Table 6 shows other identified AI-based approaches related to severity and fatality assessment models.

4.4. COVID-19 outbreak forecasting models

One of the first areas where AI was applied to the COVID-19 pandemic was related to the development of outbreak forecasting models, which had the potential to help decision makers understand the potential progression of COVID-19 in their area. One such approach was developed by Kavadi et al. [132] who suggested a partial derivative regression and non-linear machine learning (PDR-NML) model to predict the COVID-19 transmission dynamics in India. The presented model achieved better performance in terms of accuracy and prediction time over linear regression and state-of-the-art AI-based models. It secured an accuracy of 99.7% with a prediction time of 5750 ms for 5000 samples. Another approach was offered by Carrillo-Larco and Castillo-Cara [133] who presented a model based on *k*-means clustering that categorized countries sharing similar numbers of confirmed SARS-CoV-2 cases. In this study, researchers not only used COVID-19 prevalence data (deaths, confirmed cases etc.), but also considered open access predictors like the prevalence of diseases such as HIV/AIDS, diabetes, and tuberculosis in 156 countries along with their standard health system metrics, air quality, and social-economic parameters such as the gross domestic production.

A third approach was developed by Hu et al. [134], who attempted to develop an AI-based modified auto-encoder (MAE) that

Table 5
Machine Learning and Deep Learning-Empowered COVID-19 Diagnostic Applications Using Respiratory Data.

Ref	Year	Model/Method Names	Task	Modality/ Data Type	Classes	Acc	P	Sn	Sp	F1-score
[116]	June 2020	Deep Transfer Learning-based Multi-Class classifier (DTL-MC)	COVID-19 diagnosis from cough samples by examining the dissimilarities of pathomorphological alterations in respiratory system	Coughing/ Sound waves	2	92.85	91.43	94.57	91.14	92.97
					4	92.64	89.91 (CP)	89.14 (CP)	96.67 (CP)	89.52 (CP)
[117]	June 2020	CNN-based VGGish model as feature extractor along with SVM and Logistic Regression classifiers	COVID-19 diagnosis from coughing samples	Coughing and breathing/ Sound waves	2	–	80.0	72.0	–	–
[118]	June 2020	Bi-Directional Gate Recurrent Unit with attention mechanism	COVID-19 detection by analyzing thermal and corresponding RBG videos	Breathing/ Thermal videos	2	83.69	–	90.23	76.31	84.61
[114]	Feb, 2020	Bidirectional and Attentional Gated Recurrent Unit Neural Network (BI-AT-GRU)	COVID-19 detection	Breathing patterns	2	94.5	94.4	95.1	–	94.8

Acc = Accuracy, P = Precision, R = Recall, Sn = Sensitivity, Sp = Specificity, AUC = Area under Curve, CP = Values specifically pertaining to COVID-19 class classification.

Table 6
Machine Learning and Deep Learning Approaches to Predict COVID-19 Infected Patient's Survival and Mortality Rate and Disease Severity Assessment.

Ref	Year	Model/Method Names	Task/Problem	Data Type
[122]	July 2020	Deep transfer learning based VGG16 model	Severity assessment of COVID-19 infection in lungs	Radiography images
[123]	July 2020	Several ML-based approaches (Adaboost Pregressor, Decision Tree, Elastic Net, Huber Regression, Random Forest, SVM and others)	Mortality rate prediction by analysis the impact of atmospheric temperature and humidity on COVID-19 transmission	Textual and Time series
[124]	July 2020	AdaBoost with fine-tuned Random Forest model	Possible outcome (death, recovery) and COVID-19 disease severity prediction	Text
[120]	June 2020	Multi-criteria-decision-method (MCDM) and ML methods	Identifying and prioritizing critical COVID-19 patients for convalescent plasma transfusion	Blood sample Images
[125]	June 2020	Multiple linear regression (Generalised linear model, Conditional inference trees, Penalized binomial regression, and SVM with linear kernel)	COVID-19 diagnosis, volume of disease and severity prediction	CT images and Clinical data
[121]	April 2020	Partial Least Squares Regression, Logistic Regression, Random Forest, Elastic Net, and Bagged Flexible Discriminant Analysis	Mortality prediction among severely ill COIVD-19 patients	Time series
[126]	April 2020	SVM	Recovery prediction of COVID-19 patients	Text
[127]	April	SVM	Detection of critical cases from mild symptom COVID patients	Text
[119]	March 2020	Deep Learning based models with Multivariate Logistic Regression network (MLP + LSTM)	Predict COVID-19 mild severity patients	Text & CT images
[128]	March 2020	Random Forest and Linear Regression	Hospital stay prediction of COVID-19 infected patient	–
[129]	March 2020	Random Forest	Identification of risk factors linked with mortality of coronavirus infected persons	Text
[130]	March 2020	Random Forest	Severity assessment of COVID-19 infection	CT images
[131]	March 2020	XGBoost	Mortality survival ratio prediction of severely infected COVID-19	Time series

modeled multiple public health interventions by using real data to forecast a potential COVID-19 pandemic outbreak in a large geographic region and subsequently calculating the potential impact of interventions to curb the pandemic. The proposed architecture consisted of two single auto-encoders, each having three feedforward neural network layers. The used data pertained to confirmed positive COVID-19 cases and COVID-19 attributed deaths across 152 countries over the period of January 20th to March 16th, 2020. The estimate includes pandemic peak time, end time, and future cases. It concludes that MAE performed better in forecasting daily new cases in China (with an error of 0.00134) when compared with susceptible-exposed-infected-recovered (SEIR) model as used by Sameni [135] .

Beyond conventional ML-based approaches, advanced DL techniques have also been used to estimate future cases. Paul et al. [136] suggested a convolutional LSTM-based multivariate spatiotemporal model to forecast the pandemic outbreak at the world-level. The proposed framework converted the spatial features into groups of temporal/non-temporal component-based 2D images and used data from USA and Italy to train the network. The model performed well for predicting the number of cases over a 5-days period, with a mean absolute percent error (MAPE) of 0.3% and 5.57% for Italy and USA respectively.

Table 7 lists more COVID-19 outbreak forecasting models based on ML and DL techniques

4.5. VIRIONS sequence formation and drug discovery models

A final area where AI is being applied in response to the COVID-19 pandemic is related to the development of potential medica-

Table 7
Machine Learning and Deep Learning Approaches for Risk Assessment and COVID-19 Outbreak Prediction.

Ref	Year	Model/Method Names	Task/Problem	Data Type
[137]	July 2020	Least square-SVM and Autoregressive Integrated Moving Average (ARIMA)	Predicting number of COVID-19 confirmed cases in next one-month	Time series
[138]	July 2020	5 DL-based methods (Gated Recurrent Units, Long short-term memory (LSTM), Bidirectional LSTM, Recurrent Neural Network, and Variational Auto-Encoders)	Short-term forecasting of recovered and new contaminated cased	Time series
[139]	July 2020	ML-based FbProphet model	COVID-19 epidemic trend prediction	Time series
[140]	July 2020	Artificial Neural Network based adaptive incremental deep learning model	Risk based Population Compartmentalization to reduce the number of deaths, while monitoring, forecast and growth stimulation of COVID-19 disease.	Time series
[133]	June 2020	K-mean with PCA	Clustering countries in groups according to COVID-19 positive cases.	Text
[132]	June 2020	Partial derivative regression and nonlinear ML method (PDR-NML)	COVID-19 pandemic outbreak prediction across globe	Text
[141]	June 2020	ML-based models (SVM, Linear Regression, and Polynomial Regression)	COVID-19 epidemic prediction, transmission rate analysis, and growth rates and migration type analysis.	Text
[134]	May 2020	Modified Auto-Encoders	To estimate pandemic transmission and evaluate interventions and measurements to halt COVID-19 spread	Time series
[142]	May 2020	Unsupervised Self-Organizing Maps	Spatially grouping countries that share similar COVID-19 cases	Time series
[143]	May 2020	ML-based method with Cloud computing	Potential threat and growth prediction of COVID-19	Time series
[144]	April 2020	Linear Regression with LSTM	Predicting outbreak trends and COVID-19 incidence in Iran.	Time series
[145]	April 2020	Regression tree and Wavelet transform methods	Risk assessment and forecasting COVID-19 outbreak in multiple countries	Time series
[146]	April 2020	SEIR, SIR models and Neural Network	Forecast COVID-19 spread in Italy, South Korea, USA, and Wuhan (China)	Time series
[147]	April 2020	Hybridized DL-based Composite Monte-Carlo (CMC) with Fuzzy rule induction	Forecasting future possibilities w.r.t COVID-19 epidemic	Time series
[148]	April 2020	SEIR and Regression Model	COVID-19 outbreak prediction in India	Time series
[149]	April 2020	Topological Autoencoder (Simplified Soft-supervisied-TA)	Visualization of COVID-19 transmission across globe	Time series
[150]	April 2020	Variational-LSTM autoencoder	Predict COVID-19 pandemic spread across globe	Time series
[151]	April 2020	Distinct ML models (RF, MLP, LSTM-R, LSTM-E, M-LSTM)	Forecast COVID-19 cases in Iran	Text
[152]	April 2020	RNN-GRU(LSTM) and FCNN	Forecasting COVID-19 epidemic curve	Time series
[153]	April 2020	Augmented ARGONet, LASSO, GLEAM Data augmentation (Bootstrap & random Gaussian noise)	COVID-19 outbreak prediction in real time	Text
[136]	April 2020	Conv-LSTM	Estimate COVID-19	Geospatial data (text and images)
[154]	April 2020	Curve fitting with LSTM	Forecast COVID-19 cases in India and effectiveness of lockdown and social distancing	Time series
[155]	April 2020	Simple and Adjusted SEIR network, and Logistic growth model	Predicting COVID-19 worldwide outbreak	Time series
[156]	March 2020	SEIR	COVID-19 pandemic outbreak transmission and effectiveness of control measures	Time series
[157]	March 2020	MLP, LSTM, Gate Recurrent Unit (GRU) and Deep-CNN-based multiple input model	COVID-19 outbreak prediction in China	Time series
[158]	March 2020	LSTM with customized SEIR	Forecast COVID-19 epidemic curve in China	Time series

tions and vaccinations. One such example, related to vaccine development, was proposed by Ong et al. who offered a supervised machine learning reverse vaccinology model (Vaxign-ML) [159] for the reverse vaccinology system Vaxign [160]. In [161], Ong et al. trained five traditional ML algorithms (SVM, RF, *k*-nearest neighbor, logistic regression, and extreme gradient boosting (XGB) [162] on an extracted protein dataset, which was annotated with physico-chemical and biological features, under 5-fold cross-validation. It was found that the XGB model performed well by obtaining F1-score of 94%.

Another approach is offered by Magar et al. [163] who established a machine learning approach for determining COVID-19 inhibitory synthetic antibodies. In this case, graph featurization along with various ML schemes screened the dataset of virus-antibody sequences and revealed 8 stable antibodies as potential COVID-19 inhibitors.

Other identified approaches for the development of potential COVID-19 medications and vaccinations are highlighted in Table 8.

5. Discussion

The investigation of this paper reveals several AI-based approaches that have been proposed as potential ways to help, with the COVID-19 pandemic, covering everything from initial diagnoses via image diagnostics up to the presentation of models that help to understand the spread of COVID-19 and identify potential new outbreak areas. By providing this comprehensive overview and identification of the current state-of-the-art, this structured review may help assist medical and research stakeholders currently involved in the COVID-19 response.

When it comes to potential barriers to the use of AI for COVID-19 responses, one of the foremost inaccuracies is related to the failure of forming diagnostic programs that fail differentiate by symptomatic basis. Therefore, in order to attain more accurate and precise prediction models, the patient's history of other existing ailments such as diabetes, heart, liver or other chronic conditions along with his age and gender should also be taken into account. The significance of these factors greatly influences the characteris-

Table 8
Machine Learning and Deep Learning Approaches for Drug Discovery and Protein Sequence Detection to Combat COVID-19 Pandemic.

Ref	Year	Model/Method Names	Task/Problem
[161]	July 2020	ML-based Vaxign-ML reverse vaccinology tool	To predict SARS-CoV-2 vaccine candidate
[164]	May 2020	Semi-Supervised Variational AutoEncoder and LSTM model	To find Simplified Molecular-Input Line-Entry System (SMILE) fingerprint of molecules for drug discovery
[165]	May 2020	GAN	Designing of non-Cov SARs-CoV-2 drug compound
[166]	March 2020	Pre-trained Deep learning based Molecule Transformer-Drug Target Interaction (MT-DTI)	Identify antiviral drug availability to coop SARS-COV-2
[163]	March 2020	XGBoost, RF, Multilayer perceptron, SVM and LR	Discover potentially inhibitory antibodies for COVID-19
[167]	March 2020	Adaptive Network-based Fuzzy Inference System (ANFIS), Multi Layered Perception (MLP)	CRISPR-based nucleic acid detection
[168]	Feb, 2020	GAN	Generate COVID-19 drug compound formation

tics of COVID-19 for a specific patient compared with other pneumonia diseases known so far. As many countries around the world are opening up their data related to COVID-19, it becomes possible for anyone to create new AI-based services, and, additionally, if these statistics are provided in an effective way, tools for the prediction of COVID-19 diagnoses and spread could, in theory, be developed.

Another issue regarding the COVID-19 pandemic is urgency. As the government needs high-quality statistical data in almost real-time to understand the current epidemiological situation in their area and to regulate quarantine in that same area, effort should be focused on improving the availability and provision of data first. As at the beginning of the pandemic, data was often not of high quality (though this depends on a large amount on which country's data is being examined) the initially used scientific datasets were often constructed in a quick manner and may not be as precise or adequate as one would ideally like.

While considering the statistical analysis of the COVID-19 disease, the crucial challenge is to secure real-time high-quality data. As this disease is still in a rapid growth phase, the fast nature of data makes it extremely difficult to produce reliable models. Collection of regularly updated region-specific values of COVID-19 is crucial in order to overcome this issue.

A final challenge, and one of the most important, is the lack of understanding of epidemiological theory, beliefs, and knowhow of many AI researchers. This leads to a situation where many of the AI-based systems are created without input from medical professionals, thus limiting their usefulness and reliability. Thus, to this end, it is important that any implemented AI-based system aims to involve medical experts in the design and implementation.

Whilst it does appear to be the case that many AI-based approaches have been proposed, there is a limited real-world implementation of these tools. What this paper has shown, however, is that there is clearly a wide variety of potential methods that could be applied. Moving forward, it is imperative for AI-designers and researchers to work together with medical professionals to create and develop these systems that are applicable to real-world datasets and relevant to the work of the given stakeholder group (e.g. policymakers or health care workers). AI is not a cure-all that can fix the COVID-19 crisis, but it does have the potential to augment a given person's ability to handle and manage the crisis, thus, potentially, limiting the spread of the virus and leading to potentially better outcomes for infected patients.

6. Conclusion

As COVID-19 has permeated throughout the world, there is no one who has not felt its impact in some way. Thus, scientific and medical researchers are working rapidly to find a viable cure against the disease. One tool that may well help aid this effort is artificial intelligence (AI) by assisting front-line workers in numerous ways.

This paper has initially presented the details of the COVID-19 viruses including taxonomy, signs and symptoms, cause of spread, affected body organ, and hazardous impact on human society over the last century. Secondly, we mentioned the structural genome and origin of COVID-19 infectious virus, compared it with other *Coroviridae* family viruses, its transmission behavior and impact on global health. We presented an overview of potential use cases and AI-based implementations currently being developed and trialed. For instance, technological experts have developed AI-based programs for the rapid analysis, scanning and diagnosis of the coronavirus through pneumonia radiographic images or clinical blood sample data. These approaches offer an additional way to detect COVID-19, in addition to the more commonly used PCR test.

As testing capabilities continue to improve, AI-based tools become more useful to assist in clinical settings rather than to replace medical professionals. However, where AI is likely to see an increased use and benefit moving forward in the future, especially as more and higher quality data becomes available, is its use in predicting potential new areas of outbreak and forecasting the spread of COVID-19. These models are based on parameters such as the number of positive patients in different regions of a city and tracking their movements to anticipate the potential spread through contact. For example, it could be possible to apply an AI-based model to data gathered via a contact tracing application or sewer COVID-19 prevalence data, though other data could also be used, to better predict the scale and size of a new outbreak. The results thus obtained could help to manage and implement precautionary actions by defining guidelines in pandemic affected areas. It is important that AI-based tools are relevant, accurate, and impactful. In order to do this, cooperation is needed between AI-based researchers, medical professionals, and governmental agencies. Thus, further research should identify real-world empirical examples of AI being used on real-world data. This paper has made initial steps in gathering and highlighting the current state-of-the-art, but it does not differentiate between examples working "in the wild" and those that are done under laboratory conditions. So, while in theory, these approaches may well be useful, until they are evaluated within an applied context it is hard to quantify their level of usefulness, in fact, it may well be the case that AI-based tools actually inhibit effectiveness if they discreetly contain some level of bias, or replace the decision making capability of a more competent human actor.

Declaration of Competing Interest

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.

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