Overview of current state of research on the application of artificial intelligence techniques for COVID-19

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Abstract

Background Until now, there are still a limited number of resources available to predict and diagnose COVID-19 disease. The design of novel drug-drug interaction for COVID-19 patients is an open area of research. Also, the development of the COVID-19 rapid testing kits is still a challenging task. **Methodology.** This review focuses on two prime challenges caused by urgent needs to effectively address the challenges of the COVID-19 pandemic, i.e., the development of COVID-19 classification tools and drug discovery models for COVID-19 infected patients with the help of artificial intelligence (AI) based techniques such as machine learning and deep learning models. **Results.** In this paper, various AI-based techniques are studied and evaluated by the means of applying these techniques for the prediction and diagnosis of COVID-19 disease. This study provides recommendations for future research and facilitates knowledge collection and formation on the application of the AI techniques for dealing with the COVID-19 epidemic and its consequences. **Conclusions.** The AI techniques can be an effective tool to tackle the epidemic caused by COVID-19. These may be utilized in four main fields such as prediction, diagnosis, drug design, and analyzing social implications for COVID-19 infected patients.

1. Introduction

The novel coronavirus has been reported in Wuhan (China) in December 2019. Wuhan became the epicenter of coronavirus [1]. Coronavirus infected 138,987,378 persons and 2,988,860 deaths in 210 countries as on 15 April, 2021 [2, 3]. World Health Organization (WHO) entitled the disease caused by coronavirus as COVID-19 and declared it an epidemic in February 2020 [4]. The virus, also known as SARS-CoV-2, is a novel and evolving virus. The treatment of SARS-CoV-2 is based on the symptoms present in the patient. The most common and specific symptoms are fever and cough with some other non-specific symptoms such as fatigue, headache, and dyspnea [5]. Supplement Table 1 shows the contribution of these symptoms in infected persons [6]. The common transmission methods are human contact and respiratory droplets. The COVID infection

40   depends upon age, preexisting health conditions, hygiene and social habits, location, and frequency
41   of person interactions [7].

42

43   Supplement Table 2 shows the estimation of the severity of COVID-19 disease infected peoples
44   [8, 9]. The risk associated with infection is broadly classified into three categories namely infection
45   risk, severity risk, and outcome risk [10]. The infection risk is associated with a specific
46   group/person having COVID-19. The person/group having severe symptoms of COVID-19 and
47   require intensive care and hospitalization is known as severe risk. If the treatment is not effective
48   towards the infected person/group then there is less possibility to recover or die. Self-isolation and
49   social distancing are the most effective strategy to alleviate this epidemic. Isolation and house
50   quarantine are core strategies to alleviate the infectious disease and reduce the transmission via
51   diminishing the contact of those that are infected [11]. Most governments have imposed lockdown
52   to save lives. However, the economy of every country was greatly affected by the lockdown
53   process. The Organization of Economic Cooperation and Development declared that the growth
54   rate may be slow down by 2.4% [12].

55

56   The main problems associated with coronavirus's pandemic can be resolved through Artificial
57   Intelligence (AI) [13]. AI has the potential to screen the population and predicting the risk of
58   infection. The prediction process utilizes information such as how much time a person spends in a
59   highly infected area and how many persons are infected in that region. AI developed a spatial
60   prediction model based on this information and envisage the infection transmission [14]. AI-based
61   prediction model uses information about the infected person through the symptoms. Coronavirus
62   infected person does not show the symptoms in most of the cases. Due to this, it is very difficult
63   to detect an infected person. The same thing has been reported in Wuhan city. In Wuhan, 50 % of
64   the infected persons are asymptomatic carriers [15]. The exhaustive testing of coronavirus is
65   required to develop a better predictive model. The same scenario has been implemented in South
66   Korea to prevent the spread of virus infection. The exhaustive testing produces a large amount of
67   data about the infected and non-infected person. Based on these data, AI can be used to suppress
68   the spread of infection, development of vaccines, diagnosis, and social-economic impact [16, 17].
69   Recently, most of the AI researchers are working on the above-mentioned areas. The number of
70   preprints available on the Internet is a witness of this work [18]. Recently, many medical image
71   processing techniques based upon chest CT and chest X-ray images have been considered. Also,
72   meta-heuristics techniques can be useful to diagnose COVID-19 patients [19].

73

74   By the end of November 2020, more than 75,000 scholarly articles were published and indexed on
75   Pubmed on COVID-19 [20]. However, these articles did not address in-depth the key issues in
76   applying computational intelligence to combating the COVID-19 pandemic. Thus, it is time to
77   discuss and summarize studies related to artificial intelligence from such a large number of articles.
78   Considering the above observations, now it is the time to systematically categorize and review the
79   current progress of research on artificial intelligence. Accordingly, this survey aims to assemble

80   and summarize the highlights of the latest developments and insights in applying artificial
81   intelligence approaches, such as machine learning, and deep learning, to practical applications used
82   to fight against COVID-19.
83
84   The principal contributions of this review paper are as follows:
85   1. The impact of artificial intelligence techniques is assessed on early cautionary and vigilant
86   systems.
87   2. COVID-19 datasets and visualization techniques are discussed with their applications.
88   3. AI-based diagnosis and treatment of COVID patients are assessed.
89   4. The impact of AI on drug discovery and design is evaluated.
90   5. The effect of COVID-19 is evaluated on social and economic aspects.
91
92   The remaining paper is organized as follows. Section 2 presents a description of our methodology
93   used. Section 3 presents a short description of coronavirus. The data gathering tools and techniques
94   are discussed in Section 4. Section 5 presents the prediction models. The diagnosis of infected
95   patients is presented in Section 6. Section 7 describes the treatments of COVID patients. The drug
96   discovery and design of vaccines are presented in Section 8. The social and economic impacts are
97   discussed in Section 9. Future research directions are discussed in Section 10. The concluding
98   remarks are drawn in Section 11.
99

100 ## 2. Research Methodology
101
102 In this section, the surveys related to application of artificial intelligence towards COVID-19 are
103 discussed followed by the research paper selection methodology used in this paper.
104

105 ### a.   Related surveys
106 Since the start of the COVID-19 pandemic, many research paper was published (just Scopus has
107 already indexed over 50000 papers alone). Consequently, several surveys and systematic review
108 studies have tried to systemize and summarize the state of research and knowledge in this emerging
109 research sub-field, including on the use of artificial intelligence methods. Related survey papers
110 are summarized in Supplement Table 3 and discussed in more detail below.
111
112 Albahri et al. [21] reviewed the state-of-the-art techniques for coronavirus prediction algorithms
113 based on data mining and ML assessment. They used Preferred Reporting Items for Systematic
114 Reviews and Meta-Analyses (PRISMA) as a methodological guideline. The main focus of the
115 survey study was on the development of different AI and ML applications, systems, algorithms,
116 methods and techniques. However, only eight articles were fully evaluated and included in this
117 review, which outlined the insufficiency of research in this important area.
118 Lalmuanawma et al. [22] aimed to review the role of AI and ML as one significant method in the
119 arena of screening, predicting, forecasting, contact tracing, and drug development for SARS-CoV-

120 2. The study concluded that the use of modern technology with AI and ML dramatically improves
121 the screening, prediction, contact tracing, forecasting, and drug/vaccine development although
122 they also noted the lack of deployment of AI models to show their real-world operation.
123 Ozsahin et al. [23] analyzed the use artificial intelligence (AI) techniques to diagnose COVID-19
124 with chest computed tomography (CT). Their study included 30 articles from ArXiv, MedRxiv,
125 and Google Scholar identified using the selective assessment method.
126 Pham et al. [24] present an overview of AI and big data, then identify the applications aimed at
127 fighting against COVID-19, next highlight challenges and issues associated with state-of-the-art
128 solutions, and finally come up with recommendations for the communications to effectively
129 control the COVID-19 situation. They based their study on the selected assessment of peer-
130 reviewed papers and preprints from IEEE Xplore, Nature, ScienceDirect, Wiley, arXiv, medRxiv,
131 and bioRxiv.
132 Rasheed et al. [25] presented the collation of the current state-of-the-art technological approaches
133 applied to the context of COVID-19, while covering multiple disciplines and research
134 perspectives.
135 Tseng et al. [26] focused on categorizing and reviewing the current progress of computational
136 intelligence for fighting COVID-19, which additionally to machine learning and neural networks
137 also discuss fuzzy logic, probabilistic and evolutionary computation based methods. Tayarani [27]
138 presented the applications of artificial intelligence techniques in COVID-19. They discussed the
139 machine learning techniques for prediction and treatment of infected persons.
140
141 However, since the body of knowledge on COVID-19 related research problems is rapidly updated
142 and supplemented, there is a need to provide a new survey of papers to summarize the most recent
143 state-of-the-art in the application of AI techniques for in the COVID-19 related research fields.
144

b.   Survey Methodology

146
147 This survey capitalizes on previous literature to describe approaches for handling COVID-19 that
148 can empower the research community to develop new AI-based methods for the prediction of
149 cases, diagnosis of patients, drug discovery, and design of vaccines.
150
151 Similarly to the survey of Lalmuanawma et al. [22] and Pham et al. [24] we used the selective
152 assessment method, while similarly to the survey of Ozsahin et al. [23] we focused on less formal
153 databases such as BiorXiv and ArXiv, which allows to analyzes the most recent trends in research
154 without waiting for formal publication in indexation by major databases, which can take a
155 significant amount of time. Due to the nature of this study being a relatively new research subject,
156 we mostly focused on the pre-print papers.
157
158   The rationale for this survey is the extreme growth of research papers published on COVID-19
159 papers, which requires them to be analyzes, categorized, and reflected upon. Fig. 1 shows the

160   number of research papers posted on BiorXiv, ArXiv, and MedRxiv from January, 2020 to April
161   2021. This study is intended for researchers working in the intersection of computer science,
162   artificial intelligence, and biomedical domains.
163
164   This survey covers literature published in 2020 (January-September) in different fields of study
165   related to COVID-19. Because no similar efforts have yet been made, we draw on examples from
166   the previous literature. Unbiased and comprehensive coverage of the previous literature was
167   accomplished by querying online preprint research archives (BiorXiv, ArXiv, and MedrXiv) with
168   search terms directly relates to COVID-19 (e.g., "covid-19", "coronavirus", "SARS-CoV-2") and
169   with Boolean operators to find studies applying artificial intelligence (e.g., "artificial intelligence"
170   AND "neural networks"). Studies were included if they provided an overview of open science
171   concepts that were relevant to addressing COVID-19. Once the papers were selected, they were
172   categorized and analyzed based on their research aims and approaches used. Supplement Table 4
173   shows the selection and exclusion criteria for shortlisted research articles.
174

3. Coronavirus Overview

175
176
177   A coronavirus is a group of viruses that can be transferred between human beings and animals.
178   The novel coronavirus is known as SARS-CoV-2. Coronavirus (CoV) belongs to the family
179   Coronavirinae of the order Nidovirales [29]. CoV is broadly classified into four main classes
180   namely α, β, γ, and δ. The first two (i.e., α and β) contaminate mammals only. The later ones (i.e.,
181   γ and δ) contaminate birds. They may contaminate mammals in a rare case. The genome of CoV
182   consists of a single-stranded positive-sense RNA whose length is 30 kb [30]. CoV is the largest
183   among the existing RNA viruses. It has also a 5' cap and 3' poly-A tail [30].
184
185   Based on the literature available, CoVs infecting human beings include two α-CoVs (229E and
186   NL63), and five β-CoVs (OC43, HKU1, MERS-CoV, SARS-CoV, and SARS-CoV-2.
187   SARS-CoV-2 is a novel class of β-coronavirus genera that consists of bat-SARS-like (SL)-CoV
188   ZC45, bat-SL-CoV ZXC21, SARS-CoV, and MERS-CoV. From recent studies, it found that
189   SARS-CoV-2 came from wild animals. However, the exact source of this virus is unknown. There
190   is a substantial genetic difference between now and SARS-CoV and numerous similarities among
191   them in terms of chemical and physical characteristics [31].
192

4. Data Gathering Systems for COVID-19

193
194
195   As we knew that the COVID-19 is an infectious disease. The spread of this virus can be stopped
196   through no human interaction. AI-based tools are used to collect the COVID-19 data, develop a
197   vigilant system, and visualize the COVID-19 data [32]. Recently, smartphone applications are also
198   developed to diagnose the user's health and trace the spread of infection. The main intention behind
199   these applications is to identify vulnerable communities, provide real-time information to both

200   patients and medical staff, detect infected hotspot areas, and generate advice for patient's health
201   [33]. Fig. 2 shows the categorization of data gathering systems for COVID-19.
202

a. An early cautionary and vigilant system

204   BlueDot is an effective analysis tool, which is developed in Canada [34]. It utilizes natural
205   language processing (NLP) and machine learning technique. It was able to identify the outbreak
206   of COVID-19 and generated vigilant alerts to users. It was used to generate the cautionary
207   warnings to cities where the people reached from Wuhan city after January 2020 [35]. In Belgium,
208   the telecom operators are integrated with healthcare for analysing the infection spread in particular
209   areas and identifying the infected hotspot areas. They have segregated the population into different
210   regions according to the spread of infection. The same concept has also been used in some other
211   countries. It provides real-time monitoring of patients and the consultant can use this information
212   to prepare the prevention plans for virus infection in time [36].
213

214   Similarly, Austria Telecom has agreed with its authorities to deliver the customer data. The
215   customer data is used to trace their movements in the hotspot Lombardy region. MIT's consortium
216   is working on a smartphone application to detect the spread of virus infection. Global Positioning
217   System (GPS) in a smartphone is used for checking the intersection of user's trails with trails of
218   infected persons. They used cryptographic techniques to protect the data. The application generates
219   early cautionary signs to analyse the risk of infection spread after contacting with the infected
220   persons. Instagram developed a COVID-19 tracker named as 'RT.live'. It shows the state-by-state
221   information on coronavirus infection in the US. The data analysis algorithm is used to estimate the
222   reproduction of virus infection.
223

224   'HealthyTogether' application is developed by the Utah government for reducing the spreading of
225   COVID-19. It is used to analyze the symptoms, determine the nearby testing center, and
226   assessment of test results. Singapore Government agency developed a 'TraceTogether' application
227   to protect the community from COVID-19. It helps contact tracers notify quickly through
228   Bluetooth connection.
229

230   India Government developed the 'Aarogya Setu' application to monitor the infection caused by
231   COVID-19 patients. This application has used a questionnaire to determine whether the person is
232   infected or not. It is helpful to find if the infected patient was somewhere near the user. Another
233   vigilant system was HealthMap to impose quarantines and restrict the movement of peoples.
234

235   Supplement Table 5 shows a brief description of the vigilant system for COVID-19. Supplement
236   Table 6 depicts the functionality analysis of different real-time surveillance mobile apps for
237   COVID-19 [37].
238

b. Data visualization systems

240

241   Data visualization techniques/dashboards utilized AI for tracking and forecasting of COVID
242   infection. They provide a global overview of infected persons. Data visualization system is
243   categorized into two broad categories namely local and global dashboards [38]. The Center for
244   System Science and Engineering of Johns Hopkins University developed the COVID-19
245   dashboard (JHU-CSSE) for global viewing of COVID-19. NextStrain generates the genomic
246   epidemiology of COVID-19. It consists of a dropdown list for Asia, Africa, Europe, and Oceania.
247   BBC dashboard provides the visualization of coronavirus infected areas in the World. It provides
248   the effect of lockdown on the death cases in six countries namely the UK, Italy, Spain, France,
249   Germany, and the US. The New York Times offers the dashboard for virus infection in various
250   areas of the World [39]. HealthMap uses the World map for showing the visualization of infected
251   cases in a particular area. Bing's AI tracker is used to show infected, recovered, and fatal cases of
252   different parts of the World. The filter is applied to a particular country to show the infected
253   persons in a particular province. South Africa developed COVID-19 ZA South Africa dashboard
254   for tracking the infected, recovered, and death cases in South Africa. It also tracks the number of
255   tests conducted and positive cases in different provinces. Tableau implemented a COVID-19 Data
256   Hub for a daily global tracker. COVID19 India is initiated by crowdsourcing. The infected,
257   recovered, and deaths are shown in both tabular and graphical manner. Supplement Table 7 depicts
258   the comparative analysis of different dashboards concerning the statistical information reported.

259

260   ## c. COVID-19 datasets and resources

261

262   Artificial Intelligence techniques require big data for further assessing the drug discovery, risk
263   assessment, spread of infection, treatment, and cure of COVID infected patients. The datasets are
264   broadly classified into text, social media, biomedical, speech, and case studies. The classification
265   of COVID-19 datasets is shown in Fig. 3.

266

267   ### i. Text Datasets

268

269   The text datasets include risk factors, non-pharmaceutical interventions, incubation period, the
270   spread of virus infection, and stability of the environment [40, 41]. WHO Global Research
271   Database provides scientific information on COVID-19. COVID-19 Open Research Dataset is an
272   open dataset. The Kaggle challenges provide the COVID-19 data for analysis. LitCOVID and AI
273   COVID-19 dataset consist of clinical trial data.

274   ### ii. Social Media Datasets

275

276   COVID-19 Tweets and Covid-19 Twitter dataset comprise of coronavirus related tweets, which
277   are misclassified information and rumors on Twitter [42]. These datasets contain the reactions
278   from different persons on the tweets [43]. COVID-19 Real World Worry Dataset [44] consists of
279   labeled texts of persons' emotional responses towards COVID-19. It also consists of public

280 sentiment and the mental health of persons in the infected areas of the World. Institutional, News,
281 and Media Tweet Dataset consists of institutional communication of COVID infected areas in
282 different countries. Both COVID-19 Coronavirus News Article dataset and COVID-19 Television
283 Coverage dataset comprises of covering the news and prints of COVID-19 outbreak. These
284 datasets cover the spreading of the virus, misinformation about drugs, and tracking of coronavirus.
285

iii. Biomedical Datasets

288 Covid Chest X-ray dataset is available as an open-source dataset. It consists of medical images
289 that can be used to train deep learning/machine, learning models [45]. Data labeling and annotation
290 can be used by radiologists. COVID-19 Survival Calculator uses the symptoms of infected
291 patients. However, these are unmanageable and require manual maintenance. There are several
292 data repositories, which provide links to researchers to easily access the data. Data4COVID Living
293 Data and COVID-19 Dataset Clearinghouse repositories have many links to coronavirus data from
294 different parts of the world. AI-based tools and techniques are used to extract the data from
295 repositories, cleaning the data, and develop some predictions on cleaned data. The gene structure
296 of SARS-CoV-2 should be known for the development of drugs and antibodies. Nextstrain is
297 working on the gene structure of SARS-CoV-2 to illustrate the spread of coronavirus. RCSB
298 Protein Data Bank and Global Health Drug Discovery Institute developed online COVID data
299 portals for analysis of protein structure. American Chemical Society issued an open Covid-19
300 antiviral candidate compounds dataset that may be useful for the treatment of coronavirus infected
301 patients. The crowdsourced developed a Fold.it [46] science game to design antiviral protein for
302 fighting against COVID-19.

iv. Speech Datasets

306 Speech dataset consists of either cough sounds or breathing rate, which are used to detect the
307 COVID-19. The smartphone and telemedicine can be used to collect the samples of cough and
308 breathe of patients. Some researchers designed a cross platform for collection of both cough and
309 breath). COVID-19 can be differentiated through the voice sounds. The scholars from the
310 University of Cambridge made calls for voice sample collection from the participants. They made
311 open source repository for cough samples.

v. Case Studies

315 WHO and the National Centers for Disease Control released the COVID datasets for tracking the
316 progress of infection and perceiving the effect of preventive measures. Johns Hopkins and Github
317 [47] offer information about COVID-19 infected areas. Humanitarian Data Exchange hosted data
318 about the coronavirus. CHIME is a COVID-19 Hospital Impact Model for Epidemics based SIR
319 modeling that utilizes the number of infected, recovered, and fatality persons to predict the

320 infection caused by coronavirus and the requirement of hospital beds. Supplement Table 8 depicts
321 the downloadable links and description of datasets [48].
322

5. Prediction Models

324

325 AI-based prediction models can be used to predict the mortality rate, infection in patients through
326 cough and biomarkers, genome structure associated with fatality rate, and severity rate. The
327 epidemic of the tracker was developed by Metabiota. It utilized the forecasting machine learning
328 model used for the prediction of infection spread. Robert Koch Institute developed a SIR prediction
329 model, which uses quarantines, social distancing, and lockdowns. This model was implemented in
330 the R language. It was helpful to reduce the spreading of infections.
331

332 Yan et al. [49] proposed a machine learning technique to predict the severity of COVID-19. The
333 survival rate of patients at Tongji Hospital in Wuhan is assessed through the prognostic biomarker.
334 The prediction accuracy obtained from the proposed machine learning technique was
335 approximately 90%. Jiang et al. [50] developed an AI framework that has the predictive capability
336 to analyze the severity of patients. They developed an algorithm to identify the clinical
337 characteristics of infected persons. The predictive model used clinical characteristics to predict the
338 severe illness of fifty-three patients with 80% accuracy. The predictive model is tested on two
339 hospitals in Wenzhou, Zhejiang, China.
340

341 Alotaibi et al. [51] used machine learning techniques namely Support Vector Machine (SVM),
342 Artificial Neural Network (ANN) and Random forest to predict the severity of infected patients.
343 The prediction accuracies obtained from SVM, ANN, and Random forest are 86.67%, 83.33% and
344 90.83%, respectively. Chatterjee et al. [52] developed a susceptible, exposure, infectious and
345 recovered (SEIR) model to study the impact of healthcare during the pandemic situation. By using
346 this model, hospitalizations and ICU requirements can be reduced to 90%. Ghosal et al. [53] used
347 a linear regression to predict the number of deaths in India. The predicted death rate is 211 and
348 467 by the end of 5th and 6th week, respectively.
349

350 Imarn et al. [54] developed the AI4COVID-19 tool for the preliminary diagnosis of COVID-19.
351 AI4COVID used a two-second cough recording of infected persons. After the analysis of cough
352 samples, the AI tool generates preliminary diagnosis for patients. AI4COVID distinguished
353 COVID and non-COVID patients with 90% accuracy. Feng et al. [55] developed a diagnosis model
354 for the preliminary identification of infected patients. The prediction was based on travel history,
355 clinical symptoms, and test results. Lasso regression applied to features obtained from clinical
356 symptoms for prediction. The features are extracted from Rao et al. [56] implemented machine
357 learning algorithms to determine the possible causes of coronavirus in the quarantine areas through
358 a mobile-based survey. The algorithms can easily predict the no-risk, moderate risk, and high risk
359 of infection through travel history and contact with infected persons.

360
361   Tang et al. [57] implemented a machine learning technique for automatic severity assessment of
362   infected patients using chest CT images. They extracted features from lungs and applied them to
363   a random forest model for predicting the severity of COVID-19. The accuracy obtained from the
364   random forest model was 87.50%. Qi et al. [58] used logistic regression (LR) and random forest
365   (RF) to extract the features from 72 pneumonia lesions of 31patients. The sensitivity and
366   specificity obtained from LR are 1.0 and 0.89, respectively. However, the RF model provided a
367   sensitivity of 0.75 and a specificity of 1.0. Patrikar et al. [59] modified the SEIR framework to
368   study the effect of social distancing on the spread of coronavirus. They found that the infection
369   can be reduced to 78% through social distancing.
370   Supplement Table 9 shows the comparative analysis of prediction models for COVID-19.
371

6. Screening Techniques for COVID-19

373

374   The diagnosis of a COVID-19 patient is a challenging task. The testing of every patient is time-
375   consuming. Due to the pandemic situation, faster and cheaper tests are required to generate the
376   medical report. AI-based techniques are used to screen COVID-19 patients. There are three
377   different methods to screen patients using AI. These are face recognition, wearable devices, and
378   virtual healthcare assistant (see Fig. 4) [60].
379

a. Screening through patients' face

381

382   Face recognition technology is used to eliminate the spread of infection caused by coronavirus
383   through human contact. It can be used with a temperature detection tool for the efficient
384   identification of COVID-19 patients. Drones/Robots equipped with the thermal scanner are used
385   for detecting fever in patients from an appropriate distance. Chinese firm Baidu developed infrared
386   cameras to scan the crowds for temperature scanning [61]. They can screen hundreds of persons
387   within one minute. However, the fever can be wrongly detected if a person wears some items on
388   the face. AI-based face recognition tools can be installed at schools, colleges, railway, airport, and
389   community places. These tools can automatically detect the persons having fever, tracing their
390   positions, and detect whether the person has a mask or not.
391

b. Screening through a wearable device

393

394   Nowadays, wearable health devices such as Fitbits and Garmins are more popular to monitor
395   physiological parameters such as heart rate, blood pressure, oxygen levels, body temperature,
396   movement, and sleep for a better lifestyle. Apple developed an AI-based watch to determine the
397   temperature and heart rate to identify the symptoms of patients [62]. OURA developed an activity
398   tracking ring that uses body temperature, breathing rate, and heart rate to determine the onset
399   patterns, progress, and recovery of the patient [63]. Stanford Medicine and Google company came

400   together to utilize the data collected from the wearable device to detect the symptoms of an infected
401   person. They used body temperature and heart rate for fighting against the COVID-19 infection.
402   Central Queensland University collaborated with Cleveland Clinic to analyze the data collected
403   from Whoop's wearable devices [64]. Shanghai Public Health Center has developed in-built
404   temperature sensors in wearable devices to detect the body temperature for COVID-19 patients
405   regularly. The detected temperature is continuously sent to the nursing station for patient
406   monitoring. Canada based Proxxi technologies developed a wrist device named 'Halo' that
407   communicate to user through vibration [65]. It gives an alert to the user about his come within
408   range of 6 feet of another wearable user. It uses Bluetooth technology to communicate with others
409   and keep the data record about users whom the wearable user met.

c. Screening through Chatbots

413   In this pandemic situation, chatbot developers and healthcare systems are integrated for the
414   prediction of infected patients. Chatbots are used as an accelerator tool for the healthcare of
415   COVID infected persons. AI-based Stallion used the capabilities of natural language processing
416   (NLP) to develop a Chatbot as a virtual healthcare agent [66]. It endorses protection measures,
417   monitors symptoms, and generates suggestions to individuals for home quarantine or hospital
418   admissions.

420   Some countries developed a "Self-Triage" system that uses a questionnaire about the symptoms
421   of patients. Microsoft developed a healthcare virtual assistant that will help to determine the
422   appropriate action using the symptoms of patients. They included risk assessment, clinical triage,
423   and COVID-19 question-answering in their chatbot [67].

425   Google Cloud developed a virtual assistant that will provide information about COVID-19. The
426   virtual assistant quickly responds to questions raised by users and provide optimal information to
427   users [68]. BITS students developed a chatbot to yield awareness among the users. AI-enabled
428   doctor video bot, named AskDoc, is developed to provide answers about the COVID-19 queries
429   using voice and text. Facebook implemented a WhatsApp bot to support the users to update them
430   on the outbreak of COVID-19 [69]. Zoe chatbot gives users answers and appropriate information
431   [70].
432   Supplement Table 10 shows the AI-based tools/techniques for the screening of COVID-19
433   symptoms.

7. Diagnosis of COVID-19

437   In this pandemic situation, a quicker diagnosis is required. The most widely used technique for
438   diagnosis is a real-time reverse transcription-polymerase chain reaction (RT-PCR) [71]. The well-

439   known radiological imaging techniques are X-ray and computed (CT) [72]. Due to less sensitivity
440   (60%-70%) of RT-PCR, symptoms can be detected through radiological images [73]. However,
441   radiological images are sensitive to detect the infection caused by COVID-19 and can be used to
442   monitor the patients [74]. A less number of clinical expertise is available as compared to the
443   COVID-19 cases that arose in this pandemic situation [75]. Therefore, AI-based tools and
444   techniques can be used for faster diagnosis.
445

446   ## a. Radiological Imaging

447
448   Researchers studied 33% of chest CTs have rounded lung opacities. It is observed from the CT
449   scan that symptoms may not be detected in the initial two days [76]. The abnormal finding is
450   detected in the CT scan of patients after ten days of symptoms observed [77]. Initially, due to the
451   low sensitivity of RT-PCR kits, clinical experts suggested using Chest CT for diagnosis [78]. The
452   traditional methods take 15 minutes for analysis of the chest CT scan. Nowadays, machine learning
453   or deep learning techniques are used for automated analysis of CT scans and chest X-rays. These
454   techniques will help to speed up the analysis process [79, 80, 81]. Fig. 5 depicts the distribution of
455   radiological images for diagnosis of COVID-19.
456

457   ## i. AI Tools for Radiological Images

458
459   Baidu's team developed a LinerFold software that diagnoses the infection of COVID-19 in 27
460   seconds [82]. The prediction time is reduced from 55 minutes to 27 seconds and helps in
461   developing the drug for coronavirus. It can identify lesions in terms of volume, proportion, and
462   numbers. The accuracy obtained from the system is 92% on available datasets. China scientists
463   developed a healthcare application named InferVISION to investigate COVID-19 patients.
464   InferVISION utilized NVIDIA's Clara SDK [83]. It can identify the positive cases within a very
465   small amount of time. Shenzhen-based company has developed a MicroMultiCopter that can carry
466   medical samples from infected and dense areas. It can also be used for food and medical items
467   delivery. LinkingMed technique to analyze the CT scan in less than sixty seconds. It provides 92%
468   accuracy on test datasets.
469
470   Canadian based DarwinAI developed a neural network to analyze the X-rays for COVID-19
471   infection. Some hospitals do not have testing kits and radiologists to analyze the infection. In that
472   case, an x-ray is an alternative to testing kits. DarwinAI developed a COVID-Net at University of
473   Waterloo. DarwinAI trained from 17000 X-rays images. They are working on COVID-Net for
474   identifying the risk of infection associated with workers [84].
475
476   Mumbai-based company Qure.ai developed an AI-based chest X-ray system named qXR [85]. The
477   qXR is used to detect COVID patients from chest X-rays. qXR utilized deep learning models to
478   detect lung abnormalities. It will help trainee doctors for their second opinion about the patient.

479 The accuracy obtained to detect the COVID infected patients is approximately 95% over 11,000
480 patients. Lunit's software named "INSIGHT CXR" is used to scan the abnormalities of the lungs
481 [86]. These tools will help to handle the coronavirus pandemic.

482

483 Ron Li implemented an Epic model that can assess whether the patients have to shift to ICU or not
484 [87]. He explored the "Deterioration Index" to identify whether the patient's condition is
485 deteriorating or not. Epic trained 130,000 patients for assessing the validity of the Deterioration
486 Index. He modified the model for the evaluation of COVID-19 patients in March. Six different
487 organizations have been evaluated the performance of the Epic model on 3000 COVID patients
488 and proved its performance.

489

490 Johns Hopkins University (JHU) developed a diagnostics tool for coronavirus infection [87].
491 Researchers in JHU developed a vigilant system for respiratory failure that can be caused by
492 COVID. The respiratory diagnosis model will help the doctors to assess the infected patients. It
493 will also envisage the need for ventilators and critical hospital instruments.

494

495 Maghdid et al. [88] proposed a mobile application to scan the CT images. CAD4COVID is an AI-
496 based software to distinguish infected patients from chest X-rays [89]. Huazhong University of
497 Science and Technology developed an algorithm for estimation of COVID-19 infected person with
498 80% accuracy. However, they tested on 53 patients of two different Chinese hospitals. Supplement
499 Table 11 depicts the description of AI tools used for the treatment of COVID-19.

500

501 ## ii. Deep Learning Architectures for Radiological Images

502

503 Hemdan et al. [90] developed an automated diagnose framework called COVIDX-Net for the
504 analysis of X-ray images. COVIDX-Net utilizes seven different deep learning models and tested
505 over 50 X-ray images. The accuracy obtained from COVIDX-Net is 90%. Wang et al. [91]
506 developed a deep convolutional neural network (CNN) model (COVID-Net) for the identification
507 of infection in chest X-ray images. COVID-Net model tested over 13,800 chest X-ray images and
508 obtained 93.3% accuracy in recognizing normal, typical pneumonia, and COVID-19 cases. Ioannis
509 et al. [92] evaluated CNN for the classification of COVID-19 cases. They used the transfer learning
510 technique on 1427 X-ray images, achieving 98.75% and 93.48% accuracy for two and three class
511 classification, respectively. Khan et al. [93] proposed a CoroNet architecture for detection of
512 COVID-19 in chest X-ray of infected patients. CoroNet utilized the concept of Xception model.
513 The classification performance of CoroNet was 99% and 89.6% for binary and three-class,
514 respectively.

515

516 Ozturk et al. [94] developed a DarkCovidNet model for the detection of infected patients using
517 chest X-ray images. DarkCovidNet model has seventeen convolutional layers and different
518 filtering for each layer. The classification accuracies obtained from DarkCovidNet were 98.08%

519   and 87.02% for binary and multi-class, respectively. Sethy et al. [95] suggested deep learning
520   based methodology for detection of infected patients using chest X-ray images. The proposed
521   methodology used CNN models with support vector machine (SVM). The classification accuracy
522   of ResNet50 model with SVM classifier is 95.38%. To overcome the shortcoming of hyper-
523   parameter tuning associated with transfer models, Kaur et al. [96] utilized the strength Pareto
524   evolutionary algorithm-II (SPEA-II) for chest X-ray images. They modified AlexNet to extract the
525   features from X-ray images and applied on classification process. The proposed approach
526   outperforms the competitive models in terms of performance measures. Jain et al. [97] developed
527   a deep learning model for diagnosis of chest X-ray images. IncpetionV3, Xception, and ResNeXt
528   are used in the development of proposed model. The classification accuracies obtained from this
529   model are 99% and 96% for training and testing, respectively.
530
531   Chowdhury et al. [98] designed an automatic coronavirus detection technique from X-ray images.
532   This technique was evaluated on Chest X-ray dataset and attained the classification accuracy of
533   99.7%. Islam et al. [99] combined convolutional neural network (CNN) and long short-term
534   memory (LSTM) to diagnose coronavirus infection in the patients. The performance of this model
535   was validated on 4575 X-ray images. The sensitivity and specificity of this model were 99.3% and
536   99.2%, respectively. Nour et al. [100] developed a CNN model to extract discriminative features
537   from chest X-ray. These features were applied on three well-known machine learning algorithms
538   namely, k-nearest neighbor (KNN), SVM, and decision tree for classification. The sensitivity and
539   specificity obtained from SVM-based classifier are 89.39% and 99.75%, respectively. A number
540   of research articles were published in the field of diagnosis of COVID-19 using chest X-ray images
541   [101-112].
542
543   Wang et al. [113] implemented deep learning approaches to extract specific features from CT scan
544   images. These features are used to detect coronavirus infection using the transfer learning model.
545   The developed model is tested on 1065 images of COVID-19. The accuracy obtained from their
546   model is 89.5%. Tan et al. [114] hybridized super resolution generative adversarial network
547   (SRGAN) model and VGG16 to detect infected patients by chest CT. SRGAN was used to enhance
548   the resolution of CT images. VGG16 was used to differentiate the infected and healthy region of
549   CT. The developed model is validated over 275 COVID-19 and 195 normal CT images. The
550   classification accuracy obtained from the model was 97.87%. Xu et al. [115] used different CNN
551   models to detect infected patients. CT images are processed to extract the interesting regions. 3D
552   CNN model is used to segment the CT images. Thereafter, the segmented images are further
553   classified into three different classes. The overall accuracy of deep learning models was 86.70%.
554
555   Singh et al. [116] developed an automatic chest CT analysis system to classify the infected persons
556   whether these are positive or not. The CNN hyper-parameters are tuned through multi-objective
557   differential evolution (MODE). CNN with optimized parameters is used for COVID-19 patient
558   classification. The proposed model outperforms the other competitive models by 1.927%. Li et al.

559 [117] developed a COVNet model for extracting 2D and 3D global features from chest CT for the
560 classification of COVID-19 patients. The extracted features are utilized to differentiate CoVID-19
561 infected, non-pneumonia, and community-acquired pneumonia (CAP). The classification accuracy
562 obtained from COVNet was 96.00%. Mei et al. [118] utilized machine learning techniques for the
563 analysis of chest CT scans of COVID-19 patients. The clinical symptoms and laboratory testing
564 were integrated with CT scans for analysis.

566 Hasan et al. [119] combined both deep learning technique and Q-deformed entropy for
567 classification of COVID-19 using CT scan images. The features were extracted from CT scan
568 images using Q-deformed entropy and CNN. The extracted features were applied on LSTM for
569 distinguishing the COVID-19 and non COVID-19. The proposed approach attained the
570 classification accuracy of 99.68%. Wu et al. [120] developed a multi-view fusion model for
571 identification of coronavirus infection in the CT scan images. This model was evaluated on the CT
572 images of 495 patients. This model takes approximately ten minutes for analysis of CT images of
573 infected patients. They used Youden index for fusion process. For testing phase, the sensitivity
574 and specificity obtained from multi view model are 81.1% and 61.5%, respectively.

576 Ko et al. [121] developed a FCONet model for COVID-19 classification using chest CT. FCONet
577 utilized VGG16, ResNet50, InceptionV3, and Xception. The performance of FCONet was
578 validated on 3993 chest CT images. The accuracy obtained from ResNet50 was 96.97%.
579 Researchers use deep learning architectures for analysis of CT scan images [122, 123].

581 The comparative analysis of deep learning techniques on radiological images such as chest X-ray
582 and CT scan images are illustrated in Supplement Tables 12 and 13, respectively, while the usage
583 of deep learning models is summarized in Fig. 6.

585 ## b. Non-invasive techniques

587 Several techniques do not need any specialized radiological equipment for diagnosis and treatment
588 of COVID-19. Cho et al. [124] used a GRU neural network to determine the respiratory patterns
589 of patients. The developed model is trained on footage obtained from Kinect depth cameras [125]
590 and recognizes the COVID-19 patients.

592 Cascella et al. [126] suggested that COVID-19 patients have respiratory patterns, which are
593 different from the common cold and flu. However, the abnormal respiratory patterns have no direct
594 correlation with the diagnosis and treatment of COVID-19. The wearable devices and mobile
595 applications can be utilized in the diagnosis and treatment of COVID-19. These devices and apps
596 may utilize the body temperature, heart rate, cough samples, and breath rate.

598 ## 8. Drug Design

599   AI has the potential to discover, design, and repurpose the existing drugs to combat the COVID-
600   19 as shown in Fig. 7. During this pandemic situation, several research laboratories are trying to
601   develop vaccines/drugs against COVID-19. They are using AI techniques to discover new vaccines
602   or repurposing existing drugs [127].
603

604   ## a. Envisaging virus-host interactome
605

606   The prediction of protein structure is necessary to develop new drugs. Senior et al. [128] developed
607   an AlphaFold model to envisage the structures of proteins associated with SARS-CoV-2. ResNet
608   is used to extract the features from amino acid sequences [129]. Heo and Feig [130] implemented
609   dilated ResNet to envisage the protein structure of SARS-CoV-2. They refined the AlphaFold's
610   predicted structures using molecular dynamics. Ge et al. [131] suggested an approach to construct
611   a knowledge graph that involving human proteins, viral proteins, and drugs. The knowledge graph
612   is used to envisage possibly candidate drugs. Nguyen et al. [132] developed a SARS-based model
613   using mathematical deep learning to determine possible inhibitors. 84 SARS coronavirus inhibitors
614   are envisaged from ChEML and PDBind databases. Zhou et al. [133] developed network-based
615   model to repurpose the drugs for SARS-CoV-2. Hu et al. [134] implemented a neural network to
616   predict the affinities of SARS-CoV-2 proteins. They found ten possible drugs with their binding
617   affinity scores among 4895 drugs.
618

619   Exscienta designed an AI-based drug molecule for coronavirus as reported in news [135]. It is the
620   first company who has designed the drug molecule for coronavirus. The traditional drug discovery
621   research took 4-5 years for developing new drugs. However, it will take one year to develop the
622   molecular structure. Insilco Medicine company used generative adversarial networks to determine
623   the molecule structure. This structure is used to discover drugs. Insilco company screened 100
624   molecules for synthesis and testing. AI can be used to develop antibodies and vaccines for COVID-
625   19 [136]. It can be done in two ways namely, from scratch and drug repurposing. Google'
626   DeepMind developed an AlphaGo algorithm to envisage the protein structure of the virus, which
627   can help develop new vaccines against coronavirus [137]. However, the experimentation has to be
628   performed for validation of the designed protein.

629   ## b. Envisaging interaction among coronavirus and drugs
630

631   AI can be used to screen the exiting drug molecules and find their suitability against the
632   coronavirus. South Korea and the USA used an AI-based algorithm to identify the 'Atazanavir'
633   drug for repurposed to the treatment of COVID-19 [138]. Researchers of Benevolent AI identified
634   'Baricitinib' and 'Myelofibrosis' drugs for the treatment of COVID-19 [139]. Singaporean Firm
635   Gero used a deep learning technique to recognize 'Afatinib' for the treatment of COVID-19. Zhang
636   et al. [140] used fully connected ANN to envisage binding affinities from the PDBbind database.
637   They explored the existing molecules for the treatment of SARS-CoV-2 [141]. Beck et al. [139]
638   developed Molecule Transformer-Drug Target Interaction (MT-DTI) model to determine

639 antivirals drugs that may be effective against coronavirus. BERT algorithm used to compute the
640 binding affinities of existing drugs. Hofmarcher et al. [142] used Long Short-Term Memory
641 (LSTM) model on SMILES data to screen 900 mln compounds from the ZINC dataset. 30,000
642 possible compounds are selected for treatment of SARS-CoV-2. These treatments may be available
643 in near future. The main reason behind this that medical trials, checks, and control are needed
644 before the approval of these drugs. After the identification and screening of drugs, a vaccine
645 formulation may take a minimum of 18 months [143].
646
9. Social Implications
648
649 Nowadays, the different myths regarding the incorrect data of infection, unsuitable drugs, and
650 misclassified infected zones have been propagated on social media. However, these rumors and
651 hate speech can be greatly affected by the social life of human beings. WHO put these things in
652 infodemic, i.e., the huge amount of data is available with a mixture of accurate and inaccurate data.
653 Due to this, persons are unable to find verified sources whether the given information is correct or
654 not in this pandemic situation.
655
a. Analysis of Social Media
657 In this epidemic situation, social media should assess the quality and accuracy of the information
658 posted. Nowadays, Facebook and Google are working against the misinformation, phishing
659 funding websites, and viruses floating on their platforms. When you search the COVID on
660 YouTube, then it links to the user either government organization or WHO for retrieving correct
661 information. Videos posted on YouTube are screened and dropped immediately from the site after
662 the false information is confirmed. Eichstaedt et al. [144] analyzed the tweet posted on Twitter by
663 the user during this epidemic situation of COVID-19. AI-based text analyzer utilizing the number
664 of cases and death in a particular region to investigate the mental health of the user. MIT developed
665 a neural network-based model to determine the effectiveness of quarantine measures and the
666 spread of virus infection [145]. Khataee et al. [146] reported the effects of social distancing during
667 the COVID epidemic. They can assess the local elements of the pandemic. They reported that the
668 US has not taken precautionary measures to stop infection caused by a coronavirus. Rosenberg et
669 al. [7] analyzed the tweets related to coronavirus-related information. They explored the various
670 myths about the virus. Galotti et al. [147] explored the social media tweets posted on Twitter. They
671 developed an Inodemic Risk Index (IRI) to determine verified human beings, unverified human
672 beings, verified, and unverified bots. IRI utilizes the number of users and messages posted by users
673 and their reliability. They highlighted the impact of infodemics, social outcomes, and controlled
674 pandemics. Cinelli et al. [148] studied the contents of social media. They assessed the development
675 of the discourse on Twitter, YouTube, Instagram, and other social media. They analyzed the
676 comments, likes, and action upon comments for 45 days. Mejova et al. [149] studied the
677 advertisements related to coronavirus posted on Facebook. Facebook Ad Library is used to
678 examine all the advertisements that have the phrases "coronavirus" and "covid" across the world.

679   They established that 5% of advertisements having misclassified and misconception information.
680   Zarocosta [150] studied the information shared and posted on different social media regarding
681   COVID-19. AI tools can be used to track the spreading of rumors regarding the coronavirus.
682   Pandey et al. [151] reported the breach in delivering genuine information to users in India. They
683   retrieved the information and found their verified sources using artificial intelligence and NLP.
684   They tested their approach on Sanitation and Hygienic information for this epidemic situation. AI-
685   based chatbots can be used to propagate COVID-19 information that can filter the misinformation.
686   WHO developed a multilingual chatbot to explore the information posted on social media and
687   news channels [152]. This virtual assistant can be used to verifying the information before further
688   processing.
689

690   ## b. Analysis of Hate Speech
691   Hate speech is a major concern in the last few months. The verbal and non-verbal abuse statements
692   may give rise to physical violence against the corona warriors. Such instances were reported in the
693   lockdown situation of various countries. Velasquez et al. [153] analyzed the hate speeches
694   regarding COVID-19 posted on different social media and their movement from one media to
695   another. They have also analyzed the methods for transmission and found that hate speeches are
696   rapidly spread in the epidemic situation of COVID. Schild et al. [154] reported the Sinophopic
697   behavior of tweets posted on Twitter and other media. They trained machine learning models on
698   the information obtained from the contents of COVID-19. Web can be used for spreading
699   misinformation and hate speech on COVID-19 information. AI-based tools play a vital role in
700   fighting against hate speech [155].
701

702   Supplement Table 14 depicts the impact of rumors and hate speech on social life.
703

704   ## 10.   Future Research Directions
705

706   The possible research directions for application of AI on COVID-19 are described below:
707

708   ## a. Interpretable prediction
709   The results obtained from the AI-based prediction model should be interpretable and easy to use
710   [156, 157]. Therefore, soon one can utilize information extraction or image captioning kin of
711   techniques to provide more interpretable prediction results.
712

713   ## b. Mobile-based AI Tools
714   The AI based models can be deployed on lightweight devices such as mobile. Our objective is not
715   to achieve diagnostic tools for hospitals and clinics. On can work on AI-based COVID-19
716   prediction and diagnostic tools on lightweight devices [158].
717

c. Drug Discovery

719 Till now many researchers have worked on developing drugs for COVID-19 infected patients.
720 However, no effective drug is available for COVID-19 diagnosis. Therefore, one may utilize the
721 existing medicines to build an efficient drug for COVID-19 infected patients [159].
722

d. AI-based Drones to combat COVID-19

724 As we knew that the main source of infection transmission is human contact. Due to this, AI-based
725 robots are used to disinfect the patient's rooms and interact with patients. For disinfection, robots
726 are transmitting ultraviolet light over infected space to remove the virus. Robots are transferred
727 the face image and voice of doctor on their screen during the interaction with patients. Hence, the
728 medical staff is safe due to less contact with patients. Drones are widely used for transferring
729 patient samples and medical apparatus. These are also used to disinfect the unreachable infected
730 areas. During the lockdown, the drones are used to track the person who is come out from home.
731 It provides faster delivery and less risk of infection. The drones supported by AI and computer
732 vision techniques can play an essential role in the aerial monitoring of disease spread; for logistics
733 and medical supply delivery [160], as well as for social distance checking [161]. They also were
734 used to perform aerial spray and disinfection of residential areas [162]. However, there are data
735 security, and privacy concerns that need to be resolved for successful application of AI-supported
736 drone technology in public spaces on a large scale.
737

e. 3D Printing techniques for developing COVID-19 prevention and fighting tools

740

741 The 3D printing techniques may be used to design the face masks and face shields to be used for
742 protection against COVID-19 [163]. Combined with face-scanning technology and computer-
743 aided design (CAD) tools these can be made to fit the individual face and head measurements. The
744 3D techniques also can be used to build other COVID-19 fighting tools such as main components
745 of respiratory support equipment [164]. These components can be designed using low-cost
746 consumer filament extrusion printers. The 3D printing technology can quickly address the
747 deficiencies of medical materials and spare parts of medical equipment, however, the processing
748 time, high cost, and lack of manpower can be potential barriers for applying 3D printing on a larger
749 scale [165]. AI techniques can play a role in optimizing the 3D design process and reducing the
750 cost of printing [166, 167, 168].
751

11.   Findings, Lessons and Recommendations

753

754 However, numerous challenges and research limitations have been indicated in the academic
755 literature and need to be addressed in the future. Some of these challenges are related to nature and
756 behaviour of COVID-19 because understanding how the virus spreads and how people can be

757 infected caused by the complexity of this epidemic disease is extremely difficult. The lack of large-
758 scale datasets in the academic literature for COVID-19 is considered a challenging task for AI
759 researchers because it hinders the understanding of viral patterns and features. In order to make AI
760 and big data platforms and applications a trustful solution to fight the COVID-19 virus, a critical
761 challenge is the collection of large-scale datasets and making them open for research.
762
763 AI and big data-based algorithms should be optimized further to enhance the accuracy and
764 reliability of the data analytics for better COVID-19 diagnosis and treatment. AI is able to provide
765 viable solutions for fighting the COVID-19 pandemic in several ways. For example, AI has proved
766 very useful for supporting outbreak prediction, coronavirus detection as well as infodemiology and
767 infoveillance by leveraging learning-based techniques such as ML and DL from COVID-19-
768 centric modeling, classification, and estimation. Moreover, AI has emerged as an attractive tool
769 for facilitating vaccine and drug manufacturing. By using the datasets provided by healthcare
770 organizations, governments, clinical labs and patients, AI leverages intelligent analytic tools for
771 developing effective and safe vaccine/drug against COVID-19, which would be beneficial from
772 both the economic and scientific perspectives. Moving forward, it is imperative for AI-designers
773 and researchers to work together with medical professionals to create and develop these systems
774 that are applicable to real-world datasets
775

776 ## 12.   Conclusions
777
778 In this paper, the impact of artificial intelligence (AI) techniques is assessed on early cautionary
779 and vigilant systems that focus on COVID-19 warning and diagnostics. The COVID-19 datasets
780 and visualization techniques are discussed with their applications. The AI-based diagnosis and
781 treatment of COVID patients are assessed. The impact of AI on drug discovery and design is
782 evaluated. The effect of COVID-19 is also evaluated on social and economic aspects. From the
783 literature review, we can conclude that the AI techniques are widely used to identify the novel
784 drug discovery beforehand of the outbreak of COVID-19. The AI techniques can help to search
785 for the optimal drug against COVID-19. AI can be used to build the biomedical knowledge
786 structure that connects the drugs and viruses to repurpose the existing drugs that are used to treat
787 other diseases. The existing drug and coronavirus interaction can be modelled by AI techniques.
788 Other promising applications of the AI methods are contact tracing, drone-based surveillance, and
789 smart face mask design.
790

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Figure 1

Number of preprints available related to COVID-19 on different platforms (From Jan, 2020 to April, 2021)
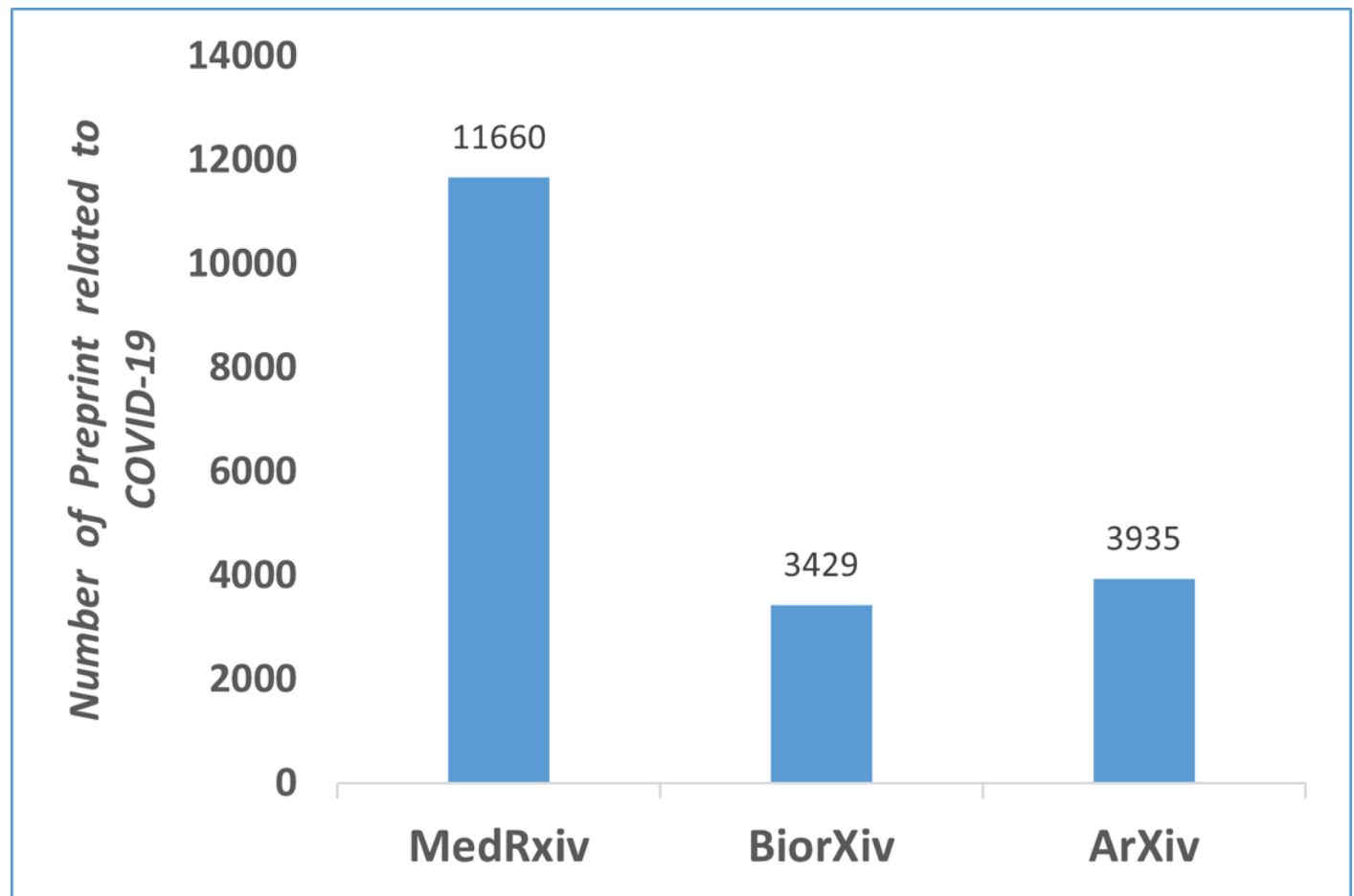
Figure 2

Classification of data gathering systems
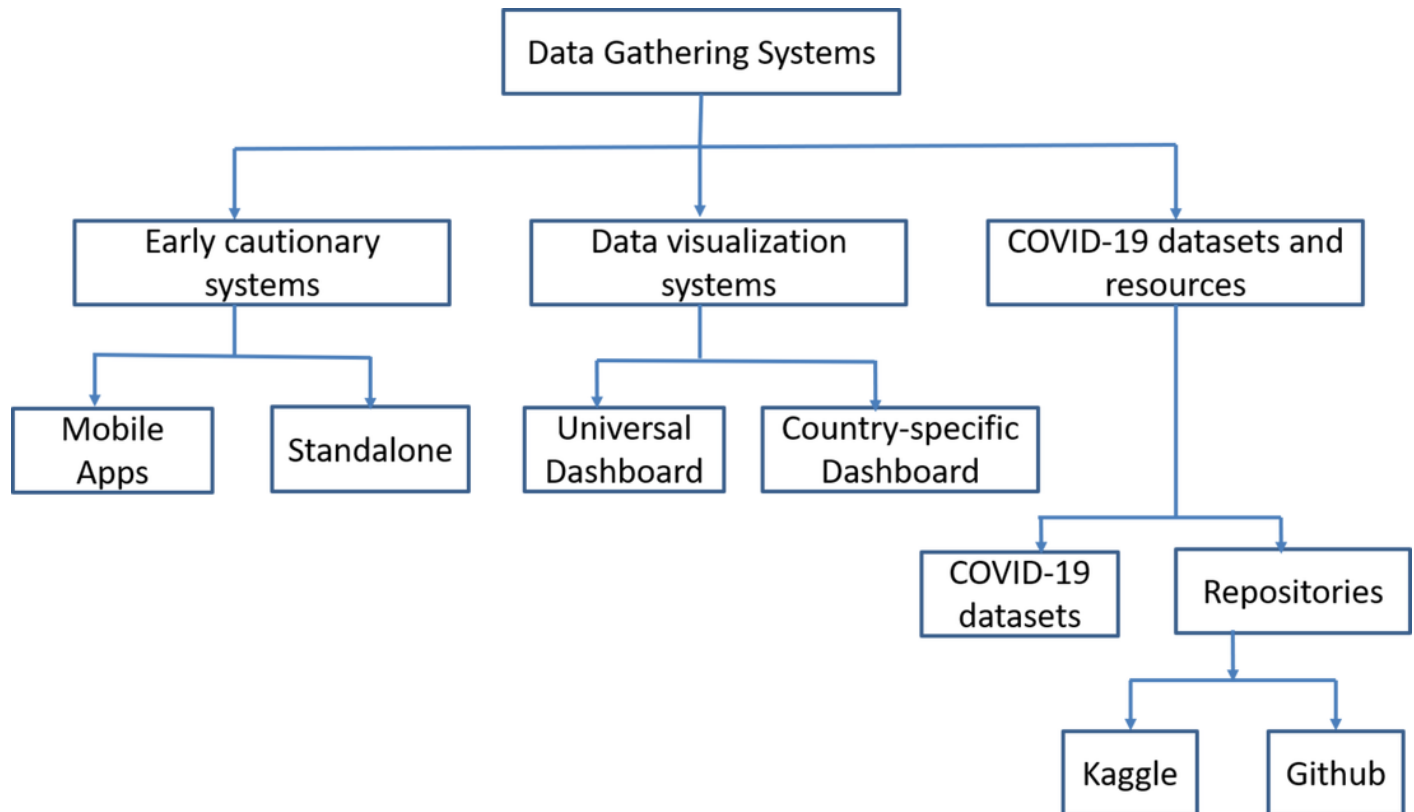
Figure 3

Classification of COVID-19 Datasets
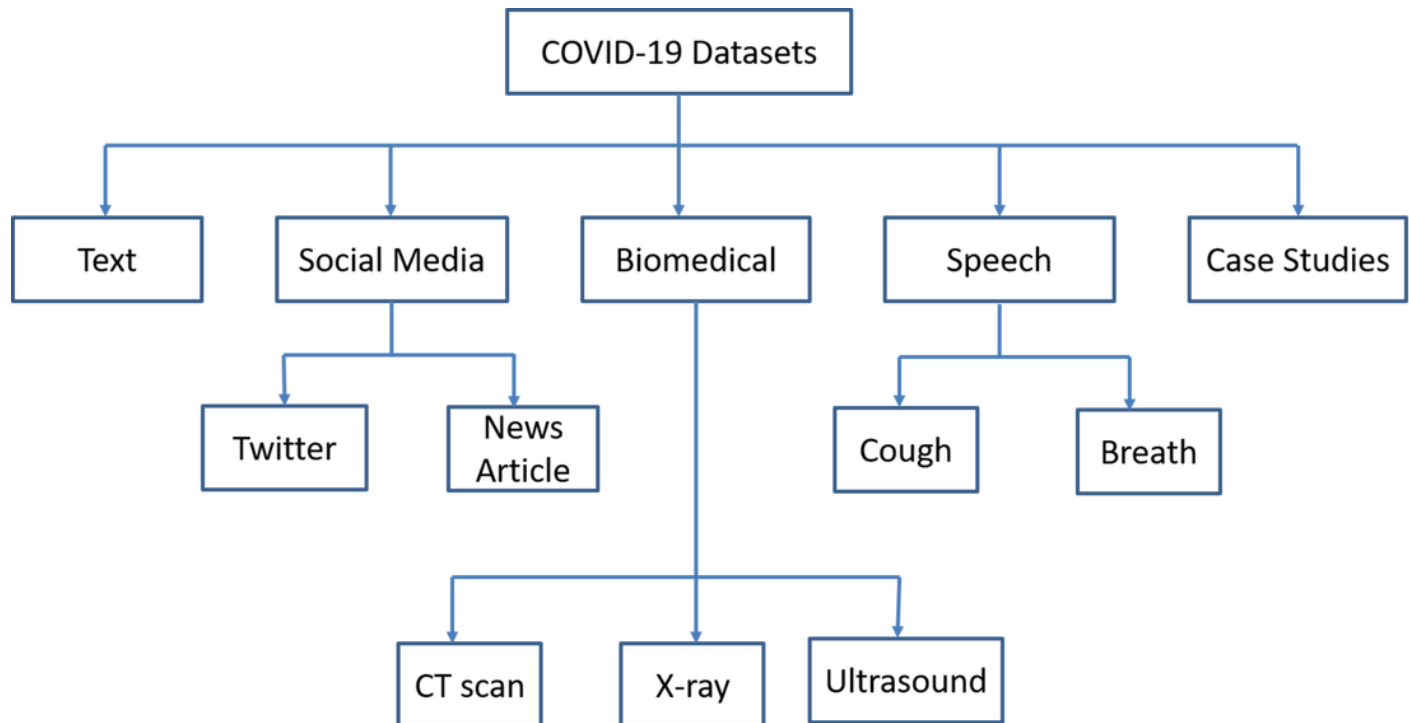
Figure 4

Screening techniques for COVID-19 symptoms
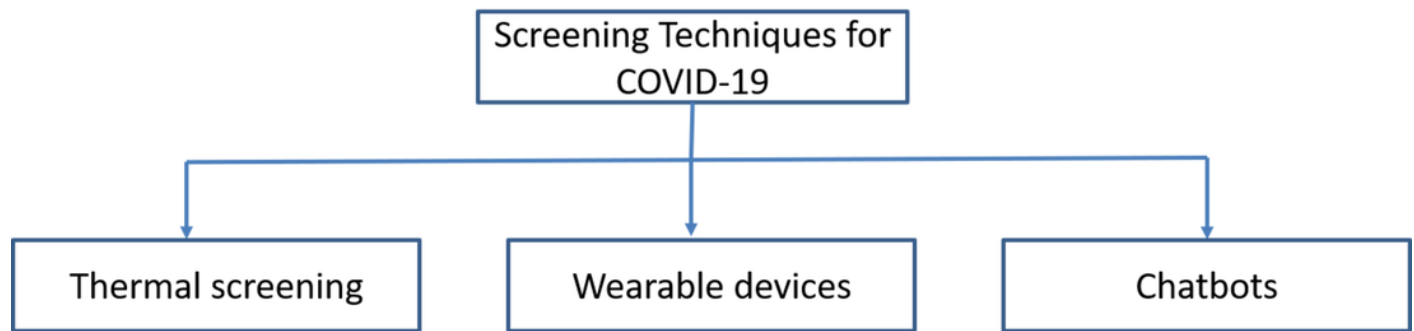
Figure 5

Different radiological modality used in deep learning techniques
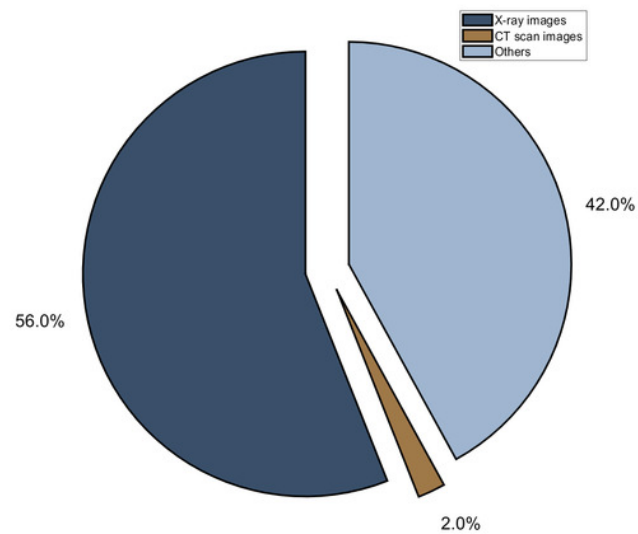
Figure 6

Different deep learning architectures used for diagnosis of COVID-19
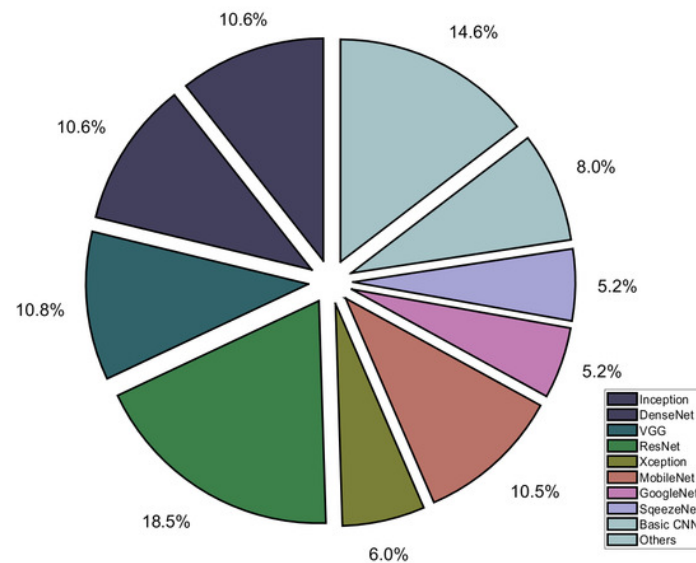
Figure 7

Deep learning and machine learning based drug synergy prediction for COVID-19