# CHAPTER 6

# Conclusions

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## 6.1 Introduction

World Health Organization (WHO), on March 11, 2020, declares COVID-19 as a pandemic caused by SARS-COV-2. COVID-19, originated from Wuhan (China), is a communicable or infectious disease [1,2]. More than 3 million people have tested positive. The disease is spreading exponentially and its effects are tremendous. People in various countries are fighting with great courage but as of now, no vaccination is invented by doctors and researchers. Time to time, Center for System Science and Engineering at John Hopkins University is providing data related to positive cases, death cases, and recovered cases globally.

This chapter presents an overview of data science research on COVID-19. Data science is a technique to analyze structured and unstructured data in order to get knowledge or information. Data science helps in analyzing different datasets to get information about pandemic COVID-19 [3]. This information can be details of COVID-19 patients, recovery rate, spreading rate, effects on different areas, and many more. The major contributions of this chapter are:

1. Different research problems related to COVID-19
2. Exploring different datasets for COVID-19
3. Latest research ideas for computer scientists and engineers
4. A bibliometric survey on COVID-19 literature
5. Challenges with data science.

All the datasets discussed in this chapter help in finding some solutions to COVID-19 pandemic. The aim of this work is to present newest topics for research and finding more solutions in this area.

The rest of the paper is organized as Section 6.2 discusses data science and its applications in medical. It explores different ways to identify COVID-19. A survey on ongoing research ideas to tackle pandemic is

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discussed in Section 6.3. Bibliometric analysis for research in COVID-19 is elaborated in Section 6.4. Section 6.5 presents cross-cutting challenges. The chapter is concluded with a short summary.

## 6.2 Data science and its applications

Machine learning, statistical learning, time series modeling, expert system, data visualization, and probabilistic reasoning are few terms, which cover some applications of data science [4]. These all applications help in fighting with pandemics like COVID-19 in different manners. It helps in managing limited resources, developing plans, understanding the uncertainty, extracting information for building collaboration, etc. Few applications of data science in identifying disease are explained further.

### 6.2.1 Patient prioritization to control risk

Various risk assessment algorithms are opted to analyze different diseases like cancer, cardiac arrest, and diabetes. Artificial neural network (ANN) introduced a number of risk assessment algorithms [5–7]. Such algorithms take patient data like age, gender, traits, symptoms, state, and stage, for efficiently analyzing or estimating the risk. But this is a bitter truth that whenever a pandemic arises, medical resources fall into scarcity. Medical resources are lean globally for any pandemic situation. So, it is the need of time and situation to efficiently and effectively utilize the limited resources. Resources in peak times are utilized rapidly to manage patient's risk. Patient prioritization data can be prepared to sustain risk. Priority constraints can be different or as per situation to control the risk level.

### 6.2.2 Diagnosis and screening

COVID-19 spreads due to lack in screening and diagnosis. From China to worldwide, it majorly spreads due to ineffectual screening facilities at airports. In the initial days of pandemic, social distancing was a challenge for everyone and hence was not taken on serious mode. Mild symptoms were often ignored that became major reasons for the enormous spreading rate. There exist various remote diagnosis tools available, which help in self-analyzing the symptoms and assist in controlling the spread rate. To self-analyze, various mobile applications are available, which use audio, video, and sound data to perform diagnosis. Such tools are helpful in diagnosing the symptoms when healthcare resources are lean. Automated tools are also encouraged at airports or at places where movement of people is nonstop [4]. For example, infra-red sensor-based temperature scanner.

**Table 6.1** Modeling of epidemic.

| S. No. | Epidemic model | Division of people |
|---|---|---|
| 1. | Compartment model | Using simple differential equation |
| 2. | SEIR | Four states: Susceptible, Exposed, Infected, Recovered |
| 3. | Generative model | Segregation of people for new cases after a particular time and some constraints like effects of herd community and social distancing |
| 4. | Social media model | Analyses on the bases of ambulance call out data and similar data [13–15] |

### 6.2.3 Modeling for epidemic

Any modeling is required to manage capacity in an effective manner. So, as per a survey, to manage epidemic, compartment models are more popular [8]. In such modeling, people are divided into compartments using a simple differential equation. The SEIR model is also used to model COVID-19 spread, where four states are assumed to model the flow of people like susceptible, exposed, infected, and recovered [9]. In generative modeling, few circumstances are observed like effects of social distancing and causes of herd community. All these models must be updated from time to time to capture the best dataset [10–12]. Some use-case data are also developed to evaluate more accurately "what if'" kinds of situations. Table 6.1 is organized to showcase a few epidemic models and its working features.

### 6.2.4 Tracing the contacted people

In few countries, it is opted in the early stage of COVID-19, to trace the contact person of infected one and send them to quarantine [11,12]. This approach is very effective and helpful in controlling the spread rate. Various mobile phone applications are proposed to quickly identify and trace the contacted person. Automated diagnosis, online surveys, and smartphone contact sensing are few measures. These measures are useful to create alert to hospitals and government, with regard to the outbreak [16]. It is also supported in logistic planning like masks, gowns, sanitizers, test kits, hospital beds, and ventilators. For such planning and management, machine learning and data science algorithms do a good job. It predicts the need of ventilators and beds in hospitals in advance so that preparation can be done on an early basis. In peak times of pandemic, shortage of not only medical resources but also healthcare workers is triggered. To mitigate this, data science introduces automated patient care tools. These tools can provide information about the outbreak, symptoms, and personal precautionary measures. WHO introduced an interactive chatbot to monitor health conditions in emergency cases [17–20], [21,22].

Data science proves its eligibility in discovering drugs and treatment through Bayesian clinical trial methods, which works on collected data. It helps in identifying eligible patients to apply to clinical trials, hence reduce time spent in examining data, predicting protein structure, and genomes. Therefore, we can say that the above fields are popular where data scientists can contribute a lot [23–31].

### 6.2.5 Acknowledging social interventions

Governments have taken various steps to control the spread rate of COVID-19. A few use cases are highlighted and briefed further.

1. **Monitoring social distancing**: To monitor social distancing, governments adopt various strategies [32–34]. However, this is a nonpharmaceutical method to control COVID-19 but very effective. Natural language processing (NLP) is used to monitor social media information for analyzing social distancing. In many areas, air pollution level is used to analyze the rate of movement of people [35]. Cellular data are also traced to monitor the mobility rate. It is accepted by all that social distancing affects the global economy as well [36,37]. It is a challenge for few organizations to get back to their previous level. For such cases, data science can be helpful in identifying optimal economic interventions. Organizations can detect unusual patterns of behaviors in the market [38,39].
2. **Spreading of false information**: Spreading false information is always harmful. Internet websites manage to maintain an up-to-date list of false information regarding COVID-19. Such false information can affect datasets also. The consumption of garlic and alcohol can get rid of COVID-19 is one such false information. Such information can harm public health. So, data science could be used to classify such misinformation. Machine learning techniques support sentiment analysis, which can help the public to be aware about false information [40–44], [22,45].

### 6.2.6 Use of case data

Almost all the countries are tracing per day growth rate on different geographical locations [46]. The data are collected under different columns like daily positive cases, total positive cases, cured cases, and mortality cases. These data are further attributed as patient location, reporting data, past history of patient, and symptoms. India is also compiling data statewise then district wise, which is very useful in maintaining up to date datasets. Data visualization and predictive analysis, can be done on collective datasets for efficient measures. But data science would not work properly, if there is divergence in testing regimes. In few countries, test kits are inadequate, due to which accurate data are not available. So, it is a challenge for data scientists to work in such an environment [47–66].

### 6.2.7 Textual data

Nowadays, people are discussing and sharing textual data on social media platforms [67]. The major keywords like COVID-19, N95 masks, pandemic, and coronavirus aid in monitoring the spread rate of COVID-19 [54]. NLP also works here to monitor people's reactions on lockdown, social distancing, and personal hygiene. NLP measures the sentiments of people on social media and the Internet [68]. The role of data science is to record social media streaming that contains the above-mentioned keywords. Apart from social media data, academic publications are also flooded these days to provide textual data [55–61]. Such bibliometric datasets are available online. Many open research article datasets are already released by publication houses to motivate research in this field. WHO is working to provide up-to-date scientific literature for COVID-19. Table 6.2 collects data for organizations, which are compiling scientific dataset on COVID-19 (freely available) [69].

**Table 6.2** Organizations compiling scientific literature on COVID-19.

| S. No | Organizations |
|---|---|
| 1. | BMJ |
| 2. | Cambridge University Press |
| 3. | Centers for Disease Control and Prevention |
| 4. | Chinese Medical Association |
| 5. | Cochrane |
| 6. | Elsevier |
| 7. | European Centre for Disease Prevention and Control |
| 8. | JAMA Network |
| 9. | The Lancet |
| 10. | LITCOVID: US National Library of Medicine |
| 11. | Oxford University Press |
| 12. | PLOS |
| 12. | Public Health England |
| 13. | Science |
| 14. | Springer Nature |
| 15. | SSRN (Preprints) |
| 16. | Wiley |

### 6.2.8 Biomedical data

Biomedical data sources are physical medical reports (X-ray reports of an individual) and clinical pathology reports (Genomic structure) [70–72]. These are helpful in diagnosis, prognosis, and treatment. Diagnosis means to check about a particular illness, prognosis means to predict the outcome of a disease and chances of recovery. So, for diagnosis and prognosis, human interpretation is required [73,74]. A number of mobile apps are developed to self-diagnose and self-prognosis. Various automated diagnosis apps are developed to test chest X-ray, lungs computation tomography (CT) scan. The X-ray scans the chest and provides results on the basis of analysis from stored datasets. Some X-ray datasets are publicly available, which contain patient's details like date, demographics, findings location, survival information, and treatment. This data are analyzed on some neural network trained model [75–79]. However, these models are not self-sufficient to identify the problem, as it requires clinical experts to label reports.

Another biomedical data source is clinical pathology reports, which contains datasets of genomic sequencing. The genomic dataset includes drug impact, protein–protein interaction, and RNA structures, which support diagnosis test evaluation. Another challenge is availability of datasets to accurately measure problem statements. Same issue arises with lung CT scan, as public availability of biomedical dataset is very difficult [80–83].

### 6.2.9 Other supportive datasets

Some other relevant datasets are air quality index statistics, and datasets for mobility of people, which monitors factors related to COVID-19. If the mobility of people is controlled, it automatically affects air quality or pollution level. After a study, it has been noticed that few popular cities' air quality has improved in recent days [35,84,85]. Google has also released datasets after mobility tracing, which is compiled through Google maps.

### 6.2.10 Competition database

Kaggle has organized various competitions to promote and facilitate research in data science. The participants use publicly available datasets and recent research articles on COVID-19. Such competitions are motivated by announcing cash prizes also.

## 6.3 Survey on ongoing research

The previously discussed datasets were publicly available and have some limitations. So, in the next section, some ongoing research ideas are discussed.

### 6.3.1 Image data analysis

Computer vision technology plays a vital role in detecting disease by tracing image dataset. This technology sped up the process of disease detection and proved its potential by outperforming expert radiologists. For COVID-19, two computer vision modalities are used. One is CT scan and another is X-ray scan. Radiologists diagnose many COVID-19 patients through chest CT scan. It is a very successful attempt because nowadays machine learning and deep learning techniques are integrated with CT scan technology, which are useful in detecting radiographical changes in patients very frequently [86–88]. Initially, it was evaluated and tested upon many COVID-19 positive cases to improve its reliability and trust factor [89–100].

### 6.3.2 Audio data analysis

Pneumonia and cough are the common symptoms of COVID-19. Change in voice due to pneumonia and cough can be taken as audio/sound analysis [101–107]. This analysis can be done with low-cost smartphones too. The speech pattern and cough pattern are the main data source to monitor the situation [108]. AI4COVID-19 is a popular app developed by preliminary diagnosis. It collects data for sound for future dataset observations and processes the feasibility of detection with 90% promising rate.

### 6.3.3 Sensor data analysis

Sensors are the tiny embedded devices, which sense the environment before processing. Sensors can be deployed anywhere in remote areas as well. In the medical field, sensors can be deployed in a patient's body to diagnose the variations of body glucose, temperature, blood pressure, heart rate, pulse rate, etc. [109]. Sensors can provide demographic data, mobility data, and disease related data and user generated data from social media. Such a system is named as $\alpha$-Satellite, which can assess risk level [110]. The data fetched from this system can be used to diagnose COVID-19. This system proves its reliability because it uses multireading to sense the symptoms of disease. Smartphones embedded with sensors can detect movement of people during pandemic. The table below has sensor based systems developed for pandemic with their specific features (Table 6.3).

The above-mentioned apps are developed by different countries to provide safe and sound surroundings to their people. These apps were developed for the safety of people but users face few privacy issues [116–119]. Many of the apps require uploading the contact list, which can reveal nationwide databases. To minimize such weakness, Pan-European Privacy-Preserving Proximity Tracing Consortium (PEPP-PT) developed an app

**Table 6.3** Sensor based COVID-19 detection systems developed by different countries.

| S. No. | Sensor-based systems | Major feature |
|---|---|---|
| 1. | α-Satellite [110] | Risk assessment |
| 2. | COVID-19 symptom tracker app | Track initial or mild symptoms |
| 3. | COVID near you | Track and alert about infected person near you |
| 4. | StayHomeSafe [111] | Track for your safety |
| 5. | Home Quarantine app [112] | Detect if quarantines rules have been obeyed or not |
| 6. | Close Contact Detector [113] | Track the infected contact persons |
| 7. | Track Together [114] | Track the infected contact persons |
| 8. | HaMagen [115] | Track the infected contact persons |

named Decentralized Preserving Proximity tracing (DP-3T) [120,121]. It provides a preservation alert to the users who may have been in contact with an infected person. Another similar app launched with homomorphic encryption features. Google and Apple have also announced to develop a privacy preserving contact tracing app based on Bluetooth.

Mobile Technologies: Mobile technologies are being used for a variety of purposes in healthcare. Most importantly, they are enabling new ways for pandemic management by providing powerful tools to both doctors and patients for effective prevention and treatment [84,85,122]. As the common risk factor of pandemic are related to human behavior, therefore, mobile phone-based health solutions can be used to combat the rising burden of pandemic by focusing on behavioral change programs to promote a healthy lifestyle. This chapter discusses the common pandemic, their burden, and future estimated projections and shows how mobile phone technologies can provide effective pandemic management in developing countries, which have a lot of issues in their healthcare systems.

### 6.3.4 Drug discovery analysis

Some researchers put extensive efforts in discovering new drugs to support SARS-COV2 [123]. To build a model to explore 3D structure of SARS-COV2, AlphaFold model has been developed, which is a deep learning based model. This model is based on dilated ResNet architecture that predicts the distance and the distribution of angles between acid residing on protein structure [124,125] (Table 6.4).

**Table 6.4** Few drug discovery models.

| S. No. | Model | Prediction |
| --- | --- | --- |
| 1. | AlphaFold | Structure of six proteins related to SARS-COV2 |
| 2. | DNN | New small molecule capable of inhibiting the chymotrypsin-like (3CL) protease. Its aim is to identify existing drugs to repurpose. It identifies 31 potential compounds as ideal candidates for testing and synthesis against SARS-COV2 [126]. |
| 3. | RT-PCR | Based on machine learning and novel genome technology |
| 4. | CRISPR | Assay designs for the detection of 67 respiratory viruses |
| 5. | Reinforcement learning based Model | Predict potential lead compounds targeting SARS-COV2 |
| 6. | Collaborative and Antiviral Discovery Model | To discover molecules to fight against COVID-19 |

After developing drugs, it should undergo clinical trials before deployment to prove its effectiveness. For such trials, randomized clinical trials (RCTs) were good. But RCT fails to prove its effectiveness for elderly patients and patients at higher risk. So, few improvements were done with RCT to demonstrate its efficiency and effectiveness. These improvements are done by integrating ML applications. Previously, in RCT trials, patients for treatment are allocated in uniform randomization, which can be highly suboptimal in terms of learning. In improved RCT, patients are first observed before sending clinical trials. It speeds up the process and has significantly reduced error rate. After successful clinical trials, data finally received are certain for targeting particular treatment. For more improvements in drug discovery, WHO, European Medicine agency, UK medicines, healthcare products regulatory, and US food are drug administration has established accelerated clearance pathways. 534 clinical trials were taken till March 24, 2020. But, a challenge in clinical trials is recruiting suitable patients [127]. So, data-driven solutions are best to identify eligible patients who have gone through remotely monitored checkups (Table 6.5).

**Table 6.5** Major dataset for COVID-19.

| Country | Name of dataset | Major attributes | Modality |
|---|---|---|---|
| All countries | CHIME | Daily data for susceptible, infected and recovered | Case statistic |
| Italy | COVID Chest X-ray | X-ray image, demographics, date, location, patient, findings, and survival information | X-ray scan of chest |
| 131 countries | COVID-19 Community mobility Report | Monitors gathering of people at essential services spots | Community mobility data along with textual reports |
| Italy | COVID-19 Database | Demographics and X-rays | Radiology information |
| Italy | COVID-19 CT segment dataset | Lung's segmented and labeled Image reports | CT scan lungs |
| All countries | COVID-19 CT dataset | Scan chest and create a labeled report | CT scan chest |
| Korea | COVID-19 Korea Dataset | Patient data or report | Case statistics |
| All countries | Coronavirus COVID-19 Tweets | Tweet, text, location with respect to USER ID | Database of tweets |
| All countries | COVID-19 open research challenge | Data related to research article | Research papers |
| All countries | Global research on COVID-19 | Data related to research article | Research papers |
| All countries | hCov-19 | Genetic sequence and metadata | Genomic epidemiology |
| All countries | Coronavirus Source data | Data related to daily confirmed cases around the world | Case statistics |
| All countries | JIIU CSSE COVID-19 Data | Data for number of infected, cured, mortality, location of patient | Case statistics |

| | | | |
|---|---|---|---|
| All countries | LitCovid | Data related to research article with geographical locations | Research article dataset |
| USA | Kinsa Smart Thermometer Weather map | Internet connected thermometer for temperature reading | Health weather map |
| All countries | RCSB Protein Data Bank | Genomic sequence | Pathology and clinical |
| Japan, Taiwan, China, Singapore, Thailand, South Korea, Hong Kong | nCOV2019 Dataset | Case history of patient | Epidemiological data |
| UK | BSTI Imaging Database | Patient CT Scan | CT Scan |
| Germany | RKI COVID-19 | Data for infected patient | Case statistic |
| All countries | Novel CoronaVirus 2019 Dataset | Patient case history | Case statistic |
| USA | New York Times Dataset | State name, Date, Infected cases daily, Mortality cases daily | Cumulative data state wise |
| All countries | Public Corona-virus Twitter Dataset | Data of tweets | User ID of tweet |

## 6.4 Bibliometric data collection

Researchers are working on writing articles for COVID-19 to spread awareness. It helps in improving data repositories. Articles are peer-reviewed and nonpeer-reviewed. Peer-reviewed articles are crawled by scopus and no-peer reviewed articles are crawled by arXiv, medRxiv, etc. [128–133]. The most popular sources for peer-reviewed article includes The Lancet with more than 228 articles, Nature with more than 204 articles and many more are arranged in table [134–137]. The dataset includes title of article, author details, journal name, publication date, etc. Basically, this dataset is extracted by keyword matching technique. The popular keywords used for extraction are CoronaVirus, COVID-19, COVID, Epidemic, Pandemic, SARS-COV2. Manual verification has also been done after keyword matching extraction to avoid not related data. The dataset covers more than 3500 publications till our study June, 2020. Most peer-reviewed and nonpeer-reviewed articles are written by Chinese researchers. After China, United States researchers contributed a lot. The pandemic situation has resulted in rapid production of academic data. Peer-reviewed journals are less in number as compared to nonpeer-reviewed journals, due to the urgency of dissemination. For more information and data, researchers are looking over preprint articles. In the end it is concluded that the rate of publication for COVID-19 is growing faster if compared with some other past epidemic like Ebola, SARS-COV, and MERMS. More than 1000 peer-reviewed publications have been recorded in around 3 months. SARS-COV1 and Ebola have reached this count in 3 years. COVID-19 is getting more attention in academics for research (Tables 6.6 and 6.7).

## 6.5 Data science and cross cutting challenges

### 6.5.1 Data confines

For machine learning models to work, they need to be fed with high fidelity and voluminous data. Data become a limitation in that sense. For use cases such as "speech analysis, extensive labeled datasets are not around yet. However, for a few other use cases such as textual analysis and medical images, the datasets needed are smaller as compared to the ones needed for deep learning models [69,138–142]. The distributed data sources being distributed contributes to measured data being scarce. For example, if we talk about electronic healthcare records, we know that these are often bucketed into several sections at national, regional, or hospital level, which brings us

**Table 6.6** Community resource for COVID-19.

| Attributes | Community resource |
|---|---|
| Recent projects and research articles are stored here | AI against COVID-19 |
| Text processing resource for COVID-19, data processed by NLP toolbox | AitsLab-Corona |
| Itis a public dataset for analysis COVID-19 | Amazon AWS |
| It is a center for disease control and prevention, contains related research articles | CDC |
| It is a repository that provides tools to visualize different statistics | COVID-19 Graphs |
| Deep learning techniques for COVID-19 detection | MATLAB resource |
| Machine learning tool for data driven research for chemical and materials | Chem ML |
| CSSE, John Hopkins University, resource link | JHU's CSSE |
| Open source codes an tools | MONTREAL AI |
| Curated literature hub for COVID-19 updated data | NIH NLM LitCovid |
| Webpage for global updates for COVID-19 | WHO Resource |

to challenge in getting consistent and measurable data, in terms of schemas. To overcome these barriers, automation algorithms for data wrangling, munging processes will become critical [122,143].

Apart from these challenges around data being available, we often see challenges with the available data as well. Due to the research being extremely time-critical, it is been hard to create reliable datasets. For example, social media data can quickly become out-to-date from the time it is captured to the time it is put into a usable format. As a result, real-time datasets are riddled with poorly quantified biases. Analytical approaches to tackle these data challenges can be an area of exploration, however, not an easy solution.

### 6.5.2 Exactitude of output versus urgency

It is a very high time to indulge in research for COVID-19. However, most of the methods that are suggested in this chapter are based on datasets and derived statistical outcomes. It is important to consider that the research outcomes can affect healthcare policy. For instance, these could be supported by several governments to come up with social distancing policies. Although people in these decision maker positions may not have the

**Table 6.7** COVID-19 data science dataset.

| Technique | Methodology | Data type |
|---|---|---|
| Evolutionary technique | Unstructured data are fetched from twitter to apply fuzzy rule based evolutionary technique | Twitter data-Text data mining |
| Topic Modeling | Twits studied using topic modelling to create structured information | Twitter data: Text data mining |
| Random forest. Naïve Bayes, SVM | A technique to predict situation information from social media | Weibo data: Text data mining |
| InceptionNet on random ROIs | Detects anomalies in lungs via CT Scan | Chest CT Scan-Image analysis |
| 3D CNNs | Infectious regions are classified in CT Scan | Chest CT Scan-Image analysis |
| UNet + + | Suspicious areas are identified | Chest CT Scan-Image analysis |
| 2D + 3D CNNs | Quantifies infection in lungs | Chest CT Scan-Image analysis |
| CNN | Detect infection in lungs | Chest CT Scan-Image analysis |
| DNN | Classify detected area for fine treatment | Chest CT Scan-Image analysis |
| DenseNet | Opt classification task for detection | Chest CT Scan-Image analysis |
| Pre-training + DNN | Detection is improved | Chest CT Scan-Image analysis |
| Conventional Feature Extraction techniques + SVM | Feature extraction technique is used | Chest CT Scan-Image analysis |
| CNN | Public dataset for COVID-19 detection | Chest CT Scan-Image analysis |
| U-Net + ResNet | Finely detect infectious area | Chest CT Scan-Image analysis |
| Fine-tuning + CNNs | Binary classification methodology to detect COVID-19 | Chest CT Scan-Image analysis |
| CNN-based models | Integrated seven CNN models to improve performance | Chest CT Scan-Image analysis |
| ResNet | It is an open source solution | Chest CT Scan-Image analysis |
| ResNet50, InceptionV3 and InceptionResNetV2 | Measure temperature of patient | Chest CT Scan-Image analysis |
| Fine-tuning + ResNet | Multistage fine-tuning for detection | Chest CT Scan-Image analysis |
| Transfer learning (TL) + CNN | Employed transfer learning | Chest CT Scan-Image analysis |
| CNN + Image argumentation | Image recognition technique | Chest CT Scan-Image analysis |
| CNN, SVM, and Random Forest (RF) | Machine learning technique | Chest CT Scan-Image analysis |

knowledge to understand the nuances of scientific study, which brings us to our second challenge of maintaining a balance between urgency and complete, reproducible results can help create healthcare policies.

To capture uncertainty of results, Bayesian methods can be used, though we have not come across many quantified studies until now [144]. Reproducible conclusions are further necessary to make sure that data analysis was conducted correctly. This task will further compound the challenges. "Explainable AI" is another route that can be explored to tackle this. However, a caveat must be added here that there is not complete confidence in whether this will guardrail against issues such as unintentional bias or adversarial scenarios.

### 6.5.3 Ethics, security, and privacy

As we start exploring the research suggestions, protecting privacy and adhering to ethical standards will become paramount. This will directly impact how much scale we can reach in adoption across populations, as infrastructure setup may continue after the pandemic. Efforts are being made around building medical analytics that can preserve privacy.

Floridi et al., outline some consensus around five major artificial intelligence ethics principles, namely (1) beneficence, (2) nonmaleficence, (3) autonomy, (4) justice, and (5) explicability. However, COVID-19's unique situation may make it tricky to balance these AI ethics virtues. Other questions that are unanswered at this point relate to the allocation of scarce resources and the tradeoffs in it. Call of action presented by a group of experts on data governance highlights the need to share data between public and private sectors to ensure that data are used for "beneficence" where it is needed and prevent maleficence [145,146].

Furthermore, privacy will become important as we start rolling out the interventions, which may have sensitive data (e.g., targeted social distancing measures). In this regard, simple steps can be taken to ensure ethical data science research. Data collection should be transparent (informing the users about the data being collected).

### 6.5.4 Requirement of multidisciplinary collaboration

COVID-19's long-term impact is still unknown. A mix of domain expertise from multiple fields is needed to draw insights, along with international collaboration and tracking of COVID-19. For instance, black-box models may result in a practical solution, but that solution could be useless with-out the involvement of (international) medical and biotechnology expert interpretations. Hence, bringing together many cohorts of complementary expertise becomes useful, which presents new challenges, such as ethics, benefits, and risks, that are clearly articulated.

### 6.5.5 Latest data modalities

Certain data modalities that can have a big role to play are not readily available for research. A huge challenge comes around adaptation of existing techniques to reflect new data types. For instance, the data science community has established good expertise in computer vision tasks, however, if we talk about processing ultrasound scans, there is a lot that is yet to be figured out. They also bring benefits around greater ease of use, absence of radiation while being a low-cost solution. Despite these known advantages, to the best of our knowledge, no study has yet explored the potential of automatically detecting COVID-19 infections via ultrasound scans. Similarly, magnetic resonance imaging (MRI) is considered the safest imaging modality as it is a noninvasive and nonionizing technique, which provides a high resolution image and excellent soft tissue contrast. Some studies such as touch upon the significance of MRI in fighting against COVID-19 infections. Yet, lack of sufficient training data restricted exploration of the data modalities. Thus, a challenge is to rapidly develop a well-annotated dataset of such medical imaging modalities.

### 6.5.6 Results for the developing world

In lots of developing nations, large populations have limited access to healthcare and information, which created unique challenges related to COVID-19 pandemic. Technology can help solve these challenges; however, the scale can be quite challenging in making it globally inclusive. The models should consider the applications in rural as well as economically deprived regions. For example, when creating a contact tracing app, a few things to be kept in mind are: is it low-cost, how many resources does it need to be used, can it be used with limited network connectivity, does it support multiple languages, is it accessible to illiterate users or those with disabilities, etc. To address this global pandemic, we must ensure emphasis on widespread accessibility of technological solutions.

## 6.6 SUMMARY

This chapter has been written to rapidly make available a summary of ongoing work for the wider community. It talks about how artificial intelligence has been used to tackle many aspects of the COVID-19 crisis at different scales including molecular, clinical, and societal applications. AI including machine learning has found many applications in understanding challenges created by COVID-19 in the medical and societal realm. Most of them, however, are in the nascent stages and it will take some time before we can show how these can create impact at scale. Let us cover each of these challenges. At the molecular scale, biochemistry applications of AI can be used to understand the proteins' structure of SARSCoV-2. Along with that, AI can be used to discover how existing drugs may be effective against the virus as well as find new compounds to make potential drugs or potential vaccines. It can also be used to improve our understanding about the virus and help improve diagnosis. At the clinical scale, AI can be applied in medical imaging to screen and diagnose the virus, while exploring alternate ways to find the disease via noninvasive devices such as mobiles. It can also help to predict prognosis of the patients by utilizing various data inputs. At the societal scale, AI applications around epidemiological research modeling empirical data have been used to forecast COVID-19 stats data such as number of cases, mortality and recovery rates. Along with that, AI has been used to look for patterns of similarities and differences in the evolution of the pandemic across regions. AI can also be used to analyze COVID-related content across social media to make sure the right kind of information is shared, and incorrect or misleading information can be controlled. To continue efforts in these directions, it becomes extremely imperative that scalable sharing and hosting of datasets and models is made possible. This will help understand where AI can be of value against the pandemic. AI targeting biomedical applications around clinical and molecular data should include direction from regulatory and quality frameworks to minimize potential risks while ensuring the validity of usage. Along with the data considerations, at the global level, international AI cooperation will become paramount as we begin research adoption to create solutions at the global scale, which can then be applied to local contexts and situations.

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