Chapter 4
Big Data and Modern-Day Technologies in COVID-19 Pandemic: Opportunities, Challenges, and Future Avenues

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Abstract  The COVID-19 pandemic has emerged as one of the most crucial health emergencies in the last decade where almost all entities of a nation’s ecosystem like inhabitants, businesses, governments, economies, and environment are impacted. The large volumes of epidemiological, clinical, personal, and environmental data generated during any pandemic can provide useful insights about the underlying causes, symptoms, relations, and correlations, which if analyzed can assist in mitigating the impact to a great extent. The cheap and easy connectivity and communication provided by the social media platforms (SMP) have established them as one of the most preferred mediums of communications among the masses. The data generated by these platforms can be analyzed in context of the ongoing COVID-19 crisis to provide critical information and insights related to the ground level realities like spread and severity of infection, the state of implementation of control measures, the mental state of individuals, and their needs. The tweets and comments of the users can provide information about the current situation and intensity of the problems in the affected regions. With the help of techniques like sentiment analysis and web mining, we can identify the emergent requirements and needs (like food, shelter, medicine, medical emergencies, security, etc.) of the population in the COVID-19-affected areas. With this chapter we aim to identify several use cases where the big medical data from the patients, epidemiological data, social media data, and environment-related data can be used to identify patterns, causes, and other growing factors of the COVID-19 pandemic with a goal to mitigate the damages and contain further spread of the disease. The chapter also discusses the impact of a preferred mitigation measure of nationwide lockdown on the number of new
novel coronavirus-positive patients as well as the impact on the environment by analyzing the available data. Since the tourism industry is now of the worst hit businesses, we also discussed the impact of COVID-19 on tourism industry. Furthermore, we identify the challenges associated with handling the massive amount of data generated during such pandemics. Finally, the future avenues of using big data for effectively devising predictive mechanisms and techniques to contain such pandemics in the initial stages are discussed. The chapter also discusses the importance of edge/fog technologies and IoT to identify possible use cases and where immediate point of contact actions is needed to mitigate the situations. Since edge computing facilitates calculations near the origin of data, it is imperative to understand the potential use cases in times of COVID-19-like pandemics.

**Keywords** COVID-19 · Big data · SMP · Epidemiological data · IoT · Nanotechnology

### 4.1 Introduction

The recent COVID-19 pandemic has created a situation of panic across the globe. The hysteria surrounding the novel coronavirus is already having devastating effects on the individual well-being and the nations as a whole. First reported in Wuhan City in China, the overall impact of the COVID-19 pandemic is so far reaching that it was declared as “public health emergency of international concern” by the “World Health Organization (WHO).” The exponential rise in the coronavirus-positive cases is creating an environment of fear and emergency where the nations across the globe are taking extreme control measures like lockdown. Considering the impact of COVID-19 pandemic, it is estimated that the after-effects may last for several years to come. The majority of the developed and developing nations (including the USA, Europe, and Asia) around the world are witnessing the devastation caused by this pandemic. However, this is not the first time that we have been hit by a novel kind of virus. In the past there were also several such cases of virus epidemics like plague, N1H1, Ebola, etc. Today, technologies have advanced to a level where if used efficiently they can lend promising support to fight such adverse situations. The modern-day technologies like big data, IoT, data analytics, sensors, etc., have enormous potential to develop solutions at various levels (individual, national, and global). Data analytics is one such technology that can provide useful insights into the various aspects of an infectious disease. The data generated from the personal records of the patients can be analyzed to identify the following as shown in Fig. 4.1:

- Which sex and age group is most affected by the epidemics?
- What are the common symptoms of the patients?
- What is the degree of potential threat to the population in general?
Similarly, the clinical data analysis can provide the causes and remedy of the epidemics. With effective analysis of clinical datasets, we are able to identify the following:

- What type of virus is affecting the population?
- Virological assessments.
- Receptor-binding and receptor recognition analysis.
- Which family of virus does it belong to?
- Which parts of the body are being affected by the virus?
- Does patient medical history (BP, sugar, hypertension, cardiac, etc.) affect the effect of virus on the person?
- Diagnostic mechanisms (testing kits and other means).
- Possible therapeutic solutions for the virus.
- Propose precautionary measures and containment plan.

In order to extract accurate insights about the pandemic, it is imperative to ensure that the data and information must be authentic, valid, verifiable, immutable, and traceable. Such information can be useful in tracking the outbreak, identifying the epicenter of the pandemics, track the carrier of the disease, and other contacts.

### 4.1.1 What Makes Big Data So Unique

“Big data” has been considered as one of the most widely used terms used in the computing domain in recent years. There is no quantifiable definition of big data in terms of its size. It is a relative term whose definition differs with different organizations. In general, we can define big data as any massive amount of data which is beyond the managing capacities of the legacy tools, devices, and systems [1, 2]. As
shown in Fig. 4.2, there are several inherent characteristics of big data which make it unique in several ways. These characteristics include [1–3]:

**Volume**: It includes the gigantic amount of data generated with time along with the archival data.

**Velocity**: It defines the rate of generation of new data. With the new age technological advancements, the data is getting generated at an exponential rate.

**Variety**: This constitutes the heterogeneity of the data at our disposal. Big data may include text, numbers, image, audios, videos, logs, etc.

**Veracity**: It defines the correctness and trustworthiness of the data. It is one of the most important characteristics of big data.

**Variability**: It defines the changing nature and type of the data. The data which is relevant at one point of time may become irrelevant in other time or situation.

**Visualization**: It is the ability to depict or portray the data using visual charts, bar graphs, and other diagrams.

**Value**: This is the most important quality of big data and the most complex one too. The ultimate goal of playing with big data resides in extracting meaningful value from the data.

Each of these characteristics makes the management of big data an intricate task. Big data includes data which may or may not be structured. Therefore, special
storage devices and procedures are adopted for storing such types of datasets. There are several solutions prevalent for managing big data which includes Hadoop, Quantcast, Cassandra, HDInsight, Andrews File System, etc. Each of these solutions has their own set of advantages, disadvantages, and use cases. Some are preferred for archival datasets, while others are used for managing real-time datasets [3].

4.1.2 Sources of Big Data in a Pandemic

Big data may be generated from several sources including social media data, news, blogs, seismic activities, weather forecasting, sensors, videos, audios, images, etc. Broadly, the sources of big data can be characterized in six parts, as shown in Fig. 4.3 [4–6].

- **Medical**: The big data generated through medical cases, tests and scan reports, prescriptions, medical history, symptoms, etc.
- **Transactional**: The data generated through online and offline transactions.
- **Logs**: This constitutes the log of the activities performed during any work or transaction.

![Fig. 4.3 Sources of big data in a pandemic](image-url)
• **Social Media:** This is the primary source of big data with more than 500 million tweets per day, 300 h of video uploaded on YouTube per minute, etc., and 29 million messages are sent via WhatsApp per minute.

• **Epidemiological:** This includes the non-experimental observations, including “population exposure levels” and “health effect values” observed from the samples.

### 4.1.3 Chapter Organization

The complete chapter is divided into seven sections. Section 4.2 discusses some of the recent researches and related works in the area of COVID-19 and big data management. Section 4.3 highlights how big data can be utilized for managing pandemics. Section 4.4 discusses the challenges in the implementation of big data solutions for combating pandemics. Section 4.5 presents the impact of social distancing and nationwide lockdowns on COVID-19 pandemics in India, the UK, Italy, France, and Spain. The impact of lockdown on tourism industry is also discussed. The role of IoT and nanotechnology in managing Covid-19 is highlighted in Sect. 4.6. Section 4.7 presents the conclusion and further scope for the integration of modern-day technologies for providing solutions in time of pandemics.

### 4.2 Related Works

The COVID-19 outbreak that emerged in Wuhan, China, has affected almost all the nations across the globe, with 7,823,289 confirmed cases and 431,541 confirmed deaths as on June 15, 2020 [7]. This pandemic has compelled the research community to mine useful information to support the preventive measures in mitigating the impact of COVID-19 spread. Many researches and studies have been published that analyze the publicly available data about the pandemic and provide many useful insights about the causes, potential threats from the pandemic, and its preventive and containment measures. The authors in [8] have introduced a model that portrays the outbreak of COVID-19 pandemic in Wuhan, China. This model reflects the impact of health strategies implemented by the Chinese government to control this epidemic, the significance of detecting and quarantining unrecorded cases, and the contribution of asymptomatic COVID-19-positive cases to virus transmission. The authors have used recorded case data from the early phase of this pandemic to estimate the final number of cases. The layout consists of basic differential equation scheme. The model demonstrates that early implementation of precautionary measures leads to dramatic reduction in cumulative number of cases. An analysis of the COVID-19 is given in [9] that outlines the existing awareness related to the worldwide COVID-19 epidemic. The paper presents a chronological sequence of events from the origin of the virus in Wuhan City to being labeled as a “global pandemic”
by the World Health Organization (WHO). The paper highlights the measures taken by countries around the world to combat this virus with an emphasis on UK cases and response. An elaboration of COVID-19 virus characteristics such as physiology, detection, treatment, prevention, prediction, and containment measures has been presented. Furthermore, the authors have discussed the impact of this outbreak on global economy and the imperative need for effective governance following COVID-19 epidemic. The authors in [10] have built a statistical model to predict COVID-19 cases in Wuhan City of China. The model derives the number of unreported cases from the data of reported symptomatic cases in Wuhan, and the forecasts obtained highlight the significance of public health policies to contain this outbreak. The authors have addressed the implications of reported and unreported cases and public safety interventions on the growth of this epidemic in Wuhan. From the model, it is observed that interventions such as lockdown and quarantine, when implemented at early stages, dramatically decrease the final scale of the outbreak. In [11], the authors have explored the COVID-19 epidemic from an urban viewpoint and focus on smart city network potential for improving standardization protocols to enhance the exchange of information in case of epidemics, contributing to greater awareness and control globally. The authors have emphasized the need of communication standardization by means of globally accepted standardized protocols and for smart city technologies to be democratized to foster equality and clarity among stakeholders, thereby allowing further collaboration in the wake of an outbreak. The author in [12] has discussed various applications in which artificial intelligence (AI) could help contain the global pandemic of COVID-19. These applications include forecasting the location of another epidemic, molecules engineered by AI algorithms to inhibit the replication of novel coronavirus, forecasting the impact of changing seasons on COVID-19 epidemic, stabilizing current economy, and rapid detection of COVID-19 from lung CT scans, among others. In [13], the author has advocated the integration of big data and advanced models for upgrading surveillance infrastructure and global cooperation for epidemic preparation. The author has discussed the benefits of big data in tackling an epidemic such as outbreak prediction and policymaking. Moreover, the paper discusses though real-time big data can enhance monitoring and control techniques in a quick-growing outbreak, the resulting challenges and privacy concerns need to be addressed. The paper recommends that versatile, dispersed teams should cover the systematic and functional dimensions of the outbreak response, in the implementation of big data schemes. In [14], the authors detail public safety approaches to contain the outbreak of COVID-19 on cruise vessels. The authors discuss that cruise passengers are highly vulnerable to outbreaks with accelerated disease transmission, requiring vigorous attempts to curb spread. Two cruise ships have been mentioned in particular, “Diamond Princess” and “Grand Princess”, both acting as COVID-19 clusters, with numerous reported cases. It is also observed that due to the closed setting of cruise ships, the COVID-19 cases increased gradually after the passengers and crew were quarantined on the vessels. The authors have highlighted that vigorous attempts were made to curb COVID-19 spread on the vessel and prevent community transmission. The authors in [15] have presented a comparison of
COVID-19 clinical traits with other types of pneumonia. For their study, the authors have selected 19 COVID-19-positive cases and 15 non-COVID-19 pneumonia cases from Hubei province of China. The authors have observed that for COVID-19 patients, the mean incubation period is 8 days, while for non-COVID-19 patients, the period is 5 days. Although both the conditions display similar symptoms, liver damage is more prevalent in COVID-19 patients, and the tests are strikingly atypical. The authors recommend CT scan for testing suspected COVID-19 cases, with “α-HBDH” and “LDH” as indicators for analysis. In [16], the authors have presented a chronology of efforts by various institutions of the USA to discover and track all individuals who had come in close proximity with reported COVID-19 patients. The paper presents elaborate statistics related to COVID-19 monitoring in the USA in the months of January and February, to facilitate swift identification, diagnosis, and treatment as well as minimize further spread. The paper stresses on disease management and prevention measures, in tandem with contact tracing initiatives, to minimize the transmission of the disease in a community. The authors in [17] have selected 1099 confirmed COVID-19 cases from 552 hospitals in China to study the clinical features of novel coronavirus. It is observed that the patients are mostly male with an average age of 47 years. Moreover, except for a small percentage, most of the patients had never come in contact with wild animals. The authors have observed that cough and fever are common, while diarrhea is rare in patients. The average duration from exposure to onset is 4 days. The results have confirmed the three-stage sequence of the epidemic, asymptomatic transmission and family cluster outbreaks. The authors in [18] have discussed the available knowledge related to other coronaviruses (SARS and MERS) in an effort to understand the effects of coronavirus virus disease 2019 (COVID-19) on pregnancy. The authors have noted that scarce information regarding COVID-19 is available and attempt to create awareness about the treatment of pregnant women with confirmed COVID-19. The authors observe that there is no data available to demonstrate higher vulnerability of pregnant women to COVID-19 or increased severity of symptoms in them.

According to Fitzpatrick et al. [19], artificial intelligence (AI) provides tremendous potential in preventing and managing infections (IPC). “Big data” determines AIs to find the correlations that may point to medically related conditions or to identify potential risk factors. AIs can also occasionally ignore small clusters of data that may be clinically relevant and unable to utilize deep knowledge of core processes. Rather than concentrating on the AI tools themselves, the emphasis should be on the IPC problem that needs to be tackled through the development of priorities, plans, and processes to support this that could involve AI. In [20] the authors discussed how Chinese government agencies explored social media to engage citizens during the COVID-19 crisis. To achieve this, they systematically examined the impact of dialogic loops, media prosperity, and type of content on citizen engagement through government social media based on “media wealth theory (MRT)” and “dialogic communication theory (DCT).” The authors in [21] suggested that large-scale data collection may help curb the COVID-19 pandemic, but it should not ignore public trust and privacy. To maintain accountable standards of data collection and data processing at a global scale, finest practices should be recognized.
According to [22], a mathematical modeling is a critical method for forecasting and estimating the severity and length of epidemics, determining the effectiveness of public health initiatives, and informing public health policy. Their study showed the challenges modelers face in predicting outbreaks of this nature and providing a partial justification for the wide variability in earlier model predictions of the COVID-19 epidemic. Their study suggested that due to the larger number of model parameters to be estimated, more complex models may not inevitably be more confident in making predictions, given the same dataset of incorrigible cases.

Through their research, the authors in [23] offer a new perspective for the inspection of epidemiological and behavioral data by proposing networks for migrants. They showed that they did not analyze traffic data (e.g., number of train or flight frequencies) but instead studied the causes of traffic relocation on social networks. This is more scientific, and it is possible to prepare simple tools to provide a method for forecasting disease transmission and calculating risk even in complex circumstances. It is hoped that as long as the approximations are clear and accurate, a continually changing understanding of the complexities of the real world can be obtained, and the approach will continue to assist in the detection and control of diseases. The authors in [24] provided extensive clinical, demographic, radiological, epidemiologic, and laboratory characteristics, and technical hitches, cure, and results of non-severe and severe COVID-19 hospitalized patients in Wuhan. They suggested that half of the patients in their study were identified as serious cases, which may vary from previous study results. In their study, the proportion of patients who were 65 years of age or older was higher than in the study conducted by Nanshan Zhong (38.8% vs. 15.1%, respectively).

Sarkodie et al. (2020) in [25] showed that their analysis was focused on phenomenological models. They demonstrated that the influence of confirmed cases on COVID-19 attributable deaths is perfectly linear, while a nonlinear direction is followed by the impact of confirmed cases on recovery cases. They used a mix of estimation approach to increase model sensitivity and robustness.

### 4.3 Managing Pandemics with Big Data

In the time of Ebola crisis, UNICEF used big data-based apps and solutions like EduTrac and U-Report to enhance the collective efforts against the crisis [26, 27]. Data was one of the most valuable assets that helped UNICEF to plan the emergency response in areas of high alerts. This was backed by the data analysis that provided valuable insights into the exact needs and conditions of the affected regions. Moreover, the data collected during the whole process was also used to develop educational resources for spreading awareness about the epidemic along with its probable causes and symptoms. Real-time data and tools can assist in emergency response systems and help the authorities to efficiently and precisely monitor, manage, and contain the spread of diseases and can play a vital role in eventually saving human lives.
A data-based global surveillance system can assist in disease tracking and mapping, for example, MagicBox v0.5 which is a data mapping tool that can provide valuable services in emergency situations.

The different types of data which can be analyzed in cases of epidemics and pandemics include [26, 27]. Table 4.1 provides the specific role of big data in each stage of the pandemic.

| Phases of pandemic | Responses                         | Role of big data                                                                                                                                                                                                 | Type of data analytics              |
|--------------------|-----------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------|
| Phase 1: Emergence | Anticipation                      | Data from various sources can be analyzed to predict the possibility of any infection or emergence of a new/existing disease. Data analysis techniques can be applied on the historical data for investigating the possible causes and sources of the spread and can assist in investigating the future possibilities. | Predictive and cognitive            |
|                    | Early detection of disease         |                                                                                                                                                                                                                 |                                     |
| Phase 2: Local transmission | Mapping of spread and containment | Data from geospatial apps and location tracking devices can be used to map the spread of infectious diseases.                                                                                                                                                          | Diagnostic and prescriptive         |
| Phase 3: Community transmission | Mapping of spread and containment | Social networking websites, web news, and individual GPS data of the affected patients can be analyzed to • Keep track of the movements of the affected patients • Isolate and quarantine the suspected cases • Identify the opinions and sentiments of the affected populations • Identify urgent needs and requirements of the affected populations • Plan the future course of actions in terms of infrastructure and logistics | Diagnostic and prescriptive         |
| Phase 4: Global spread/amplification | Control and mitigation | • Analyze the clinical data of the patients along with the epidemiological data • Identify relations and correlations and mapping them with historical datasets of similar such incidents • Identify the therapeutic solutions | Diagnostic and prescriptive         |
| Phase 5: Reduced transmission | Elimination | The data from regular monitoring of patients and mapping of the spread can provide information related to the rate of spread of disease. Decline in the number of new cases and containment of spread points toward the reduced transmission of diseases and start of elimination phase. | Prescriptive and predictive          |
1. **Genetic data collection and monitoring**: The genetic data collected over time can be analyzed to study the mutations of microbes and predicting outbreaks. It can also identify classes of viruses and their correlations.

2. **Mobility data analysis**: The mobility data of the infected person and other individuals from the epidemic hit areas can be used for mapping the spread of disease and predicting the potential areas where outbreak may occur. The mobility data also helps in tracking of the infected carriers and studying the pattern of spread and backtracking the source.

3. **Social media data analysis**: The data collected from various social media platforms can help to understand the sentiments of the affected population and give insights into the immediate needs of the masses and the points to address since with any epidemics, providing only the healthcare facilities cannot work. There must be a provision to identify the relating needs of the affected population like food, security, and other essential services. All this can be analyzed with the help of social media data, and preventive measures can be planned accordingly.

4. **Mapping of affected geographical areas**: The data collected from the hospitals and medical facilities at various locations can be analyzed and later mapped to identify the affected areas and populations. The data from the travel history of the individuals from the affected areas can provide valuable insights into the potential spread of the disease.

5. **Simulating epidemic spread on global scale**: Big data collected from population census, demographics, short-range mobility data like commuting patterns between subpopulations of an area, and long-range mobility data like air travel, frequency, and connectivity of different geographical locations, etc., can be analyzed to simulate the spread of an outbreak on a global scale.

6. **Preparedness**: Medical records of patients, symptoms, data from past pandemics and epidemics, and the corresponding preventive measures can be analyzed to take precautions to prevent future outbreaks and develop solutions and contingency plans for emergency situations.

### 4.3.1 Big Data for Containment of Pandemics

The most critical stage of any epidemics or pandemics is the community transfer stage. It is really important to restrict the spread and outbreak of the disease as much as possible before the start of such stage. Once this stage arrives in the lifetime of any epidemics, it becomes very difficult to identify the original source of disease since the spread gets exploded exponentially. Big data can provide unprecedented results in the tracking of affected patients and avoiding the community spread [26, 28–31]. Since ensuring and maintaining the veracity of big data is the most critical step in order to extract accurate value from the datasets, there must be standardized mechanisms and protocols for handling the authenticity of the source and contents of the data. The architecture presented in Fig. 4.4 explains the typical process of containing community transfer in case of any pandemics or epidemics. At the time
of disease discovery and confirmation, consent must be taken from the infected person to access the contacts in order to track the people who came in contact with the infected person. This consent can be made a mandatory step to curb the chances of spread and community transfer. Apart from the infected patients, the doctor and other medical staff involved in treating the patients may also be tracked as they are the most vulnerable classes who are in constant contact with the infected patients. Such care providers must be periodically tested even if they show no signs of any symptoms related to the deadly pandemics. This periodic testing will ensure early detection, isolation, and treatment of the care providers as well. A GPS-based physical tracker may be provided to all the infected patients who must be instructed to
carry that tracker always on and close to them so that they can be tracked. It must be ensured at all time that the data being collected from the patients conforms the standard data collection, sharing, and storage norms like prescribed in GDPR by the European Union. Further, since the community transfer cannot be solely restricted by the authorities and governments, the communities themselves are the major players who can stop the spread of such transfer of disease, and thus the consent is their responsibility to obey government directions and precautionary measures.

We can use two-way tracking of the infected person. First tracking can be done easily in coordination with the mobile service providers. Since the mobile companies always keep track of the SIM location, the infected person can be tracked using the mobile phone SIM location. Secondly a GPS-based tracking application can be installed on the infected person mobile so that they can be tracked using the application in real time through GPS/GPRS coordinates. This tracking serves two purposes. Since the tracking is done with the help of GIS system, it can be used to provide location-based services to the infected individuals. The infected person can be tracked, and necessary medical help may be provided in case of the any emergency since the patient is being continuously monitored. The healthcare officials and the government agencies can use this tracking data to identify whether the person is on the move or not and thus can restrict the movement and prevent community spread. Figure 4.5 shows the use of big data analytics in an event of pandemics like COVID-19.

4.4 Challenges with Big Data Analytics

This section provides the various challenges associated with analyzing the big data generated from multiple sources in events of any pandemics [26, 27, 32–35].

- **Infodemics**: The widespread use of social media had led to the emergence of “infodemics” that describes the spread of information which may include rumors, unreliable information, gossips, and guesses related to the concerned issues, conspiracy theories, etc. This rapid spread is facilitated by the popularity of the social media platforms and discussion forums. This false information circulated at a global scale may create panic among the masses resulting in a situation of chaos and mismanagement. Such data when reaches the data repositories may adversely affect the analysis process by manipulating the outcomes. In such situations the data needs to be checked at the source to avoid any kind of misuse and spread of misinformation.

- **Correlation and Causation**: One of the major concerns with big data analytics is the lack of causation. Data analytics majorly focuses on finding the correlations between data and establishing statistical patterns rather than figuring out the question what causes what and how. The tech giant Google felt prey to one such situation where they claimed to have successfully tracked the spread of influenza without any medical checkups [36]. This claim was made purely on the
basis of data analysis on the Google search data. The most significant aspect of the claim was that Google was faster than the Centers for Disease Control and Prevention (CDC) in tracking the spread with only a day’s delay as compared to weeks taken by CDC. The Google Flu Trends were later found to be overstated by almost a factor of two, thus concluding that theory-free correlation can be highly fragile and inaccurate [37].

- **Multiple Comparison Problem**: The size and choice of data highly affects the final outcomes. In [38] the authors presented a similar study discussing how the claims made by any scientific study cannot be considered completely accurate. This conclusion was derived based on the fact that the results of any study are dependent on various factors including the size of data, related researches and studies, relationships, number of tested relationships and correlations, etc. While

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Fig. 4.5  Big data analytics at work in COVID-19
predicting the outcomes using big data analysis especially in critical situations like epidemics, similar issues may arise jeopardizing the final outcomes.

- **Heterogeneity**: The heterogeneity of the data poses the most critical challenge in managing big data. Several types of data exist which may be structured, semi-structured, or unstructured. Tackling all such data in a similar manner cannot be an optimal solution since each of these data types requires different processing and management techniques [32–34, 39].

- **Multiple Formats and Schema**: The varied formats and schemas of big data also pose inherent complexities for its management. It is difficult to standardize the data so as to bring it to a common format for further processing. Several big data handling tools like Hadoop, Cassandra, and HDInsight process the data in their own respective formats. For example, Hadoop does not differentiate between the types of files and process them in the same manner irrespective of their type. This can cause severe performance issue for certain types of files which are much smaller in size as compared to Hadoop block size [3, 32, 40, 41].

### 4.5 Impact of Nationwide Lockdown

This section investigates the impact of social distancing and nationwide lockdowns on COVID-19 pandemics in India, the UK, Italy, France, and Spain. In order to analyze the effect of social distancing and lockdown, we have used the COVID-19 dataset from “Johns Hopkins University Center for Systems Science and Engineering (JHU CCSE).” This work also uses the publicly available data and reports about the COVID-19 spread from various government sources and analyzes the patterns in the spread of infection under various circumstances. Apart from the pandemic data, we have also analyzed the effect of social distancing and lockdowns on the environment. Specifically, we have compared the air quality index pre- and post-enforcement of lockdown in India. The results of the study and analysis indicate that social distancing and nationwide lockdown are indeed highly effective in mitigating the spread of the coronavirus with only 11.67% new cases after 1 week of lockdown for India, 12.60% for Italy, 24.32% for Spain, 23.96% for France, and 13.41% for the UK which is much less as compared to the number of new cases coming up before the lockdowns were announced.

For the empirical evaluations, we have considered India, Italy, Spain, France, and the UK in order to measure the effect of lockdowns and social distancing in COVID-19 in these countries. We analyzed the COVID-19 patient information dataset available from “JHU CCSE,” uploaded on “Kaggle” and “Github” [42–44]. This dataset contains time-series data about the number of patients found positive, number of deceased patients, and number of patients recovered from COVID-19 infection. We have analyzed the number of coronavirus-positive cases on five different intervals each before the date of lockdown and after the date of lockdown (inclusive) as shown in Table 4.2 and Figs. 4.6 and 4.7.
| Country | Date of lockdown | Before 10 days | Before 8 days | Before 6 days | Before 4 days | Before 1 day | On the day of lockdown | After 2 days | After 4 days | After 6 days | After 1 week |
|---------|-----------------|----------------|----------------|---------------|---------------|--------------|------------------------|--------------|-------------|-------------|-------------|
| India   | March 24, 2020  | 102            | 119            | 156           | 244           | 499          | 536                    | 727          | 987         | 1251        | 1397        |
| Italy   | March 10, 2020  | 1128           | 2036           | 3089          | 4636          | 9172         | 10,149                 | 12,462       | 21,157      | 27,980      | 31,506      |
| Spain   | March 14, 2020  | 222            | 400            | 673           | 1695          | 5232         | 6391                   | 9942         | 13,910      | 20,410      | 25,374      |
| France  | March 16, 2020  | 653            | 1126           | 1784          | 2281          | 4499         | 6633                   | 9043         | 12,612      | 16,018      | 19,856      |
| UK      | March 23, 2020  | 798            | 1140           | 1950          | 2689          | 5683         | 6650                   | 9529         | 14,543      | 19,522      | 22,141      |
The result of this analysis can be found in Table 4.3 where we have calculated the percentage increase of the number of coronavirus-positive cases before and after the date of lockdowns.

As it can be observed from Table 4.3, the percentage increase in the number of new coronavirus-positive cases is consistently decreasing with only 11.67% new cases after 1 week of lockdown for India, 12.60% for Italy, 24.32% for Spain, 23.96% for France, and 13.41% for the UK.

Finally, in order to measure the effect of lockdown on environment in India, we have analyzed the air quality index (AQI) of the past 3 years (2017–2019) with the current year (2020) at the five different intervals before and after the date of lockdown [45, 46]. The analysis is shown in Fig. 4.5. The chart clearly depicts the AQI for specific dates before and after lockdown from 2017 to 2020. It can be inferred from Fig. 4.8 that there is a significant improvement in the AQI after the lockdown,
Fig. 4.7  Number of coronavirus-positive cases after lockdown

Table 4.3  Percentage increase in the number of cases before and after lockdown

| Country | Date of lockdown | Percentage increase in the number of new cases |
|---------|-----------------|-----------------------------------------------|
|         | Before 8 days   | Before 6 days | Before 4 days | Before 1 day | After 2 days | After 4 days | After 6 days | After 1 week |
| India   | March 24, 2020  | 16.67         | 31.09         | 56.41         | 104.51       | 35.63        | 35.76        | 26.75        | 11.67        |
| Italy   | March 10, 2020  | 80.50         | 51.72         | 50.08         | 97.84        | 22.79        | 69.77        | 32.25        | 12.60        |
| Spain   | March 14, 2020  | 80.18         | 68.25         | 151.86        | 208.67       | 55.56        | 39.91        | 46.73        | 24.32        |
| France  | March 16, 2020  | 72.43         | 58.44         | 27.86         | 97.24        | 36.33        | 39.47        | 27.01        | 23.96        |
| UK      | March 23, 2020  | 42.86         | 71.05         | 37.90         | 111.34       | 43.29        | 52.62        | 34.24        | 13.42        |
which was announced on March 24, 2020. On a similar pattern, other countries around the world have shown improvements in the AQI as a result of nationwide lockdowns [46].

### 4.5.1 Impact of COVID-19 on Tourism

The outbreak of coronavirus virus disease 2019 (COVID-19) has plummeted global travel with flights grounded, ships docked, trains cancelled, and borders closed. The entire tourism sector including transportation means, hotels, travel operators, tourist destinations, restaurants, etc., has been affected severely. The pandemic has caused substantial damage to the global travel industry, risking 50 million jobs worldwide and estimated to shrink the travel industry up to 25%. Nearly 10% of global GDP is contributed by the tourism sector, and the current travel restrictions are expected to result in a loss of approximately 30–50 billion US dollars worldwide, according to UNWTO [47]. As reported by the “International Air Transport Association” (IATA), air travel revenues will decline by 5%, amounting to $29.3 billion globally in 2020 [48]. The aviation authorities in China, where the virus originated in late December, have reported a loss of 21 billion yuan [49]. A report by US Travel Association warns of a staggering loss of 910 billion dollars to the US economy in 2020 due to the travel restrictions [50]. Though the COVID-19 pandemic poses an imminent threat to economies throughout the world, some countries are facing more severe implications than others. This can be illustrated by the instance of Saudi Arabia that could lose nearly 12 billion dollars due to Hajj and Umrah cancellation [51]. It is estimated that the tourism industry would require 10 months to 3 years to recover completely from the losses incurred. Subsequently, international bodies such as the “United Nations World Travel Organization” (UNWTO) and “World Travel and Tourism Council” (WTTC) have emphasized the need of global cooperation and
discussion, financial and political assistance, as well as easing travel regulations, once the pandemic is contained [52].

4.6 IoT and Nanotechnology in COVID-19 Pandemic

This section highlights the role of technological advancements in the field of IoT and nanotechnology for effectively managing COVID-19 pandemics. Since IoT and nanotechnology have been widely used in several application domains and are providing exemplary solutions, it is imperative to discuss their role in COVID-19 pandemics.

4.6.1 IoT in COVID-19

The advent of the Internet of Things (IoT) and smart technologies has brought about significant changes in the way many businesses operate and in the potential that opens up, facilitating people’s lives in different ways that we did not imagine a few years ago. In times of crisis, like the one that now happens with the appearance of COVID-19 in December 2019, we have seen a suspension of some activities and the appearance of new opportunities. In the case of IoT and smart technologies, the times we live make clear the opportunity to create new solutions that make use of the combination of emerging technologies, to combat the current crisis, but mainly to act upon future pandemic crises such as the one we are experiencing today.

Detecting the spread of the virus at an early stage is of great importance to avoid spreading contamination. The use of sensor networks that can help in the detection phase is considered a very viable option by specialists, mainly in countries like China or Japan, which lead the adoption of IoT technologies. A network of surveillance sensors was once implemented by China, so the creation of an infrastructure of virus detection sensors becomes a possibility to act from an early stage in the detection of new pandemics that may exist, avoiding loss of human lives and the great impact they have on the economy and on the lives of all citizens [53].

On the other hand, aspects related to the mobility of citizens are a fundamental and crucial aspect for decision-making by the government and other responsible entities. Knowing where people are, how much time they spend outside home, and in which places is something that can bring valuable information to understand transmission chains, especially those people who are recommended to be in isolation. This monitoring can also help to regulate and better adjust the quarantine periods imposed on citizens. One of the critical factors for this location of people to be possible has to do with privacy issues, and only with legal changes at this level may it be possible to move forward with integrated and official solutions that can be used across the board by decision-making bodies. The use of monitoring solutions is
already in use in countries like Taiwan (to ensure compliance with quarantine rules), South Korea (infected monitoring and proximity alert with someone infected), or Israel (monitoring infected through your mobile phone) [54].

Drones have been widely used in several countries for various purposes, asserting themselves as an intelligent solution for a variety of applications. In some countries they are being used to guarantee social distance, for example, in China and India [55]. Drones are also being used to broadcast information relevant to the community, as in the case of Spain where a drone with a loudspeaker was used to announce measures of a state of emergency [56]. Other countries used the same method to announce measures to be taken into account to ensure social distance [57]. Mass measurement of temperature by the population has also been done using a drone with an infrared camera. In some cases, it can measure the temperature of several people simultaneously [58]. Remote monitoring of symptoms (such as respiratory diseases) is being developed in Australia by monitoring temperature and heart rate [59]. The disinfection of spaces [60] and the delivery of essential medical goods [61–63] are also other features that have been attributed to drones in these times of epidemic.

The health domain is where the greatest applications of IoT and smart technologies exist at this time of crisis. The interconnection of medical devices with devices on patients (such as smartphones or wearables) and even the medical infrastructure of information systems has brought the possibility of cross-checking data and verification and decision-making almost in real time [64]. During this pandemic crisis, there is a multiplication of remote consultations, which may open new paths for telemedicine and for remote monitoring of patients (especially for those who continue to need it and cannot be exposed due to possible viruses). The Internet of Medical Things (IoMT), or healthcare IoT, which refers to the set of medical devices, software as well as the health services offered, has known significant advances also due to the ease with which today the various devices can interconnect among themselves through various protocols such as Bluetooth or NFC [65]. Regarding IoT and IoMT, some of the technologies, devices, and services currently in use in this pandemic phase include smart thermometers, robots, autonomous vehicles, drones, telemedicine, and RFID readers [66, 67].

RFID robots have been used to distribute medicines to medical teams, as has been done at Geisinger Medical Center in Danville, Pennsylvania, USA. Likewise, the collection and processing of medical waste can be done by a robot, allowing safer treatment and avoiding unnecessary contagions on the part of medical assistants. Augmented reality (AR), in conjunction with an IoT network, can be used in patient care and early diagnosis that have to be done by doctors with experience. But the number may be limited in some circumstances, preventing doctors from being available in all necessary places. AR technologies can allow nurses or other professionals to be at the forefront assisted by doctors through computer systems that allow remote diagnosis and assistance [67].
4.6.2 Nanotechnology in COVID-19

The nanotechnology-based solutions and medical aid equipment for the patients and frontline care providers including doctors, nurses, other hospital staff along with security personnel, law makers, etc., have the potential to provide promising solutions at all levels in this fight against COVID-19, including prevention, diagnostics, and treatments [68–75]. The reusable nano-materials for face masks, nano-medicine for COVID-19 patients, and nano-based test kits are few applications of nanotechnology in COVID-19 pandemic. Many products are already available in the market, and many are being developed by scientists. Figure 4.9 presents the application areas of nanotechnology for fighting COVID-19 [68–75, 80].

In a recent development, scientists have claimed to have developed preventive products for COVID-19 using nanotechnology. A Japanese company “Nanotera Group” has developed an antimicrobial spray that coats almost all surfaces except the human skin and kills any pathogens [69]. The company claims that once sprayed, the coating works for 5 years. This spray provides promising solutions to fight pathogens, but it comes with a cost. The spray costs $3000 per hundred square meters [69, 70]. Nanofibers developed using the electro-spinning production technique are used to manufacture N95 respirators, which claims to block almost 95% of airborne particles that are more than 2.5 μm [71]. A research team from Korea

Fig. 4.9 Application domains of nanotechnology in COVID-19
Advanced Institute of Science and Technology claims to have used the insulation block electro-spinning process to manufacture nanofiber masks that are reusable even after 20 hand washes [72]. In Norway, a research team from NTNU and St. Olav’s Hospital is developing a silica coated iron oxide nanoparticle for testing of COVID-19 [73]. With all such unprecedented features and applications of nanotechnology, there exist several challenges in the mass adoption of nanotechnology-based solutions.

1. Cost and underlying infrastructure: There is a considerable amount of cost involved in the adoption of nanotechnology-based solutions. Further it involves precision-based infrastructure facilities which are hard to set up.
2. Skilled personnel to use the technology: Nanotechnology is a highly specialized domain, and thus there is a scarcity of trained professionals.
3. Awareness among masses: As a growing field of research, nanotechnology has expanded its domain and range to a large section of areas including agriculture, healthcare, transportation, building constructions, etc. However, there is still a lack of awareness among the general public about its potential.
4. Availability in marketplace: Nanotechnology-based products are very rarely available in the market. Since there are only few takers, the production is also limited or made to order.

Nanotechnology has a huge potential to help in COVID-19 pandemic. It is already being used for prevention and diagnostics of COVID-19. Further research is still going on, and very soon a breakthrough can happen with the invention of nanomedicine to cure COVID-19.

4.7 Conclusion and Future Scope

COVID-19 has been declared as a medical emergency of international concern by the WHO. Till date this outbreak has claimed thousands of lives all across the globe. The novel coronavirus is a unique class of virus which attacks the lungs of the patients. Since its emergence in Wuhan City of China along with its exponential outbreak in several other nations including Italy, the UK, the USA, France, Germany, India, etc., several measures are taken by the authorities to contain the damage and stop the further spread of the novel coronavirus pandemics.

This paper discusses the role of big data analytics techniques in curbing the affects and impact of pandemics [76–79]. The results of analysis on the publicly available data about COVID-19 show that the preventive measures like social distancing can help in the containment of the spread of the disease to a great extent. The impact of lockdown is also studied and presented. It is observed that the decrease in the human activities due to the lockdown at several locations worldwide had a positive impact on the environmental aspects like improvement of the air quality. The results of the study show that data analytics can provide significant insights related to the emergence, spread, and impact of pandemics and can also help in
predicting outbreaks and prescribing solutions based on diagnostics and symptoms. Therefore, if used efficiently, data analytics can be a potential tool in the fight against pandemics.

The nations worldwide are also spreading awareness about personal hygiene and sanitation as a preventive measure against COVID-19. The other preferred measures adopted worldwide are social distancing and lockdown. Apart from these, other mitigation measures that can reduce the impact of such pandemics may include [33, 76–79]:

- Changing the attitude of people.
- Understanding and conveying the nature and intensity of the threat to the vulnerable masses.
- Stringent rules, regulations, and laws.
- Policy to check all international travel with basic tests and health procedure which can be done at the time of visa processing.
- Helping the underprivileged groups in case of quarantine and relocations.
- Global corpus funds for such unexpected epidemics and pandemics.
- Grass-root level counseling of the inhabitants.
- Standardized environment, health, hygiene, and disaster management education must be made mandatory for all at UG and PG level of education.

Furthermore, it is imperative to track and contain the outbreak of epidemics and pandemics like COVID-19 in order to stop community transfer. The authenticity and validity of the epidemiological data are highly crucial for planning the mitigation measures. For effective and authentic tracking of the disease carriers and possible doubtful cases along with the epicenter of the pandemics, blockchain technology can be used. Blockchain is a distributed ledger technology which is immutable and transparent and thus makes it the most appropriate candidate for tracking the COVID-19 transmitters and epicenters. Blockchain consortiums like MiPasa and several other companies like “Acoer,” “Telos,” and “Algorand” have already rolled out applications to track and share the data of the patients in a transparent, secured, and privacy preserved manner. In future other modern-day enabling technologies like edge computing, blockchain, deep learning, etc., can be explored to devise novel, effective, and efficient mechanisms for tracking and containing the pandemics and epidemics.

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