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A Survey on Forecasting Models for Corona Virus (Covid-19)

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Abstract - Around the world 170 countries have affected by COVID-19. The number of infected and deceased patients has been increasing at an alarming rate in almost all the affected nations. Forecasting techniques can be inculcated thereby assisting in designing better strategies and in taking productive decisions. These techniques assess the situations of the past thereby enabling better enunciation about the situation to occur in the future. These predictions might help to prepare against possible threats and consequences. Forecasting techniques play a very important role in yielding accurate predictions. This study categorizes forecasting techniques into two types, namely, random theory mathematical models and data science/ machine learning techniques. Data collected from various platforms also play a vital role in forecasting. In this study, two categories of datasets have been discussed, i.e., big data accessed from World Health Organization/National databases and data from a social media communication. Forecasting of a pandemic can be done based on various parameters such as the impact of environmental factors, incubation period, the impact of isolation, age, gender and many more. These techniques and parameters used for forecasting are extensively studied in this work. However, forecasting techniques come with their own set of challenges (technical and generic). This study discusses these challenges and also provides a set of recommendations for the people who are currently fighting the global COVID-19 pandemic.

Keywords COVID-19 · Forecasting models · Machine learning method · Prediction · Big data · Epidemic · Pandemic

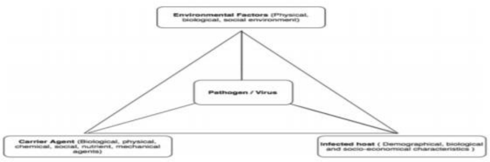
INTRODUCTION

The world has been facing threats in the form of pandemics periodically over the centuries. The aftermath of these pandemics have always had a huge impact on the world and have also turned the tables over. COVID-19, the current devastating pandemic is also running its course currently in the world. Not only economies are crashing but the overall strengths and morals of the heavily impacted nations are being compromised. In order to do accurate predictions understanding of natural progression of disease is very important. A disease generally progresses because of the exposure to the infection. Because of this exposure to infection hosts are formed. Hosts refer to the group of people who are more susceptible to get affected. When an infected host comes in contact with more people then disease starts to spread. Figure 1 depicts the host formation and progression [1]. The diseases like COVID-19, SARC, PLAGUE, etc., are acquired diseases. It means diseases spread through pathogenic agents (virus or bacteria or any microorganism). A traditional model for the cause of the infectious disease is defined. It is called as an Medical specialty Triad. It is delineated in Fig. 2. The four important factors involved in the threesome are environmental factors, carrier agent, infected hosts and the micro-organism. The agent is usually the carrier of the infection. The infection is transmitted to the host when an agent comes in contact with the host under a certain environment. A pathogen is also known as a vector. A vector is an organism that transmits the infection via virus or bacteria from one host to another [2]. Pandemics are often referred to as outbreaks because of their spread pattern. The type of the outbreak determines the mortality rate of the disease. Over the last few years, it has been seen that because of the change in lifestyle, increased global travel and urbanization, infectious diseases quickly escalate into a pandemic. To prevent these epidemics, strong policies need to be administered. Otherwise, the situation can take a drastic turn rapidly. Since the beginning, mankind has faced epidemics and pandemics. The first epidemic faced by mankind was in the early 1300's called black death. It was one of the worst pandemics seen by humankind. This epidemic took millions of lives. It has been observed that this disease targeted most of the elderly people and people who are exposed to psychological stressors [3, 4]. The next pandemic faced by people was in the early 1500's called smallpox where 50% of the mortality rate was observed [5]. After which mankind had to face one of the deadliest pandemics called the fifth cholera pandemic which took more 1.5 million lives [6]. Following this, in 1918 one of the devastating Spanish fu infuenza pandemics was observed. This pandemic took 20–110 million lives. In 1957, the Asian fu infuenza pandemic was occurred which took nearly 0.7–1.5 million lives [6, 7]. In 1981, the world witnessed a new pandemic: HIV/AIDS. It was observed that more than 70 million patients were infected with the virus. According to WHO, Global health observatory data 36.7 million deaths occurred due to this pandemic [8, 9]. After the HIV/AIDS pandemic, the world witnessed a new wave of different pandemics starting with SARS in 2003. This pandemic affected 4 continents and 37 countries across the globe [10, 11]. In 2009 swine fu pandemic took place in which about

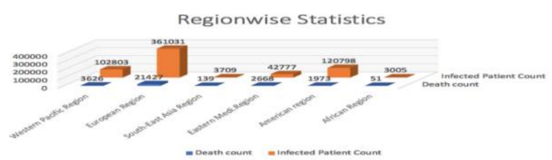
151,700–575,500 deaths were reported [12, 13]. SARS pandemic was followed by the MERS pandemic in 2012. It affected 22 countries across the globe [14]. Two pandemics then followed the MERS. First was the Ebola pandemic in 2013 followed by the tikka pandemic in 2015. Both the pandemics reported deaths in thousands [15, 16]. Currently, the whole world is witnessing the COVID-19 pandemic. More than 100 plus countries till date are majorly affected by COVID-19. This count is increasing as each passing day. Throughout the history of these epidemics, one thing was observed, that is, with the progress in time, these epidemics escalated into pandemics or many times referred to as the outbreak of the virus/ disease. An epidemic escalates into a pandemic when the situation gets out of control at the local source where the outbreak was first observed to spread. The novelty of the

Fig. 1 Host formation and progression

Fig. 2 Epidemiologic Triad



disease and the uncertainty that prevails regarding the disease has lead to a lot of rumors regarding its whereabouts. People are unclear about the diagnosing symptoms and the ways to handle it. Yet another important factor to consider is that lots of people who have diagnosing symptoms do not reach the hospitals on time due to negligence or fear of testing positive for the disease. If somebody has the symptoms they have to act on it as soon as possible. This can help to save a lot of lives. If an early outbreak in any nation is successfully controlled then the situation can be prevented from escalating into a pandemic. Whenever these pandemic occur, world economies are majorly hit. Billions of dollars need to be invested in controlling an outbreak as well as in the development of a vaccine for the new disease [17]. While studying the outbreak or spread of any disease it is imminent to take all related factors into the account. Gaudart et al. [18] have taken extensions of the classical Ross-Rickenbacker Donald approaches. These approaches are combined with demographic and spatial dependencies of the virus on the host as well as the spread of disease. This research discusses the retro prediction model to study the spread of the COVID-19. To predict the spread of the HIV/AIDS pandemic Kaplan's model was used in [19]. But the prediction focused on drug addicts using injector/syringe. Hence the study was focused on the spread pattern pertaining to the specific group of people. MERS was another pandemic faced by the world. In order to analyze the transmission route of the MERS, decision tree and apriori algorithms were used in [20]. In [21] a maximum likelihood method was used to assess the spread of the SARS epidemic using the construction of biological process tree. In [22] SVM was used to address the same issue. The neural forecasting model was used in [23] for obtaining a forecast for swine fu. COVID-19 is a novel disease that has evolved into a pandemic. This novel disease has been reported by the WHO on December 31, 2019, in Wuhan, China. Soon after the outbreak in China lots of countries were in the grasp of COVID-19. According to WHO globally 634,835 conformed cases have been registered, 29,891 deaths have been recorded till date. The region-wise statistics are shown in Fig. 3. The regions are as follows: The Western Pacific region, European region, South-East Asia region, Eastern Mediterranean region, American region and African region. Among these regions along with China, Italy, Spain, France, USA, comes under heavily infected regions. These statistics have been taken from WHO dated March 29, 2020 [24]. From the graph, it is conformed that this pandemic is spreading its arms across all regions. There are numerous techniques from the field of statistics, data science, ML and AI that can be used for prediction. The detailed study is presented in section three. In China, COVID-19 spread took place at an unprecedented rate. Quickly situation escalated into a pandemic. The noble objectives of the researchers were to present study which can be useful for further decision-making process. In decision-making process, past data are analyzed to get perspective. However, data availability in such a short time span is not sufficient to train AI models. Effectively trainable AI models for time-series data is required (insufficient amount of available data during the initial stages of an epidemic spread). The time series data helps in improvement of efficiency of forecasting. The objectives of the study are as follows: • To study existing forecasting models. • To categorize forecasting models based on type of datasets. • To study of symptomatic and asymptomatic parameters. • To derive challenges related to forecasting models. • To formulate recommendations to control the pandemic. This study is organized into four main sections. The paper starts with the natural course of the disease; categorization of the diseases, along with the global history of pandemics



where the COVID-19 outbreak is also mentioned. “Coronavirus Overview” section provides an overview of the COVID19, the different measures exercised in confining the outbreak. “Forecasting Techniques” section provides a survey of the multiple forecasting techniques and their categories. “Discussion” section deals with analysis, policies/recommendations for the control of the outbreak and the challenges that exist in the forecasting models.

CORONAVIRUS OVERVIEW

COVID-19 affect's the respiratory system of the human body which is caused due to coronavirus-2. This virus is highly contagious. It is spreading through the bodily droplets in the air. Common symptoms include fever, tiredness, and dry cough. Along with these symptoms, a patient also experiences shortness of breath, aches and pains and sore throat. Very few people have experienced diarrhoea, nausea or a runny nose. People having high fever, cough or difficulty in breathing should call their doctor and seek medical help immediately. Human to human transmission is exponentially increasing the counts of the infected people. The incubation period of this disease is 1–14 days or even longer [24]. When the COVID-19 started to spread at an unprecedented rate; preventive measures were exercised. These measures included a complete lockdown of the heavily infected areas, ban on international travels, suspending schools and other non-essential daily activities. The main aims of these measures were to limit interpersonal contact, considering the contagious nature of the disease. The curfew was imposed and strictly observed. As the incubation period of the virus is longer than other viruses it is very difficult to analyze the optimal time required to observe a curfew. If the curfew is lifted too soon the situation can become dangerous. The people who get infected fall under three categories. First in the category are the elderly, who are highly susceptible to the virus. Statistics show that because of the weak immune system the age group buckle under to the disease easily. The second category is that of the children. As the exempt systems of young children are still under development, the children are at higher risk. The third category is that of the people who have diseases like diabetes, high BP, asthma, cancer, cardiovascular disease, etc. As their immune systems have been compromised already due to a prevailing medical condition, these people become easy targets. Infections experienced by the third category of people can be fatal [17].

FORECASTING TECHNIQUES

In the literature, forecasting has been done based on various forecasting techniques and different data sources. To understand and improve the forecasting this section categorizes these techniques into multiple types for better analysis. This categorization is done based on the data sources used, i.e., big data accessed from WHO/National databases and data from social media. However, the main aim of this study is the analysis of forecasting techniques in computing and processing linear perspective. In the view of this, data in terms of population statistics is considered for discussion throughout in this paper. The main advantages of using population statistics are there is no need of sampling as the entire population is present in the data set. Population statistics also help to make reliable prediction and estimates with less computational overhead and there is a lack of bias. In the literature, many studies are also carried out on clinical data. These studies may be useful for physician, doctors, and researchers in the medical domain for investigating better diagnostic methods and for health professional industries in formulating vaccines, drugs in a short time. Categorization is also done based on techniques that are used for forecasting, i.e., data science/machine learning techniques. However, there are also a few other categories that are used in the literature for forecasting. In shell, these categories are broadly divided into the following four sets:

(a) Big data.

(b) Social media/other communication media data.

(c) Stochastic theory/mathematical models.

(d) Data science/Machine learning techniques.

Various statistical, analytical, mathematical and medical (symptomatic and asymptomatic) parameters are taken into consideration for analysis. However, major significant parameters are listed below:

(a) Daily death count.

(b) Number of carriers.

(c) Incubation period.

(d) Environmental parameters, i.e., temperature, humidity, wind speed.

(e) Awareness about COVID-19.

(f) Medical facilities available.

(g) Social distancing, quarantine, isolation.

(h) Transmission rate.

(i) Mobility.

(j) Geographical location.

(k) Age and Gender.

(l) Highly and least vulnerable population.

(m) Underlying disease.

(n) Report time.

(o) Strategic policies and many more.

Apart from these above-mentioned parameters, there can be many influential factors that need to be further investigated. The following section presents a parametricevaluation of the state-of-the-art by classifying various studies into four aforementioned categories. Every evaluation is supported by the table where work ref. represents the research work which is referred for study, studied regions indicate the countries which data is taken for study, parameters present the factors on which study is based and remark represents the outcome of the study. Big Data Effectiveness of forecasting is based upon the quality of data source used for forecasting. Forecasting results may vary based on the impurities in the data sources. Data mining and big data techniques always play a vital role in healthcare systems [25–28]. In the literature, researchers have done forecasting based upon data sources received from authenticated national and international sources. Here, analysis of big dataset is done by using various techniques like mathematical equations or machine learning techniques. Soumyabrata Bhattacharjee [29] has presented the impact of environmental factors like temperature, wind speed and humidity on the spread rate. This analysis is done based on the data accessed from the WHO and the local weather database. Dravidian [30] has presented decision-making schemes by analyzing the COVID-19 data of countries like China, Japan, Korea, European countries, and North America obtained from Johns Hopkins University. Caccavo [31], Siwiak et al. [32], Zareie et al. [33], Teles [34] and Russo [35] have analyzed COVID19 databases accessed from WHO, Italy national data and Johns Hopkins to predict the mortality rate. Liu et al. [36] presented the impact of disease control interventions and trafc restrictions on the spread rate. The analysis has been done on the dataset retrieved from US Centers for Disease Control (CDC). Nadim et al. [37], Pear Hossain et al. [38], Tarcísio et al. [39], Train et al. [40] have presented the importance of quarantine in order to reduce the spread rate of COVID-19. Giordano et al. [41] have presented the data analysis of Italy based on Italy's national data. As per Italy's ofcial release, there are a total of 27,980 infected cases and 2158 deaths of people who were positive of coronavirus. Looking at the effect of the Pandemic in Italy, Giulia Giordano has proposed the SIDARTHE Model that helps in redefning the reproduction number. This epidemic prediction model compares the infected density with the level of symptoms. Wangping [42] has presented a study in which, COVID-19 data from Jan 22, 2020, to Mar 16, 2020, has been used in time series form for analysis. The prediction has been estimated using the Markov Chain Monte Carlo method and results show that the reproductive number in Italy is 4.10 and 3.15 in Hunan. The anticipated endpoint in Italy would be April 25. Details of the literature evaluation are summarized in Table 1.

Social Media Data/Other Communication Media Data In this digital era, social media communication and internet searches are the most easily accessible platforms that provide more information about COVID-19. The social media and web search correlate with the number of daily COVID19 cases. Keeping this in mind few researchers have taken datasets from Google, Baidu search engines [43, 44], mobile phones [44, 45], newspapers [50] and various websites [47–48] like Github [49] over a particular duration of time. Analysis of these datasets is done by various techniques as discussed before, i.e., machine learning techniques or mathematical equations/stochastic theory based on the parameters which were discussed earlier. Zhu et al. [45] have presented a spatially pandemic model for predicting the death count. This study aims to build a prediction model that will analyze the growth of the virus for the next month considering the current dynamics of COVIO-19. Three different scenarios have been taken into consideration for the study which includes residents, residents with Wuhan travel history and residents affected as a result of a local outbreak. The decay rate has also been introduced in the study to appreciate the effort of different cities to assuage the spread of the disease. Phone data has been used to collect the statistics of city-wise residents who had traveled back from Wuhan and the city-based model has been trained using the prevailing statistics and validated against the new cases as on February 11. The same model has been used to predict cases up to March 12, 2020, under the aforementioned three scenarios. The study predicted that the number of infections would be around 72,172, 54,348 and 149,774 by March 12, 2020. The potential outcome of the study is a spatial model and its predictions will certainly help in optimizing the allocation of resources in each city during the next 1 month when the epidemic reaches a serious state of concern. Details of this analysis are summarized in Table 2 as follows. Stochastic Theory/Mathematical Models In a few past pandemics, the traditional approach of the mathematical and stochastic theory was used to estimate the loss of human and also to predict the total death count until a particular period or end of the pandemic. This traditional approach is very effective and shows better predictions. Hence in the current pandemic situation of COVID-19 researchers [52–57] have used the same traditional approach for estimating the death count and the spread rate of COVID19. The approach is also used to predict the total death count till the end of the pandemic. The analysis is done on databases accessed from authorized sources or search engines, mobile phone data and newspaper reports. Sameni [58] has proposed a pattern of the virus with the help of mathematical

Table 1Evaluation of COVID-19 forecasting on social media Databases

S.no	Work	St	Data	Paramet	Remarks

	ref.	udied regions	source	ers	
1	Li L, Yang Z, Dang Z, Meng C, Huang J, Meng H, Shao Y. Propagation analysis and prediction of the COVID-19.	China	Baidu Search engine and Tab	Number of basic regenerations, the incubation period and the average number of days of cure	Impact of future prediction and backward on the spread of COVID-19
2	. La S, Bogoch II, Ruktanonchai N, Watts AG, Li Y, Yu J, Lv X, Yang W, Hongjie Y, Khan K, Li Z. Assessing spread risk of Wuhan novel coronavirus within and beyond China, Januar	China	Baidu map big data	The incubation period, number of carriers, contact rate	Impact of medical facilities, Social responsibility, administrative responsibility on death count and spread rate

	y–April 2020: a travel network-based modelling study. 2020.				
3	. La S, Bogoch II, Ruktanonchai N, Watts AG, Li Y, Yu J, Lv X, Yang W, Hongjie Y, Khan K, Li Z. Assessing spread risk of Wuhan novel coronavirus within and beyond China, January–April 2020: a travel network-based modelling study. 2020.	China	Mobile phone data	Domestic and international travel	Impact of domestic and international travel on COVID global spread
4	Zhu X, Zhang	China	Mobile phon	Spatially pandemic model,	Prediction of the death count

	A, Xu S, Jia P, Tan X, Tian J, Wei T, Quan Z, Yu J. Spatially explicit modeling of 2019-nCoV epidemic trend based on mobile phone data in mainland China. medRxiv. 2020.		e	the Decay rate	
5	Volpert V, Banerjee M, Petrovskii S. On a quarantine model of coronavirus infection and data analysis. Math Modell Nat Phenomena. 2020;15:24.	China and Korea	https://www.worldometers.info/coronavirus/	Sub-population of latently infected individuals, the incubation period	Quarantine is not sufcient and stricter measures are needed
6	Anastassopoulou C, Russo L, Tsakris A, Siettos C. Data-based analysis, modelling and forecasting of the novel coronavirus (2019-nCoV) outbreak.	China	Web site	Reproduction number	Forecasting of death numbers
7	Li C, Chen LJ, Chen X, Zhang M, Pang CP, Chen H. Retrospective analysis of the possibility of predicting the COVID-19 outbreak from Internet searches and social media data,	China	Internet searches and social media data	Confrmed cases and suspected cases of COVID-19	Prediction of COVID-19 outbreak

	China, 2020.				
8	Bayham J, Fenichel EP. The impact of school closure for COVID19 on the US health care workforce and the net mortality efects.	US	Github page	Social Distancing (school closure)	Impact of social distancing on the death count
9	Giuliani D, Dickson MM, Espa G, Santi F. Modelling and predicting the spread of coronavirus (COVID-19) infection in NUTS-3 Italian regions. arXiv preprint arXiv:2003.06664. 2020.	Italy	Web sites of the main Italian news papers	Time and space	Impact of space and time on decision makers to intervene on the local policies

modeling. This study uses a model from the family of the well-known compartmental models known as susceptible infected-recovered (SIR) model. A study has shown that the measures taken by the countries are positively affecting the mortality rate. Along with that, the facilities that are created to house the infected people, has contributed greatly in stopping the spread of the disease. However, this mathematical model has limitations in terms of accuracy because it is developed for the underlined dataset. Yuan et al. [59] presented the Boltzmann's function-based analysis. It has been observed that the prediction accuracy is better and it can also help in assessment of the severity of the situation and take appropriate actions. Dowd et al. [60] proposed the impact of age and gender on the death count using mathematical modeling. It has been observed that this virus is largely affecting the elderly. Now, in this case, the age structure of a particular country plays a vital role. In Italy, 23% of the population is above 65 years of age and hence the threat is maximized for the countries having similar age structure as that of Italy. The same situation can be faced by South Korea. Hence the policies like social distancing and quarantine can help to slow down and stop the spread of the virus. He et al. [61] has presented the impact of pre-symptomatic transmission on the death count using mathematical modeling in this infector-infections and the transmission rate is studied. From the observation, it was inferred that the rate of transmission was at its peak on or before the symptom onset. 44% of transmission can be seen even before the first symptoms become physically visible. Hence the disease control authorities should take the pre-symptomatic transmission into account while implementing the measure to curb the spread. Giannakeas et al. [62] presented an online tool for healthcare management using stochastic theory. Banerjee et al. [63] presented the impact of underlying conditions like heart disease and diabetes on the death rate. The impact of mobility on the spread rate of COVID19 is presented by Alexander et al. [64]. Chen et al. [65], Ma et al. [66] and Shi et al. [67] presented the impact of environmental factors on death count and spread rate of COVID-19. This analysis is based on the parameters listed as earlier and the details of this analysis are summarized in Table 3.

DATA SCIENCE/MACHINE LEARNING TECHNIQUES

Nowadays machine learning techniques are used worldwide for predictions due to its accuracy. However, to use machine learning (ML) techniques, there are a few challenges as very little data is available. For instance, the challenges involved in training a model are the appropriate selection of parameters and the selection of the best ML model for prediction. Researchers have done predictions based on datasets that are available and used the best ML model as per the dataset [17, 69–71]. Kumar and Hembram [72] presented a model based on the Logistic equation, Weibull equation, and the Hill equation to find infection rates in China and Italy. In this research work, data analysis is done to understand the effect

Table 2Evaluation of COVID -19 forecasting based on the mathematical and stochastic theory

Sr.no	Work Ref.	Studied Regions	Data source	Parameters	Remarks
1	Lu J. A new, simple projection model for COVID-19 pandemic.	China, Italy, Iran, Germany, France, USA, South of Korea	WHO	Effectiveness of intervention, public response, and healthcare system	Forecasting numbers of COVID-19 patients
2	Webb G. Predicting the number of reported and unreported cases for the COVID-19 epidemic in South Korea, Italy, France and Germany.	South Korea, Italy, France, and Germany N	National Data	Reported and unreported numbers	Forecasting number of COVID-19 cases
3	Victor AO. Mathematical predictions for Covid-19 as a global pandemic. medRxiv. 2020	Global death count,129 countries	John Hopkins Hospital, WHO	Exposed and infected population	Prediction of infection rate
4	Wang H, Zhang Y, Lu S, Wang S. Tracking and forecasting milepost moments of the epidemic in the early-outbreak: framework and applicatio	China	Centers for Disease Control, China	Stages of spread	Prediction of spread rate

	ns to the COVID-19.				
5	Botha AE, Dednam W. A simple iterative map forecast of the COVID-19 pandemic. arXiv preprint arXiv:2003.10532. 2020.	China	WHO	Fitting parameter calculated from the total number of cases and new cases each da	Prediction of spread rate
6	Coelho FC, Lana RM, Cruz OG, Villela D, Bastos LS, Pastore y Piontti A, Davis JT, Vespignani A, Codeco C, Gomes	Brazil	Offcial Airline Guide Data SUS	Outbreak probability, efective distance, Social vulnerability	Prediction of spread rate
	MF. Assessing the potential impacts of COVID-19 in Brasil: mobility, morbidity and impact to the health system. medRxiv. 2020				
7	Weber A, Ianelli F, Goncalves S. Trend analysis of the COVID-19 pandemic in China and the rest of the world.	China, Italy, Japan and Germany J	Johns Hopkins University	Duration, number of deaths	Presented epidemic spread pattern
8	. Sameni R. Mathemat	Global death count	WHO	Mortality rate, infection rate,	Disease control measures: Lockdown, social distancing

	ical modeling of epidemic diseases; a case study of the COVID-19 coronavirus. arXiv preprint https://arXiv:2003.11371. 2020			re-infection rate, the recovery rate	
9	. Long C, Ying Q, Fu X, Li Z, Gao Y. Forecasting the cumulative number of COVID-19 deaths in China: a Boltzmann funct	China	WHO	Number of deaths	Forecasting the cumulative number of COVID-19 death

	ionbased modeling study.				
10	Dowd JB, Andriano L, Brazel DM, Rotondi V, Block P, Ding X, Mills MC. Demographic science aids in understanding thespread and fatality rates of COVID-19.	Italy, Nigeria Brazil, USA, UK	National Data	Age and gender	Impact of age and gender on spread rate
11	He X, Lau EH, Wu P, Deng X, Wang J, Hao X, Lau YC, Wong JY, Guan	China	Data of Hospital, China	The incubation period, pre-symptomatic transmission, post-symptomatic	Impact of incubation period on spread rate

	Y, Tan X, Mo X. Temporal dynamics in viral shedding and transmissibility of			transmission	
12	ianna keas V, Bhatia D, Warkentin MT, Bogoch I, Stall NM. Estimating the maximum daily number of incident COVID-19 cases manageable by a healthcare system. .	US	American Hospital Association	Type of bed acute bed, critical care bed, and ventilator	Online tool for no of patients can be admitted in hospital
13	Banerjee A, Pasea L,	UK	Electronic hea	Impact of underlying	Estimation of excess 1- year mortality from COVID-19 with underlying conditions

	Harris S, Gonzalez-Izquierdo A, Torralbo A, Shallcross L, Noursadeghi M, Pillay D, Pagel C, Wong WK, Langenberg C. Estimating excess 1-year mortality from COVID-19 according to underlying conditions and age in England: a rapid analysis using NHS health		lth records in England	conditions like heart disease, diabetic on mortality	

	records in 3.8 million adults.				
14	Siegenfeld AF, Bar-Yam Y. Eliminating COVID-19: a community-based analysis. arXiv preprint	China	Chinese Centre for Disease Control and Prevention	Mobility rate	Impact of mobility on spread rate
15	Chen B, Liang H, Yuan X, Hu Y, Xu M, Zhao Y, Zhang B, Tian F, Zhu X. Roles of meteorological conditions in COVID-19	China, Italy, Japan	WHO	Air temperature, relative humidity, wind speed, and visibility	Multi-factors can impact on spread rate rather than single factor
	transmission on a worldwide scale.				
16	Ma Y, Zhao Y, Liu J, He X, Wang B, Fu S, Yan J, Niu J, Luo B. Effects of temperature variation and humidity on the mortality of COVID-19 in Wuhan.	China	People's Republic of China	Number of death, temperature, humidity	Environment factors may impact COVID19 mortality rate
17	Shi P, Dong Y, Yan H, Li X, Zhao C, Liu W, He M, Tang S, Xi	China	China National Health Commission, meteorolo	Impact of temperature and absolute humidity on the COVID-19	Lower and higher temperatures may be positive to decrease the COVID-19, there is no major impact of humidity

	S. The impact of temperature and absolute humidity on the coronavirus disease 2019 (COVID-19) outbreak-evidence from China.		gical authority in mainland China		

of environmental factors on the spread of COVID-19. Data analysis is done on 4 cities in China namely Beijing, Chongqing, Shanghai and Wuhan and 5 cities of Italy namely Bergamo, Cremona, Lodi and Milano. The number of infected people is greater in the above-mentioned cities. Three environmental factors are mainly focused on this study, i.e., maximum environmental temperature, relative humidity, and wind speed. For data analysis, data is collected from a report published by the WHO for China and Italy. Data is taken from the ofcial GitHub repository of the Department of Civil Protection, Italy. The results show that there is a negligible relation between humidity and wind speed with the spread of COVID-19. Similarly, it has been observed that higher/maximum temperatures have a trifling to a moderate impact on the spread of the virus. The result shows that there is no sign of any major effect of temperature on the virus. However, results may vary depending on the dataset. DeCapprio et al. [73] proposed a model using logistic regression, gradient boosted trees, and a hybrid model using Medicare data. The outcome of these models will help to initiate control strategies and to initiate corrective measures in time to control the spread. The details of this analysis are explained in Table 4. From the literature review, it is evident that all studies have taken data from standardized data sources however, these datasets are not yet standardized by any standardization organization or allied bodies. In these studies, the geospatial and statistical anomalies are not considered; however, these may be interesting enablers for better forecasting. In the literature impact of environment factor and mobility on COVID-19 spread is considered [64, 65]. Various stages of COVID-19 outbreak are well-explained in [50], where the understanding of outbreak stages may help to reduce the rate of spread. Various ML models are discussed in the literature however for better accuracy deep learning models can be used for better predictions [74]. Furthermore, predictions can be more accurate using active learning models in this multitudinal and multimodal data used for predictions instead of single type of data [75]. Enormous work has been going on the COVID-19 apart from the above discussed work [77–82]. Researchers are working to investigate efficient and accurate models in order to predict the death count. Researchers are also working to provide a list of guidelines that can be followed by the people to reduce the spread rate of the COVID-19.

DISCUSSION

As stated earlier, the literature survey presented above is based on broadly four categories like the size of the dataset, source of the dataset, and techniques applied for forecasting like mathematical/analytical or machine learning/data science. This survey is carried out on various medical and non-medical parameters and it is very clear that the basic purpose of all these studies is to estimate the fnal size of this COVID -19 pandemic. However, it is very interesting to note that, all the studies have referred to the China epidemic as the basis and all forecasts have been done based on the early statistics which are available from the outbreak in China. Outcomes of these studies are very much useful for multiple purposes like controlling the spread of COVID-19 globally, controlling the spread of COVID-19 for a specific country, deciding its impact, building vulnerability index of COVID19, establishing a correlation between environmental conditions (metrological conditions) and the spread rate, deciding reproduction number, establishing the correlation between quarantine and isolation with the spread of COVID-19, trend

Table 3 Evaluation of COVID-19 forecasting based on Data Science/Machine Learning Techniques

S.no	Work ref	Studied regions	Data Source	Parameters	Remarks
1	Fong SJ, Li G, Dey N, Crespo RG Herrera-Viedma E. Finding	china	Small data set	Corrective feedbacks of model	Forecasting suspected numbers of COVID19

	an accurate early forecasting model from small dataset: a case of 2019-ncov novel coronavirus outbreak.				
2	Fong SJ, Li G, Dey N, Crespo RG, Herrera-Viedma E. Composite monte carlo decision making under high uncertainty of novel coronavirus epidemic using hybridized deep learning and fuzzy rule induction. Appl Soft Comput.	china	Chinese Center for Disease Control and Prevention	Cost of isolation, cost of treatment, no of suspects, no of conformed COVID patients	Recommendation for decision making
3	Batista M. Estimation of the fnal size of the second phase of the coronavirus COVID-19	china	WHO	Daily death count	Forecasting of death count

	epidemic by the logistic model.				
4	Hu Z, Ge Q, Li S, Jin L, Xiong M. Evaluating the efect of public health intervention on the global-wide spread trajectory of Covid19.	102 countries	WHO	Degree of intervention and starting intervention time	Impact of a public health intervention on the global-wide spread
5	Jia L, Li K, Jiang Y, Guo X. Prediction and analysis of coronavirus disease 2019.	china	2003 SARS Data	Death count	Forecasting of death numbers
6	. Kumar J, Hembram KPSS. Epidemiological study of novel coronavirus (COVID-19).	China and European countries	WHO	Infection rate	Prediction of infection rate
7	DeCaprio D, Gartner J, Burgess T, Kothari S, Sayed S. Building a COVID-19	Global Data	International Clasification of Diseases	Preexisting medical conditions	Identify individuals who are at the greatest risk

	vulnerability index.				

analysis of COVID-19 pandemic and tracking the spread of COVID-19 locally and globally. The COVID-19 pandemic having been in existence for a very short period now, it is very important to analyze the trend of its spread and infected cases. All afected nations are looking toward mitigation plans to control the spread of the disease with the help of some modeling techniques. In the sequel, the outcomes of these forecasts are multi-fold. Every forecast is carried out with some perspective irrespective of which category it may represent. From these studies and the forecasts made, it is very clear that the major outcome is to support healthcare communities to initiate critical action, decisions, control measures and public restrictions in time. Another outcome is to support in establishing mechanisms that provide control measures to be considered internationally for the global control of this pandemic as well as restrictions to the public in terms of quarantine, isolation, contact tracing, the recommendation in terms of metrological conditions (mainly Air, Temperature, relative humidity, wind speed and visibility) and its impact on the spread. However, despite these useful outcomes, there are still many issues and challenges which are still unaddressed. The first and most important issue is whether the modeling and predictions based on China's dataset would surface to address the issues of all countries. There is a need for reassessment to ensure that the control measures initiated by China to regulate the outbreak are enough to control this global pandemic. Many researchers have presented models for disease predictors to decide the reproductive number, but all of them have relied on similar datasets. It is also a crucial factor to rethink whether the same mathematical or prediction model is also suitable to predict the spread and reproduction number for all the countries across the globe. Literature shows that all the models presented are tested based on the numbers of the China epidemic. It is also equally important to ensure that the same model tested for China's dataset can also be applied to control the outbreak of COVID-19 globally. Another issue is that in the literature very limited details regarding the key characteristics of Coronavirus and the symptoms of COVID-19 are available. In this sequel, the challenge is to identify a vulnerable group of people with these limited details regarding viruses and disease. There is also a need to consider multiple peaks in the model not only for short term prediction but also to predict the outbreak later in the year. Before conforming the forecasting mechanism, there is a need to reconsider these issues and challenges for better accuracy. There are few and important medical and non-medical parameters that still need to be investigated as evident from the literature. A few of which are, the genetic relations pertaining to the geographical locations need to be studied in order to conform the forecast. The Ethnicity (civilization, society, culture) of the infected people is another important parameter that needs to be reviewed. Correlation between the spread and its impact on a specific patient considering the underlined preexisting medical complications is also another important parameter to be considered for more effective and accurate forecasting. It should be noted that not a single study or model available in the literature has considered the existing treatment options and has assumed that no vaccination option will be available for the next 1 year [83]. However, these are also some important parameters which need attention to fine-tune the model further.

CHALLENGES OF FORECASTING MODELS

Forecasting plays an important role in every domain [85–86] due to its benefits to save resources or to improve the economy. However, it comes with its challenges. In the case of COVID-19, there are also many challenges for forecasting the death count and spread rate as COIVD 19 incubation period is very much longer and very fewer datasets are available for this purpose. Few such challenges of forecasting models are listed as follows:

(1) Tracking of the people The tracking of infected personnel and other people who came in contact with them is truly one of the difficult tasks.

(2) Longer incubation period As COVID-19 has an incubation period of 14 days, it is impossible to identify patients beforehand. During the defined incubation period patients can infect all the people who come in contact with him/her.

(3) Lack of proper data Sometimes data are available in unstructured format. Hence is very necessary to maintain quality and quantity of the data before it goes in training stage. Data accuracy is an important factor in achieving effective forecasting methods.

(4) Overtiring of the data If overtiring of the data occurs then it is possible that model in question will not perform well on new data.

(5) Overly clean data It is important to have clean data for the analysis purpose but too clean data sometimes loses its integrity.

(6) Abundance of data Data are available in abundance but feeding all these data to model will not improve the accuracy.

(7) Wrong algorithm and attribute selection If wrong algorithm is selected then the result can be misleading. Same is true in case of wrong of wrong attribute selection.

(8) Model complexity If model is too complex it can affect the overall performance if the model.

Along with these challenges, some more challenges are important to make a note of:

• Proper lockdown It is very difficult for any country to implement a lockdown. To decide the proper conditions of a lockdown is a very complicated task.

• The optimal period for lockdown The optimal period for lockdown is not only crucial but also a critical task.

• Aware but do not cause panic It is important to educate people but in the process, it is important to remember not to create panic.

`• Essential services identifcation and delivery It is imminent for any country to identify essential services before lockdown. Even among lockdown lack of these services can cause a massive panic.

CONCLUSION

The COVID-19 pandemic is spreading its wings across the globe at a astonishingly faster rate and has already resulted in thousands of deaths across countries. Unfortunately, this number is sure to grow within a short period and healthcare organizations would soon face scarcity of resources. In this sequel, it is important to analyze various forecasting models for COVID-19 to empower allied organizations with more appropriate information possible. An overall comprehensive study on analysis of COVID19, its forecasting, impacts, and control measures are presented in this study. The major contribution of this study is the analysis of several forecasting models available in the literature and their classification, challenges of these models and recommendations to control this pandemic. Based on the available forecasting methods, we studied various statistical, analytical, mathematical and medical (symptomatic and asymptomatic) parameters. Also, common yet significant parameters have been taken into consideration which includes death count, meteorological parameters, quarantine period, medical resources, mobility, etc. In this study, we have done the categorization of various forecasting methods into four major sets which include big datasets accessed from WHO/National data sources, social media/other communication media data, stochastic theory/ mathematical models and data science/Machine learning techniques. This classification will surely help researchers to consolidate the forecasting methods more crisply and concisely as presented in this study. Our study indicates that there is a need to reassess control measures initiated by China and other countries. Prediction of the spread and reproduction number should be analyzed on varied datasets. The models presented in the literature should be tested globally for more accurate global forecasting. On similar grounds, there is also a need to consider multiple peaks in the model not only for short term prediction but also to predict the outbreak later in the year. This study also indicates the challenges of various forecasting models and useful recommendations for the control of this pandemic. We hope that by providing analysis of various forecasting models of COVID-19 will be more helpful for adapting better intervention policies and explicitly, it will also help to alleviate the alarming effect of this pandemic. We agree that many of the papers referred to in this study for analysis are pre-eminent, i.e., they do not peer review formally. However, due to the rapid growth of COVID-19 globally, there is a strong need for such a comprehensive survey as a contribution toward the society.

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