A Comprehensive Survey on Covid-19 Prediction Models

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ABSTRACT

The world witnessed the outbreak of the novel coronavirus (COVID-19) in late December 2019 and since then the cases have been reported in various countries across continents. The rising number of cases posed an alarming health crisis situation in the whole world. It was important for countries to understand in advance when peaks can be reported and thus accordingly prepare their systems to save lives. Forecasting the number of cases and understanding the underlying trends associated with rise and fall of infection spread became paramount for researchers. Numerous studies have been conducted and a plethora of models have been proposed to aid in forecasting the number of COVID-19 cases using deep learning and other techniques. In this paper, we have presented a review of the studies conducted in past to predict the number of COVID-19 cases. Under this study, a total of 64 papers obtained through the interfaces of Google Scholar and Carnegie Mellon University (CMU) were included and analysed. The contributions in this review: 1. Provides useful insights into the work that has been done so far in the field of COVID-19 prediction modeling. 2. Highlights the various techniques used and their respective performance. 3. Reveals the future directions.

Keywords: *Deep learning, forecasting, modeling, pandemic, coronavirus*

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INTRODUCTION

Threats in the form of pandemics have been affecting the world over the centuries. These pandemics have a huge impact in terms of public health and resources. COVID-19, a devastating pandemic that is running its course currently, is an infectious disease that posed a life-threatening situation for the whole world within a few months of its emergence in Wuhan, Hubei Province, China in December 2019 (Lu et al., 2020). COVID-19 is caused by a virus belonging to the family of coronaviruses accountable for the first known epidemic, Severe Acute Respiratory Syndrome (SARS) 2002 in Guangdong, China (Zhong et al., 2003). This new virus initially named 2019-nCoV founds to be more contagious and severe disease-causing (Lu et al., 2020). The novel virus was later renamed by The International Committee on Taxonomy of Viruses as SARS-CoV-2 (Lai et al., 2020). The outbreak of this disease was quickly observed in many other regions of the world too. The disease was named COVID-19 (Coronavirus disease 2019) by the World Health Organisation (WHO) on 11th February 2020 ("Naming the Coronavirus Disease (COVID-19) and the Virus That Causes It," 2020). A seafood market in Wuhan was recognized as the centre of the outbreak as initial cases of infection were reported to have visited this market, indicating a possible animal to human transmission. Earlier research studies also indicated a possible human-to-human transmission as some individuals got affected without visiting that market (Li et al., 2020). Considering the spreading potential of the virus, WHO declared COVID-19 a pandemic on 11th March 2020 (Culcinotta & Vanelli, 2020).

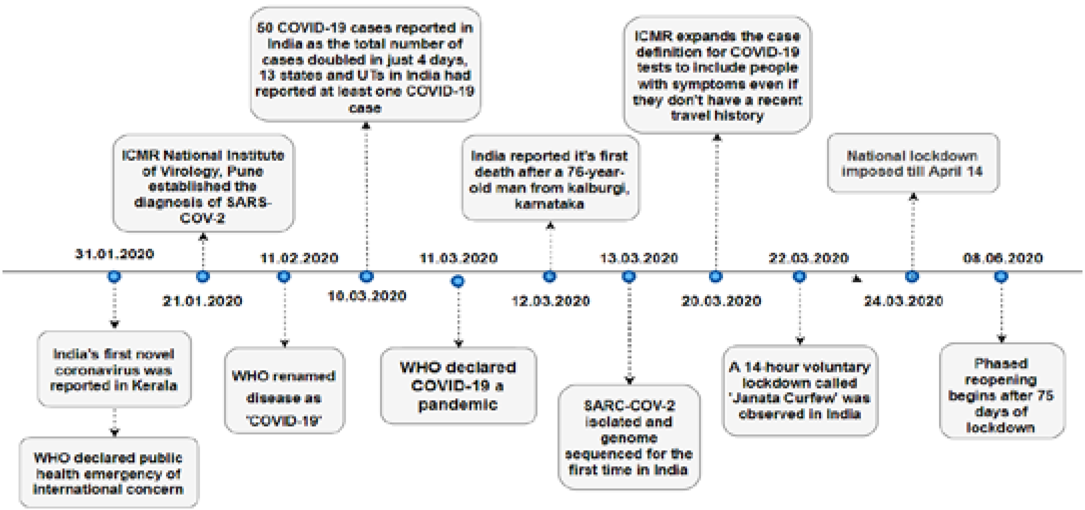
1. Covid-19 Spread: World and India

WHO announced a case in Thailand on January 13, 2020, making it the first case to be discovered outside of China ("Novel Coronavirus – Thailand," n.d.). Japan's first case was confirmed on January 16 (Press, 2020), and the Republic of Korea's National IHR Focal Point (NFP) announced the country's first case of new coronavirus on January 20 ("Novel Coronavirus (2019-NCoV)", 2020). Most countries in the world got affected by this virus in the course of a few months. The year 2020 will be remembered as a catastrophic year for humanity.

India's first coronavirus case was reported in Kerala on 31st January 2020 ("Health Ministry Reports One Positive Case of Wuhan Coronavirus in Kerala," n.d.). Soon after that, 50 COVID-19 cases were reported in total by 10th March 2020. On 11th March, WHO declared COVID-19 a pandemic (Culcinotta & Vanelli, 2020). A day later, India reported the first death of a 76-year-old man from Kalburgi, Karnataka (Staff, 2020). The government imposed some rules and regulations for the mitigation of the situation. Indian Council of

Medical Research (ICMR) expanded the case definition for COVID-19 tests to include people with symptoms even if they don't have recent travel history. On 22nd March 2020, a 14-hour lockdown called the "Janta Curfew" was observed throughout the country where people kept themselves indoors in order to contain the spread of COVID-19 ("For 14 Hours Today, India Will Be Locked Down," n.d.). A few days later, a nationwide lockdown was imposed till April 14 ("COVID Timeline," n.d.). Nationwide lockdowns kept on extending until phased reopening began after 75 days of complete lockdown on 8th June 2020 (Hebbar, 2020). The initial COVID-19 timeline for India is depicted in Figure 1. This timeline captures major events that happened during the course of the COVID-19 pandemic from the Indian perspective.

Fig.1. Initial COVID-19 timeline for India



2. Measures Adopted to Contain Spread

Countries imposed measures like quarantines, travel restrictions, social distancing, and lockdowns to safeguard lives from this deadly disease. Though lockdowns resulted in containing the spread of the disease, it has been a tough decision for the governments as it significantly impacted the economies. Not only economies but the overall strength and morale of heavily affected nations have been compromised. For developing and underdeveloped countries, this impact has proven to be far more disastrous than the lives the virus has taken. Every attempt has been taken to impede the coronavirus's spread. Medical response systems have been designed to deal with the rise of active patients and protect the front-line medical workers with sufficient supplies of personal protective equipment (PPE) kits, masks, and other necessities. Any forecast in advance will help governments to plan the usage of resources and to mitigate the risk of losing lives. Several prediction models to predict the number of COVID-19 cases have been developed which can forecast the number of cases for the next few days. In order to make accurate predictions, understanding the natural progression of the disease is very important. The literature is replete with studies on the prediction of novel coronavirus cases, and this article reviews a few of them.

RESEARCH METHOD

1. Background and Objectives

The significant spread of the novel corona virus over the world posed some serious challenges for the researchers' community. The exponential increase in the need for healthcare facilities leads to serious issues in managing affected patients. It became the need of the hour to accurately forecast the new and recovered cases for the optimal utilization of healthcare resources in order to contain the spread of this infection. Various studies were performed that suggested forecasting of COVID-19 cases using deep learning techniques. In this paper, we have identified and performed a comprehensive analysis of the articles proposed to predict COVID-19 cases using various techniques.

The literature review performed has the following objectives:

Objective 1: To recognize and describe the studies performed in forecasting COVID-19 cases.

Objective 2: To characterize and classify various proposed models in terms of techniques adopted.

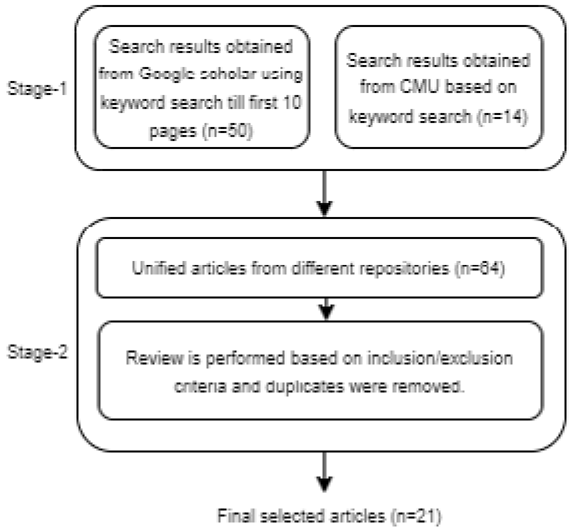
Objective 3: To suggest future research direction.

2. Bibliographic Search Process

In order to perform a comprehensive literature survey, a two-step literature search process is adopted. Figure 2 outlines the process undertaken for the search and selection of articles considered in this study for review.

Stage-1: In the first stage, a systematic search was performed on two popular databases i.e. Google Scholar and CMU in order to extract research articles using search keywords in combination like "COVID-19", "deep learning", "prediction", and "number of cases". Studies with the objective to predict COVID-19 cases using deep learning techniques were extracted from search results. The count of articles found in the two databases with the above-mentioned search criteria is listed in Table 1. In Google Scholar, the search was conducted using the filter option "since 2020" using the search string "COVID-19 deep learning prediction number of cases" for any language and with the selection of option called "not including patents". The search results were extracted from first 5 pages and 50 articles were obtained through this database. Similarly, through CMU, the articles were searched using advance search option with similar combination of keywords. The search was performed choosing search "everything" for a period from January, 01, 2020 to August 01, 2021, for any

Fig.2. Bibliographic Search Process



language and 14 search results were obtained. A total of 64 research articles were extracted after stage-1from from both repositories.

Stage-2: A review process was conducted on the articles extracted from stage-1. Abstracts of the articles obtained were thoroughly analysed. Relevant articles on prediction of COVID-19 cases using deep learning techniques were selected and duplicates were discarded. After the screening process, we are left with 21 articles for review in this study. The significant aspects in each and every article in this review were identified. Articles were characterised and compared on the basis of the methodology adopted, dataset used, geographical location of study, and performance.

Inclusion Criteria: The Inclusion criterion to include an article in this review is as follows:

IC1: All searched articles on forecasting COVID-19 cases using deep learning methods are considered.

IC2: Articles published from January 01, 2020 till August 01, 2021 are included.

IC3: Articles of all languages are considered.

Exclusion Criteria: Following criteria is used to exclude any article from the analysis

EC1: Articles that do not include the keywords such as “COVID-19”, “prediction”, “deep learning”, and “number of cases”.

The paper is further structured as follows. Section 3 visits each of the paper considered under this review and presents insights of the work done in these. Section 4 discusses the categorisation of modelling techniques. Section 5 presents the conclusion and future scope. Section 6 lists all the references used in this study.

CATEGORISATION OF MODELLING TECHNIQUES

To model the spread and to forecast the number of infected cases, its peaks, and slowdowns for effective understanding and efficient management of resources, numerous models have been proposed in the literature. In order to effectively understand the model architecture and performance, a deep understanding of the forecasting techniques used is paramount. In this paper, we have classified the forecasting models proposed in the literature into the following four broad categories based on the underlying techniques used in prediction.

- ***Compartmental Models:*** Epidemiological mathematical modelling techniques classify the population into compartments with labels where people may progress between compartments. The progression among compartments is studied and the order of labels denotes the flow. These kinds of models are useful in analysing disease progression by computing reproduction number $R_{0.}$ The most common examples are SIR (susceptible-infected-recovered), .The success of compartmental models extensively depends on selecting the right model based on relevant assumptions in the context of actions taken by nations to contain outbreaks and thus involve lots of uncertainties. Due to a high degree of complexity involved in the advancement of epidemiological models, other COVID-19 forecasting techniques were also explored by researchers.

- ***Statistical Time Series Models:*** Statistics based approaches are well adopted in time-series forecasting. Auto-regressive moving average (ARIMA) has been employed in epidemiological modelling by researchers in prediction of future values by capturing auto-correlation between previous values. Exponential smoothing methods like Holt trend model also performs well in time series forecasting. Prophet algorithm is another technique for time series forecasting that works well in case of missing values in the data.

- ***Machine Learning Models:*** To obtain better performance than statistical models, several models based on machine learning algorithms have been also used for making predictions on COVID-19. Support vector machine (SVM) employ kernel functions for non-separable classes and is extensively used to minimize error margin. Polynomial regression and multi-linear regression are also some of the machine learning approaches employed in COVID-19 forecasting.

- ***Deep Learning Models:*** Artificial neural networks were exploited for their capabilities to represent complex relationships. Recurrent neural networks with capability to capture historical dependencies using network loops are employed for short-term forecasting. Long short-term memory (LSTM) overcomes the drawback of RNN and is used widely for long-term forecasting. Stacked LSTM with multiple LSTM layers is explored for deeper representations by introducing various gating structures. Bidirectional LSTM (Bi-LSTM), Convolutional LSTM (Conv-LSTM) are some other variants of LSTM employed in prediction modelling.

Figure 3. depicts the classification of COVID-19 forecasting techniques used in the contributions reviewed in this study. Table 1 briefly describes the strengths and weaknesses of each of the techniques used for COVID-19 forecasting in the articles considered in the present study.

Table.1. Forecasting Techniques: Strengths & Weaknesses

S.No	Algorithm	Strength	Weakness
1.	Support Vector Machine	Works well for high-dimensional data. Error tolerance can be defined using error margin	Not suitable for large datasets

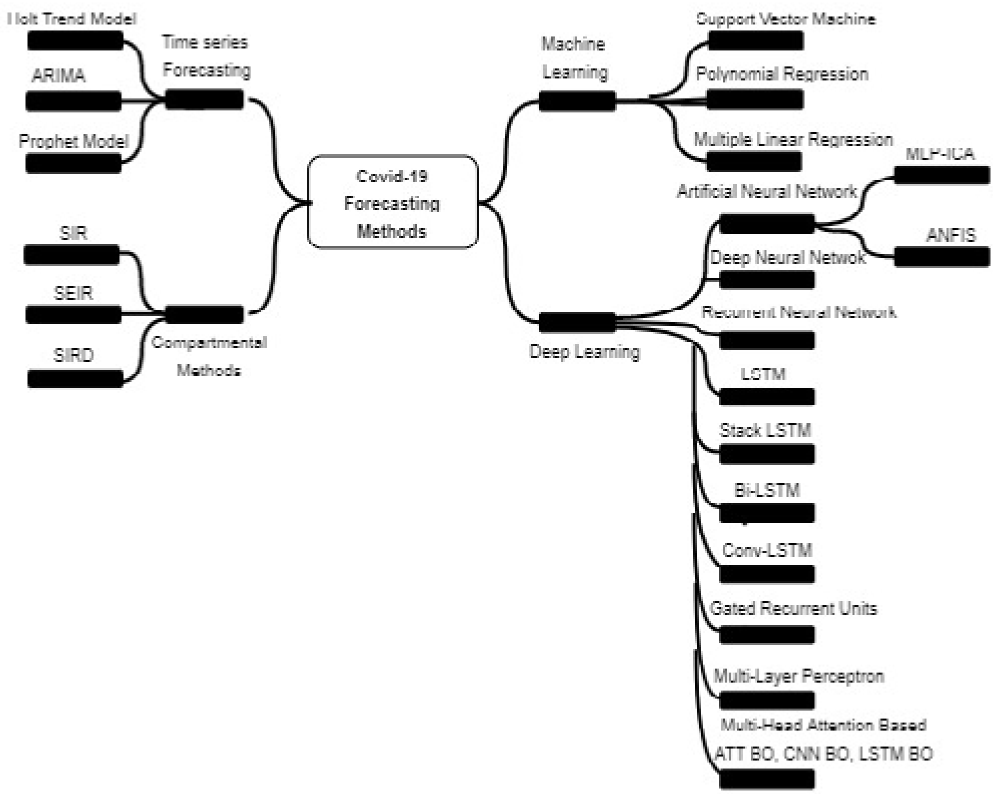
2.	Polynomial Regression	Fits a wide range of curvatures to find the best relationship between dependent and independent variables	Sensitive to outliers
3.	Multiple Linear Regression	Good for detecting outliers	Affected by outliers since it assumes linear relationship
4.	Artificial Neural Network	Robust to noise in the training data	Might be overtrained, poor interpretability
5.	Recurrent Neural Network	Remembers the previous information, helps in time series forecasting	Prone to gradient vanishing
6.	Long Short Term Memory	Capable of learning long-term dependencies	Sensitive to random weight initializations
7.	Stack LSTM	Makes the LSTM model deeper to achieve better accuracy	Prone to overfitting
8.	Bi-LSTM	Solves the problem of fixed sequence to sequence prediction	Computationally expensive
9.	Auto encoders	Capable of learning smooth latent state representations of the input data	Generate blurry outputs sometimes
10.	Multilayer Perceptron	Can be applied to complex non-linear problems	Computationally expensive and time consuming
11.	Attention Models	Ability to selectively focus on segments of the sequence	Long training time
12.	ARIMA	Can work for seasonal as well as non-seasonal data	Any change in observation makes model unsuitable
13.	Holt Trend Model	Level and trend can be smoothed with different weights	Requires two parameters to optimize
14.	Prophet algorithm	Robust to missing values	Unsuitable for multiplicative models
15.	Compartmental Models (SIR, SEIR, SERD)	Depicts effects of public health interventions	Requires huge amount of data

FORECASTING MODELS REVIEW

This section discusses and summarizes the proposed work in each of the selected contributions. Table 2 contrasts each study on parameters like purpose of study, forecasting techniques used, data source, forecasting horizon, and result obtained. The proposed work in each of the contributions is summarized as follows:

- Santosh (2020) classified forecasting models available in literature into three broad categories namely SEIR/SIR, agent based, and curve-fitting models. It was suggested that predictions from such models deviate from intended values due to certain crucial and unprecedented factors like population density, test capacity, hospital capacity, demographics, and vulnerable people. This study emphasised on the incorporation of these continuous and important factors in data-driven models which can automatically tune parameters over time.
- To understand COVID-19 disease progression under the effect of lockdown, Das (2020) developed the epidemiological SIR model for the estimation of basic reproduction number R_0 and prediction of peak. Further for short and medium-term predictions statistical machine learning (SML) model is also developed. Analysis suggested the early disease progression of India is similar to that of China.
- Rahmadani and Lee (2020) proposed a hybrid framework with an epidemic model and deep learning model. An expanded SEIR compartmental model incorporating human mobility as parameter was presented. Since the performance of epidemic models depend on the accuracy of estimated parameters, deep learning was applied for parameter estimation.
- Rahimi, Chen, & Gandomi (2021) reviewed and analysed important COVID-19 forecasting models. The important criteria and research gaps in COVID-19 forecasting were identified and highlighted to aid future research.

Fig.3. Forecasting models categorisation



- Devaraj (2021) focuses on comparative analysis of medium term predictions (infected individuals, number of deaths and number of recovered cases) using prediction models such as ARIMA, LSTM, Stacked LSTM. These models were also applied for global, country, and city specific forecast and analysed in detail. To determine the best model, statistical significance analysis was also conducted. Experimental results indicated that stacked LSTM performed best out of all models for predicting future confirmed, recovered, and death cases.
- Deng (2020) proposed an enhanced compartmental model that uses deep learning techniques in estimation of transition parameters as an alternative to stochastic parameterization to reduce data dependency. Results proved the usefulness of deep learning techniques in epidemic modelling.
- Ayyoubzadeh et al. (2020) tried to predict the incidence of COVID-19 in Iran using

data mining models built with Google search data. Linear regression and 3-layer LSTM based models were employed to estimate daily COVID-19 cases. Through results, it was indicated that data mining algorithms can be used to forecast the trends of the outbreaks which may serve as important information for policy makers and health care managers to appropriately plan usage of available resources.

- Punn et al. (2020) presented machine learning and deep learning based models to predict number of cases for the next 10 days. The models have been trained using data from John Hopkins dashboard. The experimental results depicted that polynomial regression showed least root mean square error over support vector regression, deep learning regression, and recurrent neural network using long short-term memory cells.

- Aldhyani et al. (2020), in their study presented LSTM and Holt-trend model for forecasting confirmed cases and deaths cases of three countries, namely South Africa, Spain, and Italy. Prediction results demonstrated that LSTM and Holt-trend based models performed satisfactorily and can be employed for COVID-19.

- Wang et al. (2020), performed long term epidemic trend modelling adopting LSTM with rolling update mechanism. On contrary to existing epidemic models which only capture the rising trends in epidemic, this study models daily confirmed number of cases. Diffusion Index is used to analyse the effects of preventive measures like social exclusion and lockdown on the COVID-19 epidemic.

- Shahid et al. (2020), modelled COVID-19 dataset using statistical, machine learning and deep learning techniques like ARIMA, SVR, LSTM, and Bi-LSTM for forecasting confirmed cases, deaths and recoveries of ten countries hit by COVID-19. Experimental demonstration suggested LSTM, GRU, and Bi-LSTM have shown robust predictions. However, Bi-LSTM performed best among all on error measures.

- Elsheikh et al. (2021) proposed a multi-day-ahead LSTM deep learning model for the prediction of confirmed cases, recovered cases, and deaths training models on data for two different periods of 91 days and 199 days each. LSTM performed better as compared to NARANN and ARIMA.

- Arora et al. (2020) proposed RNN and LSTM based deep learning models for COVID-19 forecast, thereby facilitating the categorization of states into mild, moderate and severe zones. On 32 states/UTs, different LSTM variants—including stacked, convolutional, and bi-directional LSTM—are used, and daily and weekly predictions are computed. Results suggested that bi-directional LSTM was accurate for short term predictions.

- Abbasimehr and Paki (2020) proposed three hybrid approaches (multi-head attention based ATT_BO, CNN-based CNN_BO, and LSTM-based LSTM_BO method) for forecasting number of infected daily cases for multiple days based on deep learning techniques combined with Bayesian optimization for optimal parameter selection. These multi-output models can be used for short as well as long term forecasting. Experimental results proved that for short term forecasting three models outperformed benchmark fuzzy fractal model (Castillo & Melin, 2020) in 6 out of 10 countries and for long term forecasting LSTM_BO performed better than ANN_BO and CNN_BO.

- Zeroual et al. (2020) presented comparative forecasting of five deep learning based confirmed and recovered cases forecasting models on data collected from six countries namely Italy, Spain, France, China, USA, and Australia. Results indicated Variational Auto Encoder based model exhibited better performance than other NN-based models including RNN, GRU, LSTM, and Bi-LSTM.

- Huang et al. (2020), suggested a multi-input CNN based model to forecast cumulative number of cases for the next day on the basis of previous five days' data of total confirmed cases, total confirmed new cases, total cured cases, total cured new cases, total deaths and total new deaths. The results demonstrated that CNN model has shown the best performance over other deep learning based models like GRU, MLP, and LSTM. The results also suggested that initial characteristic extraction through CNN and subsequent input of those characteristic values to CNN significantly aid in forecasting COVID-19 confirmed number of cases.

- Ayoobi et al. (2021) examined six deep learning methods namely LSTM, Convolutional LSTM, GRU and each of these in Bi-directional mode to forecast the new cases and new death rate time series for Australia and Iran. Results proved that bi-directional methods are superior.

- Direkoglu and Sah (2020) presented a deep learning model based on a deep neural network architecture consisting of an LSTM layer, a drop out layer and fully connected layers to forecast regional and worldwide possible spread of COVID-19. Their work was an attempt to model COVID-19 spread prediction on the basis of number of reported cases with a deep learning approach. Results found to be promising in COVID-19 prediction.

- Chen et al. (2021) performed multivariate LSTM modelling with different architectures for forecasting COVID-19 time series 1/2/3 days ahead. Multivariate LSTM outperformed univariate counterparts for 1-day ahead predictions of incident cases, total cases, and new death whereas univariate LSTM has shown better results for 2-day and 3-day ahead predictions. In addition to this, more complex LSTM architecture does not depicted any prediction superiority over less complex one.

- Pinter et al. (2020) suggested a hybrid machine learning model of MLP-ICA and ANFIS for forecasting COVID-19 outbreak in Hungary. Based on the results, machine learning could be considered a potential technology to model the outbreak and total mortality.

- Yu et al. (2021) developed an online COVID-19 pandemic AI System (CPAIS) to evaluate COVID-19 disease trend and thus facilitate its forecasting integrating data of 171 countries. This system was based on time series deep learning and statistical models. LSTM demonstrated better forecast for most countries as compared to other models.

CONCLUSION AND FUTURE SCOPE

COVID-19 suddenly posed a life-threatening situation in the world within a few months of its outbreak in China. Several studies were conducted to understand the spread progression, prediction of peaks, daily new cases, deaths, recovered cases, etc. to understand the future situation. The practical significance of these forecasts lies in planning optimal usage of healthcare resources with the objective to save lives. Numerous models have been proposed in the literature for COVID-19 forecasting. The present study reviews and analyses important COVID-19 forecasting models proposed in the literature. A table summarizing each article considered under this review is presented. The study proposed a categorization of forecasting models based on the underlying forecasting techniques adopted. Due to the high amount of uncertainties in model parameters and the availability of limited data, sometimes models deviate significantly from the expected values. The performance of one model may vary drastically from one region to another. Therefore it is important that forecasting models consider these factors. Since, the COVID-19 pandemic is still ongoing, and therefore the datasets are either limited or incomplete. The preventive measures like social distancing, quarantine rules, etc. adopted by the administration also play a critical role in the containment of spread and thus need to be considered while designing forecasting models. In future, the availability of datasets with more data will lead to improvement in the prediction capabilities of models. Machine learning and deep learning based models, when developed with robust data were found to be performing well in many studies reviewed in this paper. This paper provides useful insights of models proposed in literature for COVID-19 forecasting. In future, more accurate forecasting models can be proposed combining different techniques and incorporating significant parameters. Also, the performance of models can be enhanced with the incorporation of advanced optimization approaches.

Table. 2. Summary of existing work on COVID-19 prediction

Paper title	Forecasting method proposed/ discussed	Forecasting horizon	Type of data and sample size	Data source	Results	Purpose of study	Model category
COVID-19 prediction models and unexploited data. (Santosh, 2020)	SEIR/ SIR, agent based, and curve fitting models	-	-	-	Categorization of COVID-19 forecasting models presented. Also, importance of incorporation of continuous and unprecedented factors in models is discussed.	To emphasise the incorporation of important and continuous factors like a hospital setting, test capacity, demography, population density, and vulnerable people in COVID-19 prediction modelling.	-
Prediction of COVID-19 disease progression in India: Under the effect of national lockdown. (Das, 2020)	SIR, Statistical machine learning model	Next few days ahead forecast	Daily level cases and Testing rates of each of the Indian states before April 7, 2020 along with Hubei/ China	John Hopkins University, COVID-19India, Kaggle-COVID-19	With R_0 value similar to china, disease progression of initial stage in is comparable to China. State wise R_0 values are discussed.	To understand the severity of disease spread on ground and predict disease progression in India using the SIR and SML model	Compartmental, Machine learning

Hybrid deep learning-based epidemic prediction framework of COVID-19:south Korea case. (Rahmadani & Li, 2020)	SEIR, Meta-Population Model, DNN, LSTM	Next few days ahead forecast	Seoul: From March 12, 2020 to August 14, 2020. Daegu: April 8, 2020 to September 4, 2020.	Korea Centers for Disease Control and Prevention (KCDC)	Proposed hybrid deep learning model considering human mobility found to be effective in forecasting.	To propose a hybrid deep learning framework with the susceptible-exposed-infected-recovered (SEIR) meta-population model and LSTM for estimating transmission patterns in South Korea.	Deep Learning and Compartmental
A review on COVID-19 forecasting models. (Rahimi et al., 2021)	SER, SEIR, SIRD, Phenomenological models, ANN, SVM, ARIMA, Prophet algorithm	-	920 technical research articles published as of October 10, 2020.	Web of Science (WOS) and Scopus	Deep learning, SIR, and SEIR were the approaches that researchers most frequently utilised while studying epidemic models. Additionally, hybrid algorithms are used to improve the predictive capability of models.	To review the most important forecasting models for COVID-19	Machine Learning, Deep Learning, Time Series and Compartmental

Forecasting of COVID-19 cases using deep learning models: Is it reliable and practically significant? (Devaraj et al., 2021)	ARIMA, LSTM, SLSTM, Prophet model	30, 60, and 90 days ahead forecast	Time series data of global cases: January 22, 2020 to May 8, 2020, Simulated dataset for correlation analysis, and Combined time series dataset for multivariate analysis- January 22, 2020-November 17,2020.	Center for Systems Science and Engineering (CSSE) at Johns Hopkins University, World weather page and Wikipedia page.	The stacked LSTM model gave the best accuracy	To analyse the role of deep learning in COVID-19 forecasting using ARIMA, LSTM, SLSTM, and Prophet models globally, country-wide and in city-specific manner.	Deep Learning and Time Series
Dynamics and development of the COVID-19 epidemic in the united states: a compartmental model enhanced with deep learning techniques. (Deng , 2020)	SIRD, DNN, RNN-LSTM	Next 35 and 42 days forecast	Daily records (confirmed, active, dead, recovered, hospitalized etc.) from April 2020. Two time series tracking confirmed and dead cases both starting from January 22, 2020.	Center for Systems Science and Engineering (CSSE) at Johns Hopkins University.	An effective and easy to implement alternative to stochastic parameterization is proposed with deep learning-enhanced compartmental model.	To develop an enhanced compartmental using multistep, multivariate deep learning methodology to estimate transmission parameters and thereby reducing dependency on data to a great extent.	Deep Learning and Compartmental

Predicting COVID-19 incidence through analysis of google trends data in iran: data mining and deep learning pilot study. (Ayyoubzadeh et al., 2020)	Linear Regression and LSTM	Next few days forecast	Number of COVID-19 cases in Iran from February 15, 2020, to March 18, 2020, Google Trends data for various concepts from February 15, 2020, to March 18, 2020	Worldometer Website, Google Trends Data.	Data mining based forecasting models can be considered to predict trends of disease.	To predict incidence of COVID-19 in Iran using data mining methods and deep learning techniques.	Machine Learning and Deep Learning
COVID-19 Epidemic Analysis using machine Learning and Deep Learning Algorithms. (Punn et al., 2020)	SVR, PR, DNN, RNN, LSTM	10 days ahead forecast	Time-series of confirmed, death, and recovered cases from January 22, 2020, to April 1, 2020	Official Repository of John Hopkins University	Polynomial Regression outperformed other approaches on least root mean square error value.	To propose models based on machine learning and deep learning approaches with the objective to study the transmissibility of COVID-19 and predict its future trends	Machine Learning and Deep Learning

Deep Learning and Holt-Trend Algorithms for Predicting COVID-19 pandemic. (Aldhyani et al., 2020)	LSTM and Holt Trend Model	30 days ahead forecast	The confirmed and death cases data of 85 days between January 21, 2020 and April 15, 2020.	Datasets from WHO for three countries namely South Africa, Italy, and Spain	LSTM gave the best results for confirmed cases. On the other hand, Holt Trend model performed better for death cases prediction. Also, results indicated that proposed models showed efficient performance to predict COVID-19 cases.	To predict number of COVID confirmed and death cases using deep learning algorithms and Holt-Trend models.	Deep Learning and Time Series
Time series prediction for the epidemic trends of COVID-19 using the improved LSTM deep learning method: Case studies of Russia, Peru and Iran. (Wang et al., 2020)	LSTM	Next 150 days forecast	Data on COVID-19 from January 22, 2020 to July 7, 2020.	John Hopkins University	Proposed model based on LSTM with rolling update mechanism for long-term predictions found to be consistent with daily cases. Preventive measures adopted by government are found to be effective.	To model the epidemic trend of COVID-19 by using LSTM networks and rolling update mechanism by feeding new forecasting results into model training for the next iteration for Russia, Peru, and Iran.	Deep Learning

Predictions for COVID-19 with deep learning models of LSTM, GRU and Bi-LSTM. (Shahid et al., 2020)	ARIMA, SVR, LSTM, GRU, and Bi-LSTM	Next 48 days forecast	The number of confirmed cases, deaths, and recovered cases of 158 samples of 10 countries from January 22, 2020 to October 5, 2020	Harvard Dataverse	Bi-LSTM gave the best accuracy.	To compare the prediction models from statistics, machine learning, and deep learning on COVID-19 dataset for ten countries	Deep Learning and Time Series
Deep learning-based forecasting model for COVID-19 outbreak in Saudi Arabia. (Elsheikh et al., 2021)	LSTM	Next 10 days forecast	The total number of cases from March 2, 2020 to May 31, 2020, and from March 2, 2020 to September 15,2020, and from 1 January to 10 October 2020.	Saudi ministry of health	The LSTM model gave the best accuracy as compared to NARANN and ARIMA.	To use LSTM to forecast the number of total confirmed cases, total recovered cases, and total deaths in Saudi Arabia.	Deep Learning
Prediction and analysis of COVID-19 positive cases using deep learning models: a descriptive case study in India. (Arora et al., 2020)	RNN, LSTM, Deep LSTM / Stacked LSTM, Conv-LSTM, Bi-LSTM	Next few days ahead forecast	32 individual time-series data of confirmed COVID-19 cases in each of the states (28) and union territories (4) from March 14, 2020, to May 14, 2020	Ministry of Health and Family Welfare (Government of India)	Bi-directional LSTM exhibited best performance for short-term predictions.	To employ deep learning-based models for predicting the number of COVID-19 cases for 32 states/ union territories of India.	Deep Learning

Prediction of COVID-19 Confirmed Cases Combining Deep Learning Methods and Bayesian Optimization. (Abbasimehr & Paki, 2020)	Three hybrid models of deep learning combining Bayesian Optimization namely Multi-head attention based ATT_BO, Convolutional Neural Network based CNN_BO, and Long short-term memory based LSTM_BO.	10 days ahead forecast for short horizon whereas, more days for long horizon	COVID-19 Data of US, UK, Turkey, Spain, Mexico, Italy, Iran, Germany, France, Belgium from January 20, 2020, to August 1, 2020. COVID Data of US, Brazil, India, Russia, Africa, Mexico, Peru, Chile, Columbia, Iran from January 20, 2020, to August 3, 2020	Two datasets from Humanitarian Data Exchange (HDX).	Deep learning models proved to be superior than benchmark models for both long-term as well as short-term forecasting. LSTM_BO achieves the lowest RMSE among all models in longer forecasting horizon.	To predict the number of daily COVID-19 infected cases using deep learning methods along with Bayesian optimization for optimal parameter selection	Deep Learning
Deep learning methods for forecasting COVID-19 time-series data: A comparative study. (Zeroual et al., 2020)	RNN, LSTM, Bi-LSTM, GRU, and VAE	Seventeen days ahead forecast	Data of Spain, Italy, China, the USA, and Australia from the starting of COVID-19 till June 17th, 2020.	John Hopkins University	Results demonstrated that VAE outperformed all other methods.	To present a comparison among five deep learning forecasting.	Deep Learning

Multiple-input deep convolutional neural network model for COVID-19 forecasting in china. (Huang et al., 2020)	Multi-input CNN	Next day forecast	Datasets of COVID-19 cases from January 23, 2020, till March 2, 2020, from Hubei China province	Surging News Network (SNN) and WHO	CNN gave the best accuracy over other deep learning based counterparts.	To make a deep learning model with a small dataset in order to make it an important reference for other countries in their containment of the COVID-19 epidemic.	Deep Learning
Time Series Forecasting of New Cases and New Deaths Rate for COVID-19 using Deep Learning Methods. (Ayoobi et al., 2021)	LSTM, Bi-LSTM, Conv-LSTM, Bi-Conv-LSTM, GRU, Bi-GRU	Next 7 days forecast	COVID data of Australia and Iran. For Australia, from January 25, 2020, to August 19, 2020, and from January 3, 2020, to October 6, 2020 for Iran	WHO	Bi-directional models performed better.	To predict COVID cases and death rate using deep learning and their bi-directional models.	Deep Learning
Worldwide and Regional Forecasting of Coronavirus (COVID-19) Spread using a Deep Learning Model. (Direkoglu & Sah, 2020)	Long Short Term Memory (LSTM)	Next 10 days forecast	Time series COVID -19 data of China from January 10, 2020 to April 3,2020 and COVID Data of Europe and the Middle East from 17 January 2020 to 3 April 2020	Chinese Centre for Disease Control and Prevention, World Health Organization	Proposed approach is found to be promising for forecasting COVID-19 spread.	To design a deep learning network based model for COVID-19 forecasts of China, Europe and Middle and worldwide.	Deep Learning

Exploring Feasibility of Multivariate Deep Learning Models in Predicting COVID-19 Epidemic. (Chen et al., 2021)	One-encoder, one-decoder LSTM(E1D1) and two-encoder two-decoder LSTM (E2D2)	Next 1/2/3 days ahead forecast	Data of Hubei Province, China from January 25, 2020 to May 15, 2020.	Official Hubei Province COVID-19 press release	Univariate LSTM outperformed multivariate LSTM in forecasting new case, total case, and new death for 2 day and 3 day ahead whereas multivariate LSTM performed better for 1 day ahead forecasts. More complex architecture in multivariate LSTM did not exhibited any prediction superiority.	To explore the feasibility of data-driven DL Models, like multivariate LSTM on characterizing the COVID-19	Deep Learning
COVID-19 pandemic prediction for Hungary; a hybrid machine learning approach. (Pinter et al., 2020)	Two robust hybrid methods of ANN algorithm, i.e., Multi-layer perceptron-imperialist competitive algorithm (MLP-ICA) and Adaptive network-based fuzzy inference system (ANFIS).	Next 9 days ahead forecast	Statistical reports of COVID-19 cases and mortality rate of Hungary from 4 March, 2020 to 28 April, 2020	Worldometer website	Both models demonstrated potential in COVID-19 forecasting. MLP-ICA outperformed ANFIS with more accurate results.	To improve the quality of prediction by proposing hybrid machine learning approach for COVID-19 prediction	Deep Learning (Hybrid Models of ANN)

A COVID-19 Pandemic Artificial Intelligence-Based System With Deep Learning Forecasting and Automatic Statistical Data Acquisition: Development and Implementation Study. (Yu et al., 2021)	ARIMA, Feedforward neural network(FNN), Multilayer Perceptron Neural Network, LSTM	Next 14-day forecast	The COVID-19 Data Repository established by John Hopkins University Center for Systems Science and Engineering(CSSE) contains data of 192 countries since January 21,2020. Oxford COVID-19 Government Response Tracker (OxCGRT) contains data of 183 countries from January 1,2020.	Oxford COVID-19 government response tracker (OxCGRT) maintained by University, COVID-19 repository established by John Hopkins University Center for Systems Science and Engineering.	LSTM demonstrated better forecast for most countries as compared to other models.	To develop a COVID-19 Pandemic Artificial Intelligence-based System (CPAIS) to track variations, trends and forecasts related to COVID -19 across 171 countries.	Deep Learning and Statistical

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