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## Review article

## Application of machine learning in the prediction of COVID-19 daily new cases: A scoping review

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## ABSTRACT

COVID-19 has produced a global pandemic affecting all over of the world. Prediction of the rate of COVID-19 spread and modeling of its course have critical impact on both health system and policy makers. Indeed, policy making depends on judgments formed by the prediction models to propose new strategies and to measure the efficiency of the imposed policies. Based on the nonlinear and complex nature of this disorder and difficulties in estimation of virus transmission features using traditional epidemic models, artificial intelligence methods have been applied for prediction of its spread. Based on the importance of machine and deep learning approaches in the estimation of COVID-19 spreading trend, in the present study, we review studies which used these strategies to predict the number of new cases of COVID-19. Adaptive neuro-fuzzy inference system, long short-term memory, recurrent neural network and multilayer perceptron are among the mostly used strategies in this regard. We compared the performance of several machine learning methods in prediction of COVID-19 spread. Root means squared error (RMSE), mean absolute error (MAE),  $R^2$  coefficient of determination ( $R^2$ ), and mean absolute percentage error (MAPE) parameters were selected as performance measures for comparison of the accuracy of models.  $R^2$  values have ranged from 0.64 to 1 for artificial neural network (ANN) and Bidirectional long short-term memory (LSTM), respectively. Adaptive neuro-fuzzy inference system (ANFIS), Autoregressive Integrated Moving Average (ARIMA) and Multilayer perceptron (MLP) have also have  $R^2$  values near 1. ARIMA and LSTM had the highest MAPE values. Collectively, these models are capable of identification of learning parameters that affect dissimilarities in COVID-19 spread across various regions or populations, combining numerous intervention methods and implementing what-if scenarios by integrating data from diseases having analogous trends with COVID-19. Therefore, application of these methods would help in precise policy making to design the most appropriate interventions and avoid non-efficient restrictions.

## 1. Introduction

The novel coronavirus disease initiated in the late 2019 (COVID-19) is resulted from the infection with the severe acute respiratory syndrome-coronavirus 2 (SARS-CoV-2) [1]. Since late 2019, it has spread globally, leading to a persistent pandemic. COVID-19 spread is dependent on inter-individual close contacts and transmission of breath droplets. Prediction of the rate of COVID-19 spread and modeling of its course have critical impact not only for health systems

but also for policy makers. In fact, policy making relies on discernments formed by prediction models to propose new strategies and to measure the efficiency of the imposed policies. Based on the nonlinear and complex nature of this disorder [2] application of artificial intelligence methods is an appropriate alternative to traditional epidemic models for prediction of its spread. Although some traditional epidemic models such as Susceptible-Exposed-Infective-Recovery has been used for prediction of epidemic course [3], these methods have some limitations. For instance, the validity of the

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Susceptible-Exposed-Infective-Recovery model relies on precise appraisal of virus transmission features including the basic reproductive quantity  $R_0$  as well as incubation and infectious periods which are rather difficult to be estimated in real contexts [4]. Figure 1 shows the role of artificial intelligence approaches for prediction of COVID-19 spread.

Machine learning methods usually use data sequences retrieved over a period of time as inputs to predict course of COVID-19 epidemic. Several strategies have been implemented for prediction of COVID-19 spread. Among the applied strategies is the Long short-term memory (LSTM) model. For instance, Multilayer perceptron (MLP) has also been applied for modeling of COVID-19 spread. This method has facilitated prediction of the highest number of persons who are affected by COVID-19, the highest number of people who recovered, and the highest number of mortalities per place in each time division [5]. LSTM with the Natural language processing (NLP) module has been used to assess the infection frequency and enhance the predictive accuracy of the model [6]. LSTM can efficiently improve gradient explosion and gradient disappearance in the course of the training process by presenting the constant error

carousel unit [6]. LSTM is superior to the traditional Recurrent neural network (RNN) in term of its good enactment in apprehending the long-term dependency of sequences, thus being appropriate for the categorization, processing, and forecasting the long sequence data [7]. Based on the importance of machine and deep learning methods in the prediction of COVID-19 spreading trend, in the current study, we reviewed studies which used these strategies to envisage the number of new cases of COVID-19. The research question was: "What are the applications of machine learning systems and their performances in the prediction of COVID-19 daily new cases?". In the current study we were looking for publications that evaluate the performance of any machine learning or deep learning approaches based on the research question inclusion and exclusion criteria.

The following parameters were extracted: Root means squared error (RMSE), Mean absolute error (MAE),  $R^2$  coefficient of determination ( $R^2$ ), and Mean absolute percentage error (MAPE). These parameters are the main parameters which are applied to assess the error rates of forecasting and performance of the model in regression analysis. MAPE is calculated based on percentage errors.

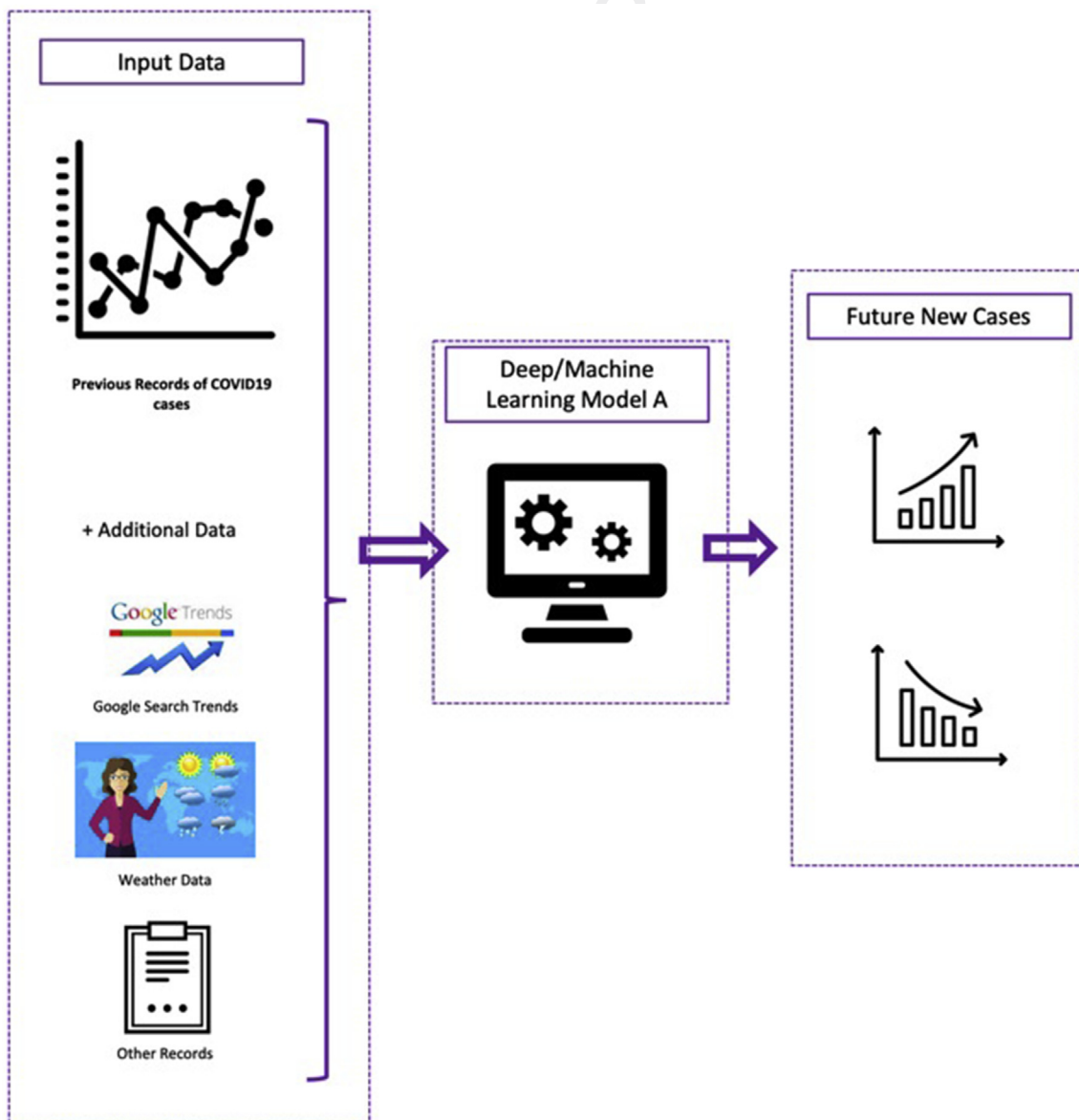


Figure 1. The role of artificial intelligence approaches for prediction of COVID-19 spread.

## 2. Materials and methods

We used PRISMA Scoping review guidelines and checklist.

### 2.1. Protocol

Reporting this scoping review is based on Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for scoping reviews [8].

### 2.2. Exclusion criteria

- 1) Studies that did not report or evaluate their prediction regarding the daily confirmed cases or cumulative number of confirmed cases.
- 2) Studies that did not report at least one of the Root means squared error (RMSE), Mean absolute error (MAE),  $R^2$  coefficient of determination ( $R^2$ ), and Mean absolute percentage error (MAPE) in their measurements.

### 2.3. Information sources and search

An electronic search was conducted in PubMed, Google Scholar, Scopus, Embase, arXiv, and medRxiv for finding the relevant literature from January 2020, to June 2021. Different combinations of the following keywords were used in the search procedure: “machine learning”, “deep learning”, “neural network”, “artificial intelligence”,

“Covid-19”, “incidence”, “prevalence”, “spread\*”, “new cases”, “predict\*”, and “forecast\*”.

### 2.4. Selection of sources of evidence

Duplicate studies were removed. Studies that were cited within the retrieved papers were reviewed for finding any missing studies. For identifying the proper journal papers and conference proceedings, our team members screened the title and abstracts based on inclusion and exclusion criteria independently. Finally, considering the inclusion and exclusion criteria, investigators identified the eligible publications in this stage independently. Figure 2 illustrates the flowchart of the protocol of systematic literature review.

### 2.5. Data charting process

Two investigators were responsible for extracting the data, separately. The charting process was followed by consensus to resolve any disagreements.

### 2.6. Data items

For the selected studies, the following data have been extracted: regions (e.g., countries, states, etc), data source, data structure, machine learning model and model performance including RMSE, MAE,  $R^2$ , MAPE (on the basis of the best model). These performance measures were

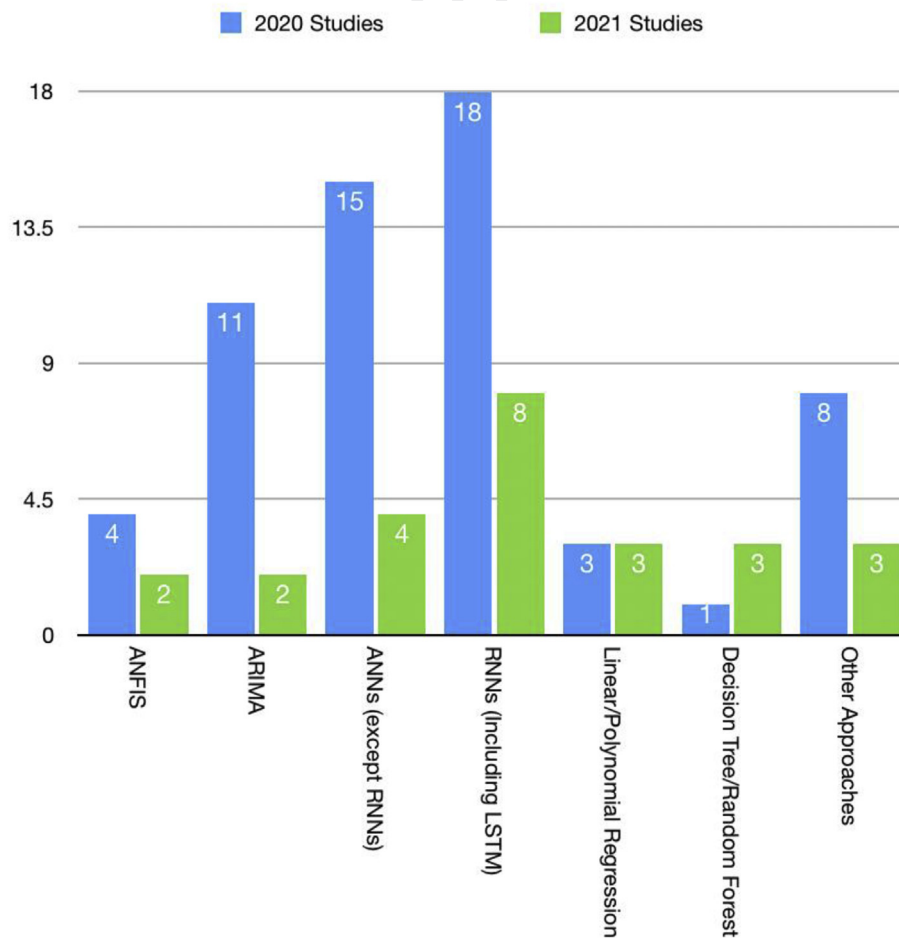


Figure 2. The flowchart of the protocol of systematic literature review.

selected, since they are the most common performance measurement among the selected studies.

### 3. Results

Several artificial intelligence strategies have been used for prediction of COVID-19 spread using different models (Figure 3).

#### 3.1. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is a type of artificial neural network being founded on Takagi–Sugeno fuzzy inference system. Architecture of ANFIS has five layers, namely fuzzification layer, the layer which generates the firing strengths for the rules (rule layer), the layer that normalizes the computed firing strengths, the layer which receives as input the normalized values and the consequence parameters, and the layer that returns the final output [9]. Al-Qanes et al. [10] have designed an upgraded kind of the ANFIS model to estimate the quantity of infected persons in four countries, namely Italy, Iran, Korea, and the USA. Their model has been founded on a novel nature-inspired optimizer, namely the marine predators algorithm (MPA). This algorithm has optimized the ANFIS variables, increasing its predicting performance. They have shown superiority of the MPA-ANFIS method to previously suggested predicting models in terms of better values for RMSE, MAE, MAPE, and  $R^2$  [10]. In another study, ANFIS was boosted using an improved flower pollination algorithm (FPA) by using the salp swarm algorithm (SSA). The suggested FPASSA-ANFIS model was then appraised using the official data

retrieved from WHO site. Moreover, the accuracy of the suggested model was then appraised using two distinct datasets of weekly influenza cases [11]. Alsayed et al. [12] have predicted the epidemic peak in Malaysia using the Susceptible-Exposed-Infectious-Recovered (SEIR) model. They have also used the ANFIS model short-time prediction of the amount of infected individuals. They have also demonstrated the impact of interventions on postponing the epidemic peak. Moreover, they have suggested that extension of the intervention period might decrease the epidemic magnitude at the peak. This study has reported RMSE,  $R^2$  and MAPE values as 46.87, 0.9973 and 2.79, respectively [12]. Thus, this study has reported the best performance measurements using this method. Behnood et al. [13] have used an integration of the virus optimization algorithm (VOA) and ANFIS to appraise the impact of numerous climate-associated parameters and population density on COVID-19 spread. They have demonstrated the remarkable influence of population density on the performance of their designed models, emphasizing on the prominence of social distancing in decreasing COVID-19 infection rate and spread. RMSE, MAE and  $R^2$  values have been reported to be 22.47, 7.33 and 0.83, respectively [13].

#### 3.2. Autoregressive Integrated Moving Average (ARIMA)

As a type of univariate regression analysis method, ARIMA forecasts upcoming values according to differences between values instead of actual figures. As a generalization of an autoregressive moving average (ARMA) model, ARIMA is fitted to time series data for better understanding of the data or predicting upcoming points in these series.

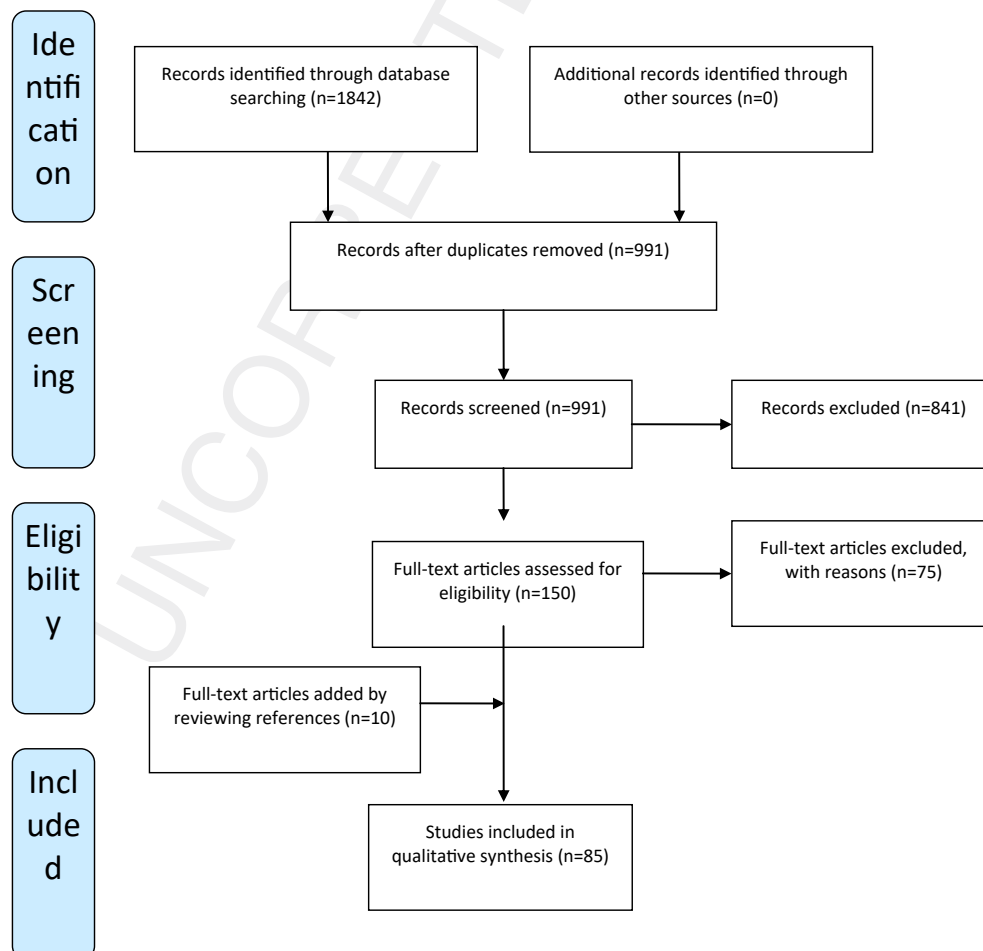


Figure 3. The number of included studies used each machine learning approaches (In two studies, more than one type of models were considered).

Alzahrani et al. [14] have used ARIMA model to predict the estimated daily amounts of COVID-19 persons in Saudi Arabia. They have reported the superiority of ARIMA to Autoregressive Model, Moving Average and an integration ARMA and ARIMA. Using ARIMA, they have reported RMSE, MAE,  $R^2$  and MAPE values as 21.17, 14.93, 0.99 and 2.16, respectively [14]. Chakraborty et al. [15] have proposed a hybrid strategy founded on ARIMA model and Wavelet-based predictive model which could produce short-term predictions of the amount of daily cases for Canada, France, India, South Korea, and the UK. The obtained RMSE and MAE values ranged from 55.25–631.91 and 24–306.78 in different regions [15]. Khan et al. [16] have used an ARIMA model for forecasting daily cases of COVID-19 in India. They selected the appropriate model according to the Bayesian Information Criteria parameters and the total maximum  $R^2$  value of 0.95 [16]. The best performance measurements using ARIMA has been reported in the study conducted by Adiga et al. (MAPE = 999.1) [17].

### 3.3. Multilayer perceptron (MLP)

MLP is a type of feedforward artificial neural network (ANN). This model has three layers of nodes, namely an input layer, a hidden layer and an output layer. With the exception of the input node, other nodes are neurons that use a nonlinear activation function. MLP uses the backpropagation supervised learning method for training [18]. Car et al. [5] have used a freely accessible time-series dataset for design of their model. They have used this dataset in training an MLP model. The finest designed models had 4 hidden layers with 4 neurons in each. This model had appropriate measures in the prediction of the deceased and confirmed cases, but it had low robustness for recovered patients [5]. Pinter et al. [19] have used the hybrid machine learning strategies of ANFIS and MLP-imperialist competitive algorithm (MLP-ICA) for prediction of time series of COVID-19 cases and mortality amount. Short-term observation has confirmed the accuracy of the proposed model. Authors have suggested that the model keeps its exactness providing no substantial interruption happens [19].

### 3.4. Long short-term memory (LSTM)

LSTM is an artificial recurrent neural network (RNN) method utilized as a deep learning strategy. In contrast to standard feedforward neural networks, this model ensures feedback connection. In addition to processing single data points, LSTM can process complete sequences of data [20]. Aora et al. [21] have used RNN-related LSTM variants on an Indian dataset of COVID-19 patients to forecast the amount of positive cases. Based on the lowest error rate, LSTM model was selected for prediction of daily and weekly new COVID-19 cases with approximate error rates of 3% and 8%, respectively. Subsequently, they classified Indian states into different zones based on the extent of positive cases and daily escalation for recognition of COVID-19 hot-spots [21]. Fokas et al. [21] have applied a bidirectional LSTM network to yield a robust generalization of RNNs. This method has been used for predication of new cases of COVID-19 in Italy, Spain, France, Germany, USA and Sweden [22].

### 3.5. Other models

Yadav et al. [23] have used six regression analysis based methods including quadratic, third degree, fourth degree, fifth degree, sixth degree, and exponential polynomial for prediction of COVID-19 cases with the sixth degree polynomial regression method representing the best model for prediction of short-term new cases [23]. Kim et al. [24] have used geographic hierarchy to create Hi-COVIDNet according to a neural network with two-level machineries that are based on data collected from country-level and continent-level systems. This method apprehends the multifaceted relations among distant countries and relates their particular infection risk to the target country [24]. Table S1 shows the

application of machine learning methods for prediction of COVID-19 spread.

## 4. Discussion

### 4.1. Synthesis of results

Accurate prediction of the time of outbreak would help in reduction of the effect of COVID-19, permit governments to modify their preventive strategies and plan in advance for the protective steps required. Modeling of COVID-19 spread is particularly important in defining its potential future impacts. Artificial intelligence methods are superior to traditional statistical modeling methods in the terms of offering high-quality predictive models [89]. These models are capable of identification of learning parameters that affect dissimilarities in COVID-19 spread across various regions or populations, combining numerous intervention methods and implementing what-if scenarios by integrating data from diseases having analogous trends with COVID-19. In the current scoping review, we compared the performance of several machine learning methods in prediction of COVID-19 spread. RMSE, MAE,  $R^2$  and MAPE parameters were selected as performance measures for comparison of the accuracy of models.  $R^2$  values have ranged from 0.64 to 1 for ANN and Bidirectional LSTM, respectively. ANFIS, ARIMA and MLP have also have  $R^2$  values near 1. ARIMA and LSTM had the highest MAPE values. These prediction models could also appraise the impact of climate-associated factors in infection rate or COVID-19 spread facilitating implementation of specific strategies for each condition. Moreover, the data obtained from these models can be used for categorization of county regions and identification of hot spots for COVID-19 to organize region-specific preventive measures. Incorporation of data from health status of affected individuals including general health situation and related risk factors would enhance the accuracy of these models. Most of the proposed models have been effective in short-term forecasting of the COVID-19-related parameters. However, their efficacy in long-term should be validated in further studies.

Modeling of the COVID-19 is practically important in defining the possible upcoming impact of this disorder and artificial intelligence methods have especial situation in this regard. These modeling strategies have implications in disease management by policy makers as they can predict the future course of the pandemic. Moreover, the impact of large-scale screening strategies and application of disease-controlling modalities can be considered in these modeling methods. ARIMA and LSTM have good performance values in this regard. In fact, ARIMA model is the furthestmost extensively used forecasting method for prediction of trends in time series. However, it is not possible to compare the results of these studies, as these methods have not been applied and trained on the same data. Moreover, although artificial intelligence strategies have been promising in prediction of COVID-19 course during the pandemics, COVID-19 continues to be an unknown disease with no historic information to predict its spreading. Therefore, integration of these methods and implementation of the results in larger populations consisting of different ethnicities would help in design of better predictive models.

ARIMA method of time has been used to predict the stability and growth of COVID-19. Recent studies have suggested that the performance of this model can be enhanced or the model can provide more precise data if more numbers of datasets are accessible [90]. The model provides results according to the data established by information provided by health organizations. Therefore, prediction may not be completely precise, yet it can confidently be used as a corrective tool [90]. Combination of new factors and algorithms with ARIMA can lead of enhancement of accuracy.

Accordingly, Abbasimehr and Paki have proposed three hybrid methods for prediction of COVID-19 time series methods according to conjoining three deep learning models, namely multi-head attention, LSTM, and CNN with the Bayesian optimization algorithm. Their analyses have shown higher performance of deep learning models compared



with the benchmark model both for short-term prediction and long-term prediction. Particularly, the mean SMAPE of the best deep learning model has 0.25 and 2.59 for the short-term and long-term predictions, respectively [25].

Deep Neural Networks (DNNs) has also been suggested as method for approximation. This method is an important alternative to estimate the solution of a Partial Differential Equation [91]. DNN has been used for detection of COVID-19 based on CT scan and chest X rays [92]. Application of unsupervised learning methods in which algorithm training is achieved using unlabeled data is another approach which is less studies in this context. A recent study has used the k-means algorithm to divide the countries into clusters based on the spread of COVID-19 in three time spans [93].

#### 4.2. Summary of evidence

These forecasts are just built on past trends of COVID-19 spread, so forecast values are not definite. Nevertheless, these predicted estimates of events can assist authorities to establish resource planning for better management of this pandemic. Moreover, these methods can be used for prediction of need for preventive measures in each geographical region, thus helping vaccine manufacturers for designing appropriate plans.

#### 4.3. Limitations

Impossibility of accurate comparison of methods, lack of consistency between study variables.

## Appendix

**Table S1.** Summary of the results of studies which used machine learning methods for prediction of COVID-19 spread.

| Author, Year                | Region(s)   | Data Source  | Data Structure   | Best Algorithm/<br>Model Structure(s)          | Performance Measurements (on the best model) |        |                |         | Ref  |
|-----------------------------|---|--|--|--|--|--------|----------------|---------|------|
|                             |   |  |  |  | RMSE   | MAE    | R <sup>2</sup> | MAPE    |      |
| Abbasimehr, H., et al. 2021 | Dataset 1: US, United Kingdom, Turkey, Spain, Mexico, Italy, Iran, Germany, France, Belgium | Humanitarian Data Exchange (Dataset 1 and 2 were used for short-term and long-term prediction, respectively) | Daily confirmed cases from 20 January to 1 August 2020 | Attention-based model using Bayesian Optimizer | 2715.12                                      | -      | -              | 0.2157  | [25] |
|                             | Dataset 2: US, Brazil, India, Russia, South Africa, Mexico, Peru, Chile, Colombia, Iran     |  | Daily confirmed cases from 20 January to 3 August 2020 | LSTM using Bayesian Optimizer                  | 25292.337                                    | -      | -              | 2.6606  |      |
| Adiga, A., et al. 2021      | Maricopa AZ   | Johns Hopkins University Center for Systems Science and Engineering dataset                                  | The 7-day smoothed version of confirmed cases          | SEIR (not machine learning)                    | -  | -      | -              | 1576.1  | [17] |
|                             | Los Angeles CA  |  |  | Spatial Autoregressive                         |  |        |                | 1678.7  |      |
|                             | San Bernardino CA   |  |  | ARIMA  |  |        |                | 999.1   |      |
|                             | Kings NY  |  |  | LSTM   |  |        |                | 2085.4  |      |
| Al-Qaness, M. A. A., 2021   | Brazil  | Official WHO data  | Daily confirmed cases from 26 March to 1 June 2020     | MPA + ANFIS                                    | 19,432                                       | 14,273 | -              | 0.3117  | [26] |
|                             | Russia  |  |  |  | 493  | 379    |                | 0.03223 |      |

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## Declarations

### Author contribution statement

All authors listed have significantly contributed to the development and the writing of this article.

### Funding statement

This study was financially supported by Shahid Beheshti University of Medical Sciences. Q2

### Data availability statement

Data will be made available on request.

### Declaration of interests statement

The authors declare no conflict of interest.

### Additional information

No additional information is available for this paper.

Table S1 (continued)

| Author, Year                       | Region(s)    | Data Source   | Data Structure   | Best Algorithm/<br>Model Structure(s) | Performance Measurements (on the best model) |          |                |       | Ref  |
|------------------------------------|--------------|---|--|---------------------------------------|--|----------|----------------|-------|------|
|                                    |              |   |  |                                       | RMSE   | MAE      | R <sup>2</sup> | MAPE  |      |
| Al-Qaness, M., A. A., et al., 2020 | Korea        | WHO website   | Daily confirmed cases in the USA, Korea, Iran, and Italy from 22 January to 7 April 2020 | MPA-ANFIS                             | 70.93  | 60.31    | 96.48%         | 0.696 | [10] |
|                                    | Italy        |   |  |                                       | 5465.66                                      | 3951.94  | 98.59%         | 2.734 |      |
|                                    | Iran         |   |  |                                       | 302.37                                       | 217.27   | 98.74%         | 0.736 |      |
|                                    | USA          |   |  |                                       | 15611  | 12,979   | 95.95%         | 5.74  |      |
| Al-Qaness, M., A. A., et al., 2020 | China        | WHO website   | Daily confirmed cases from 21 January to 18 February 2020                                | FPASSA-ANFIS                          | 5779   | 4271     | 0.9645         | 4.79  | [10] |
| Alsayed, A., et al., 2020          | Malaysia     | Ministry of Health Malaysia   | Daily confirmed cases from 22 March to 5 April 2020                                      | ANFIS                                 | 46.87  | -        | 0.9973         | 2.79  | [12] |
| Alzaharani, S., et al., 2020       | Saudi Arabia | Saudi Ministry of Health website  | Daily confirmed cases in Saudi Arabia  | ARIMA                                 | 21.17  | 14.93    | 0.99           | 2.16  | [14] |
| Ardabili, S. F., et al., 2020      | Italy        | Worldometer website   | Daily confirmed cases over 30 days   | MLP                                   | 191.27                                       | -        | 0.999          | -     | [27] |
|                                    | Germany      |   |  |                                       | 55.52  |          | 0.995          |       |      |
|                                    | Iran         |   |  |                                       | 391.8  |          | 0.998          |       |      |
|                                    | USA          |   |  |                                       | 22.1   |          | 0.999          |       |      |
|                                    | China        |   |  |                                       | 2318.22                                      |          | 0.999          |       |      |
| Arora, P., et al, 2020             | India        | Johns Hopkins University Center for Systems Science and Engineering dataset | Daily confirmed cases from 14 March to 14 May 2020                                       | Stacked LSTM                          | 3.22   | -        | -              | -     | [21] |
| Arora, P., et al. 2020             | India        | Ministry of Health and Family Welfare (Government of India)                 | State-wise daily confirmed cases from 14 March to 14 May 2020                            | Bi-directional LSTM                   | -  | -        | -              | 3.22  | [21] |
| ArunKumar, K. E., et al. 2021a     | USA          | Johns Hopkins University Center for Systems Science and Engineering dataset | Cumulative daily confirmed cases   | LSTM                                  | 1.69E + 06                                   | -        | -              | -     | [28] |
|                                    | Brazil       |   |  |                                       | 1.33E + 05                                   |          |                |       |      |
|                                    | South Africa |   |  |                                       | 6.03E + 03                                   |          |                |       |      |
|                                    | Peru         |   |  |                                       | 4.44E + 03                                   |          |                |       |      |
|                                    | Chile        |   |  |                                       | 1.22E + 03                                   |          |                |       |      |
|                                    | Iran         |   |  |                                       | 1.33E + 02                                   |          |                |       |      |
|                                    | Mexico       |   |  | GRU                                   | 4.00E + 03                                   |          |                |       |      |
|                                    | UK           |   |  |                                       | 4.21E + 02                                   |          |                |       |      |
|                                    | Russia       |   |  |                                       | 9.37E + 02                                   |          |                |       |      |
|                                    | India        |   |  |                                       | 2.14E + 04                                   |          |                |       |      |
|                                    |              |   |  |                                       |  |          |                |       |      |
| ArunKumar, K. E., et al. 2021b     | South Africa | Johns Hopkins University Center for Systems Science and Engineering dataset | Cumulative daily confirmed cases 22 January to 24 July 2020                              | Seasonal ARIMA                        | 1.48E+04                                     | 1.17E+04 | -              | 5.46  | [29] |
|                                    | Bangladesh   |   |  |                                       | 3.40E+03                                     | 2.92E+03 |                | 2.57  |      |
|                                    | Brazil       |   |  |                                       | 2.34E+03                                     | 2.13E+03 |                | 3.12  |      |
|                                    | Chile        |   |  |                                       | 9.07E+03                                     | 7.80E+03 |                | 2.53  |      |
|                                    | Colombia     |   |  |                                       | 2.38E+02                                     | 1.16E+02 |                | 0.13  |      |
|                                    | India        |   |  |                                       | 1.21E+04                                     | 7.15E+03 |                | 0.87  |      |
|                                    | Iran         |   |  |                                       | 4.65E+03                                     | 3.80E+03 |                | 0.095 |      |
|                                    | Italy        |   |  |                                       | 1.94E+03                                     | 1.79E+03 |                | 0.923 |      |
|                                    | Mexico       |   |  |                                       | 1.09E+04                                     | 8.82E+03 |                | 3.24  |      |
|                                    | Pakistan     |   |  |                                       | 3.07E+02                                     | 1.58E+02 |                | 0.078 |      |
|                                    | Peru         |   |  |                                       | 2.41E+03                                     | 1.99E+03 |                | 0.77  |      |
|                                    | Russia       |   |  |                                       | 1.40E+04                                     | 1.23E+04 |                | 97    |      |
|                                    | Saudi Arabia |   |  |                                       | 1.15E+04                                     | 1.08E+04 |                | 0.08  |      |
|                                    | Spain        |   |  |                                       | 2.00E-03                                     | 2.00E-02 |                | 0.988 |      |
|                                    | UK           |   |  |                                       | 1.45E+01                                     | 1.25E+01 |                | 0.80  |      |
|                                    | USA          |   |  |                                       | 2.46E+04                                     | 1.72E+04 |                | 1.41  |      |

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Table S1 (continued)

| Author, Year                     | Region(s)   | Data Source   | Data Structure   | Best Algorithm/<br>Model Structure(s) | Performance Measurements (on the best model) |           |                |        | Ref  |
|----------------------------------|---|---|--|---------------------------------------|--|-----------|----------------|--------|------|
|                                  |   |   |  |                                       | RMSE   | MAE       | R <sup>2</sup> | MAPE   |      |
| Ayyoubzadeh, S. M., et al., 2020 | Iran  | Worldometer website and Google Trends                                       | Customized dataset consisting of the daily incidence from 15 February, 2020, to 18 March, 2020 and Google search trends  | Linear regression                     | 7.562  | -         | -              | -      | [30] |
| Bedi, P., et al. 2020            | India   | covid19india.org website  | Daily confirmed cases 30 January to 6 September 2020   | LSTM                                  | -  | -         | -              | 0.03   | [31] |
| Behnood, A, et al, 2020          | USA   | USAFacts Website  | Daily confirmed cases in 1657 counties   | ANFIS-VOA-II                          | 22.4744                                      | 7.3337    | 0.8339         | -      | [13] |
| Borghi, P. H., et al. 2021       | Global (top 30 countries with the highest number of daily new cases)  | Johns Hopkins University Center for Systems Science and Engineering dataset | Daily confirmed cases till 11 May 2020   | ANN                                   | 2.082E+03                                    | 3.718E+06 | -              | -      | [32] |
| Car, Z., et al., 2020            | 406 locations   | Johns Hopkins University Center for Systems Science and Engineering dataset | Daily confirmed, recovered, and deceased patients in a certain location (defined by the name of location, latitude, and longitude), from 22 January to 12 March 2020 | MLP                                   | -  | -         | 0.98599        | -      | [5]  |
| Chakraborty, T., et al., 2020    | USA   | Our World in Data Website   | Daily confirmed cases  | TARNN                                 | 721.5658                                     | 468.6335  | -              | -      | [33] |
|                                  | Brazil  |   |  |                                       | 178.0458                                     | 90.2053   |                |        |      |
|                                  | India   |   |  |                                       | 201.0696                                     | 128.7718  |                |        |      |
|                                  | Russia  |   |  |                                       | 443.4280                                     | 202.6083  |                |        |      |
|                                  | South Africa  |   |  |                                       | 243.5067                                     | 160.3598  |                |        |      |
|                                  | Mexico  |   |  |                                       | 24.4335                                      | 15.1298   |                |        |      |
|                                  | Spain   |   |  |                                       | 136.3910                                     | 87.5449   |                |        |      |
|                                  | Iran  |   |  |                                       | 319.9160                                     | 182.8744  |                |        |      |
| Chakraborty, T., et al., 2020    | Canada  | Our World in Data Website   | Daily confirmed cases  | Hybrid ARIMA-WBF Model                | 149.60                                       | 40.05     | -              | -      | [15] |
|                                  | France  |   |  |                                       | 631.91                                       | 306.78    |                |        |      |
|                                  | India   |   |  |                                       | 55.25  | 24.00     |                |        |      |
|                                  | South Korea   |   |  |                                       | 90.29  | 54.06     |                |        |      |
|                                  | UK  |   |  |                                       | 180.66                                       | 100.68    |                |        |      |
| Chatterjee, A., et al. 2020      | China, Italy, Spain, Germany, Iran, Switzerland, South Korea, Belgium, Netherlands, Austria, Singapore, Malaysia, France, Australia, USA, UK and Portugal | Our World in Data Website and a simulated dataset                           | Daily confirmed, and deceased patients from 1 January to 2 April, 2020   | Bidirectional LSTM                    | 8,649.154                                    | 7,130.149 | 1              | -      | [34] |
| Chaurasia, V., et al., 2020      | Worldwide   | DataHub-Novel Coronavirus 2019-Dataset                                      | Daily confirmed, recovered, and deceased patients from 22 January to 29 June, 2020   | ARIMA                                 | 0.1517                                       | 0.12044   | -              | 0.0091 | [35] |

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Table S1 (continued)

| Author, Year                       | Region(s)  | Data Source   | Data Structure  | Best Algorithm/<br>Model Structure(s) | Performance Measurements (on the best model)                    |        |                |        | Ref  |
|------------------------------------|--|---|---|---------------------------------------|---|--------|----------------|--------|------|
|                                    |  |   |   |                                       | RMSE  | MAE    | R <sup>2</sup> | MAPE   |      |
| Chimmula, V., K., R., et al., 2020 | Canada   | Johns Hopkins University and Canadian Health authority  | Daily confirmed, recovered, and deceased cases from 22 January to 31 March, 2020  | LSTM                                  | 34.83 (short-term predictions)<br>45.70 (long-term predictions) | -      | -              | -      | [36] |
| Chowdhury, A. A., et al. 2021      | Bangladesh   | Worldometer website   | Daily confirmed cases 10 April to 30 June 2020  | LSTM                                  | 6.55  | -      | -              | 4.51   | [37] |
| da Silva, C. C., et al. 2021       | Brazil<br>Pernambuco (A state in Brazil)                             | Brasil.io portal  | Daily confirmed cases till 6 June 2020  | Linear Regression                     | 11.42%<br>1.92%   | -      | -              | -      | [38] |
| de Souza, D. G. S. et al., 2020    | Amapa (A state in Brazil)  | Health surveillance secretary of Amapa  | Cumulative confirmed cases from 20 March to 31 August, 2020   | Holt-Winters                          | 162   | -      | 0.98           | 0.34   | [39] |
| Dharani, N. P., et al. 2021        | India  | Kaggle website  | Daily confirmed cases 30 January to 21 May 2020   | Linear Regression                     | 223.89  | 157.78 | 1.0            | -      | [40] |
| Doe, S. W., et al., 2020           | USA  | Johns Hopkins University confirmed cases data for US counties                                   | Daily confirmed cases from 22 January to 31 May, 2020 and latitude, and longitude of each county  | CLEIR-Net                             | 264.33  | -      | -              | -      | [41] |
| Fokas, A. S, et al., 2020          | Italy<br>Spain<br>France<br>Germany<br>USA<br>Sweden                 | European CDC website  | Daily confirmed cases   | Bidirectional LSTM network            | 538   | -      | 0.9999         | -      | [22] |
|                                    |  |   |   |                                       | 1022  |        | 0.9998         |        |      |
|                                    |  |   |   |                                       | 821   |        | 0.9997         |        |      |
|                                    |  |   |   |                                       | 1128  |        | 0.9997         |        |      |
|                                    |  |   |   |                                       | 10754   |        | 0.9996         |        |      |
|                                    |  |   |   |                                       | 178   |        | 0.9997         |        |      |
| Ganiny, S., et al., 2020           | India  | Worldometer website, India's Ministry of Health and Family Welfare, the Covindia website        | Daily confirmed, recovered, and deceased cases from 1 March to 25 July, 2020  | ARIMA                                 | 457.61  | 330.79 | 0.99998        | 0.2471 | [42] |
| Ghany, K. K. A., et al. 2021       | Saudi Arabia<br>Qatar<br>Oman<br>Kuwait<br>UAE<br>Bahrain            | Johns Hopkins University Center for Systems Science and Engineering dataset                     | Daily confirmed cases 22 January to 24 July 2020  | LSTM                                  | 1768.35   | -      | -              | -      | [43] |
|                                    |  |   |   |                                       | 735.21  |        |                |        |      |
|                                    |  |   |   |                                       | 730.53  |        |                |        |      |
|                                    |  |   |   |                                       | 456.90  |        |                |        |      |
|                                    |  |   |   |                                       | 446.44  |        |                |        |      |
|                                    |  |   |   |                                       | 320.79  |        |                |        |      |
| Ghazaly, N., M., et al., 2020      | Egypt, Saudi Arabia, Jordan, USA, Spain, Italy, France, Iran, Russia | WHO situation reports   | Daily cases and deaths from 21 January to 2 April, 2020   | NAR                                   | -   | -      | -              | 2.6521 | [44] |
| Guo, Q. and He, Z., 2021           | Global   | Official WHO data   | Daily confirmed cases 21 January to 11 November 2020  | ANN                                   | 3102.9  | 2090.6 | 0.9683         | -      | [45] |
| Hasan, K. T., et al. 2021          | Bangladesh   | Official WHO data and the Institute of Epidemiology, Disease Control and Research of Bangladesh | Daily confirmed cases till 3 August 2020 + Government control and people's compliance data + Information of how many people will be in contact with an infected person outside of their home when they move out | LSTM                                  | 10,368.318  | -      | 1              | 5.96   | [46] |

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Table S1 (continued)

| Author, Year                  | Region(s)  | Data Source  | Data Structure  | Best Algorithm/<br>Model Structure(s)               | Performance Measurements (on the best model) |     |                                   |        | Ref  |
|-------------------------------|--|--|---|---|--|-----|-----------------------------------|--------|------|
|                               |  |  |   |   | RMSE   | MAE | R <sup>2</sup>                    | MAPE   |      |
| Hazarika, B. B., et al., 2020 | Brazil   | Our World in Data Website  | Cumulative number of confirmed cases from 11 April to 10 July, 2020   | WCRVFL (Using sigmoid or ReLu activation functions) | 0.00323                                      | -   | 0.99975                           | -      | [47] |
|                               | India  |  |   |   | 0.00147                                      |     | 0.99996                           |        |      |
|                               | Peru   |  |   |   | 0.00197                                      |     | 0.99986                           |        |      |
|                               | Russia   |  |   |   | 0.00029                                      |     | 0.99999                           |        |      |
|                               | USA  |  |   |   | 0.00524                                      |     | 0.99999                           |        |      |
| Hawas, M, et al., 2020        | Brazil   | Johns Hopkins University Center for Systems Science and Engineering dataset  | Daily cases from 22 January, 2020, to several dates   | RNN   | -  | -   | 0.665                             | -      | [48] |
| Heni, B., et al., 2020        | Phase I: 79 countries<br>phase II: China, South Korea, France, Germany, Iran, Iraq, United Kingdom, Italy, Japan, Singapore, Spain, Thailand | European CDC website   | Phase I: Daily confirmed cases from the date of the first confirmed cases to 13 March, 2020<br>Phase II: Daily recovered cases from the date of the first confirmed cases to 19 March, 2020 | LSTM  | -  | -   | Phase I: 0.999<br>Phase II: 0.996 | -      | [49] |
| Hridoy, A. E., et al., 2020   | Bangladesh   | Johns Hopkins University's GitHub repository   | Daily confirmed, recovered, and deceased cases from 8 March to 13 June, 2020  | Stacked LSTM  | 593.764                                      | -   | 0.95                              | 1.76%  | [50] |
| Kasilingam, D., et al. 2021   | Global (42 countries)  | Official WHO data, the World Bank website, the Weather Underground website   | Daily confirmed cases 22 January to 24 March 2020 + infrastructure, environment, policies, and infection-related independent variables  | Random forest                                       | -  | -   | 0.543 to 0.992 (country-wise)     | -      | [51] |
| Kırbas, I., et al., 2020      | Denmark  | European CDC   | Daily confirmed cases from the date of the first confirmed cases to 3 May 2020  | LSTM  | 54.5398                                      | -   | 0.999963324                       | 0.5033 | [52] |
|                               | Belgium  |  |   |   | 274.0248                                     |     | 0.999967249                       | 0.5422 |      |
|                               | Germany  |  |   |   | 569.4791                                     |     | 0.999987029                       | 0.3083 |      |
|                               | France   |  |   |   | 455.7141                                     |     | 0.999987339                       | 0.3155 |      |
|                               | United Kingdom   |  |   |   | 5482.2361                                    |     | 0.998923082                       | 2.5025 |      |
|                               | Finland  |  |   |   | 49.4966                                      |     | 0.999897188                       | 0.8492 |      |
|                               | Switzerland  |  |   |   | 55.8685                                      |     | 0.999996376                       | 0.1640 |      |
|                               | Turkey   |  |   |   | 640.26257                                    |     | 0.999971407                       | 0.4823 |      |
| Khajanchi, S., et al., 2020   | Jharkhand  | COVID19 INDIA Website  | Daily confirmed cases and the cumulative confirmed cases up to 24 May, 2020   | SAIUQR  | 5.23   | -   | -                                 | -      | [53] |
|                               | Gujarat  |  |   |   | 51.82  |     |                                   |        |      |
|                               | Andhra Pradesh   |  |   |   | 13.47  |     |                                   |        |      |
|                               | Chandigarh   |  |   |   | 3.82   |     |                                   |        |      |
| Kim, M., et al., 2020         | South Korea  | Johns Hopkins University Center for Systems Science and Engineering dataset, Google trends, International Roaming (by Korea Telecom), airline information system, Korean CDC | Daily confirmed cases + Searched keyword ("COVID-19," "COVID test," "Flu," "Mask") + Inter-Country Data including customers and airlines arriving in Korea, imported cases in Korea         | Hi-COVIDNet (A Customized RNN using LSTM layers)    | May 6–12: 0.4373<br>May 6–19: 0.4045         | -   | -                                 | -      | [24] |

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Table S1 (continued)

| Author, Year                | Region(s)                                    | Data Source  | Data Structure   | Best Algorithm/<br>Model Structure(s) | Performance Measurements (on the best model)    |          |  |   | Ref  |
|-----------------------------|--|--|--|---------------------------------------|---|----------|--|---|------|
|                             |  |  |  |                                       | RMSE  | MAE      | R <sup>2</sup>                                       | MAPE  |      |
| Khan, F., et al., 2020      | India  | Ministry of Health and Family Welfare, COVID19 INDIA Website                   | Daily confirmed cases up to 4 April, 2020  | ARIMA                                 | -   | -        | 0.95   | -   | [16] |
| Kufel, T., et al., 2020     | 32 European countries                        | Johns Hopkins University Center for Systems Science and Engineering dataset    | Daily confirmed, recovered, and deceased cases for 14 days in each country                               | ARIMA                                 | -   | -        | From 0.5577 to 1.0000 (depends on country and dates) | From 0.0228 to 83.3660 (depends on country and dates) | [54] |
| Kumar, S., et al., 2020     | India  | COVID19 INDIA Website  | Cumulative number of confirmed, recovered, and deceased cases  | ARIMIA                                | 641.732 (new cases)<br>705.293                  | -        | 0.987 (new cases)<br>1.000 (total cases)             | -   | [55] |
| Kumar, N., et al., 2020     | Worldwide                                    | Johns Hopkins University Center for Systems Science and Engineering dataset    | Daily confirmed, recovered, and deceased cases up to 20 May, 2020  | ARIMA                                 | 36992.53  | 34932.99 | -  | 2.523   | [56] |
|                             | US   |  |  |                                       | 33109.68  | 31899.89 |  | 15.635  |      |
|                             | Spain  |  |  |                                       | 9774.06   | 9683.45  |  | 7.361   |      |
|                             | Italy  |  |  |                                       | 13078.23  | 12910.06 |  | 12.78   |      |
|                             | France                                       |  |  |                                       | 5853.29   | 5780.87  |  | 10.574  |      |
|                             | Germany                                      |  |  |                                       | 13901.04  | 13702.61 |  | 9.808   |      |
|                             | Russia                                       |  |  |                                       | 3212.50   | 2376.69  |  | 5.103   |      |
|                             | Iran   |  |  |                                       | 4496.75   | 4213.14  |  | 4.933   |      |
|                             | UK   |  |  |                                       | 91.12   | 78.19    |  | 8.311   |      |
|                             | Turkey                                       |  |  |                                       | 4333.57   | 4242.09  |  | 4.321   |      |
|                             | India  |  |  |                                       | 1066.65   | 721.17   |  | 2.911   |      |
| Liu, Z., et al., 2020       | Wuhan, Beijing, Shanghai, Guangzhou          | Tencent news and Baidu migration websites                                      | Daily confirmed cases  | ANN                                   | -   | -        | 0.9969   | -   | [57] |
| Majhi, R., et al. 2020      | China (for training), India (for validation) | NA   | Daily confirmed and recovered cases, daily deaths, Amount of testing, Lockdown presence and its severity | Random forest                         | -   | -        | -  | 0.02  | [58] |
| Malki, Z., et al. 2021      | Worldwide                                    | Johns Hopkins University, WHO and Worldometer official website                 | Daily confirmed cases  | Decision Tree                         | 0.085   | 0.047    | 0.993  | 0.160   | [59] |
|                             | USA  |  |  |                                       | 0.068   | 0.049    | 0.995  | 0.107   |      |
|                             | Brazil                                       |  |  |                                       | 0.106   | 0.058    | 0.989  | 0.073   |      |
|                             | India  |  |  |                                       | 0.073   | 0.050    | 0.995  | 0.248   |      |
|                             | Spain  |  |  |                                       | 0.152   | 0.098    | 0.977  | 0.207   |      |
|                             | Italy  |  |  |                                       | 0.062   | 0.038    | 0.996  | 0.113   |      |
|                             | France                                       |  |  |                                       | 0.133   | 0.069    | 0.982  | 0.277   |      |
|                             | UK   |  |  |                                       | 0.075   | 0.044    | 0.994  | 0.126   |      |
|                             | Germany                                      |  |  |                                       | 0.060   | 0.040    | 0.996  | 0.050   |      |
|                             | Russia                                       |  |  |                                       | 0.094   | 0.055    | 0.991  | 0.308   |      |
|                             | Turkey                                       |  |  |                                       | 0.065   | 0.033    | 0.996  | 0.051   |      |
| Mishra, P., et al., 2020    | India  | WHO daily situation reports  | Daily new cases from 17 March to 1 July, 2020  | ANN                                   | 38.22   | 23.12    | -  | -   | [60] |
| Mohtakhar, L., et al., 2020 | Iran   | Iran Ministry of Health and open datasets provided by Johns Hopkins University | Daily new cases from 19 February to 30 March 2020  | ARIMA                                 | 1539.43   | 24.85    | -  | -   | [61] |
| Melin, P, et al., 2020      | Mexico                                       | Government of Mexico website   | Daily confirmed and deceased cases   | Modular Neural Network with Fuzzy     | From 8.6153 to 1554.0302 (Depends on the state) | -        | -  | -   | [62] |

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Table S1 (continued)

| Author, Year                        | Region(s)                             | Data Source   | Data Structure  | Best Algorithm/<br>Model Structure(s)  | Performance Measurements (on the best model) |                 |                |        | Ref  |
|-------------------------------------|---------------------------------------|---|---|--|--|-----------------|----------------|--------|------|
|                                     |                                       |   |   |  | RMSE   | MAE             | R <sup>2</sup> | MAPE   |      |
| Mollalo, A. et al. 2020             | USA                                   | USAFacts website  | Cumulative number of confirmed cases from 22 January to 30 April 2020   | ANN  | 0.722409                                     | 0.355843        | 0.645481       | -      | [63] |
| Nabi, K. N., et al. 2021            | Brazil                                | Johns Hopkins University Center for Systems Science and Engineering dataset   | Daily confirmed cases till 18 November 2020   | CNN  | 0.086  | -               | -              | 6.94   | [64] |
|                                     | Russia                                |   |   |  | 0.014  |                 |                | 0.85   |      |
|                                     | UK                                    |   |   |  | 0.048  |                 |                | 3.75   |      |
| Neeraj, et al., 2020                | Canada                                | Johns Hopkins University Center for Systems Science and Engineering dataset   | Daily confirmed, recovered, and deceased cases for 209 days in each country   | Attention-based encoder-decoder  | 12.46  | -               | -              | 0.11   | [65] |
|                                     | Italy                                 |   |   |  | 209.23                                       |                 |                | 1.71   |      |
|                                     | France                                |   |   |  | 163.78                                       |                 |                | 1.21   |      |
|                                     | Spain                                 |   |   |  | 281.03                                       |                 |                | 2.11   |      |
| Nikolopoulos, K, et al., 2020       | Germany, India, Singapore, UK, USA    | Johns Hopkins university dataset, "covid19-report" website, Mayer Brown's COVID-19 Global Travel Restrictions, the world population review, World Life Expectancy website, World Bank website | Daily confirmed, recovered and deceased cases, climate information, travel restrictions and curfews data, populations information, lung diseases data, coronary heart diseases data, diabetes prevalence data, GDP spent on healthcare data | Naive-d 0.1 for weekly prediction<br>GARCH(1,1) model with SGED for daily prediction | -  | 1.0015 (Scaled) | -              | 1.0022 | [66] |
|                                     |                                       |   |   |  |  | 0.2064 (Scaled) |                | 0.2160 |      |
| Pal, R., et al., 2020               | USA                                   | Johns Hopkins university dataset, Dark Sky website  | Daily confirmed, recovered and deceased cases from 22 January to 2 August, 2020 and weather data  | Shallow LSTM using used a Bayesian optimization framework                            | 1103.5                                       | -               | -              | -      | [67] |
| Papastefanopoulos, V., et al., 2020 | US                                    | Novel Corona Virus 2019 Dataset and population-by-country dataset on Kaggle website   | Daily confirmed, recovered and deceased cases as of 4 May 2020  | TBAT   | 0.009873                                     | -               | -              | -      | [68] |
|                                     | Spain                                 |   |   |  | 0.029295                                     |                 |                |        |      |
|                                     | Italy                                 |   |   |  | 0.005810                                     |                 |                |        |      |
|                                     | UK                                    |   |   |  | 0.004310                                     |                 |                |        |      |
|                                     | France                                |   |   |  | 0.007003                                     |                 |                |        |      |
|                                     | Germany                               |   |   |  | 0.003389                                     |                 |                |        |      |
|                                     | Russia                                |   |   |  | 0.002193                                     |                 |                |        |      |
|                                     | Turkey                                |   |   |  | 0.001946                                     |                 |                |        |      |
|                                     | Brazil                                |   |   |  | 0.005621                                     |                 |                |        |      |
|                                     | Iran                                  |   |   |  | 0.000425                                     |                 |                |        |      |
| Peng, Y., et al. 2021               | Worldwide (215 countries)             | Official WHO data, Google Trends service  | Daily confirmed cases 10 January to 16 August 2020 + Inveillance data (Google Trends (search volume of 28 COVID19-related features))  | Random forest  | 9.27   | 5.42            | -              | -      | [69] |
| Pereira, I. G., et al., 2020        | USA, Brazil, Italy, Spain, France, UK | Johns Hopkins university dataset, Natalnet's Lab and Brazil ministry of health (just for Brazil), Italy—Official Covid Data Repository.   | Daily confirmed and deceased cases  | LSTM-SAE   | -  | -               | 0.822          | 84     | [70] |

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Table S1 (continued)

| Author, Year                        | Region(s)                               | Data Source  | Data Structure  | Best Algorithm/<br>Model Structure(s)   | Performance Measurements (on the best model) |   |                |   | Ref  |
|-------------------------------------|---|--|---|---|--|---|----------------|---|------|
|                                     |   |  |   |   | RMSE   | MAE   | R <sup>2</sup> | MAPE  |      |
| Perone, G., 2020                    | Italy                                   | Worldometer website  | Daily confirmed cases (Italy (February 22–April 14), USA (March 9–May 16), Russia (March 22–May 22))  | ARIMA   | 412.79                                       | 283.49  | 0.95           | 13.039  | [71] |
|                                     | Russia                                  |  |   |   | 606.66                                       | 430.83  | 0.98           | 11.39   |      |
|                                     | USA                                     |  |   |   | 2,411.6                                      | 1,631.3   | 0.95           | 9.59  |      |
| Perone, G., 2020                    | Italy                                   | Italian Ministry of Health's website   | Daily confirmed cases from 21 February to 13 October, 2020  | ARIMA-NNAR  | 190.542                                      | 106.4554  | -              | 2.1901  | [72] |
| Pinter, G., et al., 2020            | Hungary                                 | Worldometer website  | Daily confirmed, and deceased cases from 4 March to 19 April, 2020  | MPL-ICA   | 167.88                                       | -   | -              | -   | [19] |
| Quintero, Y., et al. 2021           | Colombia                                | The National Institute of Health for Colombia and the National Administrative Department of Statistics | Daily confirmed cases from March to July 2020 + Socioeconomic data including people over 65, poverty index, total population, people per km <sup>2</sup> , Average age, average morbidity | Gradient boosting regressor   | 0.0157                                       | 0.0045  | 0.8986         | 1.5317  | [73] |
| Ribeiro, Mhdm, et al., 2020         | Brazil                                  | WHO website  | Daily confirmed, and deceased cases from 15 March to 19 April, 2020   | SVR (generally was the best algorithm, stacking-ensemble learning and ARIMA outperformed in some cases) | -  | 18–409 (One day)<br>8.5–59.67 (Three days)<br>7.83–73.17 (Six days) | -              | 0.87–3.51 (One day)<br>1.02–5.63 (Three days)<br>0.95–6.90 (Six days) | [74] |
| Rustam, F., et al., 2020            | Afghanistan, Australia, Algeria, Canada | Johns Hopkins University Center for Systems Science and Engineering dataset                            | Daily confirmed, recovered, and deceased patients   | Exponential Smoothing   | 16828.58                                     | 8867.43   | 0.98           | -   | [75] |
| Saba, A. I., et al., 2020           | Egypt                                   | The Egyptian Ministry of Health  | Accumulated confirmed cases from 1 March to 10 May, 2020  | Nonlinear Autoregressive ANN  | 10.410                                       | 7.752   | 0.999          | -   | [76] |
| Said, A. B., et al. 2021            | Worldwide data                          | Official WHO data  | Daily confirmed cases + Demographic, socioeconomic, and health sector indicators data   | Bidirectional LSTM  | 245.1  | 176.02  | 0.996          | -   | [77] |
| Saqib, M., 2020                     | US                                      | Johns Hopkins University Center for Systems Science and Engineering dataset                            | Daily confirmed patients  | Hybrid polynomial-Bayesian ridge regression model   | 723.75                                       | -   | -              | -   | [78] |
|                                     | Italy                                   |  |   |   | 418.36                                       | -   | -              | -   |      |
|                                     | Spain                                   |  |   |   | 624.27                                       | -   | -              | -   |      |
| Senapati, A., et al. 2021           | Assam (a state in India)                | Kaggle website   | Daily confirmed cases till 30 October 2020  | Piecewise linear regression   | -  | -   | -              | 0.392   | [79] |
| Shyam Sunder Reddy, K., et al. 2020 | India                                   | “Our World in Data” website  | Daily confirmed cases 15 February to 18 September 2020  | LSTM  | 0.767  | -   | -              | -   | [80] |
| Tabar, B. R., et al., 2020          | East Midlands region of England         | Public Health UK and NHS Digital   | Daily cumulative confirmed cases and the total number of daily phone calls  | MLR-T   | 19.37  | 14.16   | -              | -   | [81] |

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Table S1 (continued)

| Author, Year                         | Region(s)   | Data Source  | Data Structure  | Best Algorithm/<br>Model Structure(s)            | Performance Measurements (on the best model)                       |           |                |  | Ref  |
|--------------------------------------|---|--|---|--|--|-----------|----------------|--|------|
|                                      |   |  |   |  | RMSE   | MAE       | R <sup>2</sup> | MAPE   |      |
|                                      |   |  | received at the NHS 111 from 18 March to 19 September, 2020   |  |  |           |                |  |      |
| Torrealba-Rodriguez, O. et al., 2020 | Mexico  | Daily Technical Report" by the Mexican Ministry of Health  | Daily confirmed cases from 27 February to 8 May, 2020   | ANN  | -  | -         | 0.9999         | -  | [82] |
| Tuli, S., et al., 2020               | World   | Our World in Data website  | Daily confirmed cases   | Generalized Inverse Weibull distribution fitting | -  | -         | 0.98           | 49.14  | [83] |
|                                      | India   |  |   |  |  |           | 0.97           | 18.33  |      |
|                                      | USA   |  |   |  |  |           | 0.95           | 24.33  |      |
|                                      | UK  |  |   |  |  |           | 0.95           | 21.46  |      |
|                                      | Italy   |  |   |  |  |           | 0.96           | 14.98  |      |
| Tuli, S., et al., 2020               | World   | Our World in Data website, Index Mundi, World Bank, Oxford Government Response Tracker   | Daily confirmed cases till 19 May, 2020, Socioeconomic data, Virus Type data, Government Stringency Index   | LSTM-based Robust Weibull approach               | 559.46   | -         | 0.93           | 39.29  | [84] |
|                                      | India   |  |   |  |  |           | 4.39           | 22.00  |      |
|                                      | USA   |  |   |  |  |           | 319.37         | 26.09  |      |
|                                      | UK  |  |   |  |  |           | 99.60          | 14.93  |      |
|                                      | Italy   |  |   |  |  |           | 45.93          | 12.78  |      |
| Wang, L., et al., 2020               | Global (Austria, Brazil, India, Italy, Nigeria, Singapore, the United Kingdom)<br>US-States<br>US-Countries | UVA COVID-19 surveillance dashboard, Johns Hopkins University dataset, Google COVID-19 Aggregated Mobility Research dataset        | Weekly confirmed and deceased cases, Case count growth rate, COVID-19 testing data, aggregated relative weekly mobility flows over google users, Flow Reduction Rate of connectivity before and after the pandemic, and Social Distancing Index, All from 7 March to 22 August, 2020 (25 weeks) | Ensemble of RNNs and SEIR                        | Was 37 at minimum (depends on the algorithm, data, and the region) | -         | -              | Was 12 at minimum (depends on the algorithm, data, and the region) | [85] |
| Yadav, R. S., 2020                   | India   | COVID-19 in India Kaggle dataset   | Daily confirmed cases from 1 March to 11 April, 2020  | Sixth degree polynomial regression analysis      | -  | -         | 0.9990         | -  | [23] |
| Zawbaa, H. M., et al. 2021           | China   | Johns Hopkins University Center for Systems Science and Engineering dataset and European Centre for Disease Prevention and Control | Daily confirmed cases 22 January to 13 December 2020  | ANN  | 1460.57  | -         | -              | -  | [86] |
|                                      | Cote d'Ivoire   |  |   |  | 105.94   |           |                |  |      |
|                                      | Kenya   |  |   |  | 486.13   |           |                |  |      |
|                                      | Egypt   |  |   |  | 318.29   |           |                |  |      |
|                                      | Algeria   |  |   |  | 371.40   |           |                |  |      |
|                                      | Japan   |  |   |  | 952.29   |           |                |  |      |
|                                      | Iran  |  |   |  | 5632.84  |           |                |  |      |
|                                      | Italy   |  |   |  | 17922.58   |           |                |  |      |
|                                      | USA   |  |   |  | 77822.38   |           |                |  |      |
| Zeroual, A., et al. 2020             | Italy   | Johns Hopkins University Center for Systems Science and Engineering dataset  | Daily confirmed cases till 17 June 2020   | Bidirectional LSTM                               | 1,041,374  | 1,033,467 | -              | 4398   | [87] |
|                                      | Spain   |  |   |  | 1,194,711  | 1,187,629 |                | 4916   |      |
|                                      | France  |  |   | LSTM   | 1,085,008  | 1,075,795 |                | 5738   |      |
|                                      | USA   |  |   |  | 1,129,183  | 1,123,909 |                | 58,008   |      |
|                                      | China   |  |   | Variational Auto-encoder                         | 11,103   | 107,873   |                | 128  |      |
|                                      | Australia   |  |   |  | 18,732   | 17,186    |                | 236  |      |
| Zeroual, A., et al., 2020            | Italy   | Johns Hopkins University Center for Systems Science and Engineering dataset  | Daily confirmed, recovered, and deceased cases from 22 January to 17 June, 2020   | VAE  | 1,386,225  | 1,385,829 | -              | 5.90   | [87] |
|                                      | Spain   |  |   |  | 5,315,748  | 5,288,172 |                | 2.19   |      |
|                                      | France  |  |   |  | 3,688,083  | 3,522,353 |                | 1.88   |      |
|                                      | China   |  |   |  | 11,103   | 107,873   |                | 0.128  |      |
|                                      | Australia   |  |   |  | 18,732   | 17,186    |                | 0.236  |      |
|                                      | USA   |  |   |  | 4,079,244  | 3,976,682 |                | 2.04   |      |

(continued on next page)



Table S1 (continued)

| Author, Year              | Region(s)           | Data Source                 | Data Structure  | Best Algorithm/<br>Model Structure(s)  | Performance Measurements (on the best model) |        |                |      | Ref  |
|---------------------------|---------------------|-----------------------------|---|--|--|--------|----------------|------|------|
|                           |                     |                             |   |  | RMSE   | MAE    | R <sup>2</sup> | MAPE |      |
| Zheng, N., et al., 2020   | Wuhan               | Private dataset             | Customized dataset consist of the daily cases which are confirmed, suspected, cured, died and social and news media | A hybrid AI system through improved susceptible–infected model, NLP and LSTM | -  | 239.83 | -              | 0.52 | [6]  |
|                           | Beijing             |                             |   |  |  | 0.50   |                | 0.38 |      |
|                           | Shanghai            |                             |   |  |  | 0.17   |                | 0.05 |      |
|                           | Countrywide (China) |                             |   |  |  | 659.00 |                | 0.86 |      |
| Zivkovic, M., et al. 2021 | China               | Official WHO data           | Daily confirmed cases 21 January to 18 February 2020 + 10 November to 10 December 2020                              | Cauchy exploration strategy BAS + ANFIS                                      | 4329   | 3195   | 0.9763         | 4.08 | [88] |
|                           |                     | “Our World in Data” website |   |  | 4106   | 2994   | 0.9775         | 4.08 |      |

(Regions: Regions that model was evaluated in, Data Source: The source(s) that data were acquired from, Data Structure and Size: Data modalities and dates of data collection, Best Model Structure(s): Best machine algorithm or deep learning model reported in the selected paper based on its performance, Performance Measurements (on the best model): The measurement of the model output performance based on RMSE, MAE, R2 value, and MAPE).

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