

Review

A Review of the Potential of Artificial Intelligence Approaches to Forecasting COVID-19 Spreading

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Abstract: The spread of SARS-CoV-2 can be considered one of the most complicated patterns with a large number of uncertainties and nonlinearities. Therefore, analysis and prediction of the distribution of this virus are one of the most challenging problems, affecting the planning and managing of its impacts. Although different vaccines and drugs have been proved, produced, and distributed one after another, several new fast-spreading SARS-CoV-2 variants have been detected. This is why numerous techniques based on artificial intelligence (AI) have been recently designed or redeveloped to forecast these variants more effectively. The focus of such methods is on deep learning (DL) and machine learning (ML), and they can forecast nonlinear trends in epidemiological issues appropriately. This short review aims to summarize and evaluate the trustworthiness and performance of some important AI-empowered approaches used for the prediction of the spread of COVID-19. Sixty-five preprints, peer-reviewed papers, conference proceedings, and book chapters published in 2020 were reviewed. Our criteria to include or exclude references were the performance of these methods reported in the documents. The results revealed that although methods under discussion in this review have suitable potential to predict the spread of COVID-19, there are still weaknesses and drawbacks that fall in the domain of future research and scientific endeavors.

Keywords: artificial intelligence; COVID-19; deep learning; epidemiological disease; machine learning; LSTM; spreading; SARS-CoV-2

1. Introduction

Infectious diseases outbreaks exhibit various patterns that are complex to analyze and address. Based on these patterns, researchers can determine the transmission dynamics of the outbreak [1]. The COVID-19 outbreak is an example of an infectious disease that despite full-measured containment policies, quickly passed and affected various countries across the globe overwhelmingly [2,3]. Thus, such a pandemic is not only a health concern but also has devastating and long-lasting economic repercussions on a global scale [4]. The global nature of COVID-19 has grabbed the attention of researchers across various fields of science to analyze and predict pandemic evolution [5,6]. The usual non-linearity of such scenarios calls for systems that have the potential to address non-linear dynamic changes [1]. This is why a number of AI methods have been rendered for such a purpose.

For example, for analysis and prediction of the confirmed cases, a Convolution Neural Network (CNN) was also presented by C.-J. Huang et al. [7]. The focus of this study was on Chinese cities, which experienced most of the confirmed cases, and a forecasting model for COVID-19 was put forward according to the CNN deep neural network method. Additionally, to forecast the outbreak, a Multi-Layered Perceptron (MLP) network with two scenarios was utilized in [8], in which a set of data points regarding both scenarios was employed to train the network. Based on this research, 8, 12, and 16 internal neurons were tested for the realization of the best possible responses. RMSE and the correlation coefficient were used for evaluation and reduction in the cost function value. Furthermore, a novel modified predicting model was presented in [9], based on the Adaptive Neuro-Fuzzy Inference System (ANFIS), for prediction and estimation of the confirmed individuals involved with the virus ten days ahead of the infection based on the confirmed cases recognized in China. In addition, an enhanced Flower Pollination Algorithm (FPA) equipped by the Salp Swarm Algorithm (SSA) has been utilized [9].

The most important advantages of the proposed ANFIS-based technique are its flexibility in the process of indicating nonlinearity in the time series data and integrating the properties of fuzzy logic systems and artificial neural networks (ANNs). Furthermore, Niazkar et al. [10], applied ANN to predict the COVID-19 confirmed cases in China, Japan, Singapore, Iran, Italy, South Africa, and the United States of America. They demonstrated that the ANN-based model that takes into account the previous 14 days outperforms the other ones. They concluded that considering the incubation period of SARS-COV-2 in prediction models may generate more accurate estimations. An example of different forecasting applications was presented in [11], in which ANFIS and empirical mode decomposition were used to propose a stock price forecasting model.

Along with the extensive on-the-rise use of various countries of digital technologies in battling against the COVID-19 pandemic, there is an ever-increasing need for proper use of data and algorithms. In this regard, policymaking, health management, and benefiting from resources to control and prevent epidemic outbreaks seem impossible without data mining models. Implementation of policies, however, is highly dependent on the availability of timely and high-quality data in the early stages of the outbreak so that researchers can collaborate on data analysis and realize positive effects on resource planning related to the health care system. Technology, therefore, could extend its capabilities beyond daily life activities and needs and vigorously support people in their protection from COVID-19. The success of countries that could flatten the curve and maintain low mortality rates throughout the disease is evidence of how digital technology integration into pandemic policy and the response has come to be an adroit decision to be included in the process. This, however, could not come to reality without the existence of a global impact, large-scale

data and operational validation, model sharing, and adaptation to local special needs and unique contexts.

In the present paper, we aim to organize and provide a rapid narrative and short review of some AI-based predicting methods to forecast the trends of COVID-19 outbreaks, especially those techniques that have been employed with ML or DL structures. In this respect, the performance and efficiency of the studied techniques have been considered criteria for including or excluding the publications in this short review. Accordingly, this paper presents a few AI techniques that can be more useful and reliable in predicting the spread of COVID-19. It is emphasized that none of these methods is perfect to be used as an errorless technique, and our survey shows that several weaknesses are inevitable in the utilization of these methods. The manuscript consists of six sections, the second of which describes AI-based technique. Materials & methods and results are presented in Sections 3 and 4, respectively, while Section 5 is the discussion. Finally, the conclusion has been explained in Section 6.

2. AI-Based Techniques

There are various AI-related methods reliant on ML, DL, meta-heuristic algorithms, clustering techniques, and fuzzy methods, covering a wide variety of special problems with COVID-19 in different fields, such as sociology, learning issues, social media, risk assessment, and hazard identification [12–15]. Through the development of a neural network, it is possible to extract features to facilitate solving complex problems and modeling non-linear systems as well as predict dynamic trends [13,16–20]. Proponents of AI in analyzing complex problems make these techniques outstanding to be employed in a wide range of applications [21–27]. So far, AI has helped physicians deliver optimum care for their patients at various levels (prevention, diagnosis, and treatment). However, the potential of AI methods, especially Machine Learning (ML) and Deep Learning (DL) go beyond the mentioned applications [28,29]. AI is capable of predicting mortality risk through the analysis of patients' previous data. It can assist in population screening and can provide a variety of medical help, notification, and suggestions that could be a great help to control infection. AI-driven algorithms are also considered effective solutions for the early detection of pandemics. They are even believed to be applied more in the future as they can prepare the health care system against diseases more efficiently [30]. Not only can AI improve significantly treatment consistency, but also it enhances decision making through many effective algorithms [31]. It is capable of tracking COVID-19 occurrences in medical, molecular, and epidemiological applications [13]. In addition, due to the ongoing progress in technology, AI has already demonstrated its effectiveness in the early detection of COVID-19 [30]. Furthermore, through AI and predicting the prognosis of COVID-19 patients, healthcare providers can optimally allocate limited medical resources such as ICU beds and mechanical ventilators and can provide appropriate supportive care.

Some methods surveyed here may have a high risk in terms of their reliability as being good for practical applications. The reason for such consideration lies in their accuracy and their inattention to the importance of some parameters or details of the AI methods as well as poor analysis that could show the effectiveness of the results such as a high risk of model overfitting. While studies vary in terms of their reporting quality, few would argue that AI is causing a paradigm shift in health care. The example of predicting the location of the next occurrence of the outbreak attests to the value of AI application to the COVID-19 outbreak.

3. Materials and Methods

In this short review, 60 preprints, peer-reviewed papers, conference proceedings, and book chapters published in 2020 with a focus on AI-related methods, particularly ML, and DL techniques to predict the spread of COVID-19 are reviewed and evaluated. In other words, this review addresses the findings of relevant research on AI-powered forecasting techniques and their performance in the prediction of the spread of COVID-19 as a nonlinear

function. Although there were no special criteria to prioritize models and approaches collected in this research, we considered those techniques with better performance.

Overall, their evaluation indexes were different from each other, and this issue may influence the correctness of finding the best techniques. Moreover, to make an intelligent choice for aggregating the publications, the reputation of the sources was considered. One of the most significant contributions of this research is to emphasize introducing new AI methods in the prediction problems, and this characteristic can help researchers and scientists choose the best possible methods among the evaluated methods. Furthermore, this result would be generalized for understanding the dynamic behavior of new mutations.

In addition, an important criterion, which was utilized to choose these studies was their language. Therefore, disregarding the performance and effectiveness of the publications, only those written in English were selected for further consideration. The relevance of the sources was considered to be another index to include or exclude the papers, and articles with a low level of relevance were replaced with those that focused on the topic, including chapters, proceedings, and published or preprinted studies. Regarding the significance of the regional studies in these types of narrative reviews, countries where research documents were available, were considered as a criterion for demonstrating the results. Figure 1 shows countries that were studied to predict COVID-19 spread.

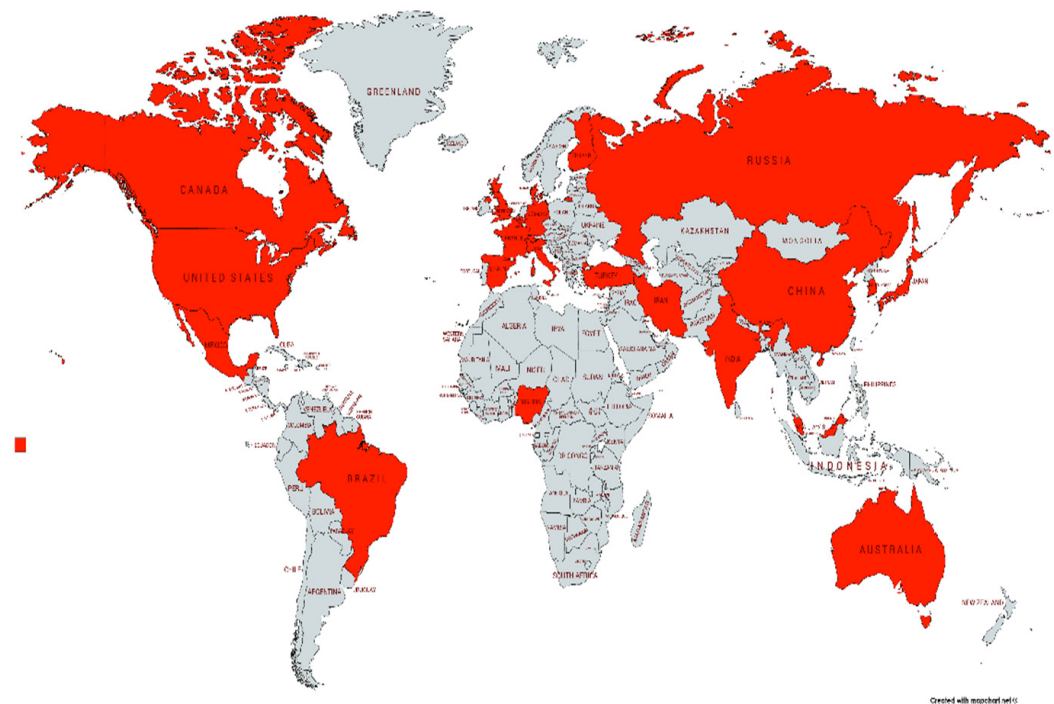


Figure 1. Global map of the countries that were studied through the AI-based methods to predict the trend of the spread of COVID-19 in this review.

In addition, Figures 2 and 3 give useful information on the daily confirmed COVID-19 deaths per million people in the aforementioned countries as logarithmic line graphs and cumulative graphs, respectively. However, similar to the graph of confirmed cases, the number of confirmed deaths is much lower than the true number of deaths. This is because of limited testing and challenges in the attribution of the cause of death. Overall, the situation in almost all countries is getting worse and worse. Therefore, the utilization of AI in predicting the spread of COVID-19 will be helpful.

In addition, to show the complex and nonlinear trends of COVID-19 in infecting people and the mortality rate, some charts are included in this section. As observed, Figure 2 gives useful information about daily confirmed COVID-19 deaths per million people in the studied countries in logarithmic form. This figure shows the fluctuations in this rate

in a specific time slot and proves why conventional methods cannot predict such trends accurately. The same scenario can be mentioned for Figure 3, depicting the daily confirmed COVID-19 deaths per million people in the studied countries. Although the behavior of this chart is more predictable, it holds many uncertainties regarding different regions. Generally, similar to the graph of confirmed cases, the number of confirmed deaths is much lower than the true number of deaths. This is because of limited testing and challenges in the attribution of the cause of death. Overall, the situation in almost all countries is getting worse and worse. Therefore, the utilization of AI in predicting the spread of COVID-19 will be helpful.

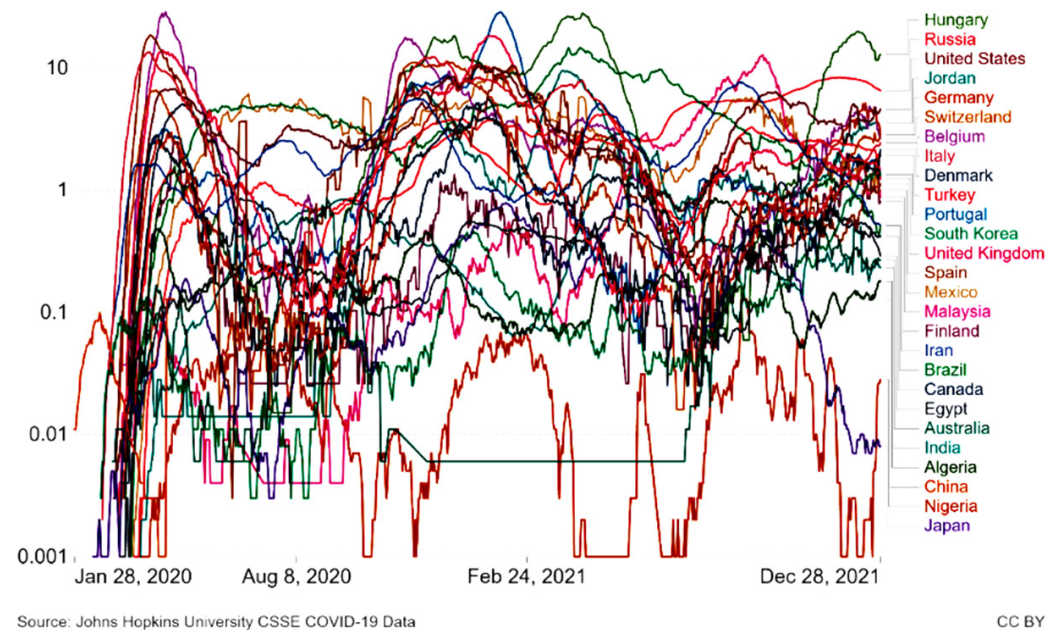


Figure 2. The daily confirmed COVID-19 deaths per million people in the studied countries in logarithmic form.

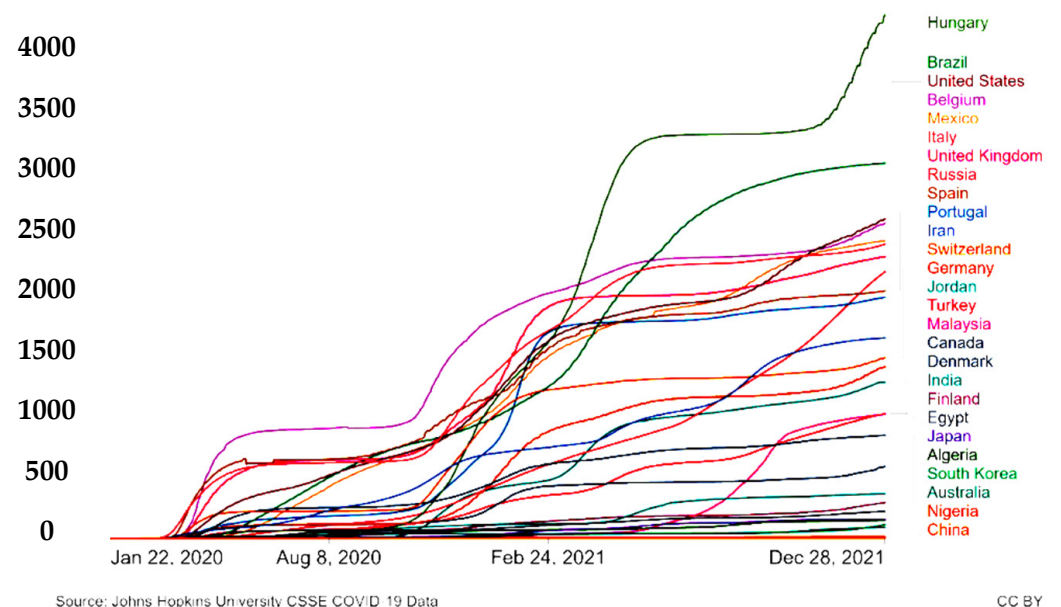


Figure 3. The daily confirmed COVID-19 deaths per million people in the studied countries.

Real-time data collected from the Johns Hopkins dashboard were used to design ML and DL models to understand the daily exponential behavior of COVID-19 and its future

reachability across the nations. New mathematical models were chosen based on ML, such as polynomial regression (PR) and support vector regression (SVR) [32], as well as DL regression models, such as a standard RNN and Deep Neural Network (DNN) using LSTM. A few significant climate parameters, such as relative humidity, daily average temperature, and wind speed as well as some urban parameters including population density, were considered to realize the analysis of their impacts on confirmed COVID-19 cases. This analysis was conducted on three case studies in Italy along with an investigation of the proposed method [33]. Moreover, the prediction of verified cases was based on an LSTM for time series [34]. Seasonal Autoregressive Integrated Moving Average (SARIMA), RNN, moving averages, and Holt Winter's Exponential Smoothing (HWES) approaches were utilized for justification [34].

4. Results

This section has been organized based on how and why the mentioned methods can be helpful to be employed in predicting and estimating the spread of COVID-19 and similar problems. Moreover, the benefits, drawbacks, or limitations of these models have been demonstrated in this section. Because of their versatility, AI technologies reviewed in this research can be generalized to be utilized in various similar areas, including biomedicine, epidemiology, and the socio-economy [35]. This adaptation and adjustment process can be facilitated by new tools and frameworks, which can forecast essential trends and parameters at individual and institutional levels efficiently [36]. In this way, such AI techniques mostly aim at avoiding critical overload of health systems and are designed to prevent such overload because it is through solutions, such as disease contention and mitigation, that the mortality rate could come under partial but promising control [37]. Nevertheless, similar to a scientific discipline, the ability to prevent chaos and predict is essential to promote the outcome of research and practice related to dynamic trends and various scientific endeavors [38]. The advantages, challenges, and restrictions of these methods have been addressed.

4.1. Why Use AI for the Prediction of the Spread of COVID-19?

To consider the significance of the AI methods in the prediction of nonlinear trends, it is helpful to report the characteristics of statistical models and the restrictions of AI methods. Having its roots in computer science, AI builds on human intelligence but extends beyond human limitations through reducing the workload; an example of such characteristics is that in contrast to traditional statistics that depend on organized and unified data, AI technology screens the original data and calculates attributes that are important [39]. While the infection rate to predict epidemic trends is analyzed according to the change in the number of infections in traditional epidemic models, these models have restrictions in differentiating between different levels of infection. The main source of this limitation originates from the fact that the same level of infection for all patients is typically calculated [40]. Lacking this level of deep insight, their output is limited to general trends only. In contrast, AI is capable of identifying, tracking, and forecasting outbreaks as well as diagnosing the virus and processing healthcare claims [41]. AI aims to present the data better since the original data might not provide a detailed or thorough presentation. Further, both manual and automatic approaches are possible; however, in the previous case, the feature construction condition has one typical application.

In [42], an ML-based improved model was employed for the prediction of potential COVID-19 threats worldwide. The findings demonstrated that a better fit in developing a prediction framework was achieved through the use of iterative weighting for fitting the Generalized Inverse Weibull (GIW) [43] distribution. Deployment on a cloud computing platform to achieve real-time and precise forecasting of the epidemic's growth behavior is one of the main features [42]. To enhance the accuracy of the predictions, health facilities, population density, weather conditions, average and median age, etc., were integrated [42]. A new analysis of the ongoing DL and ML methods to diagnose and predict the occurrence

of COVID-19 was presented in [44]. This research also compared the impact of ML and other competitive approaches such as mathematical and statistical models on COVID-19. To forecast and predict the pandemic, computing approaches, as well as factors, such as method types and the disease-related research impact on the nature of the data, were presented in [44], while a systemic review of epidemiological, clinical, chest imaging, and laboratory data available was presented in [45].

Six different ML-inspired and statistical time series approaches were developed to approximate the percentage of the active cases in comparison to the total number in the population in [46]. This was done looking one week ahead and for 10 countries that had the highest number of confirmed cases since 4 May 2020. To work as a tool for data collection, an online questionnaire was developed and used in [47]. The data collected by this method were then utilized as input for different forecasting models based on machine learning models (SVM, and MLP) and statistical models (Logistic Regression, LR). Using signs and symptoms, these models were employed for predicting potential COVID-19 patients. Ref. [48] was a case-control study in which patients whose COVID-19 infection was verified on 23 January 2020 and 6 February 2020 as well as all emergency patients, outpatients, and inpatients, except the control group (those with COVID-19 during the same period) were included. In addition to describing the sources of infection, consultation time, and incubation period in the cases, this study calculated the secondary incidents occurring in Gansu. Moreover, Ref. [49] focused on investigating the capacity of a simplified macroscopic virus-centric model to simulate COVID-19 evolution across a country with the condition that evolution of developing conditions such as behaviors and containment policies in the territory under study were sufficiently homogeneous. Using ML [50], a method to forecast poor prognosis of COVID-19 patients was suggested. The dataset for this study included information on 13,690 patients that were either dead or that had recovered and cured.

4.2. Big Data and AI and Prediction of the Spread of COVID-19

In addition, one of the significant advantages of AI is related to its prominent applicability for analyzing big data. This is why such intelligent approaches play an important role in the construction of models or infrastructures to streamline studying viral activity. Moreover, these approaches assist healthcare policymakers in preparing for an occurring or resurging outbreak more appropriately. Indeed, emerging intelligent techniques, such as those based on ML, have demonstrated that they can be of great help to trace the source or predict infectious disease trends [51]. Such an ability allows big data and intelligent analytics effective solutions to be employed for the benefit of patients, health care providers, and public health [52]. Using analogies and ideas from atmospheric sciences, the authors [53] critically assess the proposition that bigger predictions are the outcome of bigger data and conclude that compromising modeling and quantitative analysis can yield a working forecasting strategy. Extracting the features is a process during which dimensionality is reduced and an original set of raw data is refined and reduced to data that could be more conveniently managed. A large data set is characteristically assumed to have a large number of variables, making computing resources essential to perform processing.

Studies have shown that the application of technologies can help to bring pandemics under control or provide the pandemic-stricken community with enough support so that the spread of the infection comes under decisive control [54]. Admittedly, using big data to protect from COVID-19 presupposes an important role for informatics specialists who could work side by side with physicians, nurses, paramedics, health practitioners, and all other professionals in the field to provide telehealth or virtual care [55]. It is true that globally speaking, world health systems still rely on classic public-health measures to combat the pandemic of COVID-19. Nevertheless, it cannot be denied that a wide range of digital technologies available to health care providers could enormously enhance public health strategies if these technologies would have been adopted by governments and health systems [56].

In a study, a new susceptible-exposed-infected-removed (SEIR) model was utilized in which domestic reduction data before and after 23 January as well as the latest COVID-19 pandemic data for prediction of epidemiological spread were incorporated. The proposed model prediction was corroborated through the utilization of an ML approach trained on 2003 SARS coronavirus outbreak data [57]. In this regard, it should be noted that although the outbreak in 2003 did not lead to a global pandemic, SARS-CoV is the nearest human coronavirus relative of SARS-CoV-2 with an 86.85% similarity. In addition, C. Menni et al. presented a mobile application to track the symptoms showing that the virus caused the loss of smell and taste in 2,618,862 individuals, and this technique highlights the significance of big data and COVID-19-related technology [58]; (Methods) [59].

4.3. ML and DL Methods Used in the Prediction of COVID-19

In this section, the focus is on the applications of the studied methods. In this way, the applicability and performance of such techniques have been taken into consideration. Furthermore, some challenges and restrictions of these approaches in the face of epidemiological problems have been mentioned and addressed. In other words, we take a glance at some methods enabled by ML and DL to forecast the spread of the virus. Table 1 gives information about ML and DL methodologies utilized for the spread of COVID-19 without combination with statistical methods. Our goal is to describe the important studies case by case to make an overview for readers to determine a proper method for similar problems. Therefore, the organization of this section is based on the evaluation and description of these methods with an emphasis on their general structures, the purpose of their application, benefits, and limitations.

On 24 March 2020, this tracker was used in the United Kingdom, and it was then exploited in the United States; this app-based tracker is free and was installed on smartphones to collect information from symptomatic and asymptomatic persons and works in real-time to track the progress and spread of the disease through health information that was reported by the individuals themselves on a regular daily basis. This self-reported information includes PCR tests, hospitalization symptoms, prior medical terms and demographic data, logistic regressions adjusting for age, BMI, and sex to identify symptoms other than anosmia that could be related to SARS-CoV-2 infection [59]. Ironically, despite the considerable potential of AI applications in fighting COVID-19, the current literature suggests that relevant studies may not be clinically relevant [60].

In [61], a Virus Optimization Algorithm (VOA) was combined with an ANFIS to investigate the impact of population density and climate-related factors on the spread of COVID-19. Data in this study were related to climate-related factors and COVID-19 confirmed cases across U.S. counties. Ref. [62] presented a modified version of the ANFIS model for the prediction of the number of infections in four different countries. This modified ANFIS is based on the marine predators' algorithm (MPA) which is a new nature-inspired optimizer. The MPA is used to optimize the ANFIS parameters that lead to a better forecasting performance. To evaluate the proposed MPA-ANFIS, official datasets of the four countries were utilized [62].

In [63], ML tools selected three biomarkers to forecast each patient's mortality more than ten days in advance with more than ninety percent precision: high-sensitivity C-reactive protein (hs-CRP), lymphocyte, and lactic dehydrogenase (LDH). Relatively high levels of LDH had a significant role in determining a significant number of cases in dire need of instant medical attention. This confirmed the existing medical knowledge suggesting high LDH levels as being associated with tissue breakdown that happens in different diseases such as pulmonary disorders including pneumonia. Having considered COVID-19 progressive trends in China and South Korea, [64] relied on ANN-based curve fitting techniques to predict and forecast the number of occurring cases and deaths related to COVID-19 in France, the USA, India, and the UK, as well as considering progressive trends in China and South Korea.

Ref. [65] used WHO datasets and datasets presented by Johns Hopkins University for the creation of training datasets. The recurrent neural networks (RNNs) were later used to develop two prediction models. The first time-step information was collected by a dense layer of a neural network and a consequent regression output layer to make determining the next predicted value possible. Moreover, Ref. [66] was a case-control population-based study done in the Lombardy region in Italy. There were 6272 patients with SARS-CoV-2 between 21 February 2020 and 11 March 2020. Age, sex, and the municipality of residence were criteria according to which these patients were matched to 30,759 beneficiaries of the Regional Health Service (controls). Information related to the use of selected drugs as well as clinical profiles of the patients were collected from health care regional databases [66].

Ref. [67] utilized multiple ML algorithms to predict the occurrence of infection globally based on dataset analysis. The lowest R² score of 0.8273 was obtained for the ML algorithms, such as Support Vector Regressor, compared with Bayesian Ridge Regression and Polynomial Regression, and the highest RMSE value was 124,328.5297 amongst the three models, indicating Support Vector Regressor was last in line for the preferred models [67]. Using real-time COVID-19 time-series data related to the period of 22 January 2020 to 18 May 2020, [68] proposed a hybrid model incorporating an ensemble empirical mode decomposition (EEMD) ANN to forecast the COVID-19 epidemic. The time-series data were first decomposed through the use of EEMD to create sub-signals, and the original data were denoised, after which ANN architecture was implemented for training the denoised data [69]. AI-based methods and natural language processing methods with unstructured data of patients gathered by telehealth visits to improve the computer algorithms efficiency used for screening COVID-19 were used in [70]. The study consisted of segmenting and parsing documents as well as a consequent investigation and analysis of overrepresented words appearing in a patient's symptoms. The study was also marked by a word embedding-based ANN used to predict COVID-19 test results according to symptoms that patients reported themselves.

A dataset with publicly available information related to 51 days (22 January 2020 to 12 March 2020) on the number of infections, recoveries, and deaths in 406 locations was used in [71]. The initial aim of this dataset, which was a time-series dataset, had to be modified so that it could be a regression dataset to be used to train an MLP ANN. The training, in this case, was aimed at achieving a global model of the patient's maximal number in all locations across each time unit. Hyperparameters of the MLP used a grid search algorithm consisting of total hyperparameter combinations equal to 5376 [71]. Ref [72] presented a multiple ensemble ANN model with fuzzy response aggregation for the time series prediction of COVID-19 [72]. Ensemble neural networks include a set of modules employed to create various predictions regardless of existing conditions. To aggregate responses of several predictor modules, fuzzy logic was used, which in turn, improved the ultimate prediction by intelligently combining module outputs. Fuzzy logic deals with the uncertainty that may arise throughout the process of reaching the final prediction [72]. Ref. [73] proposed an ML-based approach to implement a model to firstly help doctors verify the disease within a short period and secondly predict the growth of the disease in the future on a worldwide basis. To achieve this aim, two models were used: the first model was based on the Convolutional ANN model, and the second one considered Convolutional ANN and RNN. These models were evaluated and compared to verify the results predicted by the original model [73].

The development of a comparative regressive and ANN model designed to examine COVID-19 impacts on China's demand for electricity and petroleum was reported in [74]. The environmental analysis demonstrated that the pandemic significantly affected China's demands for electricity and petroleum in direct and indirect ways [74].

Table 1. ML and DL techniques used for the prediction of COVID-19 spread independently. These papers and documents were published in 2020.

Author	Technique	Country/Region	Domain/Study Area	Data and Date	Results
Zixin Hu et al. [75]	MAE	China	Forecasting cumulative confirmed cases of COVID-19	Verified cases of COVID-19 in China from 2020 January to 2020 April	Average errors of 10-step, 9-step, 8-step, 7-step, and 6-step forecasting were 0.73%, 2.08%, 2.14%, 2.27%, and 1.64%, respectively
Zifeng Yang et al. [57]	Modified SEIR and LSTM	China	Forecasting the trend of the epidemic	The data on the SARS epidemic in 2003 data between April and June in China obtained from an archived news site (SOHU)	A new peak of infections occurred on 4 February, predicted to result in 95,000 cases by the end of April
Cristina Menni et al. [59]	Statistical analysis	UK USA	Self-reported symptoms real-time tracking by the smartphone app	in the period March 2020 up to April 2020, UK and US individuals reported symptoms	Prediction of 17.42% (140,312) participants to be positive for COVID-19
V. K. R. Chimmula et al. [1]	LSTM	Canada	Time series prediction of transmission	The available data until 31 March 2020	Based on the results of our LSTM network, the possible outbreak endpoint will be around 2020 June
M. H. D. MolinRibeiro et al. [76]	SVR	Brazil	Short-term prediction of cumulative confirmed cases	The cumulative confirmed cases until April 2020	The most suitable tools for the prediction of cases were SVR and stacking ensemble
Mohammed A. A. Al-cases et al. [9]	FASSA-ANFIS model	China	Optimization Method for Forecasting	The daily confirmed cases in the period of January 2020 up to February 2020	The confirmed case prediction from 19 February 2020 to 28 February 2020; 28 February 2020 predicted be the outbreak's highest level
Chiou-Jye Huang et al. [7]	Deep CNN, GRU, LSTM, MLP	China	Forecasting the confirmed cases	Training data: From 23 January to 17 February / Testing data: From 18 February to 2 March.	GRU and LSTM had decent efficacies
Shreshth Tuli et al. [42]	ML-based improved model	Countries worldwide	The trend and growth of the COVID-19 pandemic predicting	Our World in Data by Hannah Ritchie	The presented model had better prediction results than the baseline.
Hazem Al-Najjar et al. [77]	ANN	South Korea	Classifier prediction model	7869 patients between 20 January 2020 and 09 March 2020	The proposed predictive classifier efficiently predicted recovered and death cases

Table 1. Cont.

Author	Technique	Country/Region	Domain/Study Area	Data and Date	Results
Swapna Rekha Hanumanthu [44]	ML and DL methods	All countries	New review on several types of Intelligent Computing	Articles published using different approaches	Issuing some important research directions for further research
Narinder Singh Punnet al. [68]	SVR, PR, DNN, and LSTM	All countries	Epidemic Analysis	The data from 22 January 2020 to 1 April 2020	PR yielded a minimum RMSE score over other approaches
Steffen Uhlig et al. [36]	ANN and epidemiological method	South Korea, Germany and the USA	Modeling projections	From 1 February to 12 April	Robustness of the method against inherent disturbances in epidemiological surveillance data
Batista AFM et al. [78]	ML approaches	Brazil	diagnosis prediction in emergency care patients	235 adult patients from 17 to 30 of March 2020	The best predictive performance was obtained by SVM
Luca Falesia et al. [79]	JASP software SVM, Logistic, Naïve Bayes, Random forest	Italy	Stable psychological traits prediction	Collected Data between 20 March 2020 and 31 March 2020	High levels of perceived stress were found in the population
Giuseppe Mancina et al. [66]	STATISTICAL ANALYSIS	Lombardy region of Italy	System Blockers and the Risk	6272 case patients were confirmed between 21 February 2020 11 March 2020	The mean (\pm SD) age was 68 ± 13 years, and 37% were women, among both case patients and controls
S.K. Tamang et al. [64]	ANN	India, USA, France, UK, China, and South Korea	Forecasting	Data collected from 10 to 18 May 2020	The predictions were according to the conditions and technique applied, though the user data in the study were based on reliable sources
Kanak Kaushik [80]	SVM, PR, BRR	world-wide	Forecasting and Analysis	data collected from 22 January 2020 to the present time	BRR had R^2 score = 0.9321 and the lowest RMSE value = 71,920.7332, while SVM had the lowest R^2 score = 0.8273
Najmul Hasan [69]	EEMD-ANN	Countries worldwide	Predicting	22 January 2020 to 18 May 2020	A promising model for analysis

Table 1. Cont.

Author	Technique	Country/Region	Domain/Study Area	Data and Date	Results
Zlatan Car et al. [71]	MLP	Countries worldwide	Modeling the Spread	Dataset from 22 January 2020 to 12 March 2020 across 406 locations	Best models; R2 scores of 0.99429, 0.97941, and 0.98599 for the deceased patient model, recovered patient model, and confirmed patient model, respectively
Ebaa Fayyouni et al. [47]	SVM, LR, MLP	Jordan	Prediction	Online questionnaire	The MLP had the best precision compared with the other models.
Patricia Melin et al. [72]	MNMF, FITNESS, NAR	Mexico	Predicting	Not mentioned	Very good predicted values
Shawni Dutta et al. [73]	CNN; LSTM; RNN CNN-LSTM	Countries worldwide	Verifying Predictions	Not mentioned	The combined CNN-LSTM approach had desirable performance according to experimental results.
Mehdi Azarafza et al. [34]	LSTM	Iran	Prediction of Infection based on Deep Learning	The data from 19 February 2020 to 22 March 2020 (provincial level) and 19 February 2020 to 13 May 2020 (national level)	LSTM model had better results than RNN, SARIMA, HWES
Fernanda Sumika Hojo de Souza et al. [50]	LDA, LR, KNN, NB, DT, SVM, XGB	Brazil	Predicting the disease outcome	13,690 patients; 23 May 2020 and 30 May 2020	The disease outcome was predicted with a Sensitivity of 0.88, Specificity of 0.82, and ROC AUC of 0.92 for the best prediction model
Seyed Mohammad Ayyoubzadeh et al. [64]	RMSE of the LSTM model	Iran	predict the incidence	The daily new cases of coronavirus from 15 February 2020 to 18 March	Data mining algorithms were employed to predict trends of outbreaks
Mohammad B. Jamshidi et al. [81]	LSTM, ELM, GAN	All countries	Perspective for Diagnosis and Treatment	The medical reports and recent related publications	Generalizing strong methods based on the COVID-19 characteristics
László Róbert Kolozsvári et al. [82]	LSTM	Hungary UK, Italy, Spain, Germany, France, USA	Predicting the epidemic curve	the publicly available datasets of WHO	The AI-based models are useful tools for pandemic prediction

Table 1. Cont.

Author	Technique	Country/Region	Domain/Study Area	Data and Date	Results
Seid Miad Zandavi et al. [83]	LSTM	Several countries	Forecasting	31 December 19 April 2020	Public knowledge and behavior can directly impact the spread of COVID-19.
Shaoyi Du et al. [84]	NLP-LSTM into ISI model	China	Predicting with the use of a Hybrid AI Model	Training Data: in the period of 23 January up to 18 February/Prediction: 19 to 24 February	MAPE values of 0.52%, 0.38%, 0.05%, and 0.86% for the next six days
Ayan Chatterjee et al. [85]	LSTM models	Countries worldwide	Analysis on Spreading and Death	From 1 January 2020 to 22 April 2020	Stacked, vanilla, and bidirectional LSTM models had better performance compared to multilayer LSTM models

The analysis in [86] was founded on recent momentum management of epidemics theory, while Bessel functions were employed. The utilized parameters were the initial transmission rate that reflects the “normal” frequency and viral fitness of contacts in the infected areas and indicates the intensity of preventive measures [86].

The main characteristics of trends and patterns of the COVID-19 outbreak in Canada were evaluated based on the LSTM network [1]. One capability of recurrent LSTM networks is that they can use conventional time series predicting techniques limitations by adjusting nonlinearities of the COVID-19 dataset. Accordingly, LSTM blocks operate at different time steps to pass their output to blocks ahead of them and this continues until the sequential output is generated by the final LSTM block [87]. In separate research, data obtained from the Google Trends website were used for the prediction of COVID-19 in Iran [88]. To predict the cases, LSTM and Linear Regression methods were employed, and k-fold cross-validation and the Root Mean Square Error (RMSE) were used to validate all models as the performance metrics. The LSTM model demonstrated fluctuations in performance at a time when there was few training data. This signifies overfitting in the LSTM technique due to the limitation of training data [88].

The LSTM model is an RNN-trained model based on the 2003 SARS epidemic statistics that incorporates some epidemiological features including the transmission incubation rate, probability, recovery probability as well as death and contact number. To predict COVID-19, a hybrid AI model was suggested in [40]. Initially, an improved SI (ISI) model was proposed to analyze and scrutinize the alteration in the infectious potential of the carriers of the virus after the infection. In the next step and with due attention paid to the prevention effects, increased prevention awareness in the public, key control measures, and building the hybrid AI-based technique for predicting COVID-19, the Natural Language Processing (NLP) module and the LSTM network were both incorporated into the ISI model. In addition to the proposed hybrid method integrated with the LSTM network and NLP module described in this chapter, this article introduced information related to local and central governments’ efforts as well as public support for the process of prediction [88]. The LSTM network was also used to estimate the deviation of the epidemiological method and was combined with the introduced ISI model to estimate the number of infection occurrences.

5. Discussion

The prediction AI-empowered methods reviewed here aimed to support public health authorities, officials, and scholars as a useable reference for becoming acquainted with applications of AI in such complicated problems. Accordingly, these methods would be utilized not only by authorities, top decision-makers, and organizations to make decisions and implement policies concerning people’s health and well-being but also by researchers and scientists in fields of engineering and medicine. Such technologies, however, are not fully advanced and well-received, and their recognition and insertion in national and international policy levels take place at a very slow pace. AI techniques, nevertheless, are increasingly reshaping various aspects of humans’ lives, providing them with the opportunity for data analysis, information integration, and approaches to improve policies and decisions and enhance implementations in biotechnology, health care, speech, and voice recognition, transport, finance, and climate change, etc. [89,90].

This study had two main objectives to achieve: firstly, evaluating specific features of reviewed studies that provided an overview of the research and secondly, demonstrating how AI-based methodology could be utilized to examine and confirm future research. The core investigation is put forward in the results section to predict pandemics followed by viable prospective AI methodologies. As far as the obtained results are concerned, one can infer that SVR and the stacking-ensemble learning model are suitable tools to be used for forecasting COVID-19 occurrences in most of the adopted states provided that these approaches could learn the nonlinearities that are features of the evaluated epidemiological time series. IS has proved itself extremely effective in tracking COVID-19 and forecasting outbreak-related future events. An example is informatics experts at the Alberta University

Centre for Health Informatics stating that experts at CHI have joined together to develop an interactive and comprehensible dashboard [55].

There are points related to the limitations of our study that should be carefully considered. As COVID-19 is progressing and causing the bulk of disease-related literature to grow at an unprecedented pace, the present review is not an up-to-date list of all available and related prediction techniques of COVID-19. Further, some of the studies reviewed in our effort were preprints with the possibility of significant improvements after being peer-reviewed by specialists, experts, and authorities in the field. However, the most important results could be outlined as follows: Tracking and predicting the spread of COVID-19 could provide valuable data for public health officials that plan, prepare, and manage the COVID-19 pandemic.

AI and Big Data are assets when it comes to tracking the disease spread in real-time, planning and increasing public health interventions, monitoring their effectiveness, repurposing old compounds and discovering new medicine, identifying potential vaccine candidates, and enhancing the response of communities to the pandemic. Since the deployment of AI systems is a multidisciplinary effort, there should be serious attempts to create an extremely diverse context with complementary teams that could establish long-term partnerships. It is through sharing insights on AI systems, methods, and models that a compact form of shared knowledge is established and resources are saved to facilitate better deployments across contexts. While social distancing information is necessary for advancing the epidemiological models, no assumptions are required for modeling with ML. Disease outbreaks exhibit certain patterns whose identification depends on the outbreak's transmission dynamics.

For future goals, the presented methods could be employed for forecasting the behavior of the virus in different cities and countries, and thanks to the Johns Hopkins dashboard, as this center provides every academic or free researcher with this opportunity to access a wide range of datasets with numerous features for data mining, signal processing, system identification, and prediction of several phenomena. As the codes of many of these techniques can be accessible using a simple search on the internet, young researchers and AI enthusiasts can download several forms of these codes and develop their programs, considering their specific objectives and applications. An interesting direction to involve the aforementioned approaches, either for academic publications or for developing AI apps, is to select the best method based on the best performance. Accordingly, a dataset should be downloaded from a repository website. After that, researchers can analyze the dataset using different methods. A collection of the results would be evaluated with the use of several criteria and the best efficient method for that specific dataset or problem can be selected. The results of these simulations can be considered a component of research for publication in relevant journals or can be deployed for fundamental measures in the future.

6. Conclusions

Effective allocation of medical resources, production regulations, and countries' economic development depend on a reliable estimation of epidemiological trends and prevalence of an epidemic outbreak. That is why the techniques used in predicting an outbreak are of such substantial and crucial importance. Many approaches have been suitably applied in the process of forecasting the trends of the spread of COVID-19. However, many other approaches are deemed high risk for predicting operations due to poor reporting. Ever since the outbreak of COVID-19, various prediction methods that were based on AI have quickly entered the relevant literature to facilitate forecasting the outbreak. In this review, some important AI methods have been presented with an overview of their performance, restrictions, and trustworthiness.

The reviewed methods of this study can be employed by decision-making systems for minimizing the risks and researchers. Overall, we aimed to present an effective reference for those who are interested to start working on AI to solve COVID-19-related problems. We have also proposed a few promising future directions that can help in understanding

the predictions of the epidemiological issues and challenges. Finally, this short review can be used for developing DL platforms and frameworks as well as providing valuable insights and guidelines in future related research.

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