A Review on Potentials of Artificial Intelligence Approaches to Forecasting COVID-19 Spreading

Mohammad (Behdad) Jamshidi
Sobhan Roshani (sobhan_roshany@yahoo.ca)
Jakub Talla
Ali Lalbakhsh
Zdeněk Peroutka
Saeed Roshani
Asal Sabet
Mojgan Dehghani
Saeedeh Lotfi
Farimah Hadjilooei
Pedram Lalbakhsh

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Abstract

COVID-19 is by now one of the deadliest public health issues that as per the last announcement of the World Health Organization up to January 21, 2021, has infected more than 108,904,983 people and claimed more than 2,398,339 lives worldwide. Although different vaccines have proved and distributed one after another, several new mutated viruses have been detected, such as the new COVID-19 variant detected in the UK. Since new variants can spread so faster than the previous one and many other strains may come, it is necessary to focus on the effective methods that are able to predict the spreading trends quickly. Regarding the considerable progress in Artificial Intelligence (AI), utilizing AI-based techniques with a concentration on Deep Learning (DL) and Machine Learning (ML), which can forecast complex trends like epidemiological issues, are proposed to conquer the problems existing in statistical or conventional techniques. In this respect, the present paper reviews the recent peer-reviewed published articles and preprint reports about solutions that could efficiently address COVID-19 spread with a focus on the state-of-the-art and AI-based methods. The results revealed that methods under discussion in this paper have had significant potentials to predict epidemic diseases like COVID-19 as well as its mutations; however, there are still weaknesses and drawbacks that fall in the domain of future research and scientific endeavors.

Highlights

- Reviewing state-of-the-Art in different types of AI-based approaches to predicting epidemiological disease
- Assessing the restrictions and potentials of AI-based techniques in forecasting COVID-19 spread
- Reliance on DL and ML methods in predicting COVID-19 outbreak
- Considering the best possible intelligent methods in predicting the epidemic spread

1. Introduction

Infectious diseases outbreaks demonstrate patterns based on which researchers can tell what the transmission dynamics of the outbreak [1]. The COVID-19 outbreak in 2019 December in China, Wuhan is an example of infectious diseases that despite full-measured containment policies adopted by Chinese public officials could quickly pass the Chinese territory and overwhelmingly affect various countries across the globe[2, 3]. But the pandemic is not just a health concern as it has had devastating and long-lasting economic repercussions in a global scale [4]. The global nature of COVID-19 has grabbed the attention of researchers across various fields of science leading to sharing and contributing proposals that could be relied on to analyze and predict pandemic's evolution [5, 6]. The usual non-linearity of such scenarios calls for systems that have the potentials to address non-linear dynamic changes [1]. Although there are now many mathematical models of infectious disease, they need to be categorized to be suitably utilized by researchers and scholars [5, 7]. For example, compartmental models, including a combination of classical and more complex proposals [5, 8], have effective roles in quantification of strategies that could be employed to mitigate and control infectious diseases [5, 9]. Nevertheless, constant analysis of data must not be overlooked because the pandemic has demonstrated highest degrees of severity, and numbers have kept continuously changing [10]. Furthermore, new variants of the virus can spread so quickly and it has made the situation worst.

The used models along with important parameters, which is estimated by different methods, can be utilized to forecast the spread of the epidemic and its related fatalities in the immediate future [6]. In the case of COVID-19, however, some important information including key infection data- such as the period of mean infection and the period of mean incubation- are not available to researchers [9]. Since prediction problems with COVID-19 pandemic are not simple to be placed a binary classification task, and it is essential to use appropriate measures to work with the data [11]. Previous studies have been mostly relying on data driven approaches [12], and they are based on statistical methods often dismissing temporal components in the data [1]. The combination of such complexities with various contact patterns lead to a new challenge in predicting the behavior of COVID-19 that makes prediction processes difficult. This challenge is originated from the sole reliance on previously established compartmental models [9].

While the medical industry is currently seeking new technologies that could be utilized to monitor and track the COVID-19 spreading [13], most attempts are basically built on classical models that are customized according to the current situation with COVID-19. It is for this reason that this paper focuses on cases where AI-based techniques have been utilized for epidemiological modeling tasks. The illustration and classification of the existing AI-based epidemiological models is the most important contribution of this research that could be fruitful to predict the new mutations. It includes many reports and researches which are used for prediction purposes. For example, the AI-based methods which have been developed that to forecast new and verified cases of COVID-19 in real time and throughout Chinese territory [14].

In the present paper, we aimed for a critical appraisal and comprehensive review of the most recent achievements in AI-based predicting methods for forecasting and predicting COVID-19 outbreak trends, especially techniques based on ML or DL. To asses such techniques it is essential to understand AI methods' procedure in predicting and analyzing virus behavior when demographics and geographic locations differ. Accordingly, this paper renders AI techniques that are useful and reliable in predicting the spread of COVID-19 in a global scale. The manuscript consists of 6 sections, the second of which describes AI-based methodologies and the way of considering papers in relation to COVID-19 spreading and AI. In Section 3, materials and methods are discussed. The results and most important forecasting methods based on AI for COVID-19 are given in Section 4. This section covers the main part of this paper. In section 5, we discuss which potential or weakness can be considered for the addressed methods and what power point can be noticed for the future of this techniques. The conclusions are explained in Section 6.

2. Ai, Ml And Dl And Predicting

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, risk assessment and hazard identification. Through development of a neural network, it is possible to extract disease's visual features to facilitate proper monitoring and treatment of infected patients [15]. Proponents of AI believe that this methodology has the potential to be employed in precision medicine and image analysis in radiology and pathology [16]. A recent survey of health care providers demonstrated that 90% of responders believe in AI as a means of improving diagnosis and management of electronic health record. The potentials of AI methods, especially Machine Learning (ML) and Deep Learning (DL), however, go beyond what has been discussed so far as it can be of more usages [16–18]. AI is capable of predicting mortality risk through analysis of patients' previous data. It can assist in population screening, and provide a variety of medical help, notification, and suggestions that could be a great help to control infection [13]. AI-driven algorithms are also mentioned as effective solutions to realize early detection of pandemics and are even believed to be of greater use in the future because they can better prepare health care system against diseases [19]. Interestingly, while AI can improve treatment consistency significantly, it can also enhance decision making through many effective algorithms [20]. Besides, AI is capable of tracking COVID-19 occurrences in medical, molecular and epidemiological applications [13]. Due to the ongoing progress in technology, AI has already demonstrated its effectiveness in early detection of COVID-19 [19]. Furthermore, COVID-19 spread across the globe has come to be the focus of attention of policy makers and public health officials because numbers and locations related to the outbreak are in constant change. In addition, forecasting trends and statistics have come to be of greater importance in fighting against the disease [21].

3. Materials And Methods

This review concentrates on identifying, evaluating, and summarizing the findings of related research on AI-powered forecasting techniques and their effectiveness for COVID-19 spreading to provide health directors and researchers. One of the most important aspects of this research is to emphasis the scholarly and scientific evidence that help us to choose the best possible methods in the term of preparation and planning process. Moreover, this result could be generalized for understanding the behavior of new mutations' spread. Hence, we tried to collect the publications some reliable rescores, such as Google Scholar, Scopus and Web of Science, as well as PubMed search from 1st January, 2020 until the 4th July, 2020, 23:17:43 are databases used analyzing the related literature. The following search expression was defined for the purpose of surveying papers, '[(AI) AND (COVID-19) AND (Prediction) OR]. Only papers that were published in English were considered for the purpose of the present paper. While published research was prioritized for this paper, given that few COVID-19-related papers have been published on the subject of disease spread and AI-powered techniques, preprint databases bioRxiv, medRxiv, and arXiv, were used for access to quality preprints to be included in list of studies.

Nevertheless, only studies that could answer the defined question were selected. The criteria for choosing the studies were the extent that the resulting multivariable model or scoring system developed out of the data related to participants could contribute to prediction of COVID-19-related spread. Additionally, the chosen studies' reference lists and bibliographies were reviewed to mine useful relevant manuscripts. Regardless of book chapters, proceedings, seminar summaries, the published or preprinted studies in this review were in English. Fig. 1 presents the search flowchart that demonstrates search strategy as well as inclusions and exclusions. The four stages of work evaluation are identification, screening, eligibility, and inclusion. The identification stage is the stage in which search expressions facilitate obtaining works of interest. Screening stage is where consolidation of the results from different databases is performed to remove duplicate items. Screening stage is marked by verification of works' titles and the abstracts if they are in line with the present review's area of interest. Eligibility stage includes assessment of eligibility criteria and validity of results and conclusions. Another thing that is assessed in this stage is the quality of technique description and comparison with similar methods. The information that was obtained for each eligible study consists of authors, method, description of the paper, and the results. Fig. 2 shows countries that are studied for prediction of COVID-19 spread.

From the outset of COVID-19 pandemic scientists, researchers, medical practitioners and industries have been wholeheartedly working to fight the disease and find solutions that could assist them with faster screening, more reliable predictions, and more accurate strategies for tracing and forecasting the pandemic as well as discovering more effective drugs that could be helpful in the full-fledged fight against the pandemic [22].

4. Results

Ironically, AI has not been counted in so far as a technique which could be significantly relied on in fighting against COVID-19 in conditions of its potentials for medicinal remedy and diagnostic and pharmaceutical aspects [23]. This is while because of its versatility, AI technologies could greatly help scientists, scholars and technologists in a variety of areas, including biomedicine, epidemiology, and socio-economy [24]. This adaptation and adjustment process can be facilitated by new tools and frameworks capable of forecasting that promote management of resources at individual and institutional levels in an efficient manner [25]. Control strategies mostly aim at avoiding critical overload of health systems, and are designed to prevent such overload happen because it is through solutions, such as disease contention and mitigation that mortality rate could come under partial but promising control [26]. Notwithstanding the nature of a scientific discipline, the ability to prevent chaos and predict well is an essential ability that could promote the outcome of research and practice related to dynamical systems and various scientific endeavors [27]. An instance of such mechanism is physics where certain laws determine the evolution of physical system, and it is modeled by a dynamical system according to a set of parameters and the stable condition of the system before system's evolution [27].

Having its roots in computer science, AI builds on human intelligence, but extends beyond human limitations through reducing the workload; an instance of such characteristics is that in contrast to traditional statistics that depends on organized and unified data AI technology screens the original data and calculates attributes that are important [28].While in traditional epidemic models infection rate is analyzed according to the changing number of infections to predict epidemic's trends, these models fall short in differentiating between different levels of infection and assume the same level of infection for all patients [29]. 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 the healthcare claims [30]. AI aims at a better data representation for the desired ML algorithm because the original representation might not be as detailed and thorough as intended. Also, both a manual and an automatic approach is possible while in the before case the feature construction condition is of one typical applications [20, 31].

In addition, big data must be taken into account as an important infrastructure to facilitate modeling studies of viral activity and deeply informs healthcare policymakers to better prepare for an occurring or resurging outbreak [32]. Indeed, emerging intelligent techniques, such as those based on ML, have demonstrated that they can be a great help to trace the source or predict infectious diseases spread trends [33]. Such an ability makes big data and intelligent analytics effective solutions to be employed to the benefit of patients, health care providers and public health [34]. Using analogies and ideas from atmospheric sciences, the authors in [35] critically assess the proposition that bigger predictions are the outcome of bigger data and conclude that compromising modelling and quantitative analysis can yield to 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 which 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 [31].

On the other hand, the demand for using social media platforms by associations and organizations reach the public both on national and international level. This huge request for communication purposes leads to a confusing chaos caused by information overload and/or misinformation submersion [30]. A research showed that a better yield is to be expected when technology is employed in strategies to bring pandemic under control or provide the pandemic-stricken community with enough support so that the spread of the infection comes under a decisive control [36]. Admittedly, using big data to fight against 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 [37]. It is true that, globally speaking, world health systems are still relying on classic public-health measures to combat pandemic of COVID-19. Nevertheless, it cannot be denied that a wide range of digital technologies available to health care providers who could enormously enhance public-health strategies if these technologies would have been adopted by governments and health systems [32].

In [38] an ML-based improved model was employed for prediction of COVID-19 potential threats worldwide. The findings demonstrated that a better fit in developing a prediction frame work was achieved through the use of iterative weighting for fitting Generalized Inverse Weibull (GIW) [39] distribution. Being deployed on a cloud computing platform to achieve real-time and precise forecasting of the epidemic's growth behavior is one of the main features to rely on [38]. To enhance the accuracy of the predictions, health facilities, population density, weather conditions, average and median age, etc.

were integrated [38]. A new analysis of the ongoing DL and ML methods to diagnose and predict the occurrence of COVID-19 was presented in [40]. 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 disease-related research impact on the nature of the data were presented in [40], while a systemic review of epidemiological, clinical, chest imaging, and laboratory data available at the was present in [41].

4.1. ML and DL Methods

In this part, we take a glance at some methods enabled by ML and DL to forecast the virus spread. Table 1 gives information about ML and DL methodologies utilized for COVID-19 spread without combination with statistical methods. ANN method was used in [42] to classify the obtained data between 20 February, 2020 and 9 March 2020. Seven different parameters, namely, birth year, infection reason, country, group, confirmation date, sex, and region were used by the proposed classifier, and the most effective variables related to recovered and fatal cases were analyzed based on ANN model [42]. In addition, a new susceptible-exposed-infected-removed (SEIR) model was utilized, in which domestic reduction data prior and after January 23rd as well as latest COVID-19 pandemic data for prediction of epidemiological spread was incorporated. The proposed model prediction was corroborated through utilization of a ML approach trained on 2003 SARS coronavirus outbreak data [43]. C. Menni *et al.* presented an mobile application to track the symptom showing that the virus has caused the loss of senses of smell and taste in2,618,862 individuals this technique highlights the significance of big data and COVID-19 related technology[44]; (Methods) were investigated in [45].

On 24 March 2020, this tracker was used in the United Kingdom, and it was then exploited in United States, this app-based tracker was free and installed on smart phones to collect the information from symptomatic and asymptomatic persons and works in in real time to track the progresses of the disease and spread model through health information that are reported by the individuals themselves on a regular daily basis. This self-reported information includes PCR test, 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[45]. The risk of positive COVID-19 diagnosis with ML, through taking the results of emergency care admission exams was conducted by X. Yuan *et al.* [40]. The data is collected from the patients from a hospital located in São Paulo, Brazil, over a period of time, commencing from 17March 2020 to 30 March [46].

For analysis and prediction of the confirmed cases a Convolution Neural Network (CNN) was also presented by C.-J. Huang *et al.*[47]. The focus in this study was on Chinese cities, which experienced most of the confirmed cases and a forecasting model for COVID-19was put forward according to CNN deep neural network method. Additionally, to forecast the outbreak, a Multi-Layered Perceptron (MLP) network with two scenarios was utilized in [48], in which a set of data points regarded to both scenarios was employed to train the network. On the basis of this research, 8, 12, and 16 internal neurons were tried for realization of the best possible responses. RMSE and correlation coefficient were used for evaluation and reduction in the cost function value. Furthermore, a novel modified predicting model was presented in [49], based on Adaptive Neuro Fuzzy Inference System (ANFIS) for prediction and estimation of the confirmed individuals involved with virus in a ten-day period ahead of the infection, on the basis of confirmed cases which were recognized in China. The introduced method utilized an enhanced Flower Pollination Algorithm (FPA) which have been equipped by Salp Swarm Algorithm (SSA). 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 (ANN). An example of different forecasting applications was presented in [50], in which ANFIS and empirical mode decomposition were used to propose a stock price forecasting model. Also, in [51], a Virus Optimization Algorithm (VOA) was combined with an ANFIS to investigate the impact of population density and climate-related factors on COVID-19 spread. Used data in this study was related to climate-related factors and COVID-19 confirmed cases across the U.S counties. Ref. [52] presented a modified version of ANFIS model for prediction of the infections number in 4 different countries. This modified ANFIS is based on marine predators' algorithm (MPA) which is a new nature-inspired optimizer. The MPA is used to optimize the ANFIS parameters that leads to a better forecasting performance. To evaluate the proposed MPA-ANFIS, official datasets of the four countries were utilized [53].

In [72], 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). Relative high levels of LDH had apparently 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, [57] relied on ANN-based curve fitting techniques to predict and forecast the number of occurring cases and death related to COVID-19 in France, USA, India, UK, and considering the China and South Korea progressive trends.

The impact of COVID-19 epidemic in Italy [55] to identify mediators of perceived stress was investigated using ML models [55]. The findings have the potential of being used for early and targeted intervention and prevention programs. Ref. [73] used WHO datasets and datasets presented by Johns Hopkins University for creation of training dataset. The recurrent neural networks (RNNs) were later used to develop two Prediction Models. The first time-steps information was collected by a dense layer of neural network and a consequent regression output layer to make determining the next predicted value possible. Moreover, Ref. [56] was a case-control population-based study done on the Lombardy region in Italy. There were 6272 patients with SARS-CoV-2 between 21/2/2020 and 11/3/2020. Age, sex, and 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 [56]. Ref. [58] utilized multiple ML algorithms to predict occurrence of infection globally based on dataset analysis. The lowest R2 score of equal to 0.8273 belongs to ML algorithms, such as Support Vector Regressor, among

Bayesian Ridge Regression and Polynomial Regression, and the highest RMSE value equal to 124328.5297 amongst the three models indicating Support Vector Regressor stands last in the line of preferred models [58]. Using a real-time COVID-19 time series data related to the period of January 22, 2020, to May 18, 2020, [54] proposed a hybrid model incorporating ensemble empirical mode decomposition (EEMD) ANN to forecast COVID-19 epidemic. The time-series data first decomposed through the use of EEMD to create sub-signals and made original data denoised, and ANN architecture was implemented for training the denoised data [59]. 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 testing, were used in [74]. The study consists of segmenting and parsing documents as well as a consequent investigation and analysis of overrepresented words appearing in 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 have reported themselves.

A dataset including publicly available information related to 51 days (22/01/2020 to 12/03/2020) on the number of infection, recoveries, and deaths in 406 locations was used in [60]. The initial aim of this dataset was being a time-series dataset has 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 aiming at achieving a global model of patient's maximal number in all locations across each time unit. Hyperparameters of the MLP used a grid search algorithm consisting of a total hyperparameter combinations equal to 5376 [60]. Also, Ref [62] presented a multiple ensemble ANN model with fuzzy response aggregation for time series of COVID-19 [62]. 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 combining modules outputs in an intelligent way. Fuzzy logic deals with the uncertainty that may rise throughout the process of reaching the final prediction [62]. Besides Ref. [75] proposes an ML-based approach to implement a model to firstly help doctors verify the disease within a short time period, and secondly predict the growth of the disease in the near future of the world. To achieve this aim two models were used: the first model was based on Convolutional ANN model, and the second one considered Convolutional ANN and RNN. These models were evaluated and compared to verify the results predicted for the original one [63].

There were 6 different ML-inspired and statistical time series approaches developed to approximate the active cases percentage in comparison to total number of populations in [76]. This was done looking a week ahead, and for 10 countries that had highest number of confirmed cases ever since 4 May 2020. To work as a tool of data collection an online questionnaire was developed and used in [61]. The data collected by this method was then utilized as input for different forecasting models based on machine learning model (SVM, and MLP) and statistical model (Logistic Regression, LR). Using signs and symptoms these models were employed for predicting potential COVID-19 patients. Ref. [77] was a case control study in which patients whose COVID-19 infection was verified during 23/01/2020 and 06/02/2020 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. [78]was 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 development conditions such as behaviors and containment policies in the territory under study were sufficiently homogeneous. Using ML [65], a method to forecast poor COVID-19 patients' prognosis was suggested. The dataset for this study included information of 13, 690 patients that were either dead or recovered and cured.

The development of a comparative regressive and ANN model designed to examine the COVID-19 impacts on China's demand for electricity and petroleum was reported in [79]. The environmental analysis demonstrated that the gravity of the pandemic has significantly affected China's demands for electricity and petroleum in direct and indirect manners [79]. The analysis in [80] was founded on a recent momentum management of epidemics theory, while Bessel functions are employed. The utilized parameters were initial transmission rate that reflects the "normal" frequency and viral fitness of contacts in the infected areas, and indicates the intensity of preventive measures [80].

The main characteristics of trends and patterns of COVID-19 outbreak in Canada were evaluated based on LSTM network [1]. One capability of recurrent LSTM networks is that they can fore ground conventional time series predicting techniques limitations through adjusting nonlinearities of 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 [1]. In a separate research, data which was obtained from Google Trends website was used for prediction of COVID-19 in Iran [66]. To predict the cases LSTM and Linear Regression methods were employed, k-fold cross-validation, and Root Mean Square Error (RMSE) were used to validate all models and as the performance metric. The LSTM model demonstrated fluctuations in folds performance at the time when there was low training loss. This signifies overfitting in the LSTM technique due to the limitation of training data [66].

LSTM model is an RNN trained based on the 2003 SARS epidemic statistics which incorporates some epidemiological features including transmission incubation rate, probability, recovery probability as well as death and contact number. To predict COVID-19, a hybrid AI model was suggested in [29]. Initially, an improved SI (ISI) model was proposed analyzing and scrutinizing the alteration in the infectious potentials of the carriers of the virus afterwards the infection. In the next step and with due attention paid to the preventing effects, risen prevention awareness in the public, key control measures and with the purpose of building the hybrid AI-based technique for predicting COVID-19, the Natural Language Processing (NLP) module and the LSTM network were both incorporated into ISI model. In addition to the proposed hybrid method integrated in LSTM network and NLP module described in this paper, this article introduced information related to local and central governments' efforts as well as public support to the process of prediction calculation [29]. LSTM network was also used for estimation of the deviation of the epidemiological method and was combined with the introduced ISI model for the purpose of estimating the number of infection occurrences.

M. Niazkar *et al.* foregrounded a response to fight against virus through AI (AI), including some DL methods, such as Extreme Learning Machine (ELM), Generative Adversarial Networks (GANs), and Long /Short Term Memory (LSTM) [81]. Relying on real-time data collected from the Johns Hopkins dashboard [54] proposed ML and DL models designed to understand its day to day exponential behavior of COVID-19 and its future reachability across the nations. New mathematical models are chosen based on ML, such as polynomial regression (PR) and support vector regression (SVR) [82], and 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 taken into account to realize analysis of their impacts on COVID-19 confirmed. This analysis was made on three case studies in Italy along with an investigation of the proposed method [83]. Moreover, Prediction of verified cases was foregrounded by an LSTM for time series [64]. Seasonal Autoregressive Integrated Moving Average (SARIMA) [64], RNN, moving averages, and Holt Winter's Exponential Smoothing (HWES) approaches were utilized for justification [64].

4.2. Combination of Statistics, Metaheuristic Algorisms with AI methods

This part demonstrates those statistical and analytical methods that are combined and empowered by AI techniques, such as ML and DL. Table 2 shows techniques such as ARIMA, SEIR, MAE, SAE, and SARIMA which have been boosted by AI methods. A Modified Auto-Encoders (MAE) to realize forecasting the new infected individuals numbers were utilized by D. Charte *et al*. [20]. Auto-Encoders (AE) is a kind of ANN which is utilized to learn efficient way of coding the data without supervision [84]. While a good number of these are capable of generating reduced feature sets through fusion of the originals, AEs designed with other applications can be options to consider [20]. AEs aim to learn a representation for a set of data through training the network to ignore signal “noise” that is typically used to reduce dimensionality. While in classical AE the number of nodes in the layers increases from the hidden layers to the input layer, the numbers of the nodes in the output layer, the second hidden layer, first hidden layer, and the input layer in the MAE were 1, 4 ,32, and 8, respectively [14]. The results demonstrated high accuracy of prediction and subsequent multiple-step forecasting. Based on their experience a longer training time caused an improved forecasting [14]. In addition, a MAE was designed and developed to deal with the existing limitations [85]. Accordingly, each intervention variable was assigned a weight between 0 and 1 according to the interventions degrees while zero is an indication of no intervention and one being complete. Bringing 152 countries under scrutiny, ending time, peak time, duration, peak number and the number of COVID-19-infected persons under four intervention scenarios were estimated as a result of which critical information was available to high-official ranking and health administrators to facilitate immediate public health measures toward the plans that are suitable to slow COVID-19 spread. The results obtained from this research were in line with the dire need of urgent aggressive interventions.

An MAE-based approach is used in [86] proposing alternative strategies to model COVID-19 dynamics [87]. As the results demonstrate, this approach is superior to traditional and LSTM approaches. The proposed approach has the world regions initial clustering as its outset for which data is available. The data shows the locations with pandemic advanced stage, but does this based on a set features that are manually engineered indicating a country’s response to the early stage of pandemic spread. The TM, FM (including medical staff and hospitals), and DM constructed in [69] are to predict COVID-19 spread in top ten most-affected countries. One main factor that directly impact COVID-19 spread is public knowledge and behavior. Regional properties were exclusively used by the proposed hybrid model to provide robust estimates. To substantially improve the performance of the models extra modules could be included and real data could be employed [69]. Moreover, using seven up to nine days data sequences for predicting the trend of daily growth of COVID-19 infected cases in China, six rolling grey Verhulst models were built in [88]. Hubei province data was compared to the data related to other nine provinces to analyze characteristics and differences of the SV of COVID-19-related symptoms, and investigate the correlations between the SV of COVID-19 and the number of recent suspected / confirmed infection cases [89].

Table 2. Combination of AI techniques to enable ARIMA, SEIR, MAE, SAE, and SARIMA methods for forecasting COVID-19 spread

Author	Technique	Country/ Region	Description	Data	Results
Thadikamala Sathish, *et al.*[90]	ARIMA	India	Predictions of patients raise, recovery and death rate	from 30th Jan 2020 to 15th May 2020	Forecasting was done by using the constructed models up to July 8th 2020
Roseline Oluwaseun Ogundokun, *et al.* [91]	ARIMA; SVR, NN, and LR	India	PREDICTION	from January 2020 to April 2020	The COVID-19 disease can correctly be predicted according to the obtained results
Vasilis Papastefanopoulos, *et al.*[76]	ARIMA, HWAAS, NBEATS, TBAT, Gluonts	USA, Spain Italy, UK France, Germany, Russia, Turkey, Brazil, Iran	Forecasting	as of 4 May 2020	ARIMA and TBAT obtained better results compared with DL ones such as Deep AR and N-BEATS
Zohair Malki, *et al.* [92]	SARIMA	France, Italy, USA, UK	Predicting the End of Pandemic	Collected data from 22/1/2020 to the present time	confirmed case will slowdown in October, 2020
Leila moftakhar, *et al.* [93]	ANN, ARIMA	Iran	A Comparison between ARIMA and ANN predcition	New cases from 19/2/2020 to 30/3/2020	ARIMA model has better prediction result than ANN
Kabir Abdulmajeed, *et al.*[94]	ARIMA, GARCH	Nigeria	Online forecasting mechanism	cases from February 27, 2020, to April 5, 2020	providing academic thrust in guiding the policymakers
George Xianzhi Yuan, *et al.*[95]	iSEIR model	China	Forecasting of the Critical Turning Period	From 2020 January to early of 2020 March	Control the epidemic time should be around mid-February 2020
İsmail Kırbaş, *et al.* [96]	NARNN, ARIMA, LSTM	Germany, Denmark, France, Belgium, UK, Turkey, Switzerland, and Finland	Comparative analysis and forecasting	The data covers 97, 67, 100, 90, 94 55 68 and 90 days respectively and ends on 3/5/2020	The best model result has been obtained for LSTM
Zixin Hu, *et al.*[97]	MAE, ARIMAX, SEIR	152 countries	Forecasting and Evaluating Multiple Interventions	From 20/1/2020 to 16/3/2020	The obtained 2.5% average error of five-step ahead prediction
Farhan Mohammad Khan, *et al.*[98]	ARIMA, NAR, MoHFW	India	Forecasting model for time series analysis	from 31/1/2020 to 25/3/2020	Estimating trend in the actual and approximately 1500 cases per day on 04th April 2020
Igor G. Pereira, *et al.*[87]	LSTM-SAE MAE	Brazil	Forecasting	From Feb 2020 to May 2020	The pandemics estimated to end (with 97% of cases reaching an outcome) in some

					states in28 May and rest through 14 August
Amal I. Saba, *et al.* [99]	ARIMA, NARANN	Egypt	Forecasting the prevalence	Data collected between 1/3/2020 and 10/5/2020	NARANN has acceptable error results of less than 5%
Zixin Hu, *et al.* [100]	SEIR; AE; IAE	USA	Estimating that the peak time	From January 22, 2020 to April 24	The Covid-19 peak time in the US is estimated
Zixin Hu, *et al* [85]	MAE	Countries worldwide	Forecasting intervention	The Num. of cumulative, death cases and new cases of Covid-19 in the period of January up to March 2020	Num. of cumulative cases by January 10, 2021; under later intervention: 255,392,154 under immediate intervention: 1,530,276

Statistical and AI based approaches for modeling and predicting the epidemic in Egypt was presented in [101]. The used approaches in this study are Nonlinear Auto Regressive Artificial Neural Networks (NARANN) and ARIMA. Furthermore, Ref. [99] investigated and analyzed the environment and situation in and out of China to predict worsening the epidemic. Official data related to infections, deaths, and suspected COVID-19 were collected and the findings demonstrated the seriousness of situation in Hubei Province and Wuhan City. A trend comparison method, ARMA and ARIMA to analyze the data and predict was presented in [102]. A comparison demonstrated 19 February 2020 and 14 March 2020 when a full control of the situation was achieved as the key dates of COVID-19 The numbers related to infections and deaths and GDP growth were also predicted simultaneously. ML models' ability to forecast upcoming COVID-19 patients' numbers was demonstrated in [103]. In this study four standard forecasting models namely, least absolute shrinkage, exponential smoothing (ES) selection operator (LASSO), SVM and linear regression (LR) were utilized to forecastCOVID-19 threatening factors [104]. The potential of data science [105] for the purpose of assessing risk factors related to COVID-19 after an analysis of the datasets obtained from Oxford University database as well as and recently simulated datasets, following the analysis of different univariate LSTM models to forecast new cases and related deaths was investigated in [71].

An online forecasting procedure to stream data from the Nigeria Center for Disease Control was employed in [106] for updating an ensemble model's parameters with the purpose of updating COVID-19 forecasts every day. The ensemble realizes the combination of an ARIMA, Prophet, which is a Facebook developed additive regression model, and a Holt-Winters Exponential Smoothing model which is combined with Generalized Autoregressive Conditional Heteroscedasticity (GARCH). Such assemblage was to provide public health officials and policymakers with substantial academic guidance in the process of establishing containment strategies as well as assessment of containment interventions to deal with disease spread in Nigeria [94]. A symptom-to-disease digital health assistant called Symptoma, was used to differentiate over 20,000 different diseases demonstrating 90% accuracy.

Symptoma’ accuracy in identifying COVID-19 in relation to various sets of clinical cases and similar diseases came to be tested in [107].

In [108] the used database included 57 candidate explanatory variables for testing the MLP network performance in anticipating the cumulative occurrence rate of COVID-19 in the United States. Daily data related to the period between 30th Jan 2020 to 15th May 2020, presented by the government of India was used in Govt from [90] to implement an ARIMA model to forecast occurrence rising numbers, recovery and death in India. The autocorrelation function (ACF), partial autocorrelation function (PACF), and standardized residuals were employed to determine if the model implemented in this study is a good fit [90]. In [109], symptoms, transmission modes and putative treatments to deal with COVID-19 were investigated and reported [110]. The report summarized relevant available information on the genome, evolution and zoonosis of coronavirus. In [111] the authors aimed to synthesize the challenges that retailers have to dace and deal with during COVID-19 pandemic. To create a guideline for retailers in this study the pandemic was approached from the perspective of consumers and managers. Using 2 explainable AI methods, ECPI and SHAP, three most significant measures in countries and regions under study were investigated to construct models to forecast the instantaneous reproduction number (Rt) and to use the models as surrogates to the real world [112].

In [92] a forecasting model was developed to estimate the time of the possible halt in the activity of the virus as well as the risk of COVID-19 pandemic resurgence. SARIMA model was adopted to predict virus spread in some selected countries and predict the life cycle and end date. Since the virus acts similarly in different places, this study could be of use in all countries around the world. It yields well to governments and public health officials to make decisions and plan for future policies and actions; hence, reducing anxieties and tensions that pandemic can impose on COVID-19-stricken areas [92]. The Chinese Sina-microblog witnessed an outbreak of public opinions triggered by COVID-19 outbreak. To recognize the important information propagation patterns across social networks [113] proposed a multiple-information susceptible-discussing-immune (M-SDI) model to design effective communication strategies during a pandemic. M-SDI model was developed relying on public discussion quantity. In addition, the underlying mathematical model consisting of individual SEIR (iSEIR) model that is a set of differential equations which extends the classic SEIR model was proposed in [114]. Using the collected data between 26/03/2020 and 04/04/2020, an ARIMA model was adopted on the collected data between 31/01/2020 and 25/03/2020 [98]. In order to compare the accuracy of predicted models a nonlinear autoregressive (NAR) ANN was developed. The model was used to predict the occurrence of COVID-19 within 50 days when no additional intervention was in place [98].

A Genetic Algorithm (GA) was used to estimate parameters of Compound, Cubic, Logarithmic, Linear, Logistic, Quadratic, and exponential equations with the purpose of developing the desired model [115]. The selected population number was 300, and based on various trial and error examinations, iteration number indicated as the maximum generation was 500to decrease the cost function value. In this respect, the Mean Square Error between the output values of the system and target was defined as the cost function. Also, M. H. D. M. Ribeiro *et al.* demonstrated how stacking-ensemble learning, Support

Vector Regression (SVR), ridge regression (RIDGE), Autoregressive Integrated Moving Average (ARIMA), random forest (RF), cubist regression (CUBIST) were able to be used in time series for predicting cumulative confirmed cases of COVID-19 in ten states located in Brazil with high rate of COVID-19 spread [7]. Ref. [50] proposed an AI model called multi-gene genetic programming (MGGP) for the first time to predict the outbreak of COVID19. Despite significant fluctuations in the number of confirmed cases that makes the task a complicated one MGGP results were promising because the predicted confirmed cases were in an acceptable range near to the values that were considered for the seven countries investigated for the purpose of the study. As a result, MGGP could be a good suggestion to be employed in development of the estimation approaches for COVID-19.

Using data from Hungary presented a hybrid ML approach for COVID-19 prediction [116]. The hybrid ML method was an MLP enabled by Imperialist Competitive Algorithm (MLP-ICA) and ANFIS that predicted infected individuals time series as well as mortality rate. The prediction indicated a significant drop in the total morality and the outbreak by the end of May. Besides, having an analysis of global COVID-19 data through utilizing ML techniques, Ref. [54] demonstrated covariates associated with confirmed cases. Moreover, the forecasting for the number of infected cases in the USA, UK, and Russia based on the number of daily confirmed cases of COVID-19for these countries between January 22, 2020 to May 28, 2020 as presented on WHO database was used in [117]. This research tested Autoregressive Distributed Lag Models (ADLM) and ARIMA, and Double Exponential Smoothing (DES) [117]. Data of new cases in Iran happening was used in [93] for predicting of patients numbers. ARIMA and Artificial Neural Networks (ANN) models were used to realize prediction [93]. Open datasets provided by the JOHN Hopkins and daily reports of Iran Ministry of Health were used to prepare the data. The Gompertz and Logistic mathematical models, and the ANN computational model were applied to model the COVID-19 cases numbers of infection between 27th February and 8th May [118].

Support-Vector Machines (SVM) in ML were supervised models which included associated learning algorithms for analyzing data which are used for the purpose of regression analysis and classification. A technique is presented in 1992 to create nonlinear classifiers through the application of kernel trick to maximum-margin hyperplanes [119]. Corinna Cortes and Vapnik, however, proposed the current standard incarnation in 1993 which was published in 1995 [120]. SVM models are representations of examples as points in space which are mapped in a way that a clear wide gap could divide the examples of separate categories [120]. Synthetic Minority Over-sampling Technique (SMOTE) was basically trained from data sets which were imbalanced [121]. Contrary to standard boosting in the process of which equal weights are assigned to all misclassified examples, in SMOTE Boost synthetic examples are created from rare or minority classes, causing indirect changes to in updates of weights and skewed distributions compensations [121]. Researchers focused on tracking people's transit between Wuhan and mainland China until January 2020 through utilizing a detailed geolocation data of cell phones to calculate total population movements. This research uses the people geographical flow to anticipate the subsequent locations, severity and time of outbreaks in the other parts of mainland China until February 2020. The obtained data proved higher efficiency compared to measures, such as wealth, population size, or distance from the source of the risk. Using population flows, this research also models COVID-19 epidemic curve across different locales while deviations from model predictions were used as tools for detection of the burden of community movements [122].

Group Method of Data Handling (GMDH) refers to an algorithms family which was used in mathematical computer-based modeling of multi-parametric datasets featuring fully automatic structural and parametric model optimization [123]. Complex systems modeling knowledge discovery, data mining, prediction, pattern recognition, and optimization are among the fields in which GMDH was utilized. A main characteristic of GMDH algorithms was inductive procedure to perform sorting-out of complicated polynomial models and adopting optimal solutions through relying on external criterion [123]. Using the classification of COVID-19 confirmed cases a serious challenge in the sustainable development process was scrutinized in [124]. Accordingly, GMDH type of ANN as one of the AI methods used binary classification modeling [124]. S. Uhlig *et al.* Proposes an empirical top-down method to model and forecast the risks and calculate (local) outbreaks [25]. This research used neural networks for developing leading indicators according to data which was available in different regions. The indicators were used for estimating (new) outbreak risks or determining if a measure is desirably effective in an early stage, but they could also be employed in parametric models to ascertain an effective forecast side by side with the associated uncertainty [25]. In [61] a strategy was developed that was backed by AI, and a combination of three methods: Support Vector Machines (SVM) [119, 120], SMOTE Boost [121], and Ensemblingt [125], to conduct initial screening of probable COVID-19.It contains a ML classifier whose input consist of existing simple blood exams to be classified into two negative (not having SARS-CoV-2) or positive (having SARS-CoV-2) samples [126].

Ensemblingt integrates multiple models to build a predictive model. Ensemble methods are capable of improving prediction performance [125]. Statisticians, AI specialists and researchers from other disciplines can use ensemble methodology. It is based on weighing several individual pattern classifiers, and combining them for reaching a classification superior to those which are obtained by each one separately[125]. An important feature of an ensemble is having diversity in generation mechanism and choosing combination procedure. Z. Allam *et al.* documented AI's role in early detection of the COVID-19 as performed by two companies, BlueDot and Metabiota showing that AI-driven algorithms had been superior in rendering precise predictions and future readings through increased data sharing [17]. The findings demonstrate that taking the nature of sensitive issues of privacy and security into account, there is a dire need for an increased data sharing practice to be implemented in urban health sector [19].

A novel forecasting model, called Chaotic Learning (CL) strategy into a multi-layer Feed-Forward Neural Network (MFNN) to use the data reported as of 22 Jan 2020 to analyze and predict the CS of COVID-19 for the future days is suggested in [127]. This forecasting model known as ISACL-MFNN integrates an optimized interior search algorithm (ISA) using CL strategy into a MFNN. The ISACL incorporates the CL strategy with the purpose of enhancing ISA performance ISA and avoiding being trapped in the local optima. The purpose of this approach is tuning the neural network's parameters to optimal values to train the network so that high precision of forecast results could be achieved [127]. In another research

[128], it was suggested that situational information could be resourcefully help both the authorities and public in responding to the epidemic. This study, therefore, employed natural language processing techniques and Weibo data for categorizing information related to COVID-19 into 7 types of situational information. There are specific features found in forecasting the amount reposted for each information [128]. Because of having limited data, the authors merely trained 3 traditional classifiers based on NLP to train classifiers and identify situational information's content types.

Differential Evolution (DE) algorithm and ANN based on Particle Swarm Optimization (PSO) algorithm were two AI methods utilized in [129] with the purpose of investigating and prioritizing parameters for consequences of COVID-19 outbreak. This research was focused on prioritizing and analyzing the role of some certain environmental parameters. Scrutinizing four Italian cities in Italy some main features including climate parameters, such as relative humidity, daily average temperature, as well as urban parameters such as population density, were utilized as input data set while COVID-19 confirmed cases were considered as output dataset [129]. The information about the recent researches on prediction of COVID-19 with use of both statistical models and AI methods have been brought in Table 3.

Table 3. Combination of statistical techniques with AI-based approaches to predict the COVID-19 spread

Author	Technique	Country/ Region	Description	Data	Results
R. Sujath, *et al.* [130]	LR, MLP, VAR	India	Forecasting	80 instances from the Kaggle dataset for prediction	MLP model has obtained better precision compared to LR and VAR models
Abolfazl Mollalo, *et al.* [131]	MLP	USA	nationwide modeling of COVID-19 incidence	From 22/1/2020 to 25/4/2020	The prediction capability of the model requires a significant improvement
Xuanchen Yan, *et al.*[132]	SPSS 25.0	China	Big Data analysis	between January 23 and February 6, 2020	Middle-aged people (P=0.038) have more probability to be infected
Tajebe Tsega Mengistie [133]	Fbprophet	Countries worldwide	Analysis and Prediction Modeling	start from April 12, 2020	the last 10 days and analysis graphically by using the data mining
Abdallah Alsayed, *et al.* [134]	SEIR, ANFIS, GA	Malaysia	Prediction of Epidemic Peak	from 25 January to 05 April 2020	a NRMSE of 0.041; a MAPE of 2.45%; R^2 of 0.9964
Yu-Feng Zhao, *et al.*[88]	rolling grey Verhulst models	China	Prediction	from 21 January to 20 February 2020	The minimum and maximum MAPEs are 1.65% and 4.72%, respectively for the test stage
Ali Behnood, *et al.*[135]	ANFIS, VOA	USA	Determinants of the infection rate	1657 counties	The models could forecast the variables effects on the infection rate
Mohammed A. A. Al-qaness, *et al.*[53]	MPA-ANFIS, ANFIS	Italy, Iran, Korea, and USA	Forecasting	from 22 January 2020 to 7 April 2020	MPA-ANFIS has better results compared with the other models in almost all performance measures
Xiuyi Fan, et al. [112]	SHAP and ECPI	18 countries and regions	Spreading Factors	from 22/01/2020 to 02/04/2020	Warm temperature helps for reducing the transmission
Salgotra, Rohit, *et al.*[136]	GP, CC, DC the GEP-based models	India	Genetic Evolutionary Programming	since 24 March 2020	The GEP-based models have precise results for time series prediction
Lifang Li, *et al.* [128]	SVM, NB and RF	All countries	Characterizing the Situational Information Propagation	Weibo data: From 30/12/2019 to 1/2/2020	Indicating the necessity of information publishing strategies for situational information
Ramon Gomes da Silva, *et al.* [137]	VMD	USA and Brazil	Forecasting	Cumulative cases of COVID-19 that occurred until 28/4/2020	VMD-based models are very strong tools for prediction
Abhari, Reza S., *et al.*[138]	EnerPol	Switzerland	Containment Strategy and Growth Prediction	Available public data and adapted to Swiss demographics	Estimating deaths, recovered and cases between 22 February and 11April 2020
Ashis Kumar Das, *et al.*[139]	SVM, KNN, RF, GB, LR	South Korea	development of a prediction tool	3,128 patients	GB algorithm has the highest precision compared to the other studied models
Pokkuluri Kiran Sree, *et al.* [140]	HNLCA,	India	cellular automata classifier for trend prediction	6785 datasets and 23,078 datasets are used for test and train, respectively	The average accuracy of 78.8% is reported

Gregory Baltas, *et al.* [141]	SIR, DNN	Spain	Monte Carlo DNN model for spread and peak prediction	Total Infected Until 28th of March	The simplicity of the DNN allows to identify the SIR parameters for different COVID-19 evolution curves
Li Yan, *et al.* [142]	XGBoost ML Method	Wuhan, China	prognostic prediction	Data collected between 10/1/2020 and 18/2/2020	Quickly prediction of patients with high risk using suggested decision rule
Furqan Rustam, *et al.*[104]	LR, LASSO, SVM, ES	Canada, Australia, Algeria	Future Forecasting	dataset from 22/1/2020 to 2/3/2020 is used for training of the model	ES has the best precision, while SVM performance is not acceptable
Alistair Martin, *et al.* [107]	Symptoma	No mentioned	digitally screening citizens for risks	BMJ cases: 1,112 cases Test cases: 1,142 medical test cases	Symptoma can accurately distinguish COVID19 from diseases
Mohammad Pourhomayoun, *et al.*[143]	SVM, KNN,	Countries worldwide	Predicting Mortality Risk	117,000 patients world-wide	Obtained 93% precision in forecasting the mortality rate
Behrouz Pirouz, et al. [124]	GMDH	China Japan South Korea Italy	confirmed cases analysis using binary classification	The environmental and urban parameters from January 2020 to February 2020 (1 month)	The most effective parameters on the confirmed cases are maximum daily temperature and relative humidity had
Sina F. Ardabili, *et al.*[144]	MLP, ANFIS, GA, PSO and GWO	Iran, Germany, USA, Italy, and China	Outbreak Prediction	Data were collected for five countries on total cases in 1 month	ANFIS and MLP reported a high generalization ability for long-term forecasting
Majid Niazkar, *et al.*[145]	MGGP	China, South Korea, Iran, USA, Japan, and Italy	Country-based Prediction Models	The confirmed cases from 20 January to 5 April 2020	Each infected country has a different trend.
Rizk-Allah, *et al.* [127]	MFNN (GA, PSO, GWO, ISA, ISACL)	USA, Italy, and Spain	Forecasting the confirmed cases of three countries	The data referring to the period 22/1/2020 to 3/4/2020	The presented ISACL-MFNN model has promising forecasting results from 4/ 4 / 2020 to 15 / 4 / 2020 are presented
Hasinur Rahaman Khan, *et al.* [146]	ML Techniques	133 countries	Demonstrating ML basic to analyze global COVID-19	The data include 10 variables until 17-th April, 2020	The countries which has important role to explain the 60% variation of the total variations include USA, Iran, UK, Germany, Spain, France, and Italy
K.M.U.B. Konarasinghe [117]	ARIMA, LBQ, DES and ADLM	USA, UK, and Russia	Modeling COVID -19 Epidemic	The data of 22nd January 2020 to 28th May 2020	The ARIMA did not satisfy the model validation but the ADLM and DES did
Jayson S. Jia [122]	Statistical Methods using mobile phone	China	Spatio-temporal distribution	About 10 million counts of mobile phone data between 1/1/2020 and 24/1/2020 to 296 prefectures	Developing a spatio-temporal 'risk source' model
Gergo Pinter, *et*	ANFIS,	Hungary	Pandemic	The data from 24 March	Results Prediction from April 20 to

al. [116]	MLP-ICA,		Prediction; A Hybrid ML Approach	to 19 April	July 30
O. Torrealba-Rodriguez, *et al.* [118]	Gompertz, Logistic and ANN models	Mexico	Modeling and prediction	The data of 27 February to 8 May	R^2 of 0.9998, 0.9996 and 0.9999-Prediction of daily cases on 8 May, 25 June and 12 May

To break time series into various intrinsic mode functions, Bayesian regression neural network, quantile random forest, cubist regression, support vector regression, and k-nearest neighbors, were employed alone, and used with the recent pre-processing variational mode decomposition (VMD) [137]. Furthermore, to assess coronavirus transmission, 8.57 million Switzerland population along with cross-border commuters as well as the stimulated Swiss public and private transport network were studied [138]. Individual contacts and transmission pathways were settled by simulating day to day activities calibrated with micro-census data. Statistical data available to the public and adapted to Swiss demographics was used as the basis of COVID-19 epidemiology [138].

In [97], AI-inspired methods were developed to model the epidemic's transmission dynamics and evaluate interventions for curbing COVID-19 spread and impact. These methods focused on WHO data from March 16th, 2020 onward and were used to process data related to new COVID-19 cases as well as the cumulative data as reported by this organization. Accordingly, the timing and intervention degree were evaluated while the five-step average error prior to prediction was 2.5%. The global maximum number of cumulative cases, new cases, and total peak number of cumulative cases with complete intervention 4 weeks after the initial date (March 16th, 2020) mounted to 255,392,154, 10,086,085, and 75,249,909, respectively [97]. With the use of five ML algorithms (SVM, gradient boosting, logistic regression, random forest, and K nearest neighbor) [139] predicted confirmed COVID-19 patients mortality between 20/01/2020 and 07/04/2020 to be (n=3,022) . A comparison of performance of the algorithms demonstrated that the most suitable algorithm was deployed as the online tool for prediction.

In addition, Ref. [147] suggested a preliminary classifier which included non-linear hybrid cellular automata tested and trained to forecast COVID-19 effects with regard to the number of deaths, the number infected people individuals, the number of recovered individuals, etc. The datasets for this study was from Kaggle and other standard websites, and it could predict the epidemic trend in India.

In [141], an AI approach which is based on DNN predicted the peak of coronavirus in Spain. Data generation process in this method was based on Monte Carlo simulations of SIR epidemiology models and DNN prediction model development. This approach's simplicity with the DNN facilitated the identification of SIR parameters for various COVID-19 evolution curves that could assist researchers to identify curves related to various COVID-stricken population sizes. Although this could not be an ultimate study in this regard and further research is still needed, this study has obtained the SIR model parameters correctly and has generated a population-dependent model.

Ref. [148] too proposed a model to predict COVID-19 spread. To predict epidemiological examples of COVID-19 cases in India, this study used MLP, vector auto regression, and linear regression methods for desire on the COVID-19 Kaggle data. Statistical analysis demonstrated a correlation that exists between the swab tests numbers and mild cases admitted to hospital, daily positive cases, recovery, intensive care cases, and death rate, which provided the foundation for an AI study [114]. A multivariate linear regression (MLR) method was used for results validation. Also, Ref. [143] utilizes the data of 117,000 COVID-19 patients whose infection was confirmed by laboratories to present an AI model that could be used by hospitals and medical facilities to determine patients with a higher priority for hospitalization at the time when the system was prone to be overwhelmed by in-coming patients and significantly reduce delays in the process of care provision. Besides, the approach to forecast COVID-19 along with efforts of Public Health Agency of Canada for modeling the effects of Non-Pharmaceutical Interventions (NPIs) on COVID-19 transmission among Canadian population with the purpose of supporting public health decisions was described in [149]. Additionally, the joint effort of health care organizations, government agencies, and industry partners from around the globe to investigate pandemic's challenges during social distancing was investigated in [150]. The investigated challenges included conducting treatment research, enabling virtual health care, and scaling high-quality laboratory tests during social distancing [151].

5. Discussion

The aim of prediction methods is supporting public health authorities and officials so that they could be better informed while making decisions and implementing policies with regard to people's health and well-being. Such technologies, however, are not fully matured and well-received yet, and their recognition and insertion in national and international policy levels takes place in a very slow pace. AI techniques, nevertheless, are increasingly reshaping various aspects of humans' lives providing them with the opportunity of data analysis [152], information integration, and provision of ways to improve policies and decisions and enhance implementations in biotechnology, health care, speech and voice recognition, transport, finance, and climate change, etc. [27, 153]. An important activity to anticipate the requirement of healthcare resources and save more lives is forecasting infection occurrences [117]. Forecasting helps decision and policy makers to converge efforts toward maintaining economic and social stability. This highlights the importance of inclusion of reliable AI strategies to have optimum predictions that could be employed by various applications to yield best possible results. Accordingly, evaluation of this technique should be performed in such a way that effectiveness of the method when employed for sensitive medical issues could be guaranteed. As such, this review is committed to carefully validate the performance of AI-powered prediction methods for COVID-19 outbreak.

5.1. Main findings and Opportunities

In this review, 74 studies that described several AI-powered prediction approaches to estimate COVID-19 outbreak spread in different locations and time have been surveyed. Progressive use of predictive computing tools have by now demonstrated that they are efficient in provision of insights for better health policies and strategic management [19]. Finding and recognizing suitable models for forecasting is therefore an urgent and timely requirement, especially in this situation that the mutations of the virus are emerging while they are more potential to spread quickly. The present review is an attempt to facilitate a comprehensive study that could shed light on different aspects of effectiveness of AI methods in predicting epidemiological issues such as COVID-19. Innovative solutions are the most needed solutions at the present for development, management and analysis of big data on a continuum consisting of individual patients, community movements in the framework of clinical trials, genomic, pharmaceutical and public health data [154].

This study however had to main objectives to achieve: firstly, evaluating specific features of reviewed studies that provided an overview of the conducted research; and secondly, demonstrating how AI-based methodology could be utilized to examine and confirm future research. There has already been a lot of research on AI in general and ML in particular; however, there is still a gap to fill when it comes to a deep understanding of the pandemic. To elaborate, we have stressed the power and capability of AI applications to provide people all around the world with serious epidemiological insights. Core investigation is put forward in result sections to predict pandemic followed by viable prospective AI methodologies. As far as obtained results are concerned, one can infer that SVR and 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 which are features of the evaluated epidemiological time series [7]. IS have proved themselves as extremely effective in tracking COVID-19 and forecast the 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 with the purpose of developing an interactive and comprehensible dashboard [37].

Along with the extensive on-the-rise use of various countries of digital technologies in battling against COVID-19 pandemic, there is an ever-increasing need for proper use of data and algorithms [34]. In fact, policymaking, health management, and benefiting from resources to control and prevent epidemic outbreaks seem impossible or hardly ever possible 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 could collaborate toward data analysis and realizing positive effects on resource planning related to health care system [66]. Technology, therefore, could extend its capabilities beyond daily life activities and needs, and vigorously support people in their fight against COVID-19 [30]. The success of countries that could flatten the curve and maintain low mortality rates throughout the raid of the disease is an evidence how digital technology integration into pandemic policy and response has come to be an adroit decision to be included in the process [155]. 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 [156].

5.2. Challenges and Limitations

There are points related to limitations of our study that should be carefully considered. As COVID-19 is progressing causing the bulk of disease-related literature grow in an unprecedented pace, the present review could not boast of being an up-to-date list of all available COVID-19 related prediction techniques. Besides, 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 that make the manuscript for being launched in the present related literature. However, the most important results could be outlined as follows: Tracking and predicting COVID-19 spread could be valuable data inputs for public health officials that plan, prepare, and manage COVID-19 pandemic [157]. Also, AI and Big Data are assets when it comes to tracking the disease spread in real time, planning and lifting public health interventions, monitoring their effectiveness, repurposing old compounds and discovering new medicine, identifying potential vaccine candidates, enhancing the response of communities to the pandemic [158]. Since deployments 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 [21]. 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 [21]. While social distancing information is necessary for advancing the epidemiological models, no assumptions are required for modeling with ML [144]. Disease outbreaks exhibit certain patterns whose identification depends on the outbreak's transmission dynamics [1].

There are methods that have been rated as 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 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 next occurrence of the outbreak is one that attests the value of AI application to COVID-19 outbreak [159]. Nevertheless, from the epidemiological, diagnostic and pharmaceutical points of view, AI does not seem to be have a significant role in battling COVID-19 yet, because its use is simply limited due to lack of data and existence of too much outlier data. Big data is currently a critical element in managing the COVID-19 pandemic; therefor, having clear and transparent conditions to realize responsible data collection and processing at a global scale is of utmost importance [34]. It is also important that unbiased time series data is created for AI training [157]. However, various sources of uncertainty and unpredictability do exist in dynamical systems. A small uncertainty in the initial conditions can lead to a certain unpredictability of the final state because there is heavy dependence on initials conditions causing chaos to follow and dominate [27]. As a result, any definite conclusion drawn about the effectiveness of AI and its impact on COVID-19 could be premature and not well-evaluated. The data supply changes on a daily basis because the numbers and statistics related to infections are changing from one day to another [159]. AI's impact has been rather limited up to this point; however, the pandemic and its related policy responses can give digitalization of the economy a faster pace and speed up the move toward greater automation of human labor [157]. One of the main limitations of this study was having limited access to Google Search data. Google Trends provides data based on "interest" measure indicating that building more accurate and informative models is possible only if absolute search frequency is available to researchers [66].

Furthermore, most of the studies have been merely performed through considering features of COVID-19 and other pneumonia. The results yielded by these studies may be inaccurate because they have not taken other factors into account. Such factors include a range of significant ones such as gender, conditions such as diabetes, hypertension, chronic liver and kidney disease, etc. [40]. Considering that there is a lack of pre-existing data for the new disease, AI models could be relied on to build such data determine the extent diagnosis or prognosis could be a challenge. Such a challenge could be addressed by an AI community that uses ML to remove the barriers between data domains [160].

The findings of this study reveal that the epidemic comes with a complex behavior shaped by the effects of a number of parameters such as geography, country, region, sex, climate, humidity and etc. However, the main objective in this research was finding out if AI could successfully address the need for a reliable approach to forecast the spread of COVID-19. Without doubt, the efficiency of this response is partially dependent on ML, but it also depends on the ability to realize global collaborations and establish data-sharing agreements that could contribute in the process of accelerating the discovery and validating promising interventions[161].

6. Conclusion

Effective allocation of medical resources, production regulations, and countries' economic development depend all on reliable estimation of epidemiological trends and prevalence of an epidemy outbreak. That is why the techniques used in predicting an outbreak are of such substantial and crucial importance. There are many approaches that could suitably applied in the process of forecasting COVID-19 spread trends; however, there are many approaches too that 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 related literature to facilitate forecasting the outbreak. In the present review, 950 titles were screened, and 74 studies of the screened papers were included. This review provides a collage of applications of AI that could be conveniently employed to forecasting that demonstrate outstanding specific features of predicting methods. It also could serve health care systems in handling critical epidemiological issues, such as the outbreak of COVID-19 and its mutations. As some of the approaches discussed in this review have been poorly reported and considering that some approaches are probably optimistic we have decided not to recommend any of these reported prediction methods to be employed in the ongoing WHO practice. However, we expect that the present review could be appreciated as a significant step taken so that AI community come to appreciate AI methodology and its possible but reliable vital role in forecasting targets, and understand which methods could be more promising in estimating epidemics such as COVID-19. Besides, it figures out how research agendas could be defined and outlined so that reliable and practical predictions could be realized. The results of the study can serve well in proactive decision making that aim at minimizing the risks that humans may have encounter at the time when they are most needed because of the urgency of the matters. We have also proposed a few promising future directions that can help in understanding the predictions of the epidemiological issues and challenges. Finally, this review can be used toward realizing developments in DL and related learning systems providing valuable insights and guidelines to be used in future related research.

Declarations

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Declarations

The authors declare that they have no conflict of interest.

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Table

Table 1 is available in the Supplementary Files section

Figures

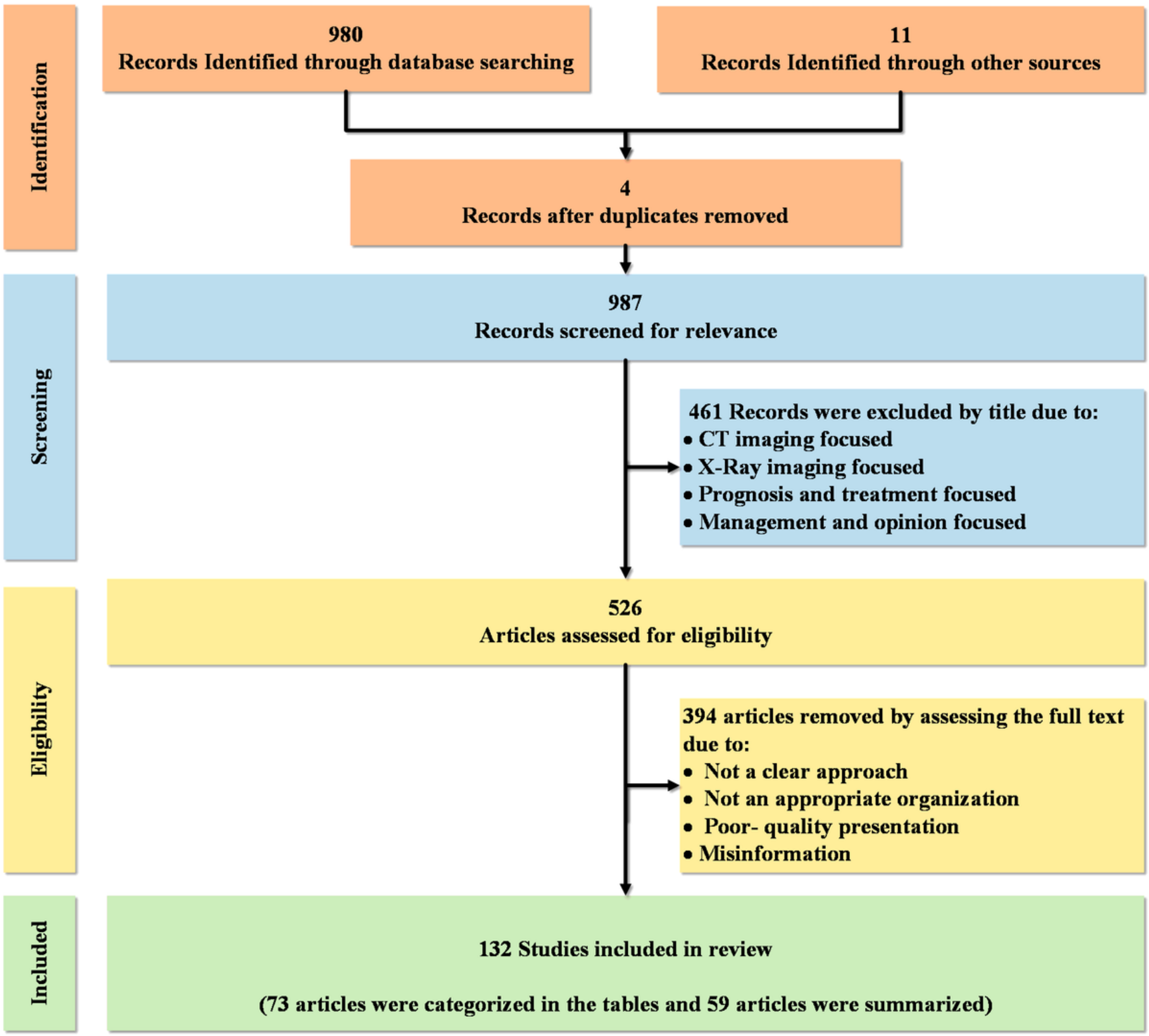

Figure 1

Flowchart showing the inclusion of studies for evaluation of AI-based techniques for predictions.

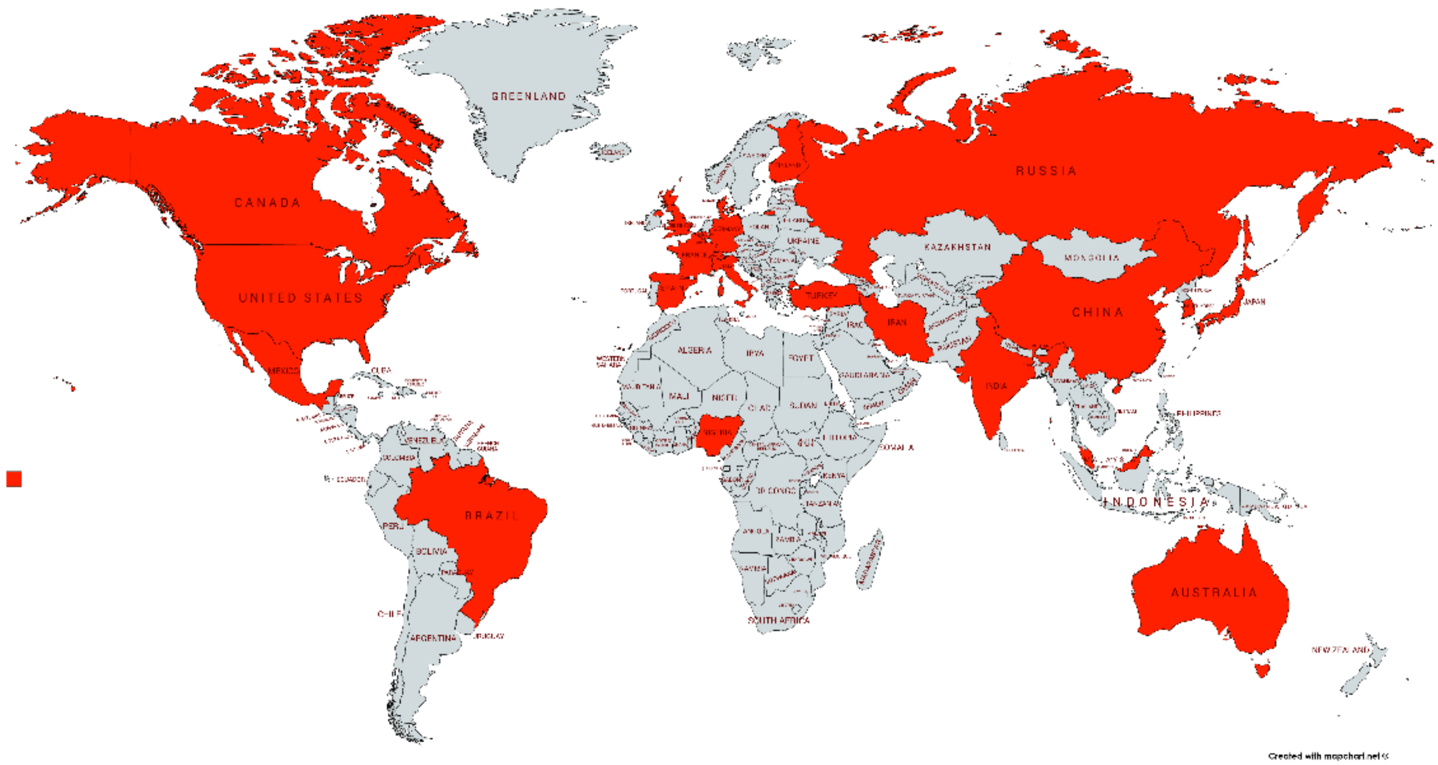

Figure 2

Global map of the countries which were studied through the AI-based methods to predict the trend of COVID-19 spreading in this review.

Supplementary Files

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