AI

Review

Hybrid Deep Learning Techniques for Predicting Complex Phenomena: A Review on COVID-19

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Abstract: Complex phenomena have some common characteristics, such as nonlinearity, complexity, and uncertainty. In these phenomena, components typically interact with each other and a part of the system may affect other parts or vice versa. Accordingly, the human brain, the Earth's global climate, the spreading of viruses, the economic organizations, and some engineering systems such as the transportation systems and power grids can be categorized into these phenomena. Since both analytical approaches and AI methods have some specific characteristics in solving complex problems, a combination of these techniques can lead to new hybrid methods with considerable performance. This is why several types of research have recently been conducted to benefit from these combinations to predict the spreading of COVID-19 and its dynamic behavior. In this review, 80 peer-reviewed articles, book chapters, conference proceedings, and preprints with a focus on employing hybrid methods for forecasting the spreading of COVID-19 published in 2020 have been aggregated and reviewed. These documents have been extracted from Google Scholar and many of them have been indexed on the Web of Science. Since there were many publications on this topic, the most relevant and effective techniques, including statistical models and deep learning (DL) or machine learning (ML) approach, have been surveyed in this research. The main aim of this research is to describe, summarize, and categorize these effective techniques considering their restrictions to be used as trustable references for scientists, researchers, and readers to make an intelligent choice to use the best possible method for their academic needs. Nevertheless, considering the fact that many of these techniques have been used for the first time and need more evaluations, we recommend none of them as an ideal way to be used in their project. Our study has shown that these methods can hold the robustness and reliability of statistical methods and the power of computation of DL ones.

Keywords: artificial intelligence; complex phenomena; complex systems; COVID-19; deep learning; machine learning

1. Introduction

Prediction models provide a historical perspective for healthcare decision-makers to adopt an evidence-based strategy and decrease morbidity, mortality, and economic losses at different levels [1–3]. Through estimations, they can better evaluate the infectious capacity of pathogens and the efficacy of public health prevention measures, which have been considered a complex phenomenon and cannot be analyzed using conventional methods. Despite numerous advantages of prediction models, some authors believe that due to the uncertainty of official data and underestimations of the infected people, who do not have access to medical services, data provided by estimation models may be biased in some cases [1–4]. Such errors and biases are important because they may lead to dire consequences. Accordingly, accuracy and reliability are two essential parts of a standard system. Mathematical or statistical models have typically appropriate reliability, but their performance in the face of big data or complex phenomena is not acceptable [1–4]. The advantage of these methods leads to using them for medical purposes. Therefore, the most significant question is how many combinations of these intelligent and mathematical techniques can contribute to more accurate and reliable methods and what kind of challenges may arise.

Although there are now many mathematical models of infectious diseases available to researchers and scholars, it is essential to categorize these models [5,6]. For example, compartmental models, including a combination of classical and more complex methods, have effective roles in the quantification of strategies that could be employed to mitigate and control infectious diseases [5,6]. Nevertheless, constant analysis of data must not be overlooked since pandemic has demonstrated the highest degrees of severity, and numbers have continuously changed [7]. Furthermore, new variants of the virus can spread so quickly and make the situation even worse.

On the other hand, there is a large number of artificial intelligence (AI) methods, deep learning (DL) or machine learning (ML) methods optimized by meta-heuristic algorithms, clustering techniques, and fuzzy methods [8] that can overcome the problems associated with the weaknesses of the analytical methods such as speed or accuracy in several areas, such as sociology, learning issues, social media, risk assessment, and hazard identification [9–12]. Regarding the accuracy and computing power of AI methods, extracting features for estimation, classification, and prediction of complex and nonlinear variables via these intelligent approaches has been popular [10,13–17] This is why AI has analyzed complex problems and found the best possible solution in a wide range of systems and mechanisms effectively [18–24]. All in all, other types of computational methods are related to those that have advantages of both and can be regarded as the best candidates for processing data with the most complexity, nonlinearities, and uncertainties, namely hybrids methods. In these methods, instead of analysis of the problem as a white box in physical models or a black box in DL models, the problem is defined as a grey box model, resulting in better reliability and accuracy compared to a purely mathematical model or AI ones.

Complex phenomena such as the spreading of COVID-19 are one of the areas in which these models can be employed [25]. In other words, these models can effectively be developed through different structures and utilized to forecast the spread of epidemiological diseases and their relevant fatalities in the immediate future [9,26]. In the case of COVID-19, some important values, including key infection data, the mean infection period, and the mean incubation period, need to be completely updated because their values may vary owing to the mutations [25]. Since prediction problems with the COVID-19 pandemic are categorized into complex problems, using appropriate methods to process such data is essential [4]. Several studies have mostly relied on data-driven approaches [27], and they have been conducted based on statistical methods, which often dismiss temporal components of the data. The combination of such complexities with various contact patterns poses a new challenge in the behavior prediction of COVID-19. This challenge is identified from the sole reliance on previously established compartmental models [25].

Regarding all of the aforementioned requirements and necessities for working with reliable and accurate methods, the proposed research has been prepared and developed. Indeed, many researchers are currently looking for new technologies to utilize, monitor, and track the COVID-19 outbreak [28], most attempts are built on purely classical models or solid AI ones that are customized according to the current situation of COVID-19 and this triggers the idea of working on this review [29–31]. In other words, this research focuses on cases where AI-based techniques combined with mathematical models have been applied for epidemiological modeling tasks as well as complex problems. Admittedly, such a study may not only increase researchers' and healthcare providers' knowledge of AI potential in combatting COVID-19, but also elucidate future studies on this subject and how they can improve the weaknesses of the method through some innovative methods. Furthermore, it helps health politicians and decision-makers to adopt evidence-based decisions and strategies with the help of AI. Hence, the absence of a review on applications of hybrid methods in epidemiological modeling of COVID-19 is one of the current gaps in the literature. 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 and possible future waves. This paper is organized as follows; the next section illustrated methods with all the important details. Section 3 offers the dissection and the last section concludes the results of this research with all limitations and future perspectives.

2. Methodology

This part demonstrates those statistical and analytical methods that are combined and empowered by AI techniques, such as ML and DL. Modified Auto-Encoders (MAE) to realize forecast the newly infected individuals' numbers were utilized by D. Charte et al. [32]. Auto-Encoders (AE) is a kind of ANN that is utilized to learn an efficient way of coding the data without supervision [33]. While a good number of them are capable of generating reduced feature sets through a fusion of the originals, AEs designed with other applications can be options to consider. 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. The results demonstrated high accuracy of prediction and subsequent multiple-step forecasting. Based on their experience a longer training time improved forecasting [34].

In addition, an MAE to deal with the existing limitations was designed and developed [35]. Therefore, considering the interventions degrees, each intervention variable was assigned a weight between 0 and 1 where zero is an indication of no intervention and one being complete. This way, bringing 152 countries under scrutiny, ending time, peak time, duration, peak number, and the number of people with COVID-19 under four intervention scenarios was noticed in this research. As a consequence, the critical information for high-official ranking and health administrators was available, facilitating immediate public health measures toward the plans and decelerating COVID-19 spread. The results obtained from this research were in line with the dire need for urgent aggressive interventions.

Moreover, a MAE-based approach is used in [36] proposing alternative strategies to model COVID-19 dynamics. As the results demonstrate, this approach was superior to traditional and LSTM approaches. The proposed approach had the world regions' initial clustering as its outset for which data is available. The data shows the locations with the pandemic advanced stage, but this is based on a set of features that are manually engineered and indicate a country's response to the early stage of pandemic spread. The TM, FM (including medical staff and hospitals), and DM constructed in [37] are to predict COVID-19 spread in the top ten most-affected countries. One main factor that directly impacts 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. Moreover, using seven up to nine days of data sequences for predicting the trend of daily growth of COVID-19 infected cases in China, six rolling grey Verhulst models were built. In another research, to analyze the characteristics and differences of the SV of COVID-19-related symptoms and to investigate the correlations between the SV of COVID-19 as well as the number of recent suspected/confirmed infection cases, Hubei province data was compared to the data related to the other nine provinces [38].

As is observed, Figure 1 demonstrates the methods, strategies, and techniques empowered by AI to forecast the COVID-19 spreading. It should be noted that the methods mentioned in Figure 1 include all popular methods that have been used in analyzing and estimating complex systems, particularly COVID-19. On the right side of this figure, the purely AI methods have been depicted, while on the left side, some statistical and hybrid methods have been demonstrated. Same as any other data mining problem, the process begins with data aggregating and ends with optimization and prediction. Moreover, some statistical information about the countries, which were studied via AI methods, is presented in this section.

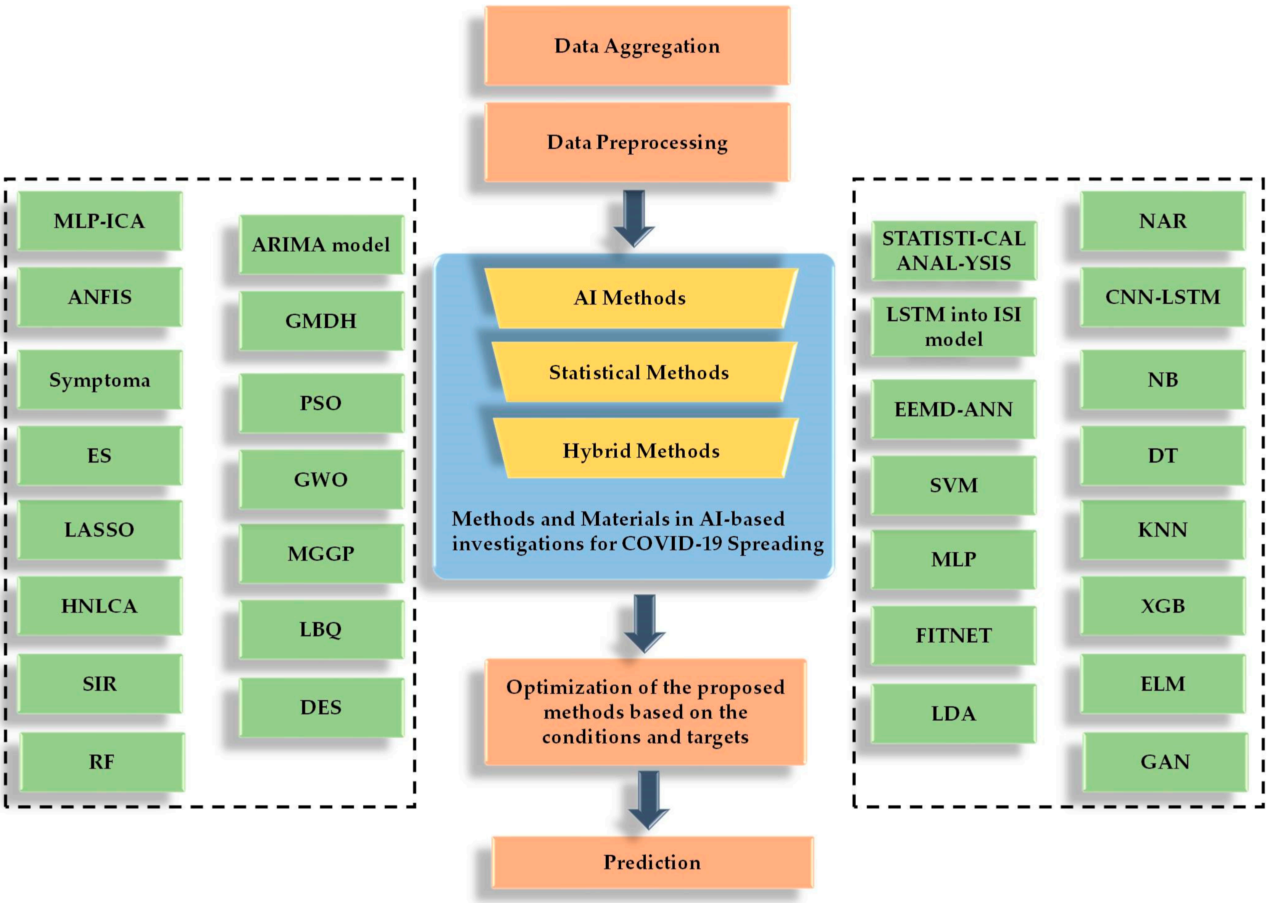

Figure 1. AI-based methods and techniques have been used for predicting COVID-19 spreading. The right side of the figure demonstrates purely AI methods without combination with statistical ones while the left side brings the hybrid methods and purely mathematical techniques used for analyzing complex phenomena.

In this section, all methods have been reviewed and categorized in specific tables. Characteristics of the sources of evidence used as eligibility criteria for the evaluation and assessment of the studied techniques brought in tables include authors and related references, techniques, country or region where the research has been conducted, a short description, date of the research, and results, which have been validated using different criteria. The name of the region is important to mention because the dynamic behavior of the used methods in different climates, countries, regions, or cities are different.

Table 1 gives useful information about the understudied techniques, such as autoregressive integrated moving average (ARIMA), compartmental models in epidemiology (SEIR), mean absolute error (MAE), statistically adjusted engineering (SAE), and seasonal autoregressive integrated moving average (SARIMA), which have been boosted by AI methods. As can be observed in this table, all aforementioned methods have been used to illustrate the characteristics of the methods.

This way Figure 2 demonstrates daily confirmed COVID-19 cases per million people in these counties based on a 7-day rolling average. However, because of some restrictions in testing, the number of confirmed cases is lower than the true number of infections. According to this figure the world is seriously has seen problems with COVID-19. This is why the organization of this research could shed light on the uncertainties in the application of AI for forecasting COVID-19 spreading around the globe.

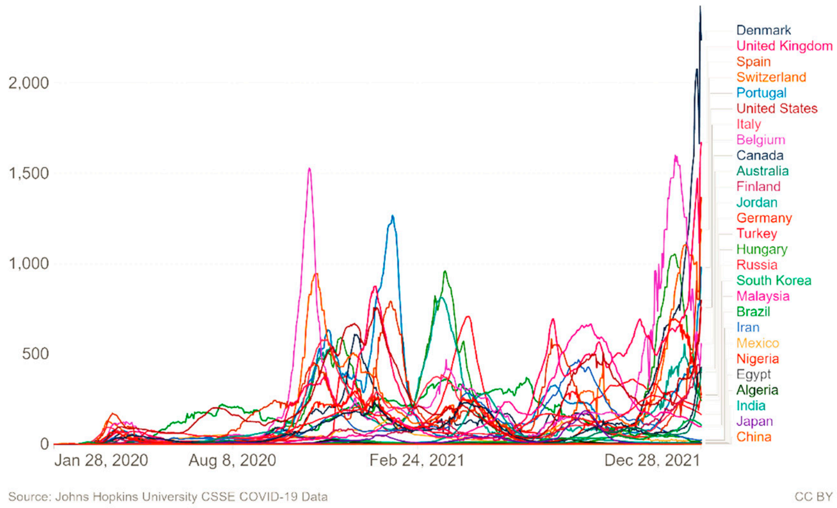

Figure 2. Daily confirmed COVID-19 cases per million people in these counties based on a 7-day rolling average.

Statistical and AI-based approaches for modeling and predicting the epidemic in Egypt were presented in [39]. The applied approaches in this study are Nonlinear Auto-Regressive Artificial Neural Networks (NARANN) and autoregressive integrated moving average with explanatory variable (ARIMAX), and ARIMA. Furthermore, Ref. [39] investigated and analyzed the environment and situation in and out of China to predict the worsening of the epidemic. In this work [39], official data related to infections, deaths, and suspected COVID-19 were collected and the findings demonstrated the seriousness of the situation in Hubei Province and Wuhan City. A trend comparison method, ARMA, and ARIMA to analyze and predict the data was presented in [39]. A comparison demonstrated 19 February 2020 and 14 March 2020 when full control of the situation was achieved as the key dates of COVID-19. Additionally, the numbers related to infections and deaths and GDP growth were also predicted simultaneously. Furthermore, the applicabilities of ML models in the prediction of upcoming COVID-19 patients' numbers were demonstrated and explained in another study [40]. In this study, four standard forecasting models namely, least absolute shrinkage, exponential smoothing (ES) selection operator (LASSO), SVM, and linear regression (LR) to forecast COVID-19 threatening factors were utilized [40]. More importantly, the potential of data science to assess risk factors related to COVID-19 after an analysis of the datasets obtained from the Oxford University database and simulated datasets, following the analysis of different univariate long short-term memory (LSTM) models to forecast new cases and deaths, was investigated [41].

Table 1. 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. [3]	ARIMA	India	Predictions of patients raise, recovery and death rate	from 30 January 2020 to 15 May 2020	Forecasting was done by using the constructed models up to 8 July 2020
Roseline Oluwaseun Ogundokun et al. [2]	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. [1]	ARIMA, HWAAS, BEATS, 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. [42]	SARIMA	France, Italy, USA, UK	Predicting the End of Pandemic	Collected data from 22 January 2020 to the present time	The confirmed case will slowdown in October 2020
Leila Moftakhar et al. [43]	ANN, ARIMA	Iran	A Comparison between ARIMA and ANN prediction	New cases from 19 February 2020 to 30 March 2020	ARIMA model has better prediction results than ANN
Kabir Abdulmajeed et al. [44]	ARIMA, GARCH	Nigeria	Online forecasting mechanism	cases from 27 February 2020, to 5 April 2020	Providing academic thrust in guiding the policymakers
George Xianzhi Yuan et al. [45]	iSEIR model	China	Forecasting of the Critical Turning Period	From January 2020 to early March 2020	Control the epidemic time should be around mid-February 2020
İsmail Kırbaş et al. [46]	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 May 2020	The best model result has been obtained for LSTM
Zixin Hu et al. [47]	MAE, ARIMAX, SEIR	152 countries	Forecasting and Evaluating Multiple Interventions	From 20 January 2020 to 16 March 2020	The obtained 2.5% average error of five-step ahead prediction
Farhan Mohammad Khan et al. [48]	ARIMA, NAR, MoHFW	India	Forecasting model for time series analysis	from 31 January 2020 to 25 March 2020	Estimating trend in the actual and approximately 1500 cases per day on 4 April 2020
Igor G. Pereira et al. [49]	LSTM-SAE MAE	Brazil	Forecasting	From February 2020 to May 2020	The pandemics are estimated to end (with 97% of cases reaching an outcome) in some states in 28 May and the rest through 14 August
Amal I. Saba et al. [39]	ARIMA, NARANN	Egypt	Forecasting the prevalence	Data collected between 1 March 2020 and 10 May 2020	NARANN has acceptable error results of less than 5%
Zixin Hu et al. [50]	SEIR; AE; IAE	USA	Estimating that the peak time	From 22 January 2020, to 24 April	The COVID-19 peak time in the US is estimated
Zixin Hu et al. [35]	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	Number of cumulative cases by 10 January 2021; under later intervention: 255, 392,154 under immediate intervention: 1,530,276

In another study, an online forecasting procedure to stream data from the Nigeria Center for Disease Control to update an ensemble model's parameters as well as update COVID-19 forecasts every day was employed [41]. 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 regarded 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 [41]. Additionally, a symptom-to-disease digital health assistant called Symptoma to differentiate over 20,000 different diseases demonstrating 90% accuracy was used [30]. The symptom's accuracy in identifying COVID-19 in various sets of clinical cases and similar diseases came to be tested in [30].

In [29], the applied 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 30 January 2020 to 15 May 2020, presented by the government of India was used in Govt from [30] to implement an ARIMA model to forecast the occurrence of 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 [30]. In [51], symptoms, transmission modes, and putative treatments to deal with COVID-19 were investigated and reported. The report summarized the relevant available information on the genome, evolution, and zoonosis of coronavirus. In [52], the authors aimed to synthesize the challenges that retailers have to face and deal with during the COVID-19 pandemic. To create a guideline for retailers in this study, the pandemic was approached from the perspective of consumers and managers. Using two explainable AI methods, ECPI and SHAP, the three most significant measures in countries and regions understudied to construct models to forecast the instantaneous reproduction number (Rt) and to use the models as surrogates to the real world were investigated [53].

In [42], 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 the life cycle and end date as well. Since the virus acts similarly in different places, this study could applicable 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 pandemics can impose on COVID-19-stricken areas [42]. The Chinese Sina-microblog witnessed an outbreak of public opinion triggered by the COVID-19 outbreak. To recognize the important information propagation patterns across social networks [54] 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 the individual SEIR (iSEIR) model, which is a set of differential equations that extends the classic SEIR model was proposed in [55]. Using the collected data between 26 March 2020 and 4 April 2020, an ARIMA model was adopted on the collected data between 31 January 2020 and 25 March 2020 [48]. In a bid 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 [48].

A Genetic Algorithm (GA) to estimate parameters of Compound, Cubic, Logarithmic, Linear, Logistic, Quadratic, and exponential equations to develop the desired model was used [56]. The selected population number was 300, and based on various trial and error examinations, the iteration number indicated as the maximum generation was 500 to decreased 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. Additionally, 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), and 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 a high rate of COVID-19 spread [6]. Ref. [57] proposed an AI model called multi-gene genetic programming (MGGP) for the first time to predict the outbreak of COVID-19. Despite significant fluctuations in the number of confirmed cases that make 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 study. As a result, MGGP could be a good suggestion to be employed in the development of the estimation approaches for COVID-19.

Using data from Hungary presented a hybrid ML approach for COVID-19 prediction [58]. 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 mortality and the outbreak by the end of May. Besides, interpreting global COVID-19 data via specific ML techniques, Ref. [59] 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-19 for these countries between 22 January 2020 to 28 May 2020, as presented on the WHO database was used [60]. This research tested Autoregressive Distributed Lag Models (ADLM) and ARIMA, and Double Exponential Smoothing (DES) [60]. Data from new cases in Iran happening was used in [43] for predicting patient numbers. ARIMA and Artificial Neural Networks (ANN) models were used to realize prediction [43]. Open datasets provided by the JOHN Hopkins and daily reports of the 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 27 February and 8 May [61].

Support-Vector Machines (SVM) in ML were supervised models that included associated learning algorithms for analyzing data that are used for regression analysis and classification. A technique was presented in 1992 to create nonlinear classifiers through the application of kernel tricks to maximum-margin hyperplanes [62]. Corinna Cortes and Vapnik, however, proposed the current standard incarnation in 1993, which was published in 1995 [63]. SVM models are representations of examples as points in space that are mapped in a way that a clear wide gap could divide the examples into separate categories [64]. Synthetic Minority Over-sampling Technique (SMOTE) was trained from data sets that were imbalanced [65]. Contrary to standard boost in the process of which equal weights are assigned to all misclassified examples, in synthetic minority oversampling technique (SMOTE), Boost synthetic examples are created from rare or minority classes, causing indirect changes in updates of weights and skewed distributions compensations [65]. This way, researchers focused on tracking people's transit between Wuhan and mainland China until January 2020 by utilizing detailed geolocation data of cell phones to calculate total population movements. This research uses the people's 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 the COVID-19 epidemic curve across different locales, while deviations from model predictions were used as tools for the detection of the burden of community movements [66].

Group Method of Data Handling (GMDH) refers to an algorithms family that was used in mathematical computer-based modeling of multi-parametric datasets featuring fully automatic structural and parametric model optimization [67]. Complex systems modeling knowledge discovery, data mining, prediction, pattern recognition, and optimization are among the fields in which GMDH was utilized. The main characteristic of GMDH algorithms was an inductive procedure to perform sorting-out of complicated polynomial models and adopting optimal solutions through relying on external criteria [67]. Using the classification of COVID-19 confirmed cases a serious challenge in the sustainable development process was scrutinized in [68]. Accordingly, the GMDH type of ANN as one of the AI methods used binary classification modeling [68]. S. Uhlig et al. propose an empirical top-down method to model and forecast the risks and calculate (local) outbreaks [64]. This research used neural networks for developing leading indicators according to data that 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 [54]. In [69], a strategy was developed that was backed by AI, and a combination of three methods: SVM, SMOTE Boost, and Ensemblingt, to conduct initial screening of probable COVID-19. It contains an ML classifier whose input consists of existing simple blood exams to be classified into two negative (not having SARS-CoV-2) or positive (having SARS-CoV-2) samples [70].

Ensembling ML techniques integrate multiple models to build a predictive model. Thus, Ensemble methods are capable of improving prediction performance. 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 that are obtained by each one separately. An important feature of an ensemble is to emphasize diversity in generation mechanism and choosing combination procedure. Z. Allam et al. documented AI's role in the early detection of 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 [71]. 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 the urban health sector [72].

A novel forecasting model, called Chaotic Learning (CL) strategy, was put into a multi-layer Feed-Forward Neural Network (MFNN) to use the data reported as of 22 January 2020 to analyze and predict the CS of COVID-19 for the future days is suggested in [73]. This forecasting model, known as ISACL-MFNN, integrates an optimized interior search algorithm (ISA) using CL strategy into an MFNN. The ISACL incorporates the CL strategy to enhance ISA performance ISA and avoid being trapped in the local optima. The purpose of this approach is to tune the neural network's parameters to optimal values to train the network so that high precision of forecast results could be achieved [73]. In another study [73], it was suggested that situational information could resourcefully help both the authorities and the 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 seven types of situational information. There are specific features found in forecasting the amount reposted for each information [73]. Due to having limited data, the authors merely trained three traditional classifiers based on NLP to train classifiers and identify situational information's content types.

In addition, To investigate and prioritize parameters for consequences of the COVID-19 outbreak, differential evolution (DE) algorithm and ANN-based particle swarm optimization (PSO) algorithm were leveraged [74]. This research was focused on prioritizing and analyzing the role of certain environmental parameters. Scrutinizing four Italian cities in Italy, some main features, including climate parameters, such as relative humidity, daily average temperature, and urban parameters such as population density, were surveyed and applied as input an dataset while COVID-19 confirmed cases were considered as an output dataset [75]. The information about the recent research on the prediction of COVID-19 with the use of both statistical models and AI methods has been brought in Table 2.

In [47], AI-inspired methods to model the epidemic's transmission dynamics and evaluate interventions for curbing COVID-19 spread and impact were developed. These methods focused on WHO data from 16 March 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 before prediction was 2.5%.

In addition, Ref. [76] suggested a preliminary classifier that included non-linear hybrid cellular automata tested and trained to forecast COVID-19 effects concerning the number of deaths, the number of infected individuals, the number of recovered individuals, etc.

The datasets for this study were from Kaggle and other standard websites, and they could predict the epidemic trend in India.

In [77], an AI approach that is based on DNN predicted the peak of coronavirus in Spain. The 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. [31] proposed a model to predict COVID-19 spread as well. To predict epidemiological examples of COVID-19 cases in India, this study used MLP, vector auto-regression, and linear regression methods using COVID-19 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 [78]. A multivariate linear regression (MLR) method was used for results validation.

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) [79]. Furthermore, to assess coronavirus transmission, the 8.57 million Switzerland population, along with cross-border commuters as well as the stimulated Swiss public and private transport networks were studied.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 [75].

Table 2. 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. [31]	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. [29]	MLP	USA	nationwide modeling of COVID-19 incidence	From 22 January 2020 to 25 April 2020	The prediction capability of the model requires a significant improvement
Xuanchen Yan et al. [80]	SPSS 25.0	China	Big Data analysis	between 23 January and 6 February 2020	Middle-aged people (p = 0.038) have more probability to be infected
Tajebe Tsega Mengistie [81]	Fbprophet	Countries worldwide	Analysis and Prediction Modeling	start from 12 April 2020	The last 10 days and analysis graphically by using the data mining
Abdallah Alsayed et al. [82]	SEIR, ANFIS, GA	Malaysia	Prediction of Epidemic Peak	from 25 January to 5 April 2020	An NRMSE of 0.041; a MAPE of 2.45%; R^2 of 0.9964
Yu-Feng Zhao et al. [83]	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

Table 2. *Cont.*

Author	Technique	Country/Region	Description	Data	Results
Ali Behnood et al. [84]	ANFIS, VOA	USA	Determinants of the infection rate	1657 counties	The models could forecast the effects of the variables on the infection rate
Mohammed A. A. Al-qaness et al. [85]	MPA-ANFIS, ANFIS	Italy, Iran, Korea, and the 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. [53]	SHAP and ECPI	18 countries and regions	Spreading Factors	from 22 January 2020 to 2 April 2020	Warm temperature helps for reducing the transmission
Salgotra, Rohit et al. [86]	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. [87]	SVM, NB, and RF	All countries	Characterizing the Situational Information Propagation	Weibo data: From 30 December 2019 to 1 February 2020	Indicating the necessity of information publishing strategies for situational information
Ramon Gomes da Silva et al. [79]	VMD	USA and Brazil	Forecasting	Cumulative cases of COVID-19 that occurred until 28 April 2020	VMD-based models are very strong tools for the prediction
Abhari, Reza S. et al. [75]	EnerPol	Switzerland	Containment Strategy and Growth Prediction	Available public data and adapted to Swiss demographics	Estimating deaths, recovered, and cases between 22 February and 11 April 2020
Ashis Kumar Das et al. [88]	SVM, KNN, RF, GB, LR	South Korea	development of a prediction tool	3128 patients	GB algorithm has the highest precision compared to the other studied models
Pokkuluri Kiran Sree et al. [76]	HNLCA	India	cellular automata classifier for trend prediction	6785 datasets and 23,078 datasets are used for test and training, respectively	The average accuracy of 78.8% is reported
Gregory Baltas et al. [77]	SIR, DNN	Spain	Monte Carlo DNN model for spread and peak prediction	Total Infected Until 28 March	The simplicity of the DNN allows identifying the SIR parameters for different COVID-19 evolution curves
Li Yan et al. [89]	XGBoost ML Method	Wuhan, China	prognostic prediction	Data collected between 10 January 2020 and 18 February 2020	Quickly prediction of patients with high risk using suggested decision rule
Furqan Rustam et al. [40]	LR, LASSO, SVM, ES	Canada, Australia, Algeria	Future Forecasting	dataset from 22 January 2020 to 2 March 2020 is used for training the model	ES has the best precision, while SVM performance is not acceptable

Table 2. *Cont.*

Author	Technique	Country/Region	Description	Data	Results
Alistair Martin et al. [30]	Symptoma	Not mentioned	digitally screening citizens for risks	BMJ cases: 1112 casesTest cases: 1142 medical test cases	Symptoma can accurately distinguish COVID19 from diseases
Mohammad Pourhomayoun et al. [90]	SVM, KNN	Countries worldwide	Predicting Mortality Risk	117,000 patients worldwide	Obtained 93% precision in forecasting the mortality rate
Behrouz Pirouz et al. [68]	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. [91]	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. [92]	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. [73]	MFNN (GA, PSO, GWO, ISA, ISACL)	USA, Italy, and Spain	Forecasting the confirmed cases of three countries	The data referring to the period 22 January 2020 to 3 April 2020	The presented ISACL-MFNN model has promising forecasting results from 4 April 2020 to 15 April 2020 are presented
Hasinur Rahaman Khan et al. [93]	ML Techniques	133 countries	Demonstrating ML basics to analyze global COVID-19	The data include 10 variables until 17 April 2020	The countries which have an important role to explain the 60% variation of the total variations include the USA, Iran, UK, Germany, Spain, France, and Italy
K.M.U.B. Konarasinghe [60]	ARIMA, LBQ, DES and ADLM	USA, UK, and Russia	Modeling COVID -19 Epidemic	The data from 22 January 2020 to 28 May 2020	The ARIMA did not satisfy the model validation but the ADLM and DES did
Jayson S. Jia [66]	Statistical Methods using mobile phone	China	Spatio-temporal distribution	About 10 million counts of mobile phone data between 1 January 2020 and 24 January 2020 to 296 prefectures	Developing a Spatio-temporal 'risk source' model
Gergo Pinter et al. [58]	ANFIS, MLP-ICA	Hungary	Pandemic Prediction; A Hybrid ML Approach	The data from 24 March to 19 April	Results Prediction from 20 April to 30 July
O. Torrealba-Rodriguez et al. [61]	Gompertz, Logistic, and ANN models	Mexico	Modeling and prediction	The data from 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

Additionally, Ref. [90] 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 incoming patients and significantly reduce delays in the process of care provision. Besides, the approach to forecasting COVID-19 along with efforts of the Public Health Agency of Canada for modeling the effects of Non-Pharmaceutical Interventions (NPIs) on COVID-19 transmission among the Canadian population to support public health decisions was described in [94]. Additionally, the joint effort of health care organizations, government agencies, and industry partners from around the globe to investigate pandemic challenges during social distancing was investigated in [95]. The investigated challenges included conducting treatment research, enabling virtual health care, and scaling high-quality laboratory tests during social distancing [95].

In this review, several AI-powered prediction approaches to estimate the COVID-19 outbreak spread in different locations and times have been surveyed. Progressive use of predictive computing tools has by now demonstrated that they are efficient in the provision of insights for better health policies and strategic management. Finding and recognizing suitable models for forecasting is, therefore, an urgent and timely requirement, especially in this situation where 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 the effectiveness of AI methods in predicting epidemiological issues such as COVID-19. Innovative solutions are the most needed solutions at present for the development, management, and analysis of big data on a continuum consisting of individual patients, community movements in the framework of clinical trials, genomics, pharmaceutical, and public health data.

3. Discussion

At the present, research and a narrative review on hybrid methods for forecasting and estimating the nonlinear behavior of complex systems have been conducted. When it comes to hybrid methods in this research, a combination of statistical or analytical methods with intelligent ones, including AI, ML, and DL have been used. The most important question to pursue in this research is how these methods are reliable and how they can overcome the problems that purely mathematical or AI ones have had in face of complex problems. An important goal to summarize and categorize these methods is a reliable collection. From an advantageous perspective, the benefits of applications of the aforementioned methods can be increasing the level of reliability in the hybrid methods compared to purely DL methods, while the level of accuracy in this comparison has been affected. In this regard, the different scenarios can be mentioned in the comparison of these methods with statistical ones. It means that while the reliability has some problems, the accuracy of the hybrid method has appropriate growth compared to purely statistical methods, indicating the role of computational intelligence in the analysis of the complex problem with the best possible precision. Forecasting helps decision and policy-makers converge their efforts toward maintaining economic and social stability. This highlights the importance of the inclusion of reliable AI strategies to have optimum predictions that could be employed by various applications to yield the best possible results. Accordingly, evaluation of this technique should be performed in such a way that the effectiveness of the method could be guaranteed when employed for sensitive medical issues. As such, this review is committed to carefully validating the performance of AI-powered prediction methods for the COVID-19 outbreak.

Nevertheless, from the epidemiological, diagnostic, and pharmaceutical points of view, AI does not seem to have a significant role in battling COVID-19 yet, because its use is simply limited due to lack of data and the existence of too much outlier data. Big data is currently a critical element in managing the COVID-19 pandemic; therefore, having clear and transparent conditions to realize responsible data collection and processing at a global scale is of utmost importance. It is also important that unbiased time series data is created for AI training. However, various sources of uncertainty and unpredictability do exist in dynamic 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.

Furthermore, several studies have been merely conducted by 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, kidney disease, etc. Considering that there is a lack of pre-existing data for the new disease, AI models could be reliable to build such data to determine the extent of diagnosis or prognosis as a challenge. Such a challenge could be addressed by an AI community that uses ML to remove the barriers between data domains.

The findings of this study reveal that the epidemic comes with complex behavior, which is affected via several parameters such as geography, country, region, sex, climate, humidity, etc. However, the main objective of this research was to find out if AI could successfully address the need for a reliable approach to forecasting the spread of COVID-19. Hence, the efficiency of this response is partially dependent on ML, and also depends on the ability to realize global collaborations and establish data-sharing agreements that could contribute to the process of accelerating the discovery and validating promising interventions.

4. Conclusions

In this narrative review, 80 documents, including preprints, peer-reviewed papers, conference proceedings, and chapter books to make a narrative review on state-of-the-art hybrid DL methods for estimating and predicting complex phenomena with a concentration on COVID-19 spreading have been aggregated and summarized. The most important contribution of this research is to summarize, illustrate, and categorize these methods. The surveyed methods were designed based on a combination of DL methods with statistical techniques. Although any definite conclusion drawn about the effectiveness of AI and its impact on COVID-19 could be premature and not well-evaluated, the investigations show these methods can be more useful than a purely statistical or DL method. One of the limitations to surveying or using these methods is originating from their heavy dependence on the data. In another word, the data supply changes daily because the numbers and statistics characteristics of infections are changing daily. Hence, applications of AI in mitigating the problems associated with pandemics with an emphasis on the digitalization of the economy need to be taken into consideration. One of the limitations of this study was limited access to Google Search data. Google Trends provides data based on "interest" measures indicating that building more accurate and informative models is possible only if absolute search frequency is available to researchers.

While 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 prevision the present review could be appreciated as a significant step because the AI community comes to appreciate intelligent techniques. These AI methods play a vital role in forecasting targets and understanding the complex behavior of the phenomenal functions.

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