Deep learning for Covid-19 forecasting: State-of-the-art review.

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ARTICLE INFO

ABSTRACT

The Covid-19 pandemic has galvanized scientists to apply machine learning methods to help combat the crisis. Despite the significant amount of research there exists no comprehensive survey devoted specifically to examining deep learning methods for Covid-19 forecasting. In this paper, we fill the gap in the literature by reviewing and analyzing the current studies that use deep learning for Covid-19 forecasting. In our review, all published papers and preprints, discoverable through Google Scholar, for the period from Apr 1, 2020 to Feb 20, 2022 which describe deep learning approaches to forecasting Covid-19 were considered. Our search identified 152 studies, of which 53 passed the initial quality screening and were included in our survey. We propose a model-based taxonomy to categorize the literature. We describe each model and highlight its performance. Finally, the deficiencies of the existing approaches are identified and the necessary improvements for future research are elucidated. The study provides a gateway for researchers who are interested in forecasting Covid-19 using deep learning.

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1. Introduction

Applications of machine learning to Covid-19 have attracted an enormous amount of interest from the research community. There exist hundreds of academic papers attempting to apply machine learning to combat the pandemic [90]. The current research trends in the field can be divided into four major categories: i) image and symptom-based diagnosis [47,101,102], ii) forecasting the number of cases [77], iii) intelligent contact tracing [63], and iv) AI-aided drug discovery [24]. In particular, there exists a large amount of research devoted to forecasting the number of infections using deep learning techniques. Various deep learning techniques have been proposed to forecast the number of infections including recurrent neural networks (RNNs), gated recurrent units (GRUs), long short-term memory networks (LSTMs), graph neural networks (GNN), and others. Despite the large amount of literature, there exists no state-of-the-art survey of the subject. In this paper,

we fill the gap in the literature by reviewing and analyzing the current studies related to forecasting Covid-19 using deep learning.

Given the large volume of research devoted to the applications of machine learning to Covid-19, it is not surprising to find a number of surveys in the literature that cover the subject. However, there is currently no a survey that targets exclusively the state-of-the-art in Covid-19 forecasting using deep learning. The existing surveys provide either a general overview of machine learning applications or an overview of forecasting methods at large. Surveys that provide a general overview of machine learning applications do not delve into an in depth analysis of forecasting methods. In most cases, general surveys focus on Covid-19 diagnosis leaving Covid-19 forecasting as a secondary topic [43,84,85]. There exists a small number of surveys dedicated to the broad review of forecasting methods for Covid-19. General forecasting reviews focus mostly on mathematical models such as the susceptible-infected-recovered (SIR) model and its variants, while deep learning methods receive little consideration. In [83], the authors divide forecasting models into mathematical and machine learning approaches, while in [69] the authors perform a scientometric analysis of the existing forecasting models with emphasis on mathematical modeling. Furthermore, given the constantly growing body of research, many of the existing surveys become quickly outdated.

There are currently over 150 research papers in the literature that propose various deep learning approaches to forecasting the number of Covid-19 infections. A number of approaches are based on MLP, RNN, and GRU models. However, the majority of the approaches are based on the LSTM model and its variants. We found that among the LSTM variants, ConvLSTM and multivariate LSTM (M-LSTM) are the most commonly used approaches. In particular, the use of M-LSTM is justified under a reasonable assumption that the number of Covid-19 cases depends on multiple factors (features). The popularity of LSTM is not entirely surprising given its successful performance on other time-series tasks. On the other hand, most models for Covid-19 forecasting use a window of 5 previous observations to forecast the next day observation. Given the shortness of the input sequences, the utility of the LSTM model is questionable. Among other existing approaches, spatiotemporal models using GNNs together with Google mobility data have shown promising results. Spatiotemporal models leverage the information about human movement traffic between cities to model the spread of the pandemic. In general, we find, that deep learning models provide mixed results depending on the country data and time frame.

Our study aims to accomplish the following four goals:

1. Use model-based taxonomy to organize the current research on deep learning for Covid-19 forecasting.
2. Describe the most commonly used deep learning architectures utilized in Covid-19 forecasting.
3. Discuss the accuracy of the deep learning models in Covid-19 forecasting.
4. Identify the deficiencies of the existing approaches and elucidate the necessary improvements for future research.

We employ a model-based taxonomy to categorize the existing research into distinct subsets (Fig. 2). For each model, we describe its general architecture along with the specific adjustments made to tailor for Covid-19 forecasting. We discuss the theoretical advantages and disadvantages of the model as well as its performance in practice. One of the main factors in the performance of a forecasting model is the training and testing data. The country source and time frame of the data can have a dramatic impact on the accuracy results. The differences in data makes it challenging to effectively compare different studies. In our survey, we provide the details of the data used in each study as a reference for the reader.

The choice of the forecast accuracy metric is an important consideration in model evaluation. Since the forecast values and errors depend closely on the population size, raw measures of accuracy such as mean absolute error (MAE) and root mean squared error (RMSE) are not appropriate for cross-study comparison. The forecast MAE for a small country is likely to be lower than the forecast MAE for a large country regardless of the model effectiveness. It is more suitable to consider the relative error to measure the accuracy of forecasts. In our survey, we employ the mean absolute percentage error (MAPE) to report the accuracy of the forecasting models. The use of MAPE allows us to compare the results from different studies.

The paper is structured as follows. In Section 2, we present the taxonomy for organizing the current research into distinct categories. In Section 3, we describe and discuss various approaches to forecasting Covid-19 infections together with the corresponding results. In Section 4, we discuss the pitfalls of the existing approaches and advise on future research and improvements. Section 5 concludes the paper.

Fig. 1. The general taxonomy of the forecasting models for Covid-19 which can be divided into three major categories: autoregression, mathematical modeling, and machine learning.

Fig. 2. The taxonomy of the deep learning models for forecasting Covid-19.

2. Taxonomy

We propose a model-based taxonomy to categorize the existing research in Covid-19 forecasting. In general, Covid-19 forecasting approaches can be grouped into 3 major categories:

1. autoregressive models
2. mathematical models
3. machine learning models

As shown in Fig. 1, each major category can be further refined into more specialized subcategories. We briefly consider each major category before delving into an in-depth analysis of deep learning models.

2.1. Autoregressive models

Autoregressive methods are based on the classical time series analysis techniques which include the autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH) models. ARIMA is a widely used model for time series analysis. In the ARIMA model, the current value of a time series depends on a linear combination of the past values together with random Gaussian noise. It is a simple yet effective approach that has been used to forecast Covid-19 in several countries [5,19,33]. In a recent study [71], the authors employed vectorized ARIMA model to obtain accurate forecasts

in the UAE and Saudi Arabia with MAPE 0.0017% and 0.002% respectively. In some cases, it has been shown to outperform the more sophisticated models. The authors in [66], compared ARIMA to Facebook's Prophet and DeepAR models and found that ARIMA generally produced more accurate forecasts than the deep learning methods. The GARCH model is used to model time series shocks such as lockdowns. In [44], the authors showed that the ARCH model can be used effectively to forecast Covid-19 in the UAE.

2.2. Mathematical models

Mathematical models are frequently employed in Covid-19 forecasting. There exists a large number of attempts to model the spread of Covid-19 using stochastic processes such as the compartamental and exponential models [69]. The most commonly used mathematical model in the literature is the susceptible-exposed-infectious-recovered model (SEIR) which is based on a set of differential equations:

$$\begin{aligned}
\frac{dS}{dt} &= \mu N - \mu S - \frac{\beta IS}{N} \\
\frac{dE}{dt} &= \frac{\beta IS}{N} - (\mu + a)E \\
\frac{dI}{dt} &= aE - (\eta + \mu)I \\
\frac{dR}{dt} &= \eta I - \mu R
\end{aligned} \tag{1}$$

The parameters of the SEIR model can be determined using an optimization procedure based on the gradient descent algorithm [6,26,103]. In [87], the authors employed the SEIR model together

with the parameter optimization procedure to forecast Covid-19 cases in China between Jan-Mar, 2020. The model produced robust accuracy with MAPE 3.8%. An extension of the SEIR model was considered in [68], where the authors used Bayesian framework to estimate the model parameters.

A large scale comparison of probabilistic models including SEIR-based methods is presented in [17]. The authors highlight the performance of two models – the COVID-19 Public Forecast model [7] and the UMass-MechBayes model [27] – as producing highly accurate county-level forecasts in the USA. The latter approach uses a nonparametric model of the transmission rate β_t which allows for the transmission rate to increase or decrease for each measurement period. The former approach employs machine learning models to dynamically quantify the transitions between model compartments.

Other frequently used mathematical models include error trend season (ETS) and exponential smoothing (ES) with and without multiplicative error-trend. The authors in [9] found that ETS outperforms ES and ARIMA in univariate long-term forecasting, while in [59] it was found that ES produces the most accurate forecasts in the short-term.

2.3. Machine learning models

Machine learning has been employed successfully in various fields [30,88]. As a result, machine learning models have been used extensively to provide data-driven forecasts of Covid-19 cases [32,53,57,79,95]. Machine learning forecasting models are divided into deep learning and traditional (nondeep learning) methods.

2.3.1. Traditional models
The traditional methods include support vector machines (SVM), gradient boosting (GB), random forest (RF), k-Nearest Neighbors (kNN), and other algorithms [76,77]. In [94], the authors implemented a Bayesian time series model together with an RF algorithm within an epidemiological compartmental model to forecast the number of Covid-19 cases. The authors in [70] introduced a dynamic model based on kNN that builds a unique model for each point of time. The model uses 11 historical inputs and is able to achieve MAPE 9% in 10-week ahead prediction. A more basic approach using polynomial curve-fitting was used in [96] to forecast the number of cases in India. On the other hand, the authors in [58] found that SVM underperforms exponential smoothing and linear regression. Machine learning is also used in conjunction with other methods. The authors in [12] combine mechanistic and machine learning approaches in a unified reinforcement learning framework. The overall trajectory of the disease is estimated by the mechanistic model which in implemented in the machine learning model to forecast local variability. A combination of machine learning and ARIMA is used to construct a hybrid model in[56]. Recently, the authors in [92] combined a differential equation model with GB machine learning algorithm to forecast Covid-19 under imperfect vaccination scenario. Further details about the applications of traditional machine learning models can be found in [4]. Overall, the use of traditional methods in Covid-19 forecasting has been relatively limited and with mixed results.

2.3.2. Deep learning models
The deep learning category comprises various neural network architectures. The success of neural networks has made them a natural candidate for forecasting [35–37] Since forecasting Covid-19 is a time-series task, the majority of the neural networks are based on the recurrent network architecture. In the recurrent model, the forecasted values from the previous time-steps are used as part of the input to forecast the value in next time-step of the series. These models have received a large amount of attention in the literature and are the primary focus of our survey.

The deep learning category has attracted the greatest amount of interest among the researchers with over 150 research papers devoted to the subject. As shown in Fig. 2, deep learning includes several models. The most basic model is the multi-layer perceptron (MLP) which consists of the input layer, several fully-connected hidden layers, and the output layer. The MLP model fits a nonlinear function to the data. It can be used in any regression problem and serves as a robust benchmark. Although the MLP model does not perform well in comparative studies against other more sophisticated models, it is successfully used to estimate the coefficients of the SIR model.

Convolutional neural networks (CNN) are a popular class of machine learning models. The strong performance of CNN models in image classification led to their application in other fields. In particular, CNNs are used in several studies in forecasting Covid-19. The CNN models have produced robust results, especially when combined with other approaches.

The most popular type of neural network is the recurrent model. Recurrent neural networks (RNN) were designed specifically for dealing with sequential data. In the recurrent model, the output from the previous time-step is used to forecast the value of the series in the next time step. There exist several extensions of RNN aimed at addressing the problem of exploding and vanishing gradients that occurs in long sequences. As shown in Fig. 2, the family of recurrent models includes the plain RNN, gated recurrent unit (GRU), and long short-term memory (LSTM). The success of LSTM on speech recognition tasks has prompted its use in many other applications including forecasting. In particular, LSTM has been the most widely applied model in the literature. A number of different extensions of the LSTM architecture have also been proposed to forecast Covid-19. As shown in Fig. 2, the LSTM-based models include the plain LSTM, convolutional LSTM (ConvLSTM), bi-directional LSTM (BiLSTM), and multivariate LSTM (M-LSTM). Despite the popularity of LSTM, its use in Covid-19 forecasting is often questionable given the small window of previous of values used for forecasting. A number of forecasting models in the literature employ LSMT with window size of 5 or less. In this case, MLP or the plain RNN should be equally effective.

Among other approaches employed in Covid-19 forecasting are graph neural networks (GNN) and variational autoencoders (VAE). GNNs use spatiotemporal information to model the spread of the pandemic. A number of studies have been proposed based on GNN that utilize Google mobility data together with Covid-19 time series to forecast the future number of infections.

3. Deep learning models for Covid-19 forecasting

In this section, we go through each deep learning model presented in Fig. 2. We provide the details about the architecture of the models and their application to Covid-19 forecasting. During the initial review of the existing literature we discovered 152 existing publications related to forecasting Covid-19 with deep learning, of which 53 were selected for further analysis in our study. The distribution of the articles according to the model type is presented in Fig. 3. The left bar plot in Fig. 3 contains the results of the initial search of the existing literature, while the right bar plot shows the number of papers selected for further analysis and inclusion in our study.

As shown in the Fig. 3, LSTM and its variants are the most widely used and accurate models; however, their performance depends on the data (country and time frame). Among the LSTM extensions, convolutional LSTM and bidirectional LSTM have shown the highest accuracy in comparative studies. We note that
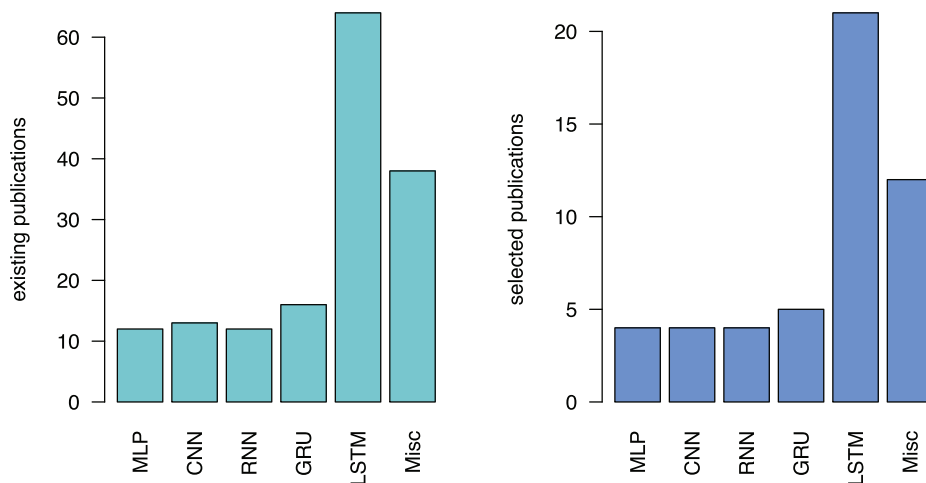
Fig. 3. The distribution of publications related to forecasting Covid-19 according to model type. The left subplot describes the number of publications discovered during the initial search, while the right subplot shows the number of publications selected for further review in our study.

other misceleneous deep learning methods such as GNN and VAE have also shown promising results.

3.1. Multi-layer perceptron

The most basic deep learning architecture is the multi-layer perceptron (MLP). The MLP model is a nonlinear regression algorithm that employs a layered structure to learn the patterns within the data. Concretely, the MLP architecture consists of the input layer, one or more fully connected hidden layers, and the output layer. The size of the input layer is equal to the number of features in the data. In Covid-19 forecasting, the number of features often equals the number of previous time-steps used to predict the value in the next time-step. The size of the hidden layers is set by the expert user. The number of nodes in each layer is often chosen to decrease by a factor of 2 between consecutive layers. The number of hidden layers, in Covid-19 forecasting literature, ranges between 1–3. Finally, in a regression task, the size of the output layer is 1 which represents the forecasted value.

Most of the MLPs used in the Covid-19 forecasting have relatively small sizes. In Fig. 4, we illustrate the architecture of a typical MLP. The model presented in Fig. 4 has 5 nodes in the input layer corresponding to the window of 5 past observations used to make the next-day prediction. The input layer is followed by 2 fully connected layers which is a typical arrangement. In the end,
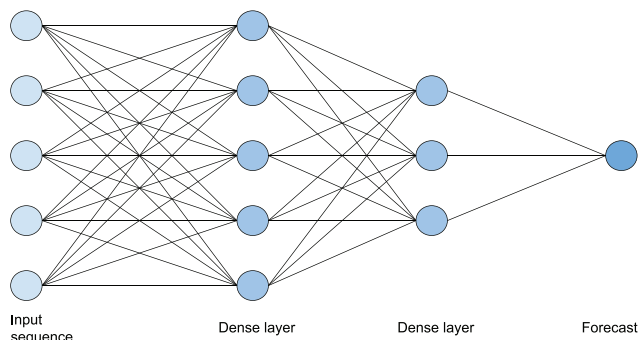
the MLP outputs a single value representing the forecasted value for the number of cases.

MLP has been used sparingly in Covid-19 forecasting. It was used in a comparative study based on data from several countries [41], where it showed average performance. Similarly, the authors in [86] compared the performance of linear regression, MLP, and vector autoregression in forecasting the number of cases in India. Although MLP has not been utilized successfully as a standalone model, it was shown to be helpful in estimating the optimal coefficients of the SEIR model [25]. In [93], the authors use a SEIR-based teacher simulation model to obtain projection sequences which are used together with the original sequences to train the student MLP model to make accurate forecasts. The proposed model was successfully applied to forecast Covid-19 cases in USA, Mexico, and Brazil. A summary of the current studies is provided in Table 1.

3.2. Convolutional neural networks

Convolutional neural networks (CNN) were originally designed for image processing [21]. Given a 2D image, a small window is slid across the image while calculating the convolution between the window (matrix) and the corresponding region of the image (matrix). CNNs allow to capture local patterns and share parameters of the network. Similarly, CNNs can be employed to process 3D RBG images using a 3D sliding cube. The success of CNNs on image classification tasks has led to their application in other fields. In particular, it has been used to process temporal data. Given a sequence of time-series values, a 1D window is slid across the sequence to capture the local information at each time-step. This technique is used in Covid-19 forecasting. It is a reasonable approach to analyze time series data because it emphasizes neighboring connections within a sequence. As shown in Fig. 5, the input in CNN consists of the number of Covid-19 cases over a fixed period of time. Several 1D sliding windows are applied to learn the patterns within the sequence. The values in the convolution layer are flattened into a single dense vector which is then used to produce the final forecast.

CNN has been used in several studies for Covid-19 forecasting, where it was shown to perform reasonably well. While it was able to achieve the top accuracy in some comparative studies, it still lags behind the LSTM-based models. In [38], the authors compared the performance of ARIMA, LSTM, CNN, and MLP forecasting models based on a large dataset of 266 countries over the period of Jan

Fig. 4. A typical MLP architecture used in Covid-19 forecasting. The input consists of the number of cases from the previous *k* days, while the output is the forecast for the next day.

Table 1
Summary of MLP-based studies for Covid-19 forecasting.

| Study	Methodology	Data	MAPE
Farooq et al., 2021 [25]	Used MLP to estimate the optimal coefficients of a SIRVD model. Incremental learning approach was utilized due to continuously changing time series values.	5 states in India; Mar - Jun, 2020 (train), Jun - Jul, 2020 (test)	1.86–19.79.
Wang et al., 2021 [93]	Used SEIR-based teacher model together with MLP-based student model to build a forecast model.	USA, Mexico, and Brazil; Apr - Aug, 2020 (train), Aug - Sep, 2020 (test)	0.03–0.13.
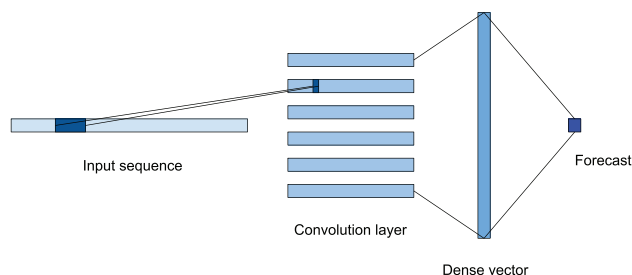
Fig. 5. A typical CNN architecture used in Covid-19 forecasting. A convolution matrix is slid across the input sequence to collect information at the local level.

Fig. 6. A typical RNN architecture used in Covid-19 forecasting. The output of the recurrent layer from time-step t is used as an input to the recurrent layer for time-step $t + 1$.

22 - Jun 30, 2020 and found that CNN achieved the optimal results. Similarly, in [60], the authors compared LSTM, GRU, CNN and MCNN models on data from Brazil, Russia, and the UK over the time period Jan 1 - Nov 18, 2020. The results showed CNN achieved the lowest error, while LSTM yielded the highest error. In [1], the authors used auxiliary time series features such as variance, auto-correlation, spectral entropy, and others together with the main time series inputs to forecast Covid-19. They showed that the addition of the auxiliary inputs improves the performance of the CNN model and outperforms LSTM. On the other hand, a comparative study by [18] showed that CNN does not produce the best forecasting results. A summary of the current studies is provided in Table 2.

3.3. Recurrent neural networks

Recurrent neural networks (RNN) are designed specifically for processing sequential data. Therefore, RNNs are well suited to handle time series data such as the daily number of Covid-19 cases. RNN's distinguishing feature is that the information from the previous time-step is used to predict the series' value in the next time-step. In addition, the design of RNN allows parameter sharing. Thus, patterns learned in one part of a sequence can be applied to other parts of the sequence. Due to their success in other time series applications [39,40], RNNs and their extensions have been widely employed in Covid-19 forecasting.

As shown in Fig. 6, the typical structure of an RNN-based model for Covid-19 forecasting starts with an input layer which receives a
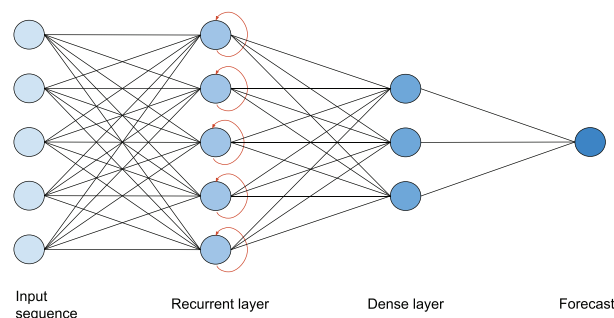
sequence of previous observations (5–7 days). The input sequence is processed by several RNN units followed by a dense layer. Finally, the dense layer activations are used to calculate the forecasted number of Covid-19 cases.

There exist several extensions of the basic RNN design. Fig. 2 depicts the main subgroups of RNN including the plain RNN, GRU, and LSTM. Among all the RNN variants, LSTM is the most widely used model for Covid-19 forecasting in the literature. In the following subsections, we provide a more detailed description of each RNN subgroup and its application for Covid-19 forecasting.

3.3.1. Plain RNN

One of the first designs of the basic RNN was proposed by Elman [22]. In the plain RNN design, the activation from the previous time-step h_{t-1} is combined with the input from the current time-step x_t to compute the activation for the current time step h_t. It allows RNNs to exhibit temporally dynamic behavior. The unrolled structure of the plain RNN cell is presented in Fig. 7. RNN employs the same weights at each time-step leading to a more efficient network. In addition, parameter sharing allows to apply the learned features across different time-steps.

Given its specialization for analyzing ordered sequences, RNN is well suited for short-term forecasting. However, the application of the basic RNN model in Covid-19 forecasting has been limited. In [99], the authors include RNN in their comparative study but did

Table 2
Summary of CNN-based studies for Covid-19 forecasting.

| Study	Methodology	Data	MAPE
Nabi et al., 2021 [60]	Compared LSTM, GRU, CNN and MCNN models and found that CNN achieved the smallest error.	Brazil, Russia, and the UK; Jan - Nov, 2020	0.85–6.94.
Istaiteh et al., 2021 [38]	Compared ARIMA, LSTM, CNN and MLP models. CNN achieved the smallest error.	266 countries; Jan - Jun, 2020	3.13.
Abbasimehr et al., 2021 [1]	Used auxiliary time series features together with the main series inputs to improve the performance of CNN. The resulting model outperformed LSTM and original CNN.	10 countries; Jan - Aug, 2020	0.42–8.34.
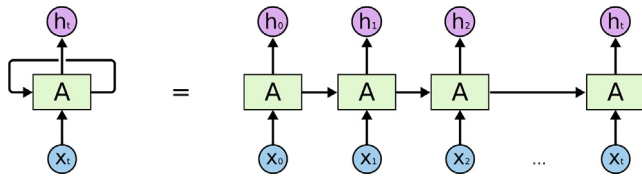
Fig. 7. Unrolled structure of an RNN cell [64]. The hidden layer h_t is calculated based on the value from the previous layer h_{t-1} and the current input x_t.

Fig. 8. The structure of the GRU cell [64]. It is an extension of RNN with an added gate to control the gradient flow.

not find it to perform well. Nevertheless, the relative lack of consideration of RNN even for comparative purposes is puzzling. It would be informative to include RNN in comparative studies as a benchmark model.

Although the plain RNN model has seen limited application, its variants have in fact been used in Covid-19 forecasting. In [74], bidirectional RNN was shown to outperform CNN and LSTM models on data from India over the period Jan 22 - Dec 12, 2020. The proposed approach used both the previous number of cases and weather data to forecast Covid-19 cases. A summary of the existing studies is provided in Table 3.

3.3.2. Gated recurrent unit

Gated recurrent unit (GRU) is a variant of the basic RNN featuring a forget gate. It was originally proposed by Cho et al. [16]. GRU was designed to address the issue of vanishing (exploding) gradients which can occur in the basic RNN. As shown in Fig. 8, the current input x_t and the activation from the previous step h_{t-1} pass through several transformations aimed at controlling the flow of information inside the GRU. We find the design of GRU to be well suited for Covid-19 forecasting. It combines the simplicity of the basic RNN with the ability to control the gradient in LSTM.

GRU-based models have been considered by several authors in forecasting Covid-19. The performance of GRU-based models has ranged from average to good. In [65] the authors compared GRU to LSTM in forecasting Covid-19 in Egypt, Saudi Arabia, and Kuwait using data from May 1 - Dec 6, 2020. The results showed that GRU achieved the lowest MAPE 0.466 and 0.731 in Egypt and Kuwait, respectively. On the other hand, it failed to achieve the best performance in some other comparative studies [60,99]. A summary of the current studies is provided in Table 4.

3.3.3. Long short-term memory

Long short-term memory (LSTM) is another variant of RNN that is designed to address the issue of vanishing (exploding) gradients. The LSTM design was proposed by Hochreiter et al. [34]. As shown in Fig. 9, the structure of the LSTM cell features three gates i) input gate, ii) output gate, and iii) forget gate. Together the three gates control the information flow inside the LSTM cell. LSTM has shown robust performance in speech and hand-writing recognition [13,31]. It is has also been widely used in a number of other sequence learning applications [42,45,75].
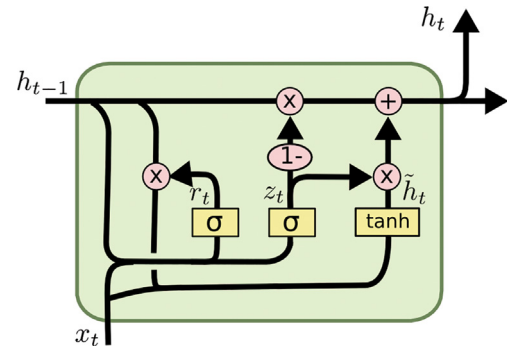
In addition to the basic LSTM, there exist several extensions that have been used in Covid-19 forecasting. As shown in Fig. 2, the LSTM extensions include bi-directional LSTM (BiLSTM), multivariate LSTM (M-LSTM), and convolutional LSTM (ConvLSTM). In the BiLSTM design, the information is propagated both forward and backward, while in M-LSTM the input features are multidimensional including the previous number of cases and deaths, and other potentially relevant variables such as weather and population features. ConvLSTM is designed by taking fully connected LSTM to have convolutional structures in both the input-to-state and state-to-state transitions. The ConvLSTM design has been particularly effective by combining the power of CNN and LSTM [100].

LSTM-based models have been the most popular approach to Covid-19 forecasting. It has been used as the primary forecasting model in several studies [2,23]. LSTM and its variants have also shown the best performance in several comparative studies [18,20,41,29,81]. In [54], the authors demonstrated that LSTM produced higher accuracy than CNN and MLP in forecasting Covid-19 in Egypt. The authors used data over the period Feb 14 - Aug 15, 2020 and employed a window of size 20. Similarly, in [98], the authors conducted a large scale study comparing LSTM with MLP and ARIMA using 12-month data for 171 countries. The results show that in majority cases LSTM outperforms other models. In another recent comparative study LSTM-based forecasting model outperformed CNN and exponential regression models [67].

Among the LSTM variants, ConvLSTM achieves the best performance. In [81], the authors compared ConvLSTM to LSTM and BiLSTM using data from India and USA over the period Feb 7 – Jul 7, 2020. The results showed that ConvLSTM achieved the lowest forecast error. Similarly, ConvLSTM achieved the best results in a comparative study against 5 other models using data from 8 different countries over the period Jan 22 - Sep 6, 2020 and achieved MAPE in the range 0.628–6.021 [18]. Other LSTM variants such as multivariate LSTM and encoder-decoder LSTM have also shown promising results [15]. A summary of the current studies is provided in Table 5.

Table 3
Summary of RNN-based studies for Covid-19 forecasting.

STUDY	METHODOLOGY	DATA	MAPE
Mohimont et al., 2021 [55]	Proposed several temporal CNNs based on different datasets including Covid-19, mobility, and hospitalizations data.	France; Mar - May, 2020	1.
Niu et al., 2021 [62]	Used an RNN model based on spatial as well as temporal inputs. The proposed model outperformed GRU, SEIR, and others.	USA, China, Italy; Jan - Mar, 2020	0.19– 1.92
Ronald et al., 2021 [74]	Proposed a BiRNN model that used both the previous number of cases and weather data to forecast Covid-19 cases. The model outperformed CNN and LSTM.	India; Jan - Dec, 2020	0.82

Table 4
Summary of GRU-based studies for Covid-19 forecasting.

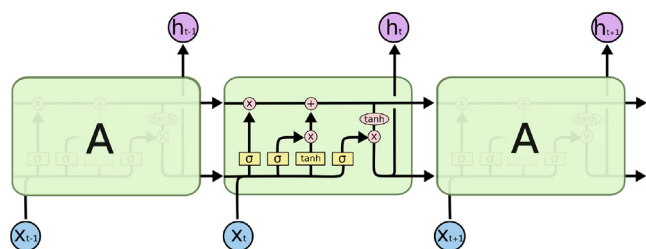| Study	Methodology	Data	MAPE
Khennou et al., 2021 [48]	Compared ARIMA, LSTM, and GRU models and found GRU to achieve the lowest error.	Canada; Mar - Nov, 2020	0.30.
Omran et al., 2021 [65]	Compared LSTM and GRU models and found GRU to achieve the lowest error.	Egypt, Kuwait; May - Dec, 2020	0.47, 0.73.
Arun et al., 2022 [8]	Compared GRU and LSTM vs ARIMA and SARIMA models and found GRU and LSTM to achieve the lowest error in most cases.	Top 10 countries; Jan, 2020 - Jun, 2021	RMSE 8 K- 25 K.

Fig. 9. The structure of LSTM [64]. Similar to GRU, it contains several gates to control the gradient flow.

Despite the popularity of LSTM it is important to note that it does not always produce the best forecasting results. There exist several studies showing that LSTM and its variants underperform against other deep learning models [46,60,99].

3.4. Deep dive: GRU and LSTM

To provide a more in-depth view of the existing RNN-based forecasting models, we focus on five representative studies: Arun et al. [8], Dairi et al. [18], Ma et al. [52], Omran et al. [65], and Pavlyutin et al. [67].

Table 5
Summary of LSTM-based studies for Covid-19 forecasting.

Study	Methodology	Data	MAPE
Chandra et al., 2022 [14]	Compared LSTM and its variants in 2-month ahead forecasting of cases in India and found that ED-LSTM achieves the lowest error.	India; Apr 2020 - Sep, 2021	
Chen et al., 2021 [15]	Used M-LSTM with 10 input variables. The mutivariate model was shown to perform better than the individual univariate models.	China; Jan - May, 2020	1.24– 3.94
Devaraj et al., 2021 [20]	Compared ARIMA, LSTM, S-LSTM and Prophet model and found that S-LSTM achieved the lowest error.	India; Jan - May, 2020	<2.
Dairi et al., 2021 [18]	Compared GAN-GRU, LSTM-CNN, GAN, CNN, LSTM, and RBM models and found that CNN-LSTM achieved the lowest error.	Brazil, France, India, Mexico, Russia, Saudi Arabia, the US; Jan - Sep, 2020	0.63– 6.02.
Gomez et al., 2021 [28]	Compared univariate population growth models, VAR, and M-LSTM and found that the M-LSTM model achieved the lowest errors.	Mexico; Jan - Mar, 2020	0.47
Kafieh et al., 2021 [41]	Compared RF, MLP, LSTM-R, LSTM-E, M-LSTM models and found that M-LSTM achieved the smallest error.	Iran, Germany, Italy, Japan, Korea, Switzerland, Spain, China, and the USA; Jan - Jul, 2020 (train), Aug, 2020 (test)	0.51– 2.3.
Kumar et al., 2021 [49]	Used LSTM-based model to predict the dates when countries would be able to contain the spread of Covid-19. A 2-step procedure of first estimating the peak point of the pandemic and then its regression was employed.	New Zealand; Feb - Dec, 2020	1–5
Marzouk et al., 2021 [54]	Compared LSTM, CNN, and MLP models. LSTM was shown to outperform other models.	Egypt; Feb - Aug, 2020	0.9998
Pavlyutin et al., 2022 [67]	Compared long-term (48 days) forecasting accuracy of LSTM, CNN, and exponential regression models and found the LSTM to be the best.	Moscow city; Oct - Dec, 2021	5.4
Rguibi et al., 2022 [73]	Compared LSTM and ARIMA models and found similar performance.	Morocco; Jan – Nov, 2020	40.99
Sesti et al., 2021 [80]	Implemented GNNs within the gates of an LSTM to explore the spacial information.	37 European countries; Jan 2020 - May 2021	0.27
Shastri et al., 2020 [81]	Compared S-LSTM, BiLSTM and ConvLSTM models. ConvLSTM achieved the lowest error.	India and the USA; Feb - Jul, 2020	2.00, 2.17
Shastri et al., 2021 [82]	Compared BiLSTM, ConvLSTM, and proposed ensemble ConvBiLSTM models. ConvBiLSTM achieved the smallest error.	the US, India, Brazil; Jan, 2020 - Apr, 2021	0.87– 1.90
Tian et al., 2020 [89]	Compared LSTM to hidden Markov chains and hierarchical Bayes. LSTM achieved the lowest average RMSE.	6 countries; Jan - Apr, 2020	63.88
Vadyala et al., 2021 [91]	Used Xgboost-Kmeans pipeline to identify the relevant features which were then employed to train LSTM model.	Louisiana, USA; Mar - May, 2020	0.12
Yu et al., 2021 [98]	Compared LSTM, ARIMA, and MLP models. LSTM was shown to outperform other models.	171 countries; Jan - Dec, 2020	0.27

The authors Arun et al. (2022) compared the performances of deep learning models GRU and LSTM versus autoregressive models ARIMA and SARIMA. The authors considered data from the top 10 countries such as USA, Brazil, Russia and others between Jan 2020 - Jun 2021 related to the cumulative number of confirmed, recovered, and deaths. The input window size of 30 days was used in forecasting. The forecast was made for the next 60 days. The last 14 days of the dataset was used as the test set, while the rest as the train set. The data was normalized using the min–max scaler. The models were trained using the Adam optimizer with different number of epochs to minimize the RMSE. The deep learning models where optimized over a range of hyperparameter values including the number of nodes (10, 100, 200, 300), the number of hidden layers (1, 2, 3, 4, 5) and learning rate (0.1, 0.01, 0.001, 0.0001). The final model parameters depended on the country and the forecasted quantity. The results showed that GRU and LSTM outperformed ARIMA and SARIMA in most cases. For example, in the case of USA, the optimal parameter values for cumulative confirmed cases were (5, 2, 2) and the corresponding lowest RMSE was 10,951 which was achieved by GRU. Further country specific results are available in [8].

The authors Ma et al. (2021) proposed to improve the long-term forecast of the traditional LSTM model by combining it with the Markov model. The proposed LSTM-Markov model was tested on data from US, Britain, Brazil and Russia. The data is dated between Mar - Dec 2020. The first 70% of the data was used for training, while the remaining 30% was used for testing the models. The models were trained using the Adam optimizer for 50 epochs. The optimal input window size was determined via trial-and-error. In the end, the input time-steps for the US, Britain, Brazil and Russia were set to 9, 7, 10 and 7 days, respectively. The results showed that the average prediction error of LSTM-Markov is reduced by more than 75% compared to the regular LSTM model.

LSTM and GRU were employed by Omran et al. (2021) to forecast the number of confirmed cases and deaths in Egypt, Saudi Arabia, and Kuwait using data between May - Dec, 2020. The data was split into train/test subsets according to 80/20 ratio and normalized using the min–max scaler. The models were tuned over a range of hyperparameter values including dropout rate (0.1 to 0.9) and number of nodes (10 to 500). The models were trained for 100 epochs using batch size 50. The final LSTM parameters were 1 layer, 390 neurons, and dropout rate of 0.3 for the first experiment and 2 layers, [200, 460] neurons, and dropout rates of 0.3 and 0.2 for the second experiment. The final GRU parameters were 1 layer, 360 neurons, and dropout rate of 0.2 for the first experiment and 2 layers, [320, 190] neurons, and dropout rates of 0.3 and 0.2 for the second experiment. The authors found that GRU produced the lowest forecast error.

Dairi et al. (2021) used LSTM, GAN-GRU, and LSTM-CNN to forecast the number of confirmed cases in seven large countries using the data between Jan - Sep, 2020. The data was split into train/test subsets according to 75/25 ratio and normalized using the min–max scaler. The authors used input window size of 5 days. All three models were trained with learning rate of 0.0001 for 200 epochs. Furthermore, the model architecture was chosen as follows: LSTM with 3 layers [32,32,1], GAN-GRU with 2 layers [32,1], and LSTM-CNN with 4 layers [16,32,32,1]. The results showed that LSTM-CNN achieved the lowest forecast error.

Pavlyutin et al. (2022) used LSTM to forecast the number of cases in the city of Moscow between Mar 2020 - Dec 2021. The data was split into train/test subsets according to 67/33 ratio and normalized using the min–max scaler. The model's parameters included 144 LSTM blocks in the first hidden layer with the tanh activation function and 48 LSTM blocks in the second layer with the ReLU activation with dropout rate 0.3. The MAPE for the city of Moscow was relatively low for the short-term forecast (14 days ahead), but significantly higher in the long-term forecast (48 days).

3.5. Alternative deep learning methods

In addition to the classical deep learning models such as CNN and LSTM, researchers have also used more recent deep learning architectures including graph neural networks (GNN), variational autoencoders (VAE), non linear autoregressive nets, Fb-Prophet, and others to forecast Covid-19. These modern approaches have proven to be effective in several studies. In particular, spatio-temporal models that combine time series data with mobility data have shown promising results. A team of researchers from Google used GNNs together with spatio-temporal data to forecast the pandemic in the US during Feb - May, 2020 [46]. In the proposed framework, nodes represent the region-level human mobility, spatial edges represent the human mobility based inter-region connectivity, and temporal edges represent node features through time. The proposed GNN-based approach outperformed LSTM in the numerical experiments. The values predicted by the model achieved 0.9981 correlation with the true values of the time series. Similarly, in another recent promising spatio-temporal approach dubbed Covid-LSTM the authors used the weekly number of new positive cases as temporal input, and hand-engineered spatial features from Facebook movement and connectedness datasets to capture the spread of the disease in time and space [51]. The model was used to make county-level predictions in the US over 1 to 4 week horizons outperforming state-of-the-art models. VAE-based models have also shown promising results. In [99], the authors found that VAE outperformed RNN, LSTM and GRU in forecasting Covid-19 in 5 different countries over the period Jan 22 - Jun 17, 2020. The proposed VAE-based model achieved MAPE in the range 0.128–5.90. A summary of the current studies is provided in Table 6. A forecasting method based on nonpharmaceutical intervention and cultural dimensions was proposed in [97].

Since the dynamics of a pandemic depend on population mobility, spatio-temporal models provide a natural candidate for modeling the spread of the virus and forecasting the number of cases. The availability of Google mobility data and other data sources make these approaches viable. However, more detailed information about population movements is required to achieve robust forecasting accuracy.

4. Analysis

The above survey of the current literature demonstrates the advantages of deep learning models over traditional approaches in forecasting Covid-19. In particular, several studies found that deep learning models such as LSTM and GNN provide more accurate forecasts than ARIMA and SEIR models. Since deep learning is a data-driven approach it does not require expert knowledge. Thus, medical researchers with little background in computer science can apply deep learning models to forecast Covid-19. The ease of use and high accuracy are the main advantages of deep learning. In addition, spatio-temporal models provide a framework to capture information about the spread of the infection that is otherwise impossible to model.

Unlike traditional models, deep learning does not require any strong assumptions about the functional spread of an infection. Therefore, it is less susceptible to the problem of incorrect model selection. Deep learning models are flexible enough to adapt to the data and construct an appropriate model based primarily on the data. On the other hand, statistical and mathematical models such as ARIMA and SEIR are restricted by their model equations.

Table 6
Summary of studies for Covid-19 forecasting using alternative deep learning approaches.

Study	Methodology	Data	MAPE
Adiga et al., 2021 [3]	Used Bayesian ensemble consisting of ARIMA, LSTM, SEIR, and Kalman filter. The ensemble was shown to outperform individual models as well as other state-of-the-art models.	USA; Aug, 2020 - Feb, 2021	
Battineni et al., 2020 [10]	Used Fb's Prophet to achieve high R^2.	USA, Brazil, India, Russia; Jan - Jul, 2020	99.91–99.99
Bhattacharyya et al., 2022 [11]	Compared the theta autoregressive neural network model against several benchmarks and found it to achieve the best results in 3 out of 5 countries.	US, UK, India, Canada, Brazil; Jan, 2020 - Feb, 2021	1.05–5.07
Kapoor et al., 2020 [46]	Proposed GNN based on spatiotemporal data. The proposed model was shown to outperform benchmark methods including LSTM.	USA; Feb - May, 2020	0.998
Liu et al., 2020 [50]	Used ARGOnet with multiple inputs such as health reports and web search queries. The proposed model outperformed the benchmarks.	Chinese provinces; Jan - Feb, 2020	
Lucas et al., 2021 [51]	Proposed a spatiotemporal model based on LSTM using weekly number of new positive cases as temporal input and hand-engineered spatial features from Facebook to forecast new cases 1–4 weeks in advance.	USA; Oct, 2020 - Feb, 2021	22.06–38.30
Namasudra et al., 2021 [61]	Used nonlinear autoregressive neural network time series model and achieved high correlation between the predicted and actual values.	India; Jan - Aug, 2020	1
Ray et al., 2021 [72]	Proposed an ensemble model based on a combination of MLP, reservoir computing, and LSTM.	Brazil; Feb, 2020 - Apr, 2021	0.1483
Zeroual et al., 2020 [99]	Compared RNN, LSTM, BiLSTM, GRUs, and VAE models and found that VAE achieved the lowest error.	Italy, Spain, France, China, USA, and Australia; Jan - Jun, 2020 (train)	0.13–5.90.

As a result, deep learning models have outperformed the traditional approaches in forecasting Covid-19.

Our study reveals several avenues for future research and improvement. In particular, we identified two main gaps in the literature: i) inadequate data and ii) inappropriate prediction target. First, there is a need for more up-to-date studies that are based on a larger amount of data. Most of the existing studies are based on data prior to the year 2021. Studies with more recent data are required. The length of the studies is often too short. In some cases, authors employed as little as two weeks worth of data to build forecasting models. Models based on limited data have small generalization capacity and cannot be confidently relied upon to make future predictions. In addition, the recent vaccination drive around the globe has drastically altered the dynamic of the pandemic. Thus, new studies based on post vaccination rates are needed. Second, the forecasting objective should be changed from the cumulative number of cases to the new number of cases. Since the cumulative number of cases is a monotonically increasing function with only a small relative daily change, it is an easily estimated quantity. The majority of studies use mean average percentage error (MAPE) as the performance measure. However, in forecasting the cumulative number of cases the MAPE is automatically bound to be small. Even employing the naive strategy of forecasting the next day number of cases to be the same as the previous day one can usually achieve MAPE less than 0.5%. On the other hand, forecasting the number of new cases is a challenging task given the volatile fluctuations in daily numbers. In summary, we recommend that researchers use data from a longer time period to build their forecasting models and aim to forecast the number of new cases instead of cumulative cases.

The review of the literature showed that LSTM-based models are the most popular approaches in Covid-19 forecasting. Several comparative studies demonstrated their superior performance over other methods. However, given a small window of input sequence (5–7 days) that is often employed in Covid-19 forecasting, it is surprising to observe the advantage of LSTM over RNN or MLP. Since the LSMT is designed primarily for processing long sequences, their advantage over RNN or MLP for short input sequences should be minimal. Further studies are required to determine the true effectiveness of LSTM. In general, the use of any deep learning model in forecasting Covid-19 must be theoretically justified. Too often authors employ a forecasting model simply because it performs well numerically without any valid

analytical justification. Models that are used without a plausible justification will fail to generalize.

Although LSTM and its variants are currently the most popular forecasting models in the literature, alternative methods that employ spatio-temporal data have also shown promising results [46,51]. Given the importance of mobility and interconnectedness in the spread of the virus, spatial data provides useful information about the pandemic. Indeed, the most prominent forecasting models in production employ mobility data in addition to the historical values.

The performance of the forecasting model depends largely on the training and testing data. A model that performs well on data from one country may not perform well on data from another country. Similarly, a model may forecast accurately over the initial period of the pandemic while producing inaccurate forecasts over the middle span of the pandemic. Therefore, it is important to bear in mind the source (country) and the time frame of the data used to train the forecasting model.

The majority of the existing studies employ univariate data, i.e., the input features consist simply of the previous number of cases. While using only the previous values of a time series to forecast the future values maybe sufficient, it is worth exploring more sophisticated input features. As shown in [1,46,74], the use of multivariate features can help improve the accuracy of the forecasting models. Finally, despite the success of various deep learning models it is important to remember that the traditional autoregressive and mathematical models may still provide a useful alternative [78].

There exist two major challenges in applying deep learning to forecast Covid-19: model selection and data availability. There are many potential candidates for a forecasting model including recurrent neural networks, graph neural networks, and fusion models. Given the large number of deep learning models, it is not easy to identify the right model. Indeed, it may be necessary to create a completely new deep learning architecture to address the specific issues related to the unique way the Covid-19 infection spreads through population. In addition, identifying the optimal hyperparameters of the chosen model poses a significant challenge.

Second, deep learning models require a large amount of data. For instance, the state of the art computer vision models are trained on millions of images. In contrast, there is relatively limited amount of data available related to Covid-19. Thus, researchers

must find a way to train their forecasting models more efficiently. The right model architecture and regularization play a significant role in mitigating the issue of limited data availability.

5. Conclusion

This systematic review was conducted based on 53 selected studies that describe deep learning approaches for Covid-19 forecasting. We proposed a model-based taxonomy to categorize the current research into distinct groups. The review of the literature revealed that LSTM and its variants are the most popular forecasting methods. At the same time, the use of LSTM over simpler approaches such as RNN and GRU requires more theoretical justification. Spatio-temporal models that utilize both Covid-19 times series and mobility data have also shown great promise.

Our survey identified two main gaps in the literature: i) inadequate data and ii) inappropriate forecast value. The majority of the existing studies are based on data over a short time frames. Studies over longer time horizons are needed to obtain more robust models. In addition, forecasting the cumulative number of cases is a relatively easy task given that it is a monotonically increasing time series. Studies that accurately forecast the new number of cases would be more challenging and effective.

As a future research avenue, models with solid theoretical grounding that leverage the power of deep learning are desirable. Studies that simply apply deep learning to Covid-19 time series without theoretical justification are not scientifically sound. On the other hand, methods that combine mathematical modeling of the spread of the infection together with the processing power of deep learning have the potential to provide the true picture of the pandemic. As another avenue for future research, comparison of forecasting models by country would provide an additional insight into the current state of research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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