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COVID-19 Case Forecast with Deep Learning Bi-LSTM Approach: The Turkey Case

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Abstract - The 21st-century coronavirus epidemic (COVID-19) has spread around the world in a short time, claiming hundreds of thousands of lives. Countries have taken immediate action and developed several strategies to combat the epidemic. The most important achievement to fight the epidemic has been the discovery of a vaccine. To successfully fight the disease, it is of great importance to be able to predict the number of cases. There are many methods for making estimations. Due to their high performance, many studies have recently used deep-learning methods. The study estimated the number of Covid 19 cases for Turkey using the deep learning approach Bidirectional Long-Short-Term Memory (Bi-LSTM). Cases, deaths, positive rates, and people vaccinated data in Turkey between February 12, 2021, and December 01, 2021, were used. The effect of the vaccine on the epidemic was analyzed, especially by taking the data of the vaccination period and the number of people vaccinated. The performance indicators with high correlation coefficient (R) and lowest root mean square error (RMSE) of the Bi-LSTM analysis results yielded mean absolute error (MAE) values. A high predictive value was obtained in the Bi-LSTM model proposed in the study. Thus, it is aimed to be useful for the measures to be taken during the pandemic period.

Index Terms - Machine learning, forecasting, Bi-LSTM, COVID-19, Turkey.

INTRODUCTION

Mankind has struggled with various epidemics from past to present. The Covid-19 virus, which emerged in the 21st century, has also entered the literature as a pandemic disease by the World Health Agency (WHO) [1]. The Covid-19 virus first appeared in China in December 2019. It is an RNA virus that causes upper respiratory tract diseases. The coronavirus epidemic was transmitted very quickly and spread very quickly around the world [2]. Within the scope of combating the virus, countries have developed measures for pandemic conditions [3]. Strict controls have been introduced and vaccination studies have been carried out. Like every virus, Covid-19 has changed over time. While most of the changes in question do not change the basic features of the virus; Some changes, called "mutations", have significantly changed the basic properties of the virus and thus its effect. According to its studies, the World Health Organization (WHO) has defined four of the mutations of Covid-19 as 'Concerning Variant (VOC)'. He warned that these variants can "increase the contagiousness and risk of spread of the virus, alter its lethality or symptoms, and reduce the effectiveness of prevention and control measures". These variants are called Alpha, Beta, Gamma, and Delta. Apart from these, he defined eight variants as 'variants to watch'. These variants are named Epsilon (2 variants), Zeta, Eta, Theta, Iota, Kappa, and Lambda. Of the worrying variants, "Alpha" was first detected in the UK, "Beta" in South Africa, "Gamma" in Brazil, and "Delta" in India. Finally, the Omicron variant has emerged. WHO has not made a statement that the effects of the Omicron variant differ from the others [4]–[6] .

Although some measures are still being implemented within the scope of the fight against Covid-19, great importance is attached to vaccination studies [8]. According to the data of December 2021 for Covid-19, a total of 279,114,972 cases were detected in the world and 5,397,580 deaths occurred. The first case in Turkey was detected on March 11, 2020 [7]. Changes related to the disease The change in the number of new cases, new deaths, positive_rate, and vaccinated people in the world over time can be seen in Fig.1.

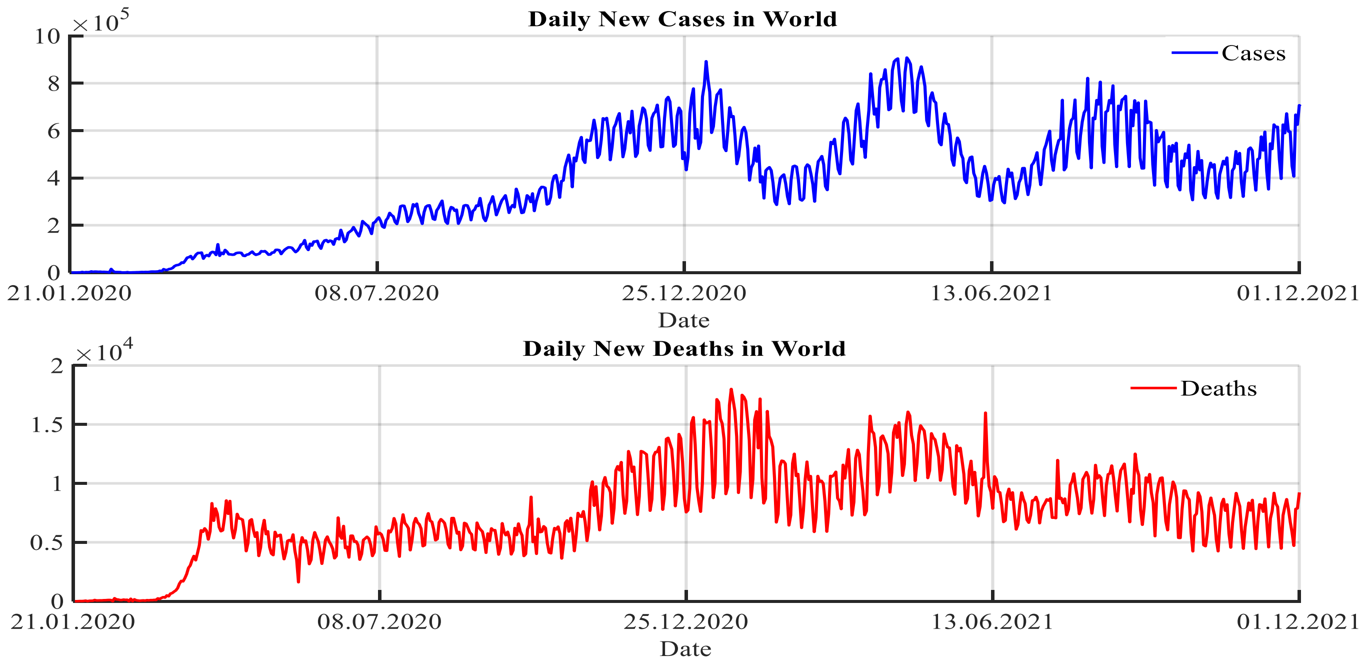

Figure 1. Number of Covid-19 new cases and deaths in the world ("Johns Hopkins Coronavirus Resource Center," n.d.)

A. *Related Works*

Being able to predict disease in advance is important for both ecological and health predictions of countries. With the correct predictions about the disease, the steps are taken in many areas such as the health sector, education and economy will be controlled. Many studies have been carried out on the prediction of disease from past to present and continue to be done. The work done in Table 1 is summarized below.

Table 1. Covid-19 forecasting studies

Author	**Forecasting methods**	**Forecasting Horizon**
Kırbas¸ et al. [5]	ARIMA, Nonlinear Autoregression Neural Network (NARNN), and Long-Short Term Memory (LSTM)	14 day ahead forecast
Arora et al. [9]	Deep LSTM/Stacked LSTM, Convolutional LSTM and Bidirectional LSTM	Daily and weekly predictions
Zeroual et al.[10]	RNN (Recurrent Neural Network), LSTM, Bi- LSTM(Bi-directional), VAE (Variational AutoEncoder)	17 days ahead forecast
Shahid et al. [1]	ARIMA, support vector regression (SVR), long short-term memory (LSTM), Bi-LSTM	48 days ahead forecast
Chimmula and Zhang [11]	LSTM	14 days ahead forecast
Alzahrani et al. [12]	ARIMA, Autoregressive Moving Average (ARMA)	1 month ahead forecast
Ogundokun et al. [13]	Linear regression model	8 days ahead forecast
Ribeiro et al. [14]	ARIMA, cubist regression (CUBIST), random forest (RF), ridge regression (RIDGE), support vector regression (SVR), and stacking-ensemble learning	1,3 and 6 days ahead forecast
Tomar and Gupta [15]	LSTM	30 days ahead forecast
Shastri et al. [16]	LSTM, Stacked LSTM, Bi-directional LSTM and Convolutional LSTM	30 days ahead forecast
Papastefanopoulos et al.[17]	Six different forecasting methods are presented. ARIMA, the Holt-Winters additive model (HWAAS), TBAT, Facebook's Prophet, Deep AR	7 days ahead for the ten countries

Contributions of the proposed study;

• In the proposed study, the first vaccination date for Turkey was taken as a reference in the Covid-19 estimation study.

• In the study, daily new cases, deaths, and vaccination numbers for Turkey between 12 February 2021 and 01.12.2021 were taken.
• Estimation of the number of cases was made. For this reason, the case number data was decomposed into its components by the EMD method. In this way, it is aimed to analyze the data better.
• Estimation study was carried out by using the Bi-LSTM method as the estimation algorithm in the data set.

MATERIAL AND METHOD

In the study, the number of Covid-19 cases for Turkey was estimated using the Bi-LSTM method. As can be seen from the studies, the Bi-LSTM method provides high accuracy in estimation studies. For this reason, it was chosen in this study. In this part of the study, dataset definition, proposed method, EMD method, preprocessing and reconstruction method, Bi-LSTM model will be explained.

A. Data Description

Covid-19 has spread rapidly in Turkey as well as all over the world. Extensive measures have been taken to combat the disease. Strict measures have been implemented to prevent the rapid spread of the disease. Despite this, thousands of people fell ill with the disease and died. The discovery of the vaccine has been the most important step during the Covid-19 pandemic period. For this reason, data between February 12, 2021, and December 01, 2021, which is the first vaccination time for Turkey, were taken in the study. Daily new death and positive rate and number of people vaccinated were used as input data. As a target, the number of new cases per day will be estimated. The number of new cases, the number of new deaths, and the number of new people vaccinated daily for Turkey in the mentioned period are as seen in Figure 2.

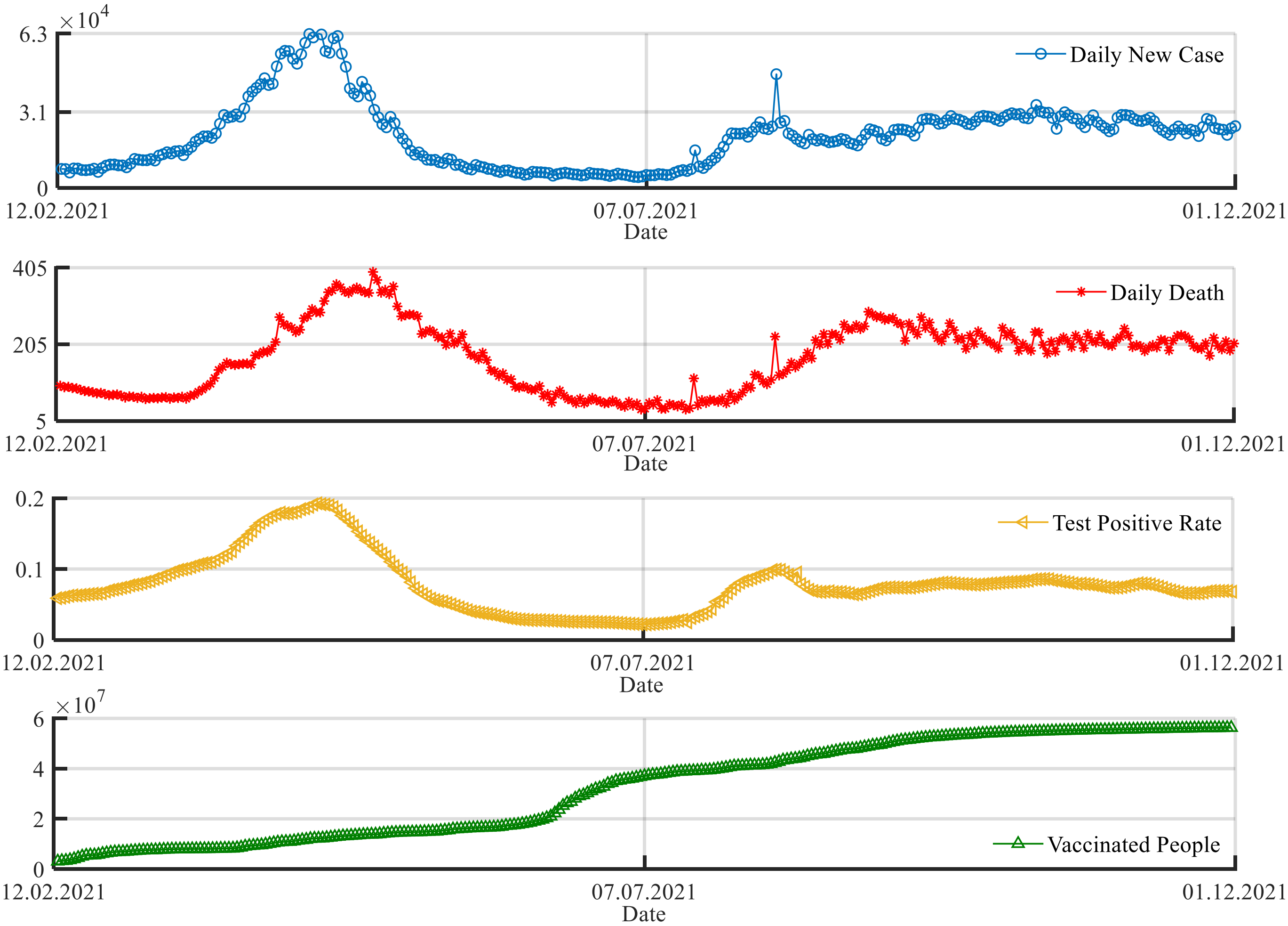

Figure 2. Turkey's coronavirus data [7].

As can be seen from the data, while the number of new cases for Turkey was 7763 on 12.02.2021, 4678 on 07.07.2021, it was recorded as 22556 on 01.12.2021. When the death numbers for the same dates are examined, they were 97, 35, and 196 for 12.02.2021, 07.07.2021, and 01.12.2021, respectively. When the test results were examined, it was seen that the positive test rates were 0.0588, 0.0225, and 0.0662 for the same dates, respectively. The numbers of people vaccinated for the same dates were 3067822, 36416034, and 56288895, respectively [7]. As can be seen from the data, the course of the disease shows ups and downs over time. The effects of the precautions and vaccination in these ups and downs are great.

B. Proposed Model

The flow diagram of the model proposed in the study is given in Figure 6. In the study, confirmed cases, new deaths, positive test rates, and vaccinated people data were taken as inputs. Confirmed cases are separated into their components by the EMD (Empirical Mode Decomposition) method [18]. In the estimation model, the Bi-LSTM algorithm was preferred by making use of the literature research. Input data is divided into training and test data. The number of new cases was estimated from the predicted model from the trained Bi-LSTM model. The proposed estimation flow diagram is as in Figure 3.

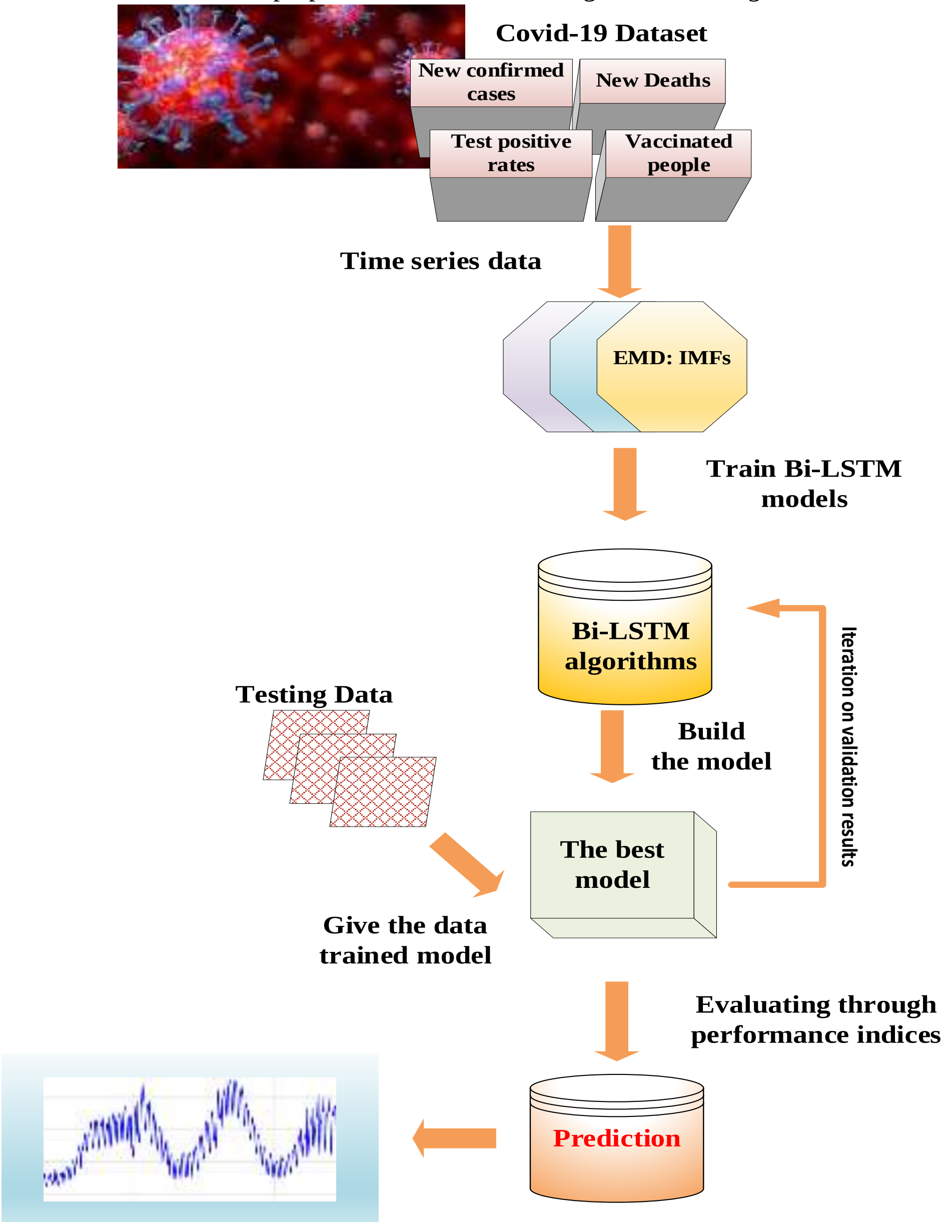

Figure 3. Proposed forecasting model flowchart.

C. Bidirectional Recurrent Neural Networks with Long Short-Term Memory (Bi-LSTM) Architecture

Bi-LSTM networks are a set of processing deep neural networks consisting of two LSTMs. It works similarly to LSTM networks. It is a type of Recurrent Neural Network (RNN) that works with a series of observations [1]. Unlike classical neural networks, RNNs can use their input memory to process different orders of input. Bidirectional LSTM takes forward and backward inputs in a neural network and connects them to predict the output. In other words, in Bidirectional LSTMs, the learning algorithm is fed with the original data once from start to finish and once again from end to end. In this neural network, since the inputs enter in two directions, it improves the relationship between the network inputs, effectively increasing the amount of information available in the network. An example Bi-LSTM network is shown in Figure 4 [1].

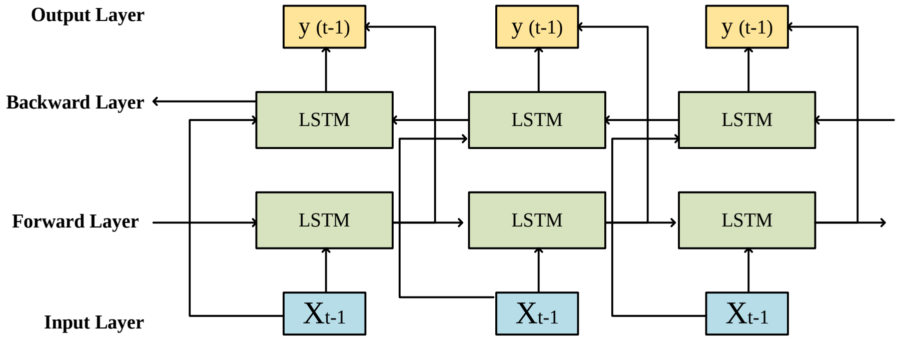

Figure 4. An example BiLSTM architecture.

The mathematical operations in Bi-LSTM architecture are as given in Equation (1-3) [19];

$$\overrightarrow{h_t} = \mathcal{H}(W_h x_t + U_h \overrightarrow{h}_{t-1} + \overrightarrow{b_h}) \quad (1)$$

$$\overleftarrow{h_t} = \mathcal{H}(W_h x_t + U_h \overleftarrow{h}_{t-1} + \overleftarrow{b_h}) \quad (2)$$

$$y_t = W_h \overrightarrow{h_t} + U_h \overleftarrow{h_t} + b_y \quad (3)$$

Here; $\mathscr{H}$ is usually the sigmoid function. $\overrightarrow{h_t}$ processes forward and left-to-right information, $\overleftarrow{h_t}$ processes backward and right-to-left information, yt represents the output vector of the Bi-LSTM architecture (combination of forwarding information and backward information) [18], [20].

D. Emprical Mode Description (EMD)

The EMD method tries to explain the input time series as the sum of several intrinsic mode functions (Intrinsic Mod Function, IMF). In the EMD method, the envelope of the signal is reached by interpolating the points obtained from the local minimum and local maximums of the signal, given in Equation (4) [18].

$$y(t) = \sum_{i=n}^{n} I_i(t) + r_n(t) \quad (4)$$

where y(t) is the measured data at time t, n is the IMF number, $I_i(t)$, i at time t. The value of the IMF function and $r_n(t)$, represent the residual information at time t. The I_i expression is obtained by taking the average of the upper and lower curves obtained by interpolation. By subtracting this expression from the input data, the oscillator mode is obtained. If the obtained oscillator expression meets the termination criteria of the algorithm, the oscillator data is assigned as the last internal mode, otherwise, the decomposition process is continued by using the oscillator expression as input [21].

E. Evaluation Metrics

In this study, MSE, RMSE, MAE, MAE, which are frequently used error measurement metrics, were used. Error measurement metrics measure the difference between predicted values and actual evaluation values. The fact that the error measurement values are low indicates that the model is of high accuracy, its mathematical equations are as given in Equation (5-7) [20] ;

$$R = \frac{\sum_{i=1}^{n}[(P_i^f - P^f)(P_i - P)]}{\sqrt{\sum_{i=1}^{n}(P_i^f - P^f)^2 \sum_{i=1}^{n}(P_i - P)^2}} \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i^f - P_i)} \quad (6)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|P_i^f - P_i\right| \quad (7)$$

Here P and P_f are the measured and predicted load, respectively. $\bar{P}$ and $\bar{P}^f$ is the mean of the measured and predicted load data. In performance measurement parameters, it is desired that the R-value be high and the MAE and RMSE values should be low [14], [22], [23].

RESULTS AND DISCUSSIONS

In the study, new confirmed cases, new deaths, vaccinated people, and positive test data in Turkey between 12.02.2021 and 01.12.2021 were obtained. In the data set, new confirmed cases data were separated into IMF components by the EMD method and added to the data set. Confirmed new cases EMD components and layer layers of the proposed model are shown in Figure 5 and Figure 6, respectively. The layer parameters of the proposed model are summarized in Table 2.

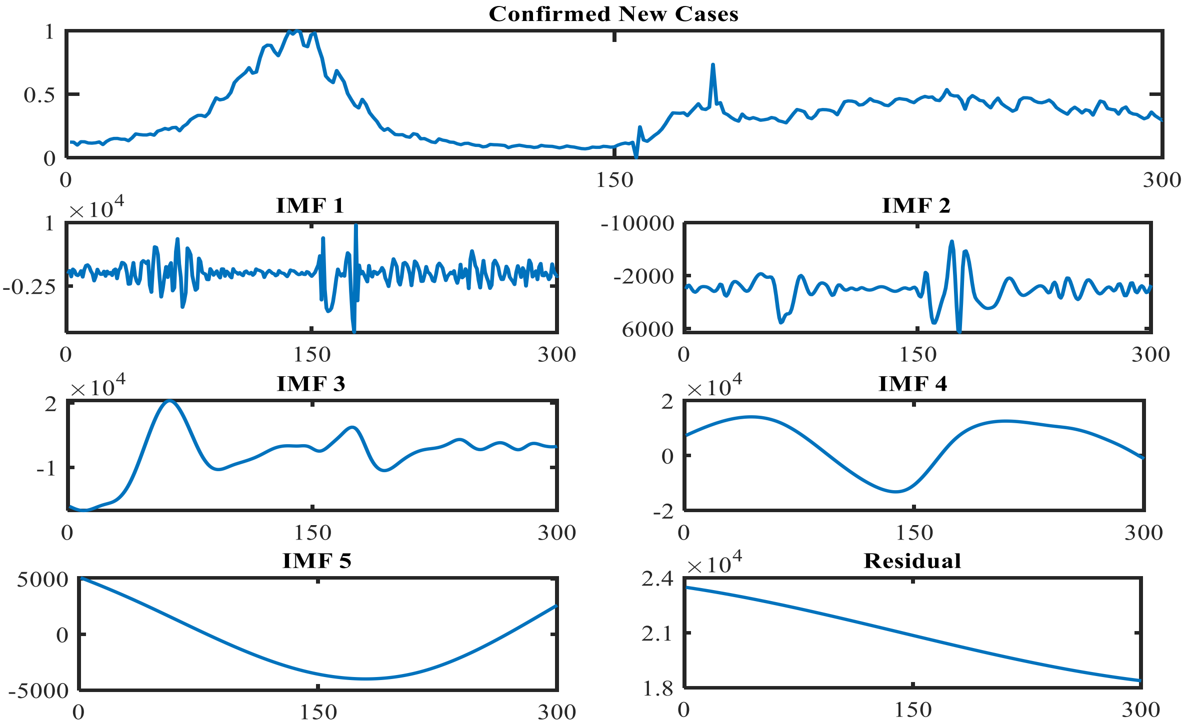

Figure 5. Components of Confirmed new cases in EMD.

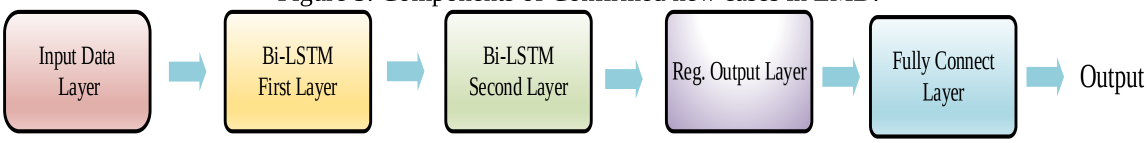

Figure 6. The layer structure of the proposed model.

Table 2. Layer parameters of the proposed model

Type	**Name**	**Activations**	**Learnable**
Sequence input	Sequence input	8	-
Bi-LSTM_1	BiLSTM	1024	Input weights 4096x8 Recurrent weights 4096x_ Bias 4096x1
Bi-LSTM_2	BiLSTM	2048	Input weights 8192x_ Recurrent weights 8192x_ Bias 8192x16
Fully Connect	FC	1	weights 1x2048 Bias 1x1
Regression output	Reg. Output	-	-

In the study, the number of new patients per day, EMD components, the number of people vaccinated, the number of deaths, and positive rate data in the data set were given to the network as input. It is the number of new cases we want to estimate. In the model designed accordingly, 80% of our data was used as training data and 20% as test data. The results of the estimation analysis and comparison with the actual values were obtained as seen in Figure 7. In addition, forecast analysis performance metrics are summarized in Table 3.

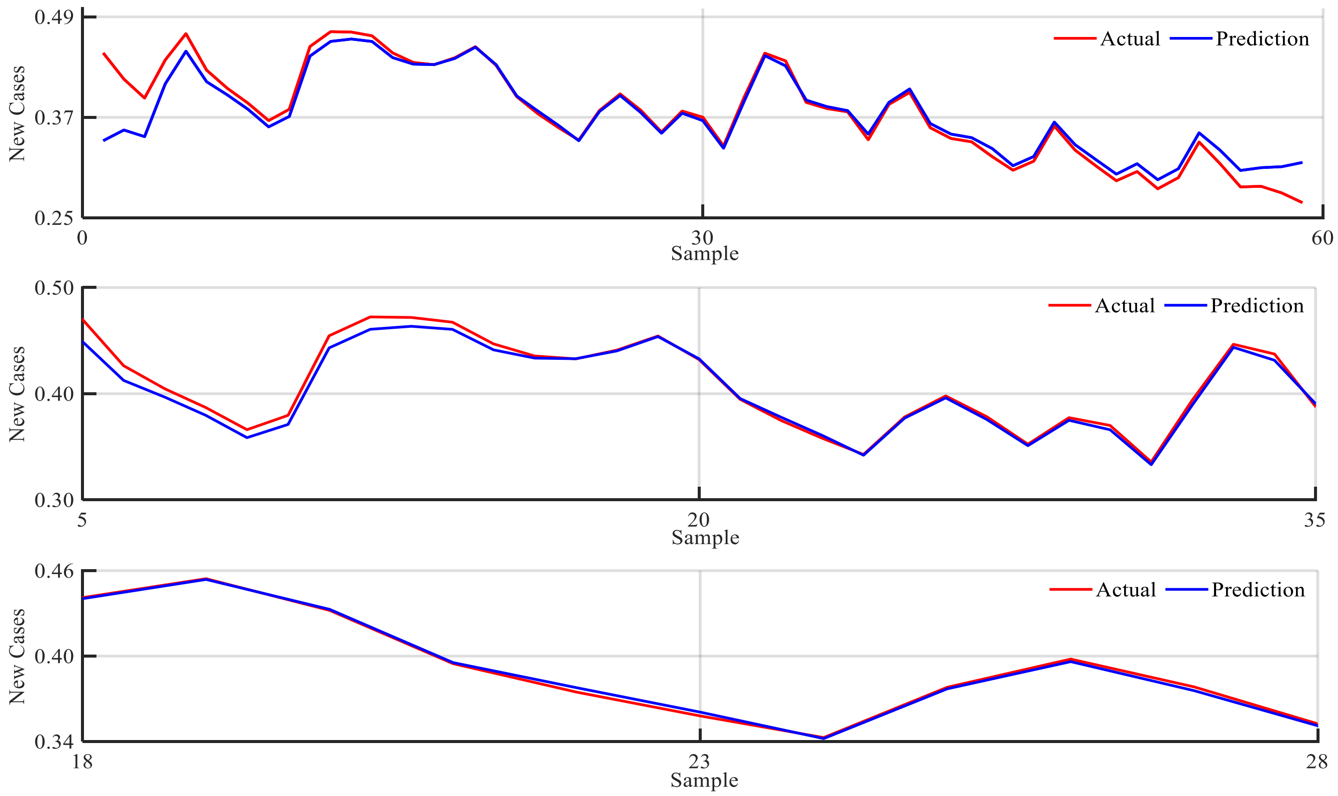

Figure 7. Comparison of forecast analysis results and actual values.

Table 3. Forecast analysis performance metrics

Metrics	**RMSE**	**MAE**	**R**
Values	0.004	0.008	0.986

In the analysis performed, the RMSE value was calculated as 0.04, the MAE value was 0.008, and the correlation coefficient value (R) was 0.986 in the estimation study with the bi-LSTM model. The most important advantages of the designed model are its basic structure and short analysis time.

CONCLUSIONS

Since the time of its emergence, the covid-19 disease has harmed humanity as a deadly, pandemic disease that has affected the whole world. Every day, thousands of people in the world have been affected by the disease and a significant part of it has resulted in death. The disease has also mutated over time, so the fight against the disease has become more difficult. Although many measures have been developed within the scope of the fight against the disease, they have not been sufficient. The fact that the course of the disease can be predicted in advance is important both economically and socially. For this purpose, the bi-LSTM model designed in this study has been a useful study due to its simple network structure and high success rate. The effect of the number of deaths, positive rates, and the number of people vaccinated in the dataset used in the estimation of the number of new cases was examined. The predictive success of the disease was evaluated with deep learning metrics R, RMSE, and MAE values. As a result, the R-value made a correct prediction with 98% success. In future studies, it will be possible to predict the course of the disease by adding different data sets.

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