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RESEARCH ARTICLE

An Accurate Model for Covid-19 Positive Cases in India by using Traditional ARIMA and Artificial Neural Networks (LSTM and Bi-LSTM)

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Abstract

Objective: This study focuses on evaluating the accuracy of models that can be identified by taking the data of COVID-19-positive cases in India. **Methods:** To build the models by using the procedures, Artificial Neural Networks (ANN) and Auto Regressive Integrated Moving Average (ARIMA). The data has been taken for various time periods of (Covid-19 positive cases) from March 2022 to July 2023; March 2022 to Nov. 2022 and from Nov. 2022 to July 2023. The data was collected from the official website of the World Health Organization (WHO). The traditional ARIMA and Long Short-Term Memory (LSTM) deep learning methods were applied to build models for various time periods. **Findings**: Model performance is being measured with the error parameter (Root Mean Square Error) RMSE (215.74, 100.36 and 127.81) respectively for all the time periods. LSTM is performing better than the ARIMA with a minimum value of RMSE. **Novelty:** The study has been done for the time periods of Covid-19 positive cases with the help of LSTM, Bi-LSTM and ARIMA methods. The outcome of these methods gave; LSTM is the accurate and best performance model.

Keywords: ARIMA; Neural Networks; LSTM; RMSE

1 Introduction

Corona virus caused by Severe Acute Respiratory Syndrome Corona virus 2 (SARS-Cov-2). It was induced by slow illness and respiratory problems in human health. It began with animals to human beings, later it was first reported in December 2019 in Wuhan, China. The first case of Covid-19 disease in India was found in Thrissur, Kerala on 27th January, 2020 when a twenty-year-old female student came from Wuhan City, China to visit India [1]. The COVID-19 cases spread to most of the countries around the World. The World Health Organization announced it as a pandemic. The data was provided by the website http://www.covid-19india.org/ [2].

There was a major impact on health, economy, infrastructure, medicine, employment and agriculture during the pandemic throughout the World [3]. According to WHO, two hundred million people were infected by SARS-Cov-2, all over the World [4]. The COVID-19 data is suitable to build the models by the Deep learning methods; in which the models were followed by multi-head attention, Long short-term memory (LSTM), and Convolutional Neural Networks (CNN) with the Bayesian optimization algorithm [5]. The LSTM and Recurrent Neural Networks (RNNs) followed the latest best methods for the solution to predict the time series data [6]. The study of research can be useful for government organizations while working against COVID-19 data. It also guides their future plan of action [7].

Around two hundred countries were affected by the SARS-Cov-2. Most of the developing and developed countries like the USA, Spain, South Africa, Brazil, India and Saudi Arabia were affected by health and wealth [8–10]. Basically, the models which are used like Neural Networks, Artificial Neural Networks were deterministic models [11]. The research paper discussed Deep learning-based models (RNN, LSTM and Convolutional LSTM) for predicting the number of COVID-19 positive cases for 32 states and Union Territories of India. The preventive measures have been advised to reduce the Covid-19 positive cases in respective zones [12]. The accuracy of model has been given by LSTM and ARIMA, among this best performance has been revealed by LSTM. Meanwhile, the researchers discussed Deep learning with hybrid methods to build prediction models and to predict the mortality risk in patients of COVID-19 [13].

The proposed Neural network model (ANN) had supported the system, it could be considered as a suitable computational method for the frontline practitioner in easily detection effective intervention and possibly a reduction of mortality in patients with COVID-19 [14]. The ARIMA and LSTM and combined ARIMA-LSTM model have constructed to predict construction data. The optimal model was ARIMA (3, 1, 0) by combining the Auto-Correlation function (ACF) and partial correlation function (PACF) with the Bayesian Information Criterion. The results of LSTM-ARIMA have higher accuracy then the other two ARIMA and LSTM models. ARIMA-LSTM combined model is suitable for this gas time series production [15].

2 Methodology

2.1 Procedure of ARIMA:

The Time series analysis projects and deals with the data, in which scales are according to the time and the goals of the projects. It aims to predict the future values of the time series and it depends on the following factors Stationarity, Seasonality and Auto-Correlation. Time series analysis can be implemented by using different methods and technologies but choosing an efficient technique can increase the accuracy rate of our forecasting values [16–18]. One of the best applications of time series analysis is ARIMA, which stands for "Auto Regressive Integrated Moving Average". A few years back, Statistics analyzed by time series trends that could be forecasted without considering the non-stationary data and performed better than other models. George Box and Gwilym Jenkins have developed an approach that converts non-stationary data into stationary. The traditional ARIMA model is being deployed when data has no linear trend, which means data is stationary [19,20].

Mathematically it can be stated as: $z_t = a_{t+1}+a_t$

Where: z_t is a variable that we are trying to predict.

a_{t+1} : are the present trend data points of an instance.

The traditional mathematical
equation is :$z_t = \emptyset . z_{t-1} + \theta . \varepsilon_{t-1} + E_t$

z_t: Our integrated bit.

z_{t-1}: The autoregressive bit is being managed by the autoregressive part.

$\theta . \varepsilon_{t-1}$: The moving average bit.

E_t: Basic error.

These are called the predictions and while the actual forecasting can be done mathematically by referencing a variable a_k which are our future predictions in the given trends, and it relates with a_l: The last recorded data, the final summation of all the differences in previous trends mathematically has given by

$$\sum_{i=1}^{k=l} z_i = z_{k-1} + a_l$$

The above statement explains ARIMA and its mechanism of work. It always is attentive meanwhile, the data is stationary, and it revealed the best results for future COVID-19-positive cases in India. This technique is followed by better controlling for the pandemic situations.

2.2 Augmented Dickey-Fuller test

The test has a hypothesis that states:

i. Null Hypothesis H_0: Time series data has a unit root

ii. Alternative Hypothesis H_1: Time series data has no unit root

The null hypothesis cannot be rejected when the p-value exceeds the critical value (α = 5%). The Null hypothesis is rejected when the p-value is lower than or equal to 0.05.

2.3 Artificial Neural Networks:

The artificial neural networks behave like the functioning of the human brain. ANN is a computational network. Artificial Neural Networks were built with perceptron-like neurons of the human brain that are linked to each other in various layers of networks and these perceptions are also called nodes. ANN is the part of Artificial Intelligence (AI) where its functional operations behave like the networks of neurons that make up a human brain so that computers will have a choice to understand things and make human-like decisions. There are 86 billion neurons in every person's brain. Human intelligence is being made up of relatively terrific parallel processors. [21,22]

Input layer: The input layer accepts different formats of inputs from programmers.

Hidden layer: A hidden layer lies between the input and output layers and gives the features of patterns. It is an intermediate layer between the input and output layers.

Output layer: A series of transformations were done by the input layer while using the hidden layer, which results in the output that is conveyed using this layer. ANN takes input, computes the weighted sum of the input and includes a bias representing this computation.

Bias is an adjusted error parameter in ANN. This can be used to adjust the output value along with the weighted sum of input nodes. In the form of a transformation function $\sum_{i=1}^{n} w_i x_i + b$, it determines the total weighted sum passed as input data to the activation function to decide whether a node should terminate or not.

2.4 Recurrent Neural Networks (RNN):

It is a type of Neural Network where the output from the previous step is fed as input to the present step. In traditional neural networks, all the inputs and outputs are independent of each other. While it is required to predict the next word of a sentence, the previous words are required and hence there is a need to remember the previous words. The RNN came into existence, which solves the issue with the help of a hidden layer. The first and foremost feature of RNN is its hidden state, which remembers some information, regarding a sequence. The state is also referred to as Memory state since it remembers the previous input to the network. It uses the same parameters for each input as it performs the same role on all the inputs or hidden layers to produce the output. This reduces the complexity of parameters, unlike other neural networks.

2.5 Long short-term memory networks (LSTM) and Bi-LSTM

Long short-term memory networks (LSTM) have other features rather than RNNs. LSTMs are the extension of the memory of RNNs; it means that they can remember important information having long gaps between them. LSTMs are made by RNNs, they remember inputs for a longer time. LSTMs also contain the information in memory likely to be a computer. LSTMs can read, write, and delete the data. Let us consider a memory box for containing information. LSTMs are trained to decide whether the information in the boxes is valuable or not. It determines whether the information is made or not in the boxes and it is available to the algorithm for an input to generate an output. A box that was assigned importance determined by weights learned by an Algorithm. LSTM contains an input, forget and output gate. This evaluation leads to whether or not to let a new input value into a box. After that it erases previous input-related information, there is no need or let it impact the output at the present step. The figure was an explanation of RNN given below [23,24] Figure 1, Bi-LSTM (Bidirectional Long Short-Term Memory) is also one of the recurrent neural network (RNN) that processes sequential data in both backward and forward directions. It combines the power of LSTM with bidirectional process. It allows the model to capture both future and past context of the input sequence.

2.6 Evaluation Measurement Metrics

Evaluating the best forecasting model is significant because it indicates that forecasting and accurate predictions are being found. Usually, a good forecast was determined by differentiating the predicted value from the actual value. Researchers discussed different tools to assess the performance of predictions. In this case, the study uses RMSE, MAPE, and R-square to determine

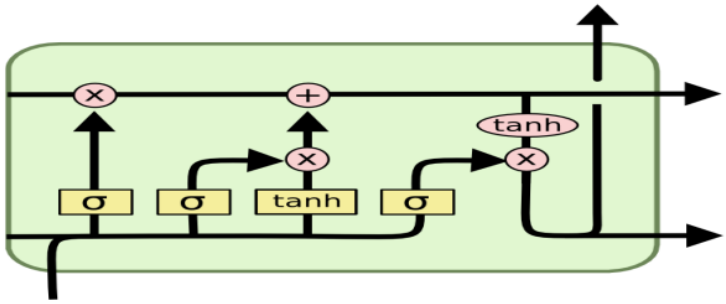

Fig 1. Artificial Neural Network (Long Short-term Neural Network) general architecture

performance. Root mean square error (RMSE) is a standard deviation of predicting error. It gives the best fit of the regression line. It means that the RMSE explores data and it was distributed around the line of best fit.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - A_i)2}{n}}$$

Where

O_i = observed value

A_i = Actual value

Mean absolute percentage error (MAPE). This metric is the most commonly used measure for comparing and measuring forecast performance. It measures correctness by calculating the mean absolute percentage error by subtracting the actual value divided by the actual value.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i - A_i}{A_i}\right|$$

Where

O_i = observed value

A_i = Actual value

The value R^2 is a coefficient of determination, which lies between 0 and 1. The Regression is fitted well when the highest value of R^2.

$$R^2 = 1 - \frac{R_{res}}{R_{tot}};$$

Where

R_{res} = sum of squares of residuals

R_{tot} = total sum of squares

3 Results and discussion

3.1 Pre-processing data

Here data is standardized to rescale data values so that they have a mean of 0 and a standard deviation of 1. The final aim of standardization is to bring down all features into a common scale without disturbing the differences in dataset range values.

Standardization process applied on data set by the following formula.

$$Xscaled = \frac{x - mean}{Sd}$$

After standardization data values made a finite number of sequences by following Figure 2 showing the manner [Figure 2]. The Covid-19 positive cases for 513 days are available as training set $x_1, x_2 \ldots x_{513,}$ and the next 411 days can be used to test the fitted LSTM model. The remaining serves as the test set for validating the results. The COVID-19 positive cases dataset was downloaded from the website https://covid19.who.int/WHO-COVID-19-global-data.csv. The data is classified into three periods of time i) From March 2022 to July 2023, ii) From March 2022 to Nov 2022, iii) From Nov 2022 to July 2023 and graphically represented as follows [Figure 3]. The pattern of Figure 3 trend shows upward and downward over a long period [Figure 4]. The trend of Figure 4 represents a slightly left-sided skewed distribution as compared with normality. [Figure 5] The trend of Figure 5 represents high peakedness and right-sided skewed distribution as compared with normality[25].

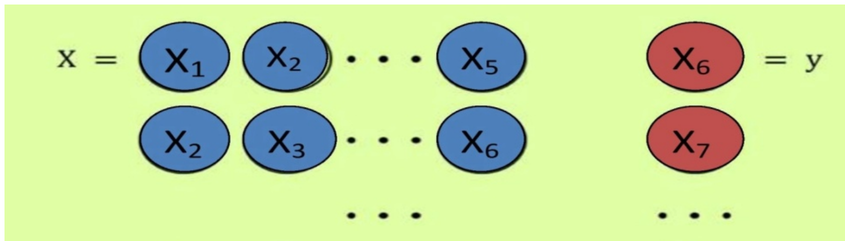

Fig 2. Data Standardization Process

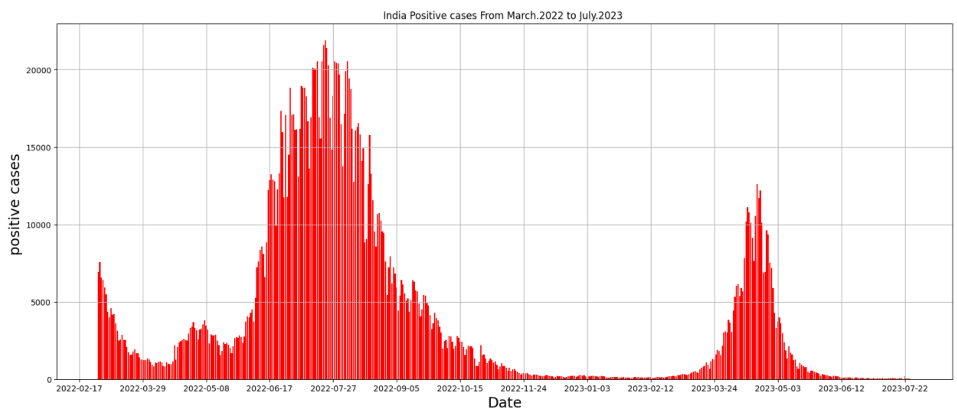

Fig 3. Number of covid-19 positive cases from March 2022 to July 2023

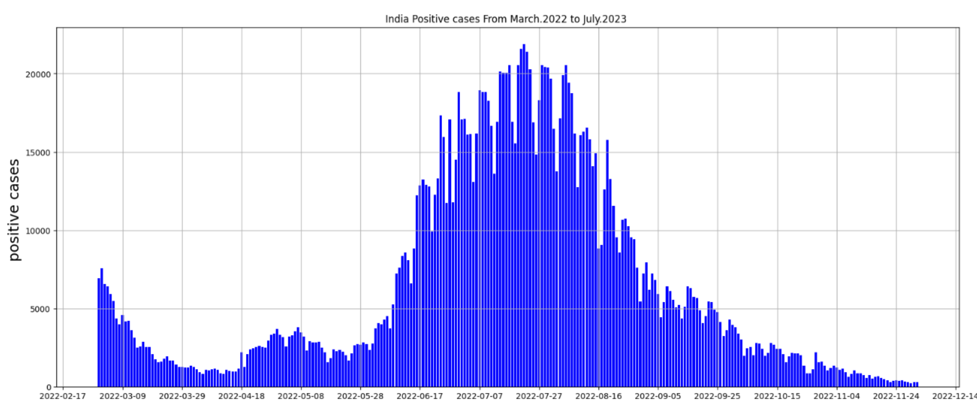

Fig 4. Number of India Covid-19 positive cases from March 2022 to Nov 2022

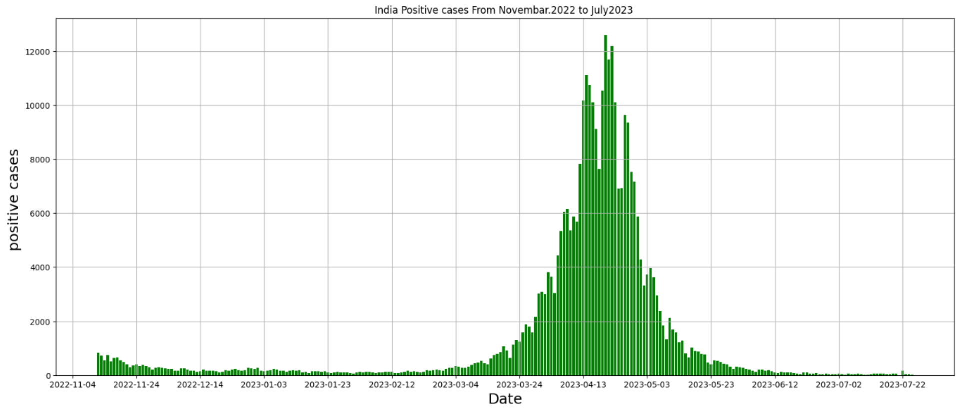

Fig 5. Number of Covid-19 positive cases from Nov. 2022 to July 2023

3.2 Results of ARIMA

Total data divided into 80% for train data and 20% for test data were utilized. Plots have been drawn for the Covid-19 Positive Cases by applying the Auto Correlation Function and Partial Auto Correlation Function. To test the Stationarity, the Augmented Dickey-Fuller test (ADF) test was utilized for the train data set. ADF test of the first difference has become Stationarity for the following period of time.

i) ARIMA model for (March 2022 to July 2023):

The ARIMA model was developed with the help of the statistical packages and its parameters (p, d, q) = (4,1,3) which is the best model. It has shown by the minimum Akaike Information Criterion (AIC =6713.1). The best model is given by

$$\widetilde{Y_t} = 0.1537*\widetilde{Y}_{t-1}+0.0103*\widetilde{Y}_{t-2}-0.5807*\widetilde{Y}_{t-3}-0.3749*\widetilde{Y}_{t-4}+e_t-0.4055*e_{t-1}-0.3345*e_{t-2}+0.7937*e_{t-3}$$

ii) ARIMA model (March 2022 to Nov 2022):

ARIMA model fitted as ARIMA model with parameter r (4, 1, 3) with minimum AIC is 3677.22, RMSE value of 1102.33 and MAPE value 11.54 and the optimum ARIMA (4, 1, 3) equations

$$\widetilde{Y_t} = 0.1699*\widetilde{Y}_{t-1}+0.0348*\widetilde{Y}_{t-2}-0.5689*\widetilde{Y}_{t-3}-0.3442*\widetilde{Y}_{t-4}+e_t-0.5021*e_{t-1}-0.3975*e_{t-2}+0.8277*e_{t-3}$$

iii) ARIMA model (Nov 2022 to July2023):

India covid-19 positive cases data to fit a ARIMA model with Parameters (p, d, q)=(0,1,2) with minimum value of AIC is 3314.6 and RMSE is 492.92 and MAPE values 11.0 and optimum ARIMA model equations is

$$\widetilde{Y_t} = 0.4041*e_{t-1}-0.3180*e_{t-2}+e_t$$

3.3 Vanila LSTM Model

LSTM model was built by 50 nodes, one hidden layer and one dense output layer. Model has been iterated 200 times in which trained were having 10451 parameters to reduce error in the model. Compared to Covid-19 positive cases of test data against the predicted covid-19 positive cases values, the root mean squared error is 215.74. Moreover, the Predicted values are 3.3% far away from the actual values for March2022 to July.2022; the root mean squre error is 100.360, MAPE (1.05) for March 2022 to Nov. 2022 and RMSE (127.8), MAPE (5.56) for Nov.2022 to July 2023 respectively. The learning about trainable parameters as follows.

Model: “Sequential”

Table 1.

Layer (type)	Output Shape	Parameters
Lstm (LSTM)	(None, 50)	10,400
Dense	(None, 1)	51

Continued on next page

Table 1 continued

Total parameters: 10,451
Trainable parameters: 10,451
Non-trainable Parameters: 0

In [Figures 6, 7 and 8] the prediction curve is constructed with vanilla LSTM behaviour exploring a curve with real values. Both curves mostly behave in the same manner, indicating the performance of comparison between RMSE values of ARIMA, LSTM and Bi-LSTM have shown in the following Table 2.

Table 2.

Time period in India covid-19 positive cases	ARIMA		LSTM		BI-LSTM	
	RMSE	MAPE	RAME	MAPE	RMSE	MAPE
March 2022 to July 2023	847.7	13.58	215.74	3.13	257.48	3.73
March 2022 to Nov 2022	1102.33	11.54	100.36	1.05	218.74	2.28
Nov 2022 to July 2023	492.92	21.8	127.81	5.65	251.37	11.11

Results-I: (March 2022 to July 2023): LSTM(215.74) < Bi-lstm (257.48) < ARIMA (847.70)

Results II: (March 2022 to Nov.2023): LSTM(100.36)< Bi-lstm (218.74) < ARIMA (1102.33)

Results III: (Nov. 2022 to July 2023): LSTM (127.81) < Bi-lstm (251.37) < ARIMA (492.92)

Among these, results found that the error parameters of LSTM is less than Bi-LSTM and is less than ARIMA. The least value was given by LSTM Method which is an efficient. Therefore, LSTM has shown the best performance from all the time periods of Covid-19 positive cases.

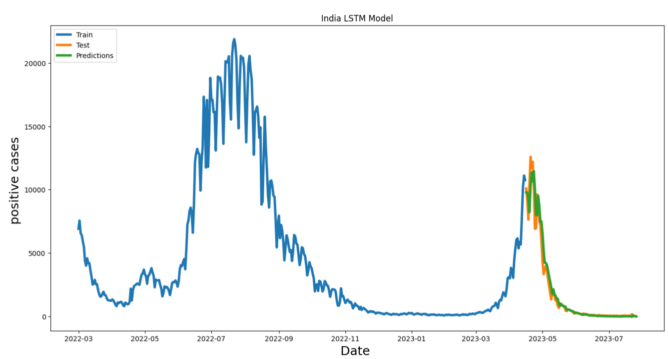

Fig 6. LSTM Model Prediction Covid-19 positive cases from March 2022 to July 2023

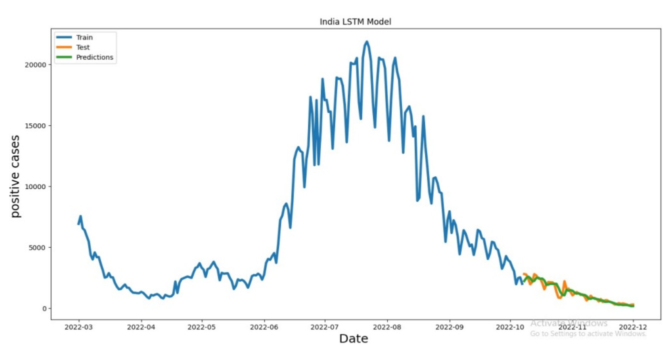

Fig 7. LSTM Model Forecasting values Covid-19 positive cases for March 2022 to Nov 2022

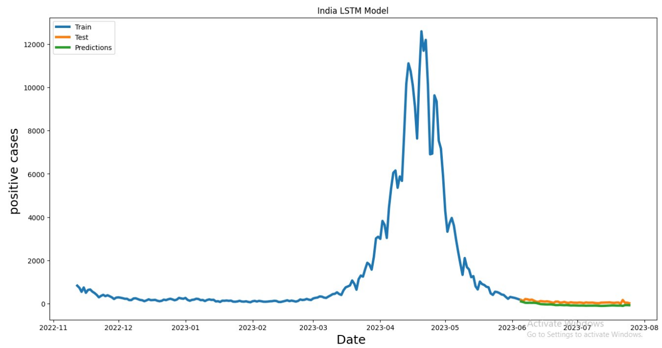

Fig 8. Prediction of Covid-19 positive cases of LSTM (November 2022 to July 2022)

4 Conclusion

The Time series models, and Neural Networks models have helped to find the prediction of the Covid-19 positive cases of India. The traditional ARIMA, Neural Networks models Bi-LSTM and LSTM have been utilized for tracing the best models. In these models the accuracy and efficient was given by Neural Networks models (LSTM) procedures. The best models have been traced by the minimum error values. The Root mean square error (RMSE) is the parameter which gives the best performance of the model. The results have shown from LSTM models RMSE values are 215.74, 100.36 and 127.81 are minimum. Conclude that by comparing ARIMA, Bi-LSTM and LSTM procedures, the best accurate models have been obtained by LSTM. Therefore, accurate and an efficient models have revealed by the Artificial Neural Networks (LSTM) model.

References

1) Hasan I, Dhawan P, Rizvi SAM, Dhir S. Data analytics and knowledge management approach for COVID-19 prediction and control. *International Journal of Information Technology*. 2023;15(2):937–954. Available from: https://dx.doi.org/10.1007/s41870-022-00967-0.
2) Vig V, Kaur A. Time series forecasting and mathematical modeling of COVID-19 pandemic in India: a developing country struggling to cope up. *International Journal of System Assurance Engineering and Management*. 2022;13(6):2920–2933. Available from: https://dx.doi.org/10.1007/s13198-022-01762-7.
3) Chandraid R, Jain A, Chauhan DS. Deep learning via LSTM models for COVID-19 infection forecasting in India. *PLoS ONE*. 2022;17(1):1–28. Available from: https://doi.org/10.1371/journal.pone.0262708.
4) Xu L, Magar R, Farimani AB. Forecasting COVID-19 new cases using deep learning methods. *Computers in Biology and Medicine*. 2022;144:1–7. Available from: https://doi.org/10.1016/j.compbiomed.2022.105342.
5) Abbasimehr H, Paki R. Prediction of COVID-19 confirmed cases combining deep learning methods and Bayesian optimization. *Chaos, Solitons & Fractals*. 2021;142:1–14. Available from: https://doi.org/10.1016/j.chaos.2020.110511.
6) Moudhgalya NB, Divi S, Ganesan VA, Sundar SS, Vijayaraghavan V. DeepTrace: A Generic Framework for Time Series Forecasting. In: International Work-Conference on Artificial Neural Networks. Advances in Computational Intelligence;Springer, Cham. 2019;p. 139–151. Available from: https://doi.org/10.1007/978-3-030-20521-8_12.
7) Ayoobi N, Sharifrazi D, Alizadehsani R, Shoeibi A, Gorriz JM, Moosaei H, et al. Time series forecasting of new cases and new deaths rate for COVID-19 using deep learning methods. *Results in Physics*. 2021;27:1–15. Available from: https://dx.doi.org/10.1016/j.rinp.2021.104495.
8) Elsheikh AH, Saba AI, Elaziz MA, Lu S, Shanmugan S, Muthuramalingam T, et al. Deep learning-based forecasting model for COVID-19 outbreak in Saudi Arabia. *Process Safety and Environmental Protection*. 2021;149:223–233. Available from: https://dx.doi.org/10.1016/j.psep.2020.10.048.
9) Painuli D, Mishra D, Bhardwaj S, Aggarwal M. Forecast and prediction of COVID-19 using machine learning. In: Data Science for COVID-19. 2021;p. 381–397. Available from: https://doi.org/10.1016/B978-0-12-824536-1.00027-7.
10) de Araújo Morais LR, da Silva Gomes GS. Forecasting daily Covid-19 cases in the world with a hybrid ARIMA and neural network model. *Applied Soft Computing*. 2022;126:1–5. Available from: https://dx.doi.org/10.1016/j.asoc.2022.109315.
11) Rahimi I, Chen F, Gandomi AH. A review on COVID-19 forecasting models. *Neural Computing and Applications*. 2023;35:23671–23681. Available from: https://dx.doi.org/10.1007/s00521-020-05626-8.
12) Aroraa P, Kumar H, Panigrahi BK. Prediction and analysis of COVID-19 positive cases using deep learning models: A descriptive case study of India. *Chaos, Solitons and Fractals*. 2020;139:1–9. Available from: https://doi.org/10.1016/j.chaos.2020.110017.
13) Sunjaya BA, Permai SD, Gunawan AAS. Forecasting of Covid-19 positive cases in Indonesia using long short-term memory (LSTM). *Procedia Computer Science*. 2023;216:177–185. Available from: https://dx.doi.org/10.1016/j.procs.2022.12.125.
14) de Araújo Morais LR, da Silva Gomes GS. Forecasting daily Covid-19 cases in the world with a hybrid ARIMA and neural network model. *Applied Soft Computing*. 2022;126:1–5. Available from: https://doi.org/10.1016/j.asoc.2022.109315.
15) Shanbehzadeh M, Nopour R, Kazemi-Arpanahi H. Developing an artificial neural network for detecting COVID-19 disease. *Journal of Education and Health Promotion*. 2022;11(1):1–10. Available from: https://journals.lww.com/jehp/fulltext/2022/11000/developing_an_artificial_neural_network_for.2.aspx.

16) Rajendar M, Reddy DM, Nagesh M, Nagaraju V. Progression of COVID-19 Cases in Telangana State by using ARIMA, MLP, ELM and LSTM Prediction Models by Retrospective Confirmation. *Indian Journal of Science and Technology*. 2024;17(12):1159–1166. Available from: https://doi.org/10.17485/IJST/v17i12.211.
17) Zhang Y, Tang S, Yu G. An interpretable hybrid predictive model of COVID-19 cases using autoregressive model and LSTM. *Scientific Reports*. 2023;13(1):1–12. Available from: https://dx.doi.org/10.1038/s41598-023-33685-z.
18) Wang Y, Yan Z, Wang D, Yang M, Li Z, Gong X, et al. Prediction and analysis of COVID-19 daily new cases and cumulative cases: times series forecasting and machine learning models. *BMC Infectious Diseases*. 2022;22(1):1–12. Available from: https://dx.doi.org/10.1186/s12879-022-07472-6.
19) Zhao D, Zhang R, Zhang H, He S. Prediction of global omicron pandemic using ARIMA, MLR, and Prophet models. *Scientific Reports*. 2022;12(1):1–13. Available from: https://doi.org/10.1038/s41598-022-23154-4.
20) Jin YC, Cao Q, Wang KN, Zhou Y, Cao YP, Wang XY. Prediction of COVID-19 Data Using Improved ARIMA-LSTM Hybrid Forecast Models. *IEEE Access*. 2023;11:67956–67967. Available from: https://dx.doi.org/10.1109/access.2023.3291999.
21) Sembiring I, Wahyuni SN, Sediyono E. LSTM algorithm optimization for COVID-19 prediction model. *Heliyon*. 2024;10(4):1–14. Available from: https://dx.doi.org/10.1016/j.heliyon.2024.e26158.
22) Chang TY, Huang CK, Weng CH, Chen JY. Feature-based deep neural network approach for predicting mortality risk in patients with COVID-19. *Engineering Applications of Artificial Intelligence*. 2023;124:1–11. Available from: https://dx.doi.org/10.1016/j.engappai.2023.106644.
23) Zeroual A, Harrou F, Dairi A, Sun Y. Deep learning methods for forecasting COVID-19 time-Series data: A Comparative study. *Chaos, Solitons & Fractals*. 2020;140:1–12. Available from: https://dx.doi.org/10.1016/j.chaos.2020.110121.
24) Chimmula VKR, Zhang L. Time series forecasting of COVID-19 transmission in Canada using LSTM networks. *Chaos, Solitons & Fractals*. 2020;135:1–6. Available from: https://doi.org/10.1016/j.chaos.2020.109864.
25) Vega-Márquez B, Rubio-Escudero C, Nepomuceno-Chamorro IA, Ángel Arcos-Vargas. Use of Deep Learning Architectures for Day-Ahead Electricity Price Forecasting over Different Time Periods in the Spanish Electricity Market. *Applied Sciences*. 2021;11(13):1–19. Available from: https://dx.doi.org/10.3390/app11136097.