Real-time estimation of COVID-19 cases using machine learning and mathematical models - The case of India

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***Abstract*—COVID-19 pandemic has stressed out the economy and resources of major countries across the world due to its high infection and transmission rate. The count of COVID-19 cases skyrocketed in the past few days, which creates immense pressure on health officials and governments. Therefore, prediction models to determine the number of new infections are urgently required in such grave times. In the present study, a machine learning technique, namely artificial neural network (ANN) is proposed to forecast the COVID-19 outbreak in India, for the first time. Moreover, in our study, we have additionally attempted to use a mathematical curve fitting model to ascertain the performance of the proposed ANN-based machine learning model. In addition, the impact of preventive measures such as lockdown and social distancing on the spread of COVID-19 is also analyzed by estimating the growth of the epidemic under different transmission rates. Moreover, a comparison between the proposed and existing COVID-19 prediction models is also demonstrated. Intriguingly, the proposed model is found to be highly accurate in estimating the growth of COVID-19 related parameters with the lowest MAPE values (cumulative confirmed cases (3.981), daily confirmed cases (4.173) and cumulative deceased cases (4.413)). Hence, the present study can assist the health officers and administration in getting prepared with the beforehand arrangement of the required resources and medical facilities.**

***Index Terms*—Covid-19, infectious disease, prediction, machine learning, artificial neural network**

I. Introduction

COVID-19 or the novel coronavirus disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is a highly communicable infection and declared a global pandemic by the World Health Organization (WHO). COVID-19 belongs to a family of zoonotic coronaviruses, similar to Middle East Respiratory Syndrome Coronavirus (MERS-CoV) and SARS-CoV-2 seen in past decades. The virus has high infectivity and shows a high morbidity rate on elderly people and those suffering from severe diseases such as asthma, cancer and diabetes [1]. As of July 20, 2020, more than 14M confirmed cases and 609,279 deaths had been reported worldwide. Some European countries, including Spain (307,335 cases), UK (294,792 cases) and more recently, the United States of America (3,898,550 cases), are the few most affected countries by this global health crisis [2]. The worsening conditions warrant immediate implementation of containment strategies to stop the spread. Since there is no treatment and medicine available for the virus, effective planning of health services and infrastructures are highly required. Administrators and public health officers are under immense pressure to manage the accommodation of the patients having COVID-19 symptoms. For this reason, some prediction tools must be needed to estimate the possible new COVID-19 cases in the near future for organizing the resources and materials required to handle the outbreak. Public health officers may utilize the beforehand prediction of disease for the effective and prompt arrangement of the resources necessary for medical treatment to overcome the pandemic [3].

In this regard, the community of mathematicians and scientists working in artificial intelligence are coming forward to develop accurate prediction models to predict COVID-19 cases in different countries. Recently, Zhao et al. [3] developed a mathematical model to forecast COVID-19 cases in the first half of January in China. Similarly, Tang et al. [1] proposed a mathematical model to determine the transmission rate of COVID-19 to predict the COVID-19 confirmed cases in the next seven days. Roosa et al. [4] applied a generalized logistic growth model to determine the count of cumulative confirmed cases in China from 5th to 24th February, 2020. In addition, various statistical methods such as Autoregressive Integrate Moving Average (ARIMA), Moving Average (MA), Auto Regressive (AR), multivariate linear regression have been used to predict COVID-19 cases. For instance, Ceylan [5] applied ARIMA to predict the prevalence of COVID-19 in the three most affected European countries, including Italy, Spain and France. Dehesh et al. [6] developed the ARIMA model to predict confirmed COVID-19 cases in different countries. Similarly, Benvenuto et al. [7] used Johns Hopkins epidemiological data to determine the prevalence and incidence trend of COVID-19 by applying ARIMA model for Italy. However, these reported statistical methods are linear models that cannot capture the non-linearity in data. Moreover, these models utilize regression without modeling non-linear functions, and hence, can't learn the dynamics of the transmission rate

TABLE I
STUDIES ON ESTIMATION OF GROWTH RATE OF SEVERAL EPIDEMICS USING ARTIFICIAL NEURAL NETWORK (ANN).

Methods	Disease	Reference
ARIMA, ANN	HAV	[13]
BPNN, RBFNN, and ERNN	Typhoid Fever	[14]
ARIMA, BPNN	HEV	[15]
ARIMA, GRNN, and NARNN	HFRS	[16]
ARIMA, GRNN	Hepatitis	[17]
ARIMA, ANN, and MPR	Dengue Fever	[12]

Abbreviations have the following meaning: ANN: Artificial Neural Networks, BPNN: Back Propagation Neural Networks, RBFNN: Radial Basis Function Neural Networks, ERNN: Elman Recurrent Neural Networks, NARNN: Nonlinear Autoregressive Neural Network, GRNN: Generalized Regression Neural Network, MPR: Multivariate Poisson Regression, HAV: Hepatitis A Virus, HEV: Hepatitis E Virus, HFRS: Hemorrhagic Fever with Renal Syndrome,

of such infectious disease. Besides, statistical models like ARIMA are parametric methods that massively rely on several assumptions. Such hypothesized parameters lead to poor data fitting and low accuracy while predicting COVID-19 growth. Therefore, the statistical models are not sufficient to develop generalized models to capture the randomness in the current epidemic.

Recently, few researchers have used several machine learning techniques as an alternative to statistical methods. For example, Hu et al. [8] developed an auto-encoder to predict COVID-19 growth in China. Al et al. [9] developed an Adaptive Neuro-Fuzzy Inference System to estimate confirmed COVID-19 cases in the next ten days in China. Similarly, Chimmula et al. [10] proposed a long short term memory (LSTM) model to forecast COVID-19 confirmed cases. It is worth noting that LSTM is a big data-driven model, which is not suitable for small sample learning problems and leads to a high risk of over-fitting that is easy to occur in small sample learning [11]. Next, the Artificial Neural Network (ANN) is one of the machine learning algorithms that have been widely applied in time-series prediction problems because of its simple architecture, fast implementation and capability to process non-linear data [12]. Owing to their excellent performance in many prediction problems, ANN and its variants have been extensively employed to predict the growth of various infectious diseases such as hepatitis mortality, typhoid fever incidence, HEV, tuberculosis, etc., as shown in Table I. Unlike statistical methods, ANNs are non-parametric models and do not require much knowledge of the statistical background. Moreover, ANNs are non-linear models, which are relatively easy to use and understand for the end-users. However, the ANN-based prediction models have not yet been used for this novel cause (spread of COVID-19).

Therefore, in order to overcome the limitations of statistical models, in this work, an ANN-based machine learning model is proposed to predict the outbreak of COVID-19 cases in India for the first time. The model is developed using the available historical time-series data. Moreover, in our study, we have attempted to use a mathematical curve fitting model to ascertain the proposed ANN-based machine learning model's performance. Further, the developed mathematical model is utilized to predict the epidemic's growth under different transmission rates. Overall, the developed models can approximate new COVID-19 cases, which may alert the administration about the crisis, necessary preparations and health infrastructure required to accommodate the patients. The rest of the study is organized as follows. The data collection and applied method are discussed in detail in Section 2. The results are extensively discussed in Section 3, while Section 4 presents the conclusions of the study.

II. METHODS

A. Study location and data collection

In this pandemic, the entire world is discussing the second most populated country in the world, India [18]. Initially, the number of confirmed cases in India were significantly less; however, it has increased rapidly in the past few weeks. Till July 20, 2020, a total of 1,119,412 confirmed cases and 27,514 deaths have been reported all over India [19]. The Indian government imposed a prolonged lockdown from March 24, 2020, to May 31, 2020, in several phases to contain the spread of the virus [20]. However, the government has lifted the lockdown from June 1, 2020, with certain rules and restrictions. Based on the increased transmission rate, experts are warning that India may be the next epicenter of the COVID-19. The time-series data of COVID-19 used in the present study is collected from the official website of the Government of India [19]. The extracted data includes several parameters such as cumulative confirmed, new and cumulative deceased cases recorded daily. The available dataset is time-series data with date, month and year information. The data recorded for a time period from January 30, 2020 (when the first COVID-19 case was reported in India) to July 10, 2020 (162 days) is utilized to develop the prediction model.

B. ANN model

An artificial neural network (ANN) is known as the most utilized technique in the artificial intelligence field. Many researchers have applied ANNs to solve various problems like classification, regression and optimization, etc. ANN-based models are highly capable of modeling non-linear data and hence widely applied in time-series prediction problems [21]. ANNs imitate the behavior of a human brain and learn in the same way as a human learns. The basic building blocks of neural networks are highly interconnected artificial neurons or nodes. Neural network architecture is composed of multiple layers: one input layer, one or multiple hidden layers and one output layer, as shown in Fig. 1. Each layer performs a specific function on the data. Initially, input layer nodes receive the inputs and compute their weighted sum as follows:

$$X = x_1.w_{1,j} + x_2.w_{2,j} + ...x_n.w_{n,j} + b_j \tag{1}$$

where X is the net input and b is the bias. The weighted sum is transferred to the subsequent hidden layers. The hidden layers extract features from the input data and transform it into

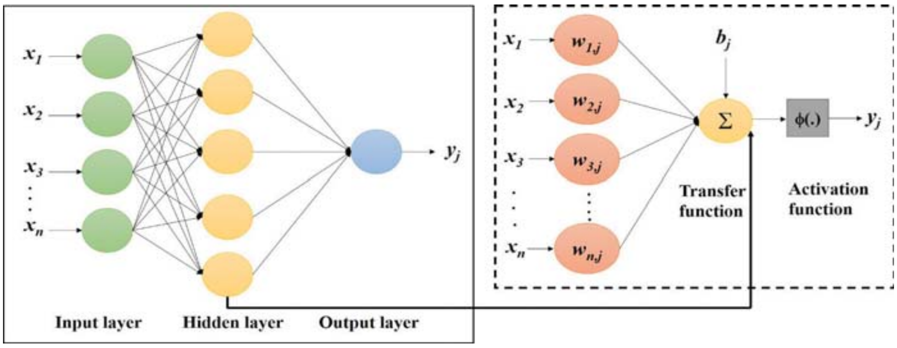

Fig. 1. Basic architecture of artificial neural network.

useful information for output layer. A non-linear activation function is applied to get the output (y_j). In this model, a sigmoid function is applied as an activation function, as shown below:

$$y_j = \frac{1}{1+e^{-X}} \tag{2}$$

The output of neural network (y_j) is compared to the actual value (a_j) using an error function:

$$\delta_k = (a_j - y_j)y_j(1-y_j) \tag{3}$$

The error for the hidden layer is calculated as follows:

$$\delta_j = y_j(1-y_j)\sum_k \delta_k w_k \tag{4}$$

where δ_k is the error term of the output layer, and w_k is the weight between the hidden layer and output layer. To adjust the weights of the connection links, the error is back propagated from output layer to the input layer as follows:

$$w_{ji}(t+1) = w_{ji}(t) + \eta\delta_j y_j + \alpha(w_{ji}(t) - w_{ji}(t-1)) \tag{5}$$

where η denotes the learning rate and α denotes the momentum factor. These parameters highly influence the training and accuracy of the ANN model. The learning rate (η) helps decide the speed of convergence of the model, i.e., a low learning rate will slow down the convergence rate, whereas a large learning rate will increase the size of oscillations. Regularization term (α) guarantees the stability of the network by reducing the chances of over-fitting by penalizing the network weights. The network is trained until the minimum error value reaches a decided threshold value. Finally, the neural network architecture with optimized weights is further utilized in the testing phase.

A three-layer feed-forward neural network trained with a back-propagation algorithm is developed in the present study. The previous days' data values are given as inputs to the input layer. ANN model with different configurations of hidden neurons was tested. Levenberg Marquardt (LM) learning algorithm was employed to optimize the weight matrices during the training of the proposed ANN model [23]. The model is trained until the network weights are optimized and mean square error (MSE) is minimized. Table II shows the architecture of the developed ANN model.

C. Performance evaluation metrics

The performance of a predictive model are generally evaluated by correlating the predicted values to the actual values. In present work, three performance evaluation metrics, including root mean square error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE) are utilized to analyse the performance of the proposed ANN models [24], [25]. These metrics can be described mathematically as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{7}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{8}$$

TABLE II
ARCHITECTURE AND PARAMETER SETTINGS OF ANN MODELS DEVELOPED IN PRESENT STUDY.

Architecture	Inputs	4
	Outputs	1
	Number of layers	3
	Neurons in hidden layer	10
	Activation function	Sigmoid
Parameters	Learning function	Levenberg-Marquardt
	Performance function	MSE

TABLE III
THE PERFORMANCE EVALUATION OF STUDIED MODEL ON TESTING DATASET.

	RMSE	MAE	MAPE
Cumulative confirmed cases	1638.649	514.813	3.981
Daily confirmed cases	1793.188	686.396	4.173
Cumulative deceased cases	1908.963	794.395	4.413

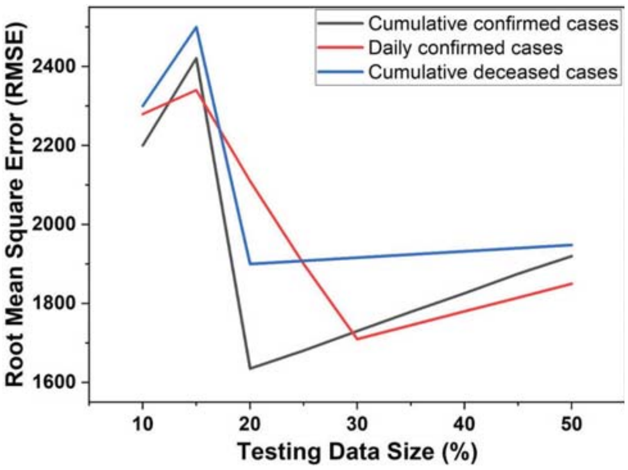

Fig. 2. Split of dataset to determine the optimal train and test size for ANN model.

where y_i and $\hat{y}_i$ are the actual and predicted values, respectively. Also, n denotes the number data instances. The lower values of RMSE, MAE and MAPE indicate the higher performance of the model.

III. Results and discussion

A. Performance of ANN model

This section presents the prediction results of developed models for India. To decide the optimal size of the train and test dataset, the ANN model is evaluated for different train-test splits. For this, the test size is varied from 10% to 50%. For cumulative confirmed cases and cumulative deceased cases, the lowest RMSE value is obtained when the model is trained with 80% data and tested with 20% data, while in the case of daily confirmed cases, the lowest RMSE is obtained when the ANN model is trained with 70% data and tested with 30% data, as shown in Fig. 2. Table III shows the accuracy of the developed ANN model in terms of RMSE, MAE and MAPE. Further, Fig. 3(a) shows the resulting plot of the fitted and predicted cumulative confirmed cases. In this figure, the observed data of 130 days (black color) is used for training of the ANN model, predicted data (red color) indicates the predicted cumulative confirmed cases and official (blue color) shows the actual data. It can be observed from Fig. 3(a) that predicted cumulative confirmed cases are in good agreement with the corresponding actual values.

Similarly, accurate prediction results are also observed for daily confirmed and cumulative deceased cases, demonstrated in Fig. 3(b) and (c), respectively. Table III and Fig. 3 suggest that the developed ANN model fitted the COVID-19 data very well, with a minimum MAPE value of 3.981, 4.173 and 4.413 for cumulative confirmed cases, daily confirmed cases and cumulative deceased cases, respectively. Moreover, to verify the proposed model's prediction results, the predicted cumulative confirmed cases and daily confirmed cases, from July 5, 2020, to July 10, 2020, are compared with the actual data, as shown in Table IV. In addition, the performance of the proposed ANN model is compared with the previously reported COVID-19 prediction models, as shown in Table V. The demonstrated MAPE values in Table V illustrate that our proposed ANN model exhibited superior performance over many reported models and comparable with the best-performing ones.

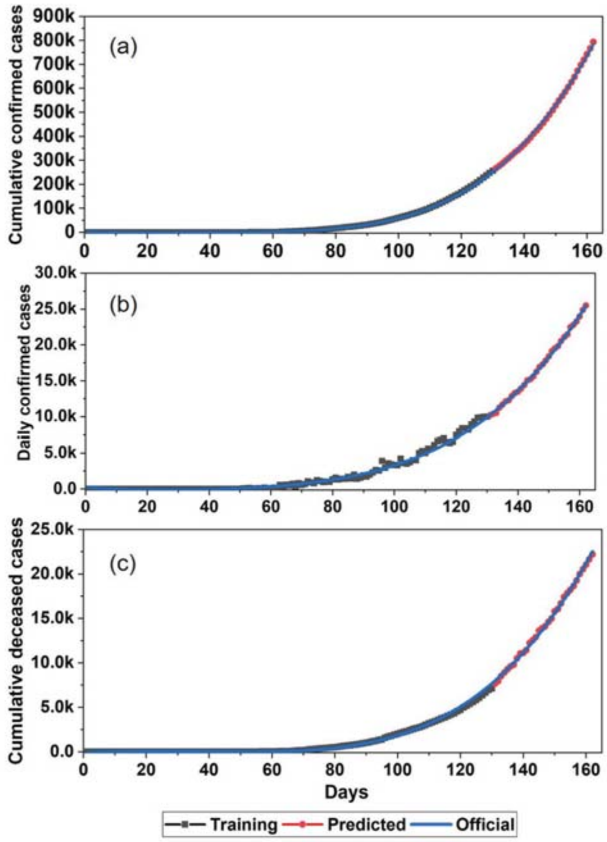

Fig. 3. ANN predicted (a) cumulative confirmed cases, (b) daily confirmed cases and (c) cumulative deceased cases.

TABLE IV
Comparison between actual and ANN-predicted cases.

Date	Day	Official	Predicted	Error (%)
Cumulative confirmed cases				
6th July 2020	158th	697,413	693,163	-0.609
7th July 2020	159th	719,665	716,318	-0.465
8th July 2020	160th	742,417	748,164	0.774
9th July 2020	161st	767,296	770,689	0.442
10th July 2020	162nd	793,802	796,525	0.343
Daily confirmed cases				
6th July 2020	158th	24,248	23,708	-2.226
7th July 2020	159th	22,252	22,815	-2.530
8th July 2020	160th	22,752	23,584	3.656
9th July 2020	161st	24,879	25,155	1.109
10th July 2020	162nd	26,506	26,250	-0.965

TABLE V
COMPARISON OF PROPOSED MACHINE LEARNING MODEL WITH EXISTING COVID-19 PREDICTION MODELS.

Study	Country	Proposed method	Mape (%)
[5]	Europe	ARIMA	4.752
[26]	India	ARIMA	4.1
[9]	China	ANFIS	4.79
Present study	**India**	**ANN**	**3.981**

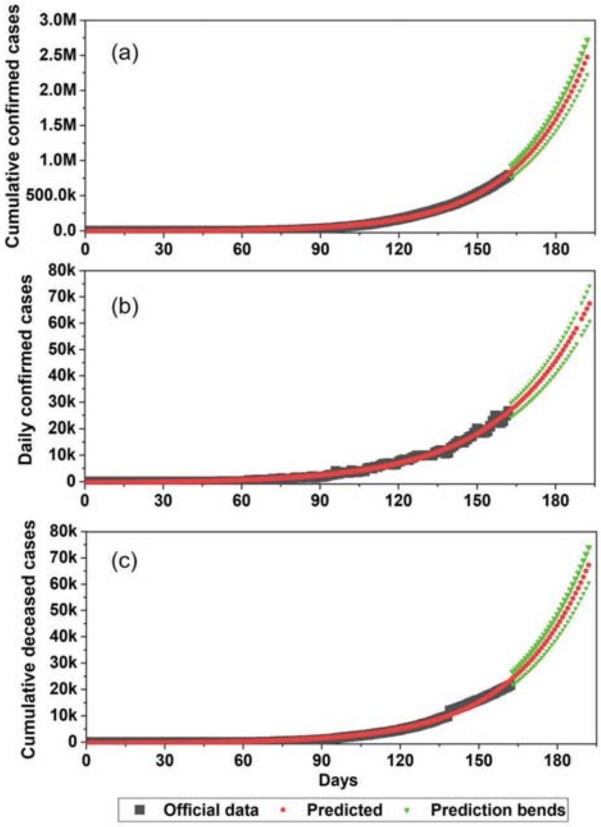

Fig. 4. Prediction using mathematical curve fitting model for (a) cumulative confirmed cases, (b) daily confirmed cases and (c) cumulative deceased cases.

B. Performance of mathematical model

Next, a mathematical model through curve fitting is also developed for the following reasons: Firstly, to verify the above-discussed machine learning model and secondly, to study the effect of lockdown under different transmission rates. As the community transmission of the virus has started in India, the infection seems to spread exponentially. Our developed mathematical model also verified that the present data follows an exponential function ($f(x) = ab^x$). The resulting prediction of cumulative confirmed cases, daily confirmed and cumulative deceased cases through the mathematical model are shown in Fig. 4 (a), (b) and (c), respectively. The mathematical model is applied on official data available for 123 days (from January 30, 2020, to July 10, 2020) to make predictions for the next 30 days (from July 11, 2020, to August 9, 2020). The prediction bends around the predicted curve in these figures represent the confidence of prediction, which is considered as ±5% in the present study. If the virus continues to spread at the same rate, then the cumulative confirmed cases, daily confirmed cases and cumulative deceased cases in India may increase up to 2.5M, 70,000 and 65,000 respectively, by the mid of August (Fig. 4 (a), (b) and (c)).

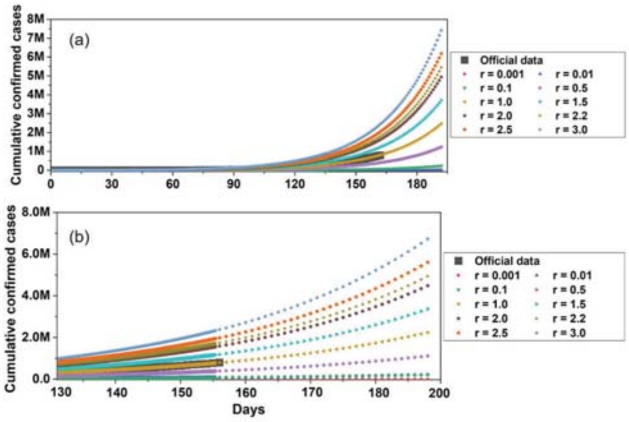

Fig. 5. Impact of preventive measures on cumulative confirmed cases under different transmission rate considering (a) January 30, 2020 and (b) July 10, 2020 as initial point.

From the above results shown in Fig. 3, 4 and Table III, IV, it can be concluded that the developed machine learning model with the available time-series data can be used to estimate the COVID-19 positive cases.

C. Impact of lockdown on the COVID-19 growth

The COVID-19 outbreak has led to the implementation of various restriction measures by the Government of India as a containment strategy to reduce the human to human transmission of the disease (Covid-19.in, 2020). The government imposed a complete lockdown across the nation to prevent human movement from one area to another. In addition, all the places of social gatherings such as shopping complexes, schools, universities, cinemas were supposed to be closed to maintain social distancing. These restriction measures highly reduce the chance of transmission of COVID-19 from an infected individual to a healthy person. The impact of preventive measures with different transmission rates (r) (from r = 0.001 to 3.0) has also been analyzed in the current study. The transmission rate represents the average number of healthy people to which an infected individual can transmit the virus. The strict implementation of lockdown measures and social distancing may help to attain a low transmission rate [27]. Let us assume a scenario in which r was 3.0 before lockdown (i.e., one contaminated person may transmit the virus to three persons) in India, which reduced to 0.15 during the lockdown. In this case, the predicted cumulative confirmed cases are compared with actual cases under different transmission rates, as shown in Fig. 5(a). It can be observed from Fig. 5(a) that preventive measures such as social distancing and lockdown have played an influential role in reducing the spread of the disease. Now let us consider another scenario in which July 10, 2020, having 793,802 confirmed positive cases as the start and social distancing and other preventive measures followed attentively. In this case, the estimated number of cumulative confirmed cases with different transmission rates is shown in Fig. 5(b). It can be observed from Fig. 5(b) that the strict implementation of preventive measures will be highly effective in minimizing the COVID-19 growth and flattening the curve.

IV. Conclusion and Future Work

In present work, a machine learning model (i.e., ANN) is proposed to estimate the growth of COVID-19 infection in India. The developed models are utilized to predict the number of cumulative confirmed cases, daily confirmed cases and cumulative deceased cases of COVID-19. In addition, a mathematical model is also developed to verify the performance of the proposed ANN model. According to the prediction model, the transmission rate in India is witnessing exponential growth, due to which the number of confirmed cases is supposed to show a massive increment in the coming days. Moreover, the impact of preventive measures such as lockdown and social isolation has also been analyzed under different transmission rates. The obtained results confirmed that the strict implementation of lockdown is highly desirable to slow down the spread of the disease. To sum up, this is the first study that has used the ANN model to predict the outbreak of COVID-19 in India. The findings of the present study give insight into the future, which can be used by the government and health officers to organize the required medical facilities and resources. For future work, the present study can be extended to predict the growth of COVID-19 at the province level.

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