Realtime forecasting of COVID 19 cases in Karnataka state using Artificial neural network (ANN)

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Research Article

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Abstract

COVID-19 is a pandemic that has caused lot of deaths and infections in the last 6 months and is showing an increasing trend not only in the number of infections and deaths, but also in the recovery rate. Accurate prediction models are very much essential to make proper forecasts and take necessary actions. This study demonstrates the capability of Multilayer Perceptron (MLP, an ANN model for forecasting the number of infected cases in the state of Karnataka in India. It is trained using a fast training algorithm namely, Extreme Learning machine (ELM) to reduce the training time required. The parameters required for the forecasting model have been selected using partial autocorrelation function (PACF), which is a conventional method and its performance has been compared with parameters selected using cuckoo search (CS) algorithm, which is a very popular nature-inspired optimization algorithm. The testing of the forecasting model has been done and comparison between the two parameter selection methods has been carried out. Use of CS algorithm has resulted in a better forecasting performance based on mean absolute percentage error (MAPE), with a value of 6.62 % on training data and 7.03% on the test data. Further to check the efficacy of the model, the data of COVID-19 cases of Hungary from 4th March to 19th April 2020 has been used, which resulted in a MAPE of 1.55%, thereby establishing the robustness of the proposed ANN model for forecasting COVID-19 cases for the state of Karnataka.

Keywords: Forecasting, artificial neural network, multilayer perceptron, partial autocorrelation function, cuckoo search, mean absolute percentage error.

1. Introduction

Severe acute respiratory syndrome (SARS) corona virus 2 is a virus strain that is causing severe respiratory disease, which is popularly known as Covid-19. World Health Organization (WHO) has declared it as a pandemic as on 11th March 2020. As on 11-08-2020, 2, 20, 284, 482 confirmed cases have been reported by the Johns Hopkins University (https://coronavirus.jhu.edu/map.html). In India, as on 12-08-2020, 23,32, 908 cases have been reported with 46,216 deaths (https://www.worldometers.info/coronavirus/country/india/). This has disturbed the normal life of ordinary people and has affected many both economically and from other aspects. The lockdown imposed by the government in the initial stages has affected the livelihood of millions of people and has significant repercussions. There has been lot of stress on the administration for managing the spread of this virus and accordingly there is a need for forecasting the probable number of cases, so that the infections can be managed effectively without undue strain on the health infrastructural facilities of the country.

There have been several efforts regarding use of mathematical models and artificial intelligence (AI) tools in modeling, prediction and forecasting of the infected cases, recovered cases, mortality rate etc. in the last several months. It is very important to model the spread and effect of such diseases, particularly creating a pandemic. AI modeling techniques are able to generate high quality predictive models and can help in the various aspects of disease management. The data is readily available and they are valid and from reliable sources. There is a need for a mechanism to manage the data efficiently and AI and in particular machine learning models can help in doing the same [1].

This paper presents a real time forecasting model based on multilayer perceptron, a popular, supervised and feed forward neural network model. The parameter selection for the model is based on PACF and using Cuckoo Search algorithm. The model has been checked for its efficiency, based on the data pertaining to Hungary.

2. Related work

There has been a lot of work reported about the use of Artificial Intelligence and Machine learning (ML) for studying the various aspects of Covid-19. To review a few literatures, Shinde et al [2] presented an overall, comprehensive analysis of different forecasting models for Covid-19 to help the organizations. The aspects covered include forecasting, impacts and control measures. The models have been studied from the point of view of challenges in using these and recommendations. The forecasting methods have been grouped into four namely big data sets accessed from WHO and national data sources, social media data, stochastic models and use of machine learning techniques. They recommend the need to test the models globally for better global forecasting.

Swapnarekha et al. [3] presented a state-of-the-art analysis regarding use of machine learning and deep learning (DL) methods in the diagnosis and prediction of Covid -19 for its effective control. The analysis is done based on the journals by country and performance analysis of statistical, ML and DL approaches. The study helps researchers to develop more accurate prediction models for predicting the disease. Pinter et al. [4] proposed an alternative to the susceptible-infected-resistant (SIR)-based models by proposing hybrid learning methods which use adaptive network-based fuzzy inference system (ANFIS) and multi-layered perceptron with imperialist-competitive algorithm (MLP-ICA). These models have potential when compared to epidemiological models and MLP-ICA performed better than ANFIS and gave good results on validation data.

Rustam et al. [5] studied different ML models to forecast the number of upcoming patients affected by the disease and included linear regression (LR), least absolute shrinkage and selection operator (LASSO), support vector machine (SVM) and exponential smoothing (ES). Three types of predictions are made namely, number of newly infected cases, the number of deaths and number of recoveries in the next 10 days. ES performs well in the current forecasting domain based on the nature and size of the data. LR and LASSO perform well for forecasting death rate and confirmed cases. Sujath et al. [6] presented a model to predict the spread of Covid-19. The models studied include LR, MLP and Vector autoregression (VAR) method using Kaggle data to anticipate the epidemiological example of the ailment and pace of number of cases in India. Comparing the predicted values with cases from John Hopkins University data, MLP method is giving good prediction results than LR and VAR using Weka and Orange.

Saba and Elsheikh [7] studied statistical based method namely autoregressive integrated moving average (ARIMA) and nonlinear autoregressive artificial neural networks (NARANN) for modeling and forecasting the prevalence of this epidemic in Egypt. The confirmed cases are considered as time series data to train the proposed models. NARANN performed better than ARIMA and can be used for multi-step forecasts for further days with high coefficient of determination and the forecasted error was less than 5 %. Hassan [8] proposed and investigated a hybrid model namely ensemble empirical mode decomposition (EEMD) – ANN technique to predict the daily trend of Covid-19 based on the real time series data set. The EEMD technique is used for denoising the data and ANN is used to build the model. The proposed model has been compared with traditional statistical techniques like regression analysis and moving average. The proposed model has very low mean squared error (MSE) and high R^2 values. Car et al. [9] used a publicly available data set, containing information about infected, recovered and deceased patients in 406 locations in 51 days, which is a time-series data set, which was converted into a regression data set and used to train a MLP model. . From among the three categories of models, the deceased patient model was highly robust, there was good robustness for the infected patient model and poor performance for the recovered patient model. Tamang et al [10] used ANN curve fitting techniques in predicting and forecasting the confirmed and death cases of Covid-19 in India, USA, France and UK using the data from China and South Korea. The results indicate that ANN can be used efficiently to forecast the future cases of Covid-19 outbreak of any country. Mollalo et al.[11] made a review of nationwide modeling of Covid-19 cases in the USA, particularly using ML algorithms. They identified 57 candidate explanatory variables to examine the performance of MLP in predicting the cumulative Covid-19 incidence rates in continental USA. The proposed model was able to establish 65 % correlation with the ground truth for the hold out samples.

The review highlights the wide range of models and areas covered, with scope for application of machine learning related techniques for modeling, prediction and forecasting of the disease.

3. Multilayer Perceptron based Neural network model

ANN due to its ability to map meaningful relationships in the data is becoming popular day by day in medical field for clinical diagnosis, drug development, improved gene editing and in prediction and forecasting of diseases. Feed forward neural networks are the simplest but powerful class of neural networks which find wide application due to their ability to model any nonlinear relation underlying the data, which otherwise are difficult to be handled by conventional techniques.

The main feature of ANN which makes its application universal is its learning ability and thereby adjusts synaptic weights and biases to best fit the given environment. Back Propagation (BP) algorithm, though very popular and used in many areas, suffers from many problems. This iterative algorithm in addition to being slow and time consuming, suffers from local minima problem. There are most chances of overtraining of the network, if the appropriate stopping criteria is not set during learning. Use of many simulation parameters makes it sensitive to parameter tuning and needs more human intervention [12]. Extreme learning machine (ELM) is a powerful algorithm introduced recently by G. B Huang [13], which overcomes the disadvantages of BP. Good generalization performance with less simulation parameters are the added advantages of ELM in training MLP, when compared to use of BP in training MLP as well as support vector machines (SVM) [14].

4. Methodology

4.1 Multilayer Perceptron Neural Network

Multilayer perceptron is a popular feed forward model, which uses Backpropagation (BP) algorithm. It consists of one or more hidden layer with non linear sigmoidal activation function as given in (1)

$$V_j^{\mu} = \frac{1}{1+e^{\sum w_{ji}\, x_i + b}} \qquad (1)$$

where, x_i is the input pattern with $i = 1,2, \ldots . s$ input features, j = 1,2,3...p is the neurons in the hidden layer, b and $w_{ji}$are the bias and weights respectively between hidden and input layer. MLP possesses high degree of connectivity and constructs global approximation. Hence it is capable of mapping any nonlinear relationship [12].

4.2 Extreme Learning Machine (ELM) algorithm

Extreme learning machine algorithm, being a simple and non-iterative method, draws the attention of researchers from various fields. The one pass learning helps in saving the learning time considerably and thus finds a major application in emerging areas such as pattern recognition, image analysis, bioinformatics and other prediction and forecasting purposes involving big data [13].

The ELM algorithm is as follows:

For N arbitrary distinct training data (x_i, t_i), where $x_i \epsilon R^n$ is $nx1$ input and $t_i \epsilon R^m$ is $mx1$, target vector and Q hidden nodes, if the activation function $g(x)$ is used, then the output O_j of the model can be expressed mathematically as:

$O_j = \sum_{i=1}^{Q} \beta_i g_i(w_i x_j + b_i)$, j=1,…, N. (1)

where, w_i and β_i are the weight matrix between hidden and input layers and between output and hidden layers respectively. b_i is the bias of ith hidden node. Equation (1) can be expressed as

$$H\beta = T \qquad (2)$$

where,

$$H(w_1, \ldots w_N, b_1, \ldots . b_N, x_1, \ldots \ldots x_N) = \begin{bmatrix} g(w_1 x_1 + b_1) & \ldots & g(w_Q x_1 + b_Q) \\ . & & . \\ . & \ldots & . \\ . & & . \\ g(w_1 x_N + b_1) & \ldots & g(w_Q x_N + b_Q) \end{bmatrix}_{NXQ} \qquad (3)$$

$$\beta = \begin{bmatrix} \beta_1^T \\ . \\ . \\ . \\ \beta_Q^T \end{bmatrix}_{QXm} \qquad (4) \qquad \text{and } T = \begin{bmatrix} t_1^T \\ . \\ . \\ . \\ t_N^T \end{bmatrix}_{NXm} \qquad (5)$$

The output weight matrix can be found by $\beta = H^{\dagger} T$ (6)

where $H^{\dagger}$ is the Moorse- Penrose generalized inverse of matrix H [13].

4.3 Cuckoo Search (CS) algorithm

The metaheuristic algorithms are inspired by natural processes and are stochastic in nature. In 2009, Yang and Deb introduced cuckoo search algorithm, which works on the basis of cuckoo bird's obligate brood parasitic nature and Levy flight behavior of animals. This algorithm is fast and efficient in exploring the optimal solution and has less chances of getting trapped in local minima, because of the Levy flight mechanism to generate new solutions and is a popular nature inspired optimization algorithm [14-16].

4.4 PACF

Partial autocorrelation function is a method used to perform time series data analysis. It is used to evaluate the order of the autoregressive model. It is mainly useful in determining the lag in autoregressive (AR), ARIMA models. It is helpful in understanding the linear dependence of a value in the timeseries data with its lagged value [18].

4.5 Model development

Two MLP based forecasting models have been developed, using ELM learning algorithm by using CS and PACF for selection of input parameters. Details of the models developed has been given in Table 1. When sigmoidal activation function is used in the ELM based model, there are no simulation parameters to be tuned.

Table 1. Model details

Models	Input parameter selection	Input	Output	Learning algorithm
Model-1	PACF	Xt-1	Xt	ELM
Model-2	CS	Xt-5, Xt-4, Xt-3, Xt-2, Xt-1	Xt	ELM

4.6 Data collection

Data of COVID-19 infected cases in Karnataka state of India is provided by the government and is available in https://www.google.com/search?client=firefox-b-d&q=covid+19+tracker. Figure 1 presents the daily reported cases of COVID-19 cases in Karnataka from 10th March 2020 to 21st July 2020, which shows a steep increase after 10th June. The data has been normalized to bring it in 0-1 range by using Equation (7). This helps in providing uniform contribution of each data in model building.

$$X' = \frac{X}{X_{max}} \qquad (7)$$

Where $X'$the data is after normalization, X is the actual data and X_{max} is the maximum value in the dataset. The simulation of the present work has been done in MATLAB R2014a on a personal computer with an Intel i5-6200U 2.3 GHz CPU and 4 GB RAM.

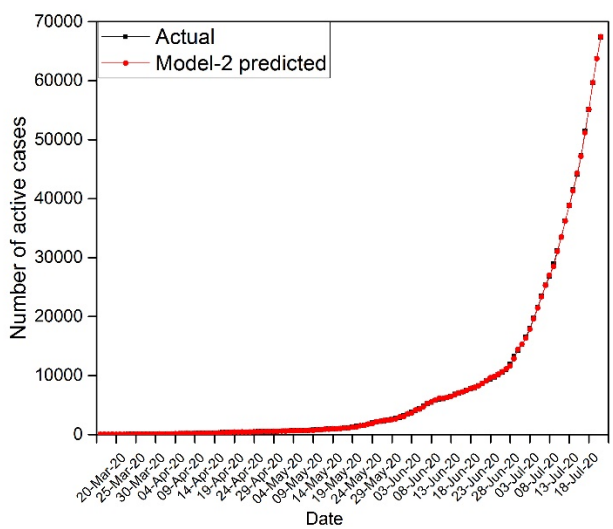

Figure 1. Statistics of number of active COVID-19 cases in Karnataka from 10th March to 21th July 2020

4.7 Selection of input parameters

Once the optimum number of input parameter is selected, the data set is prepared accordingly. The objective function for CS algorithm has been considered as, minimize the mean absolute percentage error (MAPE) between actual and predicted values as given in equation (14). CS algorithm selected the optimum number of input parameters as 5. The partial correlogram of PACF method for the data has been presented in Figure 2. From the figure, it can be seen that only one input parameter is having high correlation with more than 95% significance level. Hence 128 and 131 datasets from 135 total data, are generated with input and output as detailed in Table 1 for CS based and PACF based parameter selection respectively. Out of which 85% has been used for training the ANN model and rest for the testing the same.

$$\text{MAPE (\%)} = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_p(i)-y_a(i)|}{y_a(i)} \times 100 \qquad (14)$$

Where $y_p(i)$, $y_a(i)$ are predicted and actual values of number of COVID-19 cases at i^{th}datapoint and N represents the total number of datapoints considered.

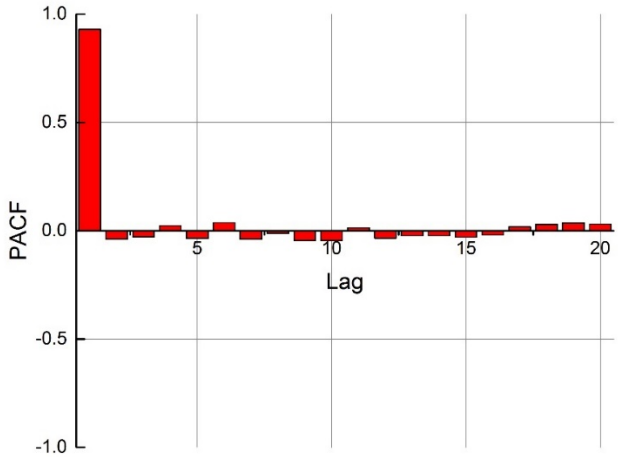

Figure 2. Partial correlogram of COVID-19 data

The values of the parameters set for CS algorithm working in this work has been provided below.
1. Probability $P_a = 0.25$.
2. Stopping criteria = 100 iterations.
3. Population size $n = 10$.
4. Distribution factor $\beta = 1.5$. [19]

5 Results and Discussion

To evaluate the performance of the models, mean absolute percentage error (MAPE) as given in equation (14) has been used as the performance metric.

5.1 Model-1

The number of hidden neurons for Model-1 has been varied to obtain better accuracy. The performance of Model-1 for different hidden neurons is presented in Table 2. It can be observed that the model gives minimum MAPE (%) of 20.73 for 25 hidden neurons on test data. Hence the optimum model configuration is 1:25:1. The actual and Model-1 predicted values are shown in Figure 3.

Table 2: Forecasting performance of Model-1

Number of hidden neurons	**10**	**15**	**20**	**25**	**30**
MAPE (%) on training data	39.33	22.20	19.90	**16.97**	19.25
MAPE (%) on test data	66.70	37.09	26.14	**20.73**	27.92
CPU Time (s)	0.003127	0.003074	0.003973	**0.003910**	0.004148

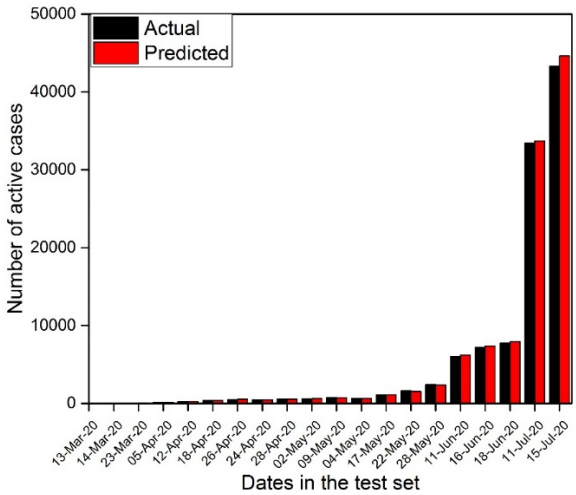

Figure 3: Actual vs predicted number of cases from Model-1

5.2 Model-2

Performance of Model-2 for varied number of hidden neurons has been shown in Table 3. It is noted that when the number of neurons is 10, the model showed best performance with least MAPE (%) value of 7.03 on test data. It can also be observed that further increase in number of hidden neurons lead to decaying model accuracy. Hence the optimal model configuration is found to be 5:10:1. Figure 4 shows actual and Model-2 forecasted values for the test set.

Table 3: Forecasting performance of Model-2

Number of hidden neurons	**5**	**10**	**15**	**20**	**25**
MAPE(%) on training data	15.85	**6.62**	9.69	14.27	14.86
MAPE (%) on test data	17.54	**7.03**	11.52	17.07	17.98
CPU Time (s)	0.04551	**0.04910**	0.05262	0.05280	0.04551

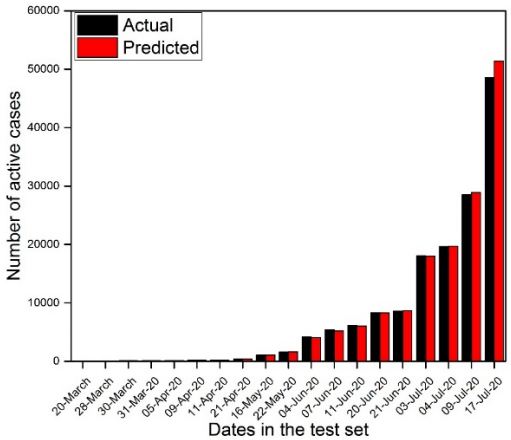

Figure 4: Actual vs predicted number of cases from Model-2

5.3 Comparison of ANN Models

Both the models use MLP with ELM algorithm, but the difference is in the approach used to select the input parameters. The summary of model structure, performance and time taken by the models has been presented in Table 4. It can be noted that Model-1 which used PACF used only one input parameter in comparison to 5 input parameters selected by CS algorithm in Model-2. Model-2 with CS algorithm uses iterative procedure in selecting the optimum number of input parameters, with objective of minimizing training MAPE (%). Hence, it takes more computation time in comparison to Model-1. However, it is worth noting that proper selection of input parameters has a considerable effect on model performance, thus resulting in lower MAPE (%) value of 7.03 by Model-2 in contrast to 20.73 of Model-1 on test data. Graphical illustration of Model-2 predicted and actual COVID-19 infected cases has been presented in Figure 1. A good agreement of predicted values with actual is found. Thus, the CS algorithm which is used in a wide variety of applications is proved to be successful in improving the forecasting accuracy of the ANN model, when used for optimal input parameter selection.

Table 4: Comparison of performances of Mode-1 and Model-2

Model	**Optimal configuration**	**MAPE(%) on training data**	**MAPE (%) on test data**	**CPU Time (s)**
Model-1	1-25-1	16.97	20.73	0.003910
Model-2	5-10-1	6.62	7.03	0.04910

5.4 Efficiency of the proposed ANN model (Case Study)

To prove the effectiveness, the proposed Model-2 has been applied to COVID-19 data of Hungary from 4-March 2020 to 19-April 2020 available at: https://www.worldometers.info/coronavirus/country/hungary/ and used by Gergo Pinter et al [4]. The results obtained from the model is provided in Table 5. It can be noted from the table that least MAPE (%) of 1.55 and 5.34 is obtained on training and test data respectively for 45 number of hidden neurons. The optimum number of input parameters has been selected as 4 by the CS algorithm. The actual and forecasted values illustrated graphically in Figure 5 shows good agreement. The proposed Model-2 in this work proves to be superior to the hybrid MLP-ICA model used by [4], as Model-2 has resulted in a MAPE (%) of 1.55 in contrast to 23.15% for MLP-ICA. Further, since Model-2 uses ELM learning algorithm, it takes only 0.05807 s, as it works only in one epoch. But since MLP-ICA uses an iterative learning method, it certainly consumes more computation time. Hence Model-2 which uses ELM for learning and CS for input parameter selection proves to be faster with better generalization performance.

Table 5: Model-2 forecasting performance for Hungary data (Case study)

Number of hidden neurons	**25**	**30**	**45**	**50**	**55**
MAPE(%) on training data	18.31	4.06	**1.55**	2.15	3.65
MAPE (%) on test data	23.58	9.17	**5.34**	5.98	8.95
CPU Time (s)	0.05745	0.05906	**0.05807**	0.06674	0.07020

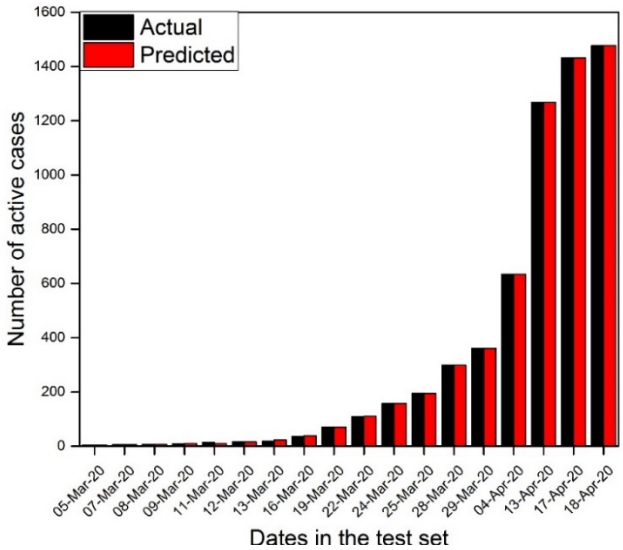

Figure 5: Actual vs predicted number of cases for Hungary data set from Model-2

6 Conclusions

Artificial neural network models based on extreme learning machine (ELM) technique have been developed for forecasting Covid-19 cases in state of Karnataka, India. An effort has been made to use an efficient metaheuristic algorithm namely cuckoo search (CS) for selection of input parameters for the forecasting model. The results are then compared with that of partial autocorrelation function (PACF) based parameter selection to demonstrate the advantage of using CS in forecasting model building. To establish the effectiveness of the forecasting model, the model has been tested using Covid-19 data of Hungary.

The results of this study reveal that

i) MLP-ELM based forecasting model results in quick learning with less number of simulation parameters.

ii) Use of CS optimization algorithm in Model-2 for input parameter selection results in noticeable reduction in MAPE (%) to 7.03 in contrast to 20.73 of Model-1, which is based on PACF on test data.

iii) The proposed forecasting model that combines ELM and CS is found to be effective, when tested using Hungary data and compared with MLP-ICA method found [4], resulting in 1.55 MAPE (%) against 23.15% on training data.

Thus, this research work proposes an effective ANN based forecasting model, which can be used for forecasting Covid-19 cases, in the state of Karnataka, India which shows a gradual increase from May to June 2020 and a steep increase in cases beyond 4th July 2020. To further validate the proposed model, it can be tested using data from the states of India, with increased reported cases similar to Karnataka and may be considering India as a whole. The model has worked well for Hungary data, where the number of reported cases is significantly lower than the state of Karnataka and the increase is very gradual and not as significant as in Karnataka in the last one month. Further the model can be broad based to include other types of data like number of cases recovered and mortality rate. MLP, a simple, tried and tested ANN model applied in various applications in last 25 years has proved effective for an important application like forecasting the number of infected cases of a pandemic like Covid-19.

Authors have no conflict of interest to disclose

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Figures

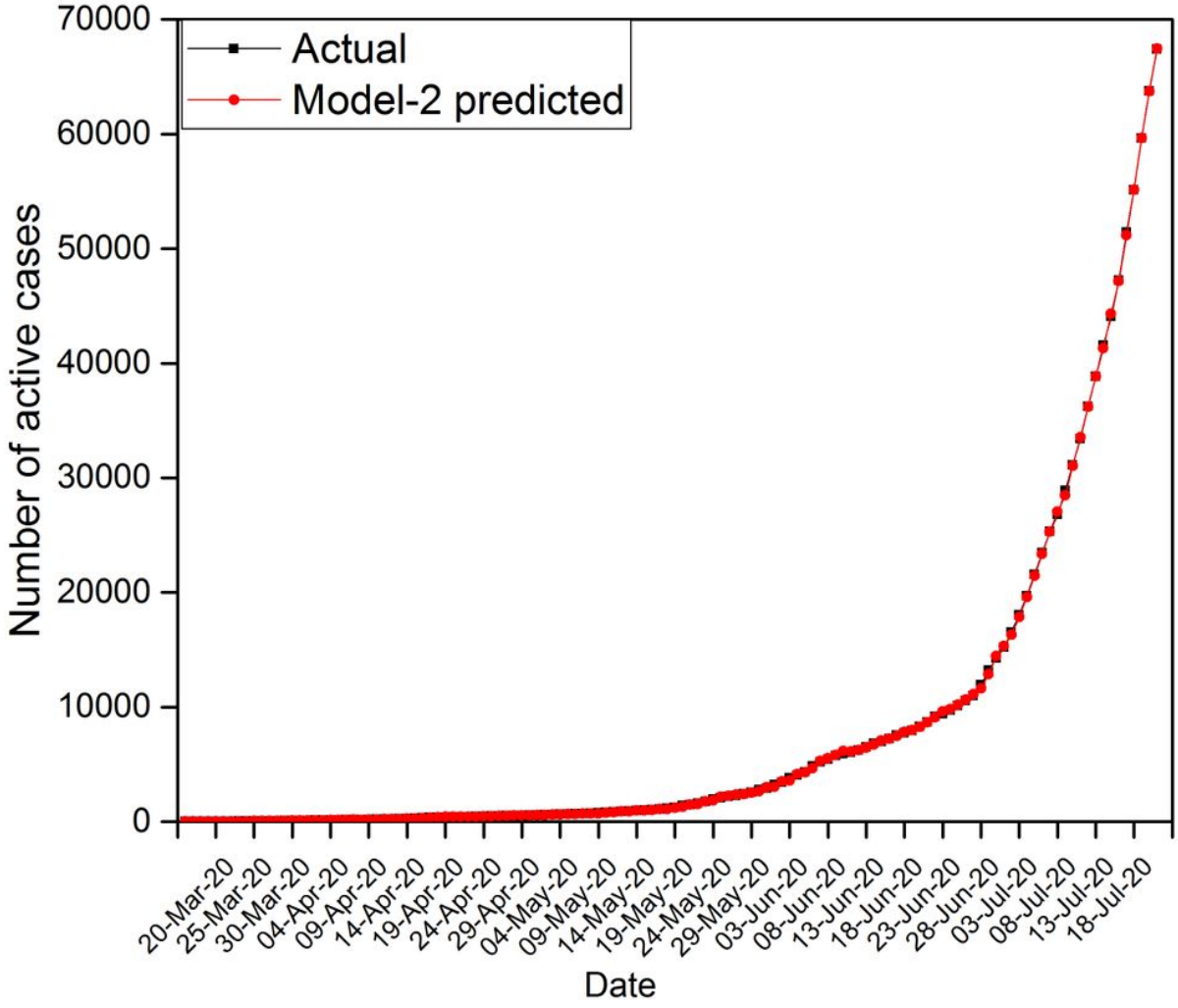

Figure 1

Statistics of number of active COVID-19 cases in Karnataka from 10th March to 21th July 2020

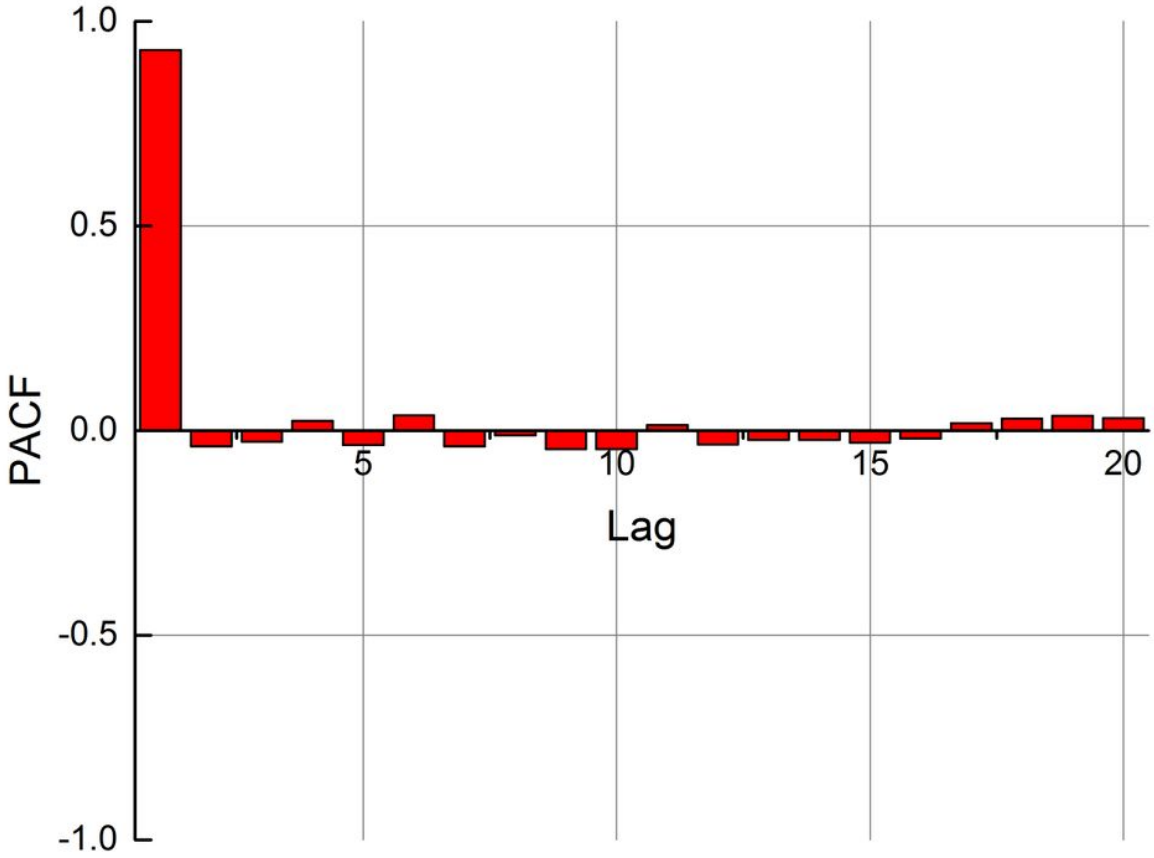

Figure 2

Partial correlogram of COVID-19 data

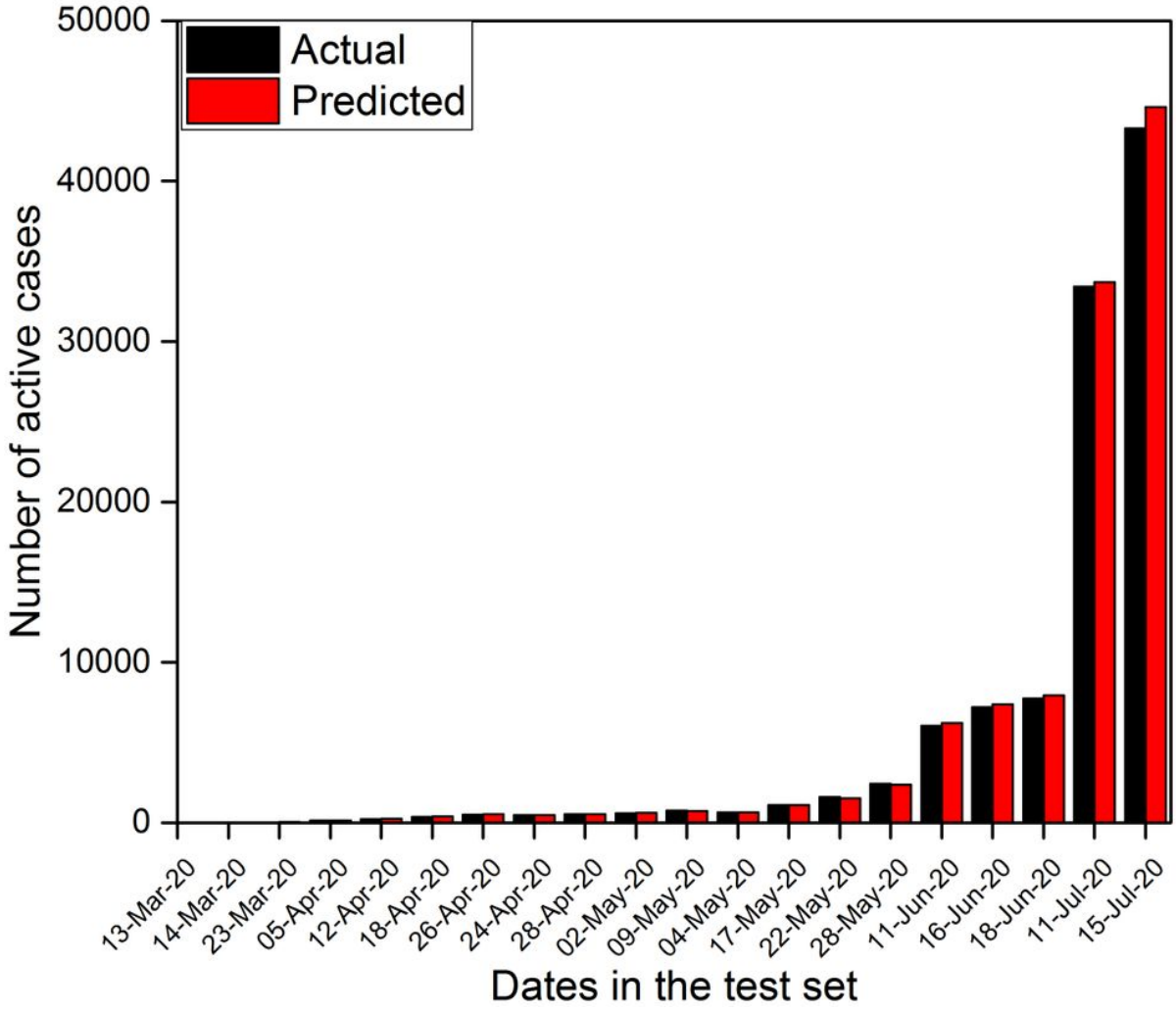

Figure 3

Actual vs predicted number of cases from Model-1

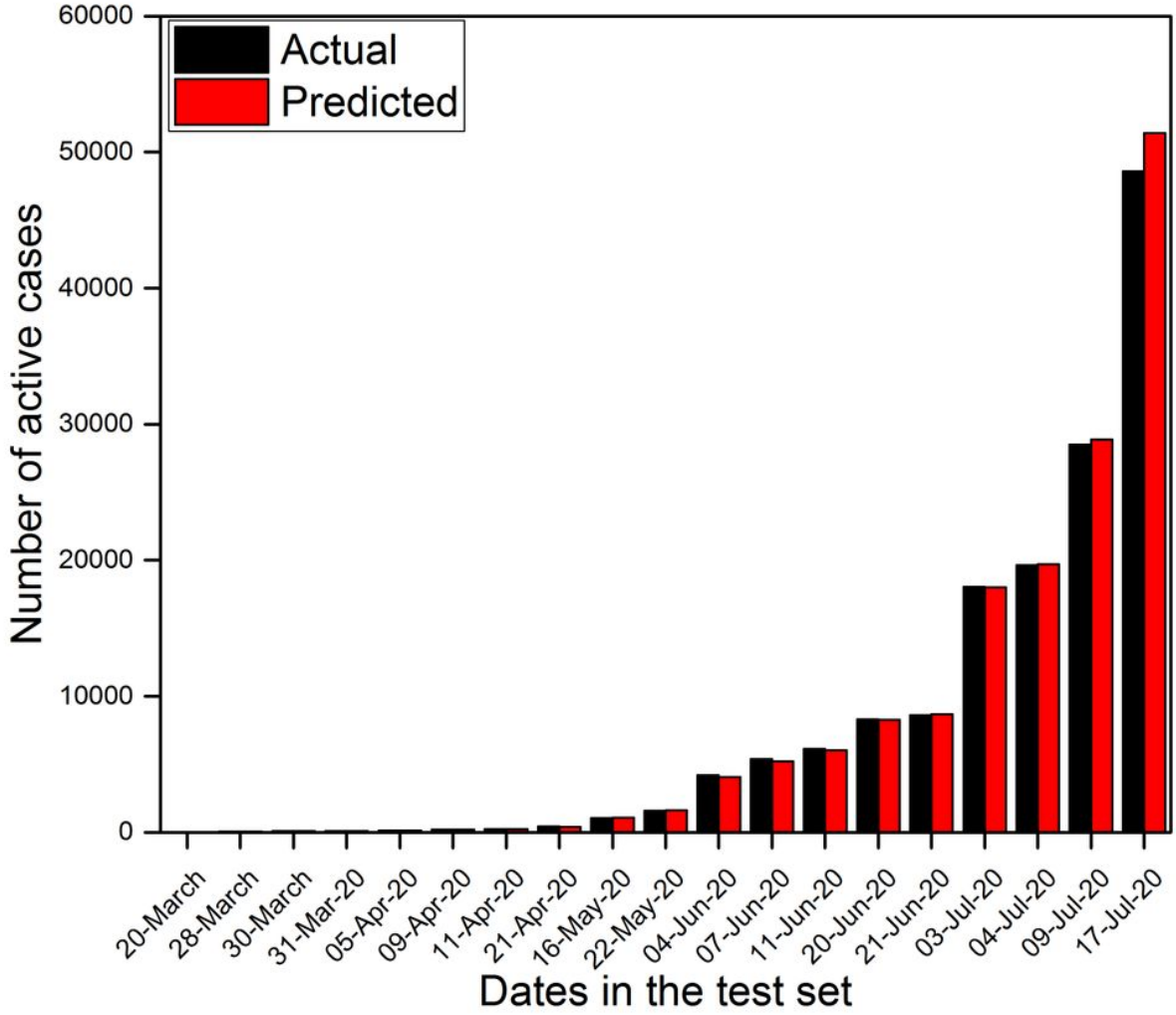

Figure 4

Actual vs predicted number of cases from Model-2

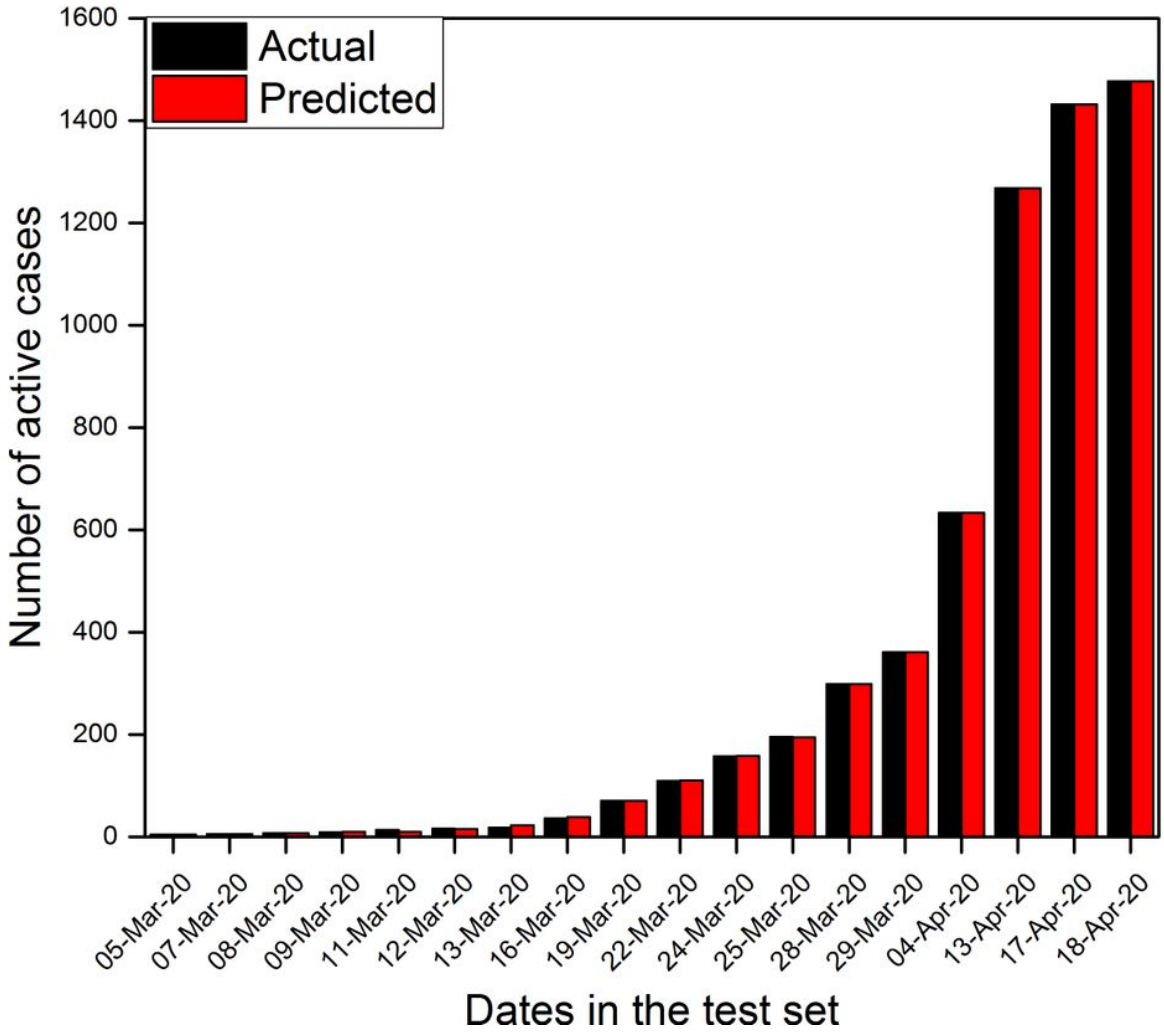

Figure 5

Actual vs predicted number of cases for Hungary data set from Model-2

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Hungarydata.xlsx
- COVID19TrackerforIndia.xlsx