Covid-19: Predicting affected patients using AI and vulnerability to environmental and demographic factors for India

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Abstract

After the COVID-2019 outbreak in Wuhan, one of the city in China in December, 2019 several countries started reporting of theconfirmed cases of COVID-19. India also reported its first case of COVID-on 30 January, 2020 in Thrissur, Kerala. This study uses artificial neural networks (ANN) to predict Covid-19 positive cases in different states of India detected till April 4, 2020. A feed forward back-propagated neural model with Levenberg-Marquardt (LM) algorithm was used. The model showed good results with correlation coefficient (R) as 0.87 during training and 0.78 during testing between COVID-19 cases detected in actual and predicted by model (ANN). This study uses climate and demographic variables such as date on which case detected, location where the case was detected, humidity, minimum temperature, maximum temperature of that region on the day of case detection, population density were considered to predict Covid-19 cases across different states. The sensitivity analysis of model revealed that humidity of the region was affecting Covid-19 positive cases by 19.41% while day of the year i.e. the day on which case was detected was contributing 18.39% while the demographic factor i.e. population density contributed 14.0%. The results therefore showed that humidity is one of the important environmental factors that were affecting the number of Covid-19 cases detected across India in different states from 30 January, '20 to 4 April, '20.

Keywords: *Covid-19, ANN, Sensitivity analysis, environment and demography, India*

1. Introduction

Coronavirus, a kind of mammalian avian virus, has affected thousands of population. In 2003 and 2015, large scale public health events; 'severe acute respiratory syndrome (SARS)' and the 'Middle East respiratory syndrome (MERS)' disrupted the health of people on a larger scale respectively. Again in the end of 2019, another coronavirus1, termed as 2019-nCoV, was discovered and transmitted in Wuhan City, Hubei Province, China which causes respiratory illness termed as Covid-19 (Zeng et al.,20, Unhale et al., 20). Respiratory transmission of the disease from one effected individual to other resulted in rapid spread of the disease and became an epidemic (Narin et al. 20). WHO declared COVID-19 as a Public Health Emergency of International Concern (PHEIC) on 30 January, '20 and as this disease was fast spreading and imperilling the health of large population, immediate action are needed to be taken (Binti et al., 2020). As Covid-19 has been declared as a pandemic, it is important to have tools which can help in prediction and analysis of Covd-19 cases in the country. With detection of the first case in India on 30 January, 20; the same day when WHO declared public health emergency for all countries, it is important to have models and tools that can help in better understanding of the spread of disease across the country with reference to demography and environmental factors on the scale of time. Knowing the complexity of the situation Artificial Intelligence (AI) based neural model can help in reviewing the existing situation and classifying areas based on many factors (Bhatnagar et al., 2018; Al-Najjar et al., 2020). The rapid uptake of AI for making increasingly complex decisions across different sectors (Bhatnagar and Poonia, 2020), health care challenges like an epidemic can also be integrated with such decision support systems (Shahid et al., 2019; Singh et al., 2020). Therefore, in this study artificial neural networks (ANN) have been used to predict the number of detected cases across different states and Union Territories till 4 April, 2020 with inclusion of demographic, environmental and time scale variables which will help in understanding the growth of disease (AL-Rousan et al., 2020). The paper is organized under four main sections viz. study area which included Indian states and UT's that had reported Covid-19 cases, methodology for constructing neural models for Covid-19 cases prediction, results and discussions highlighting the efficiency of neural model. The model constructed was used to highlight the significant parameters contributing to Covid-19 cases and finally the conclusions which stated the measures to be adopted for preventing Covid-19 spread.

2. Study area and methods

2.1 Study area

In this study, all the Indian states and Union territories which reported Covid-19 cases from 30 January, 2020 to 4 April, 2020 (Fig. 1) were included in the neural model

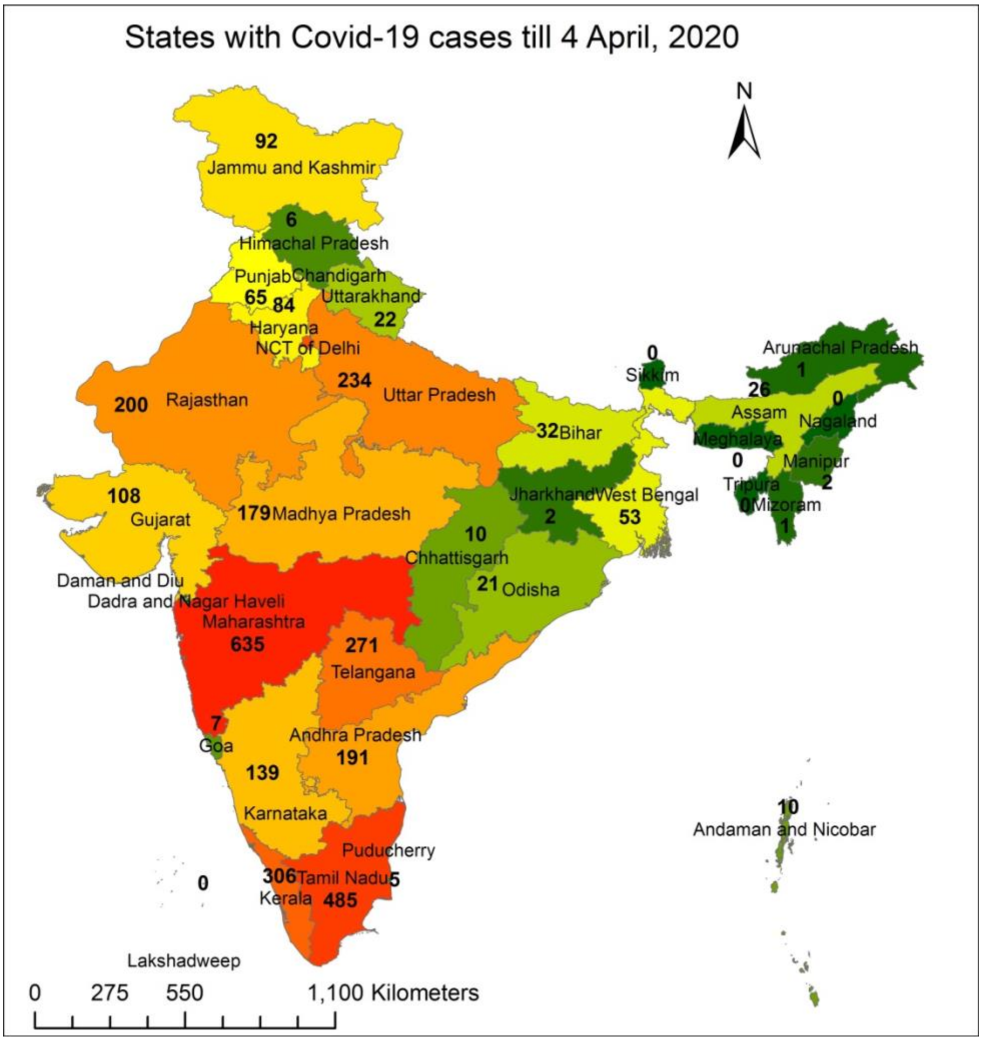
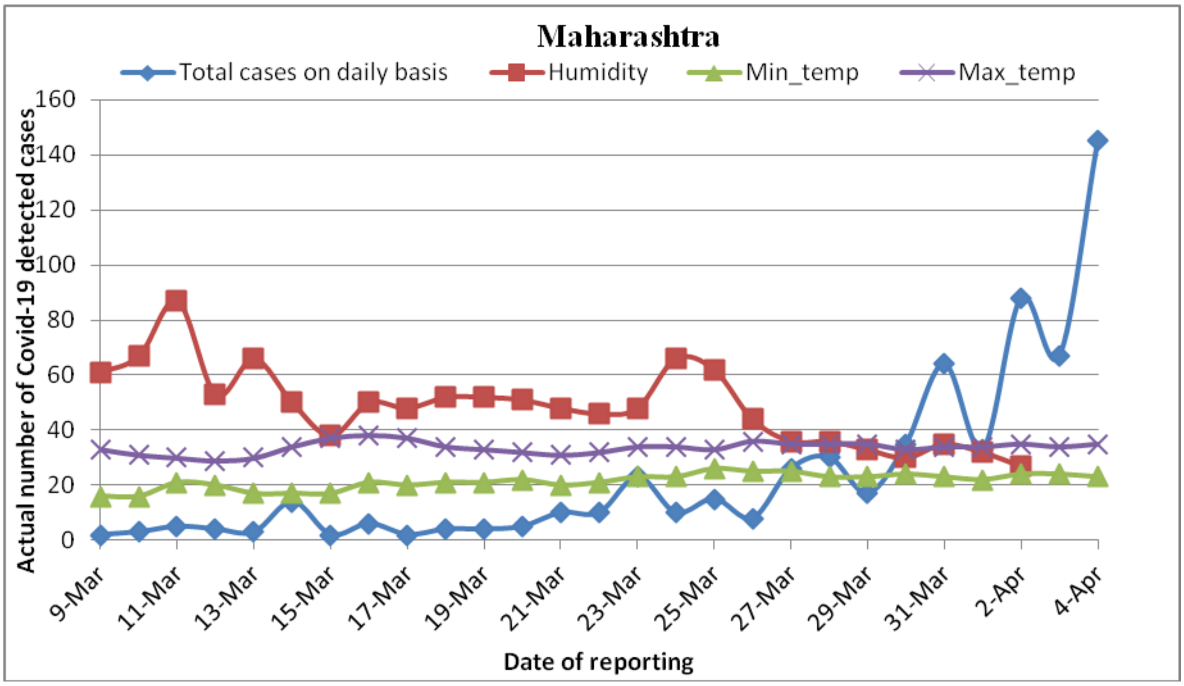


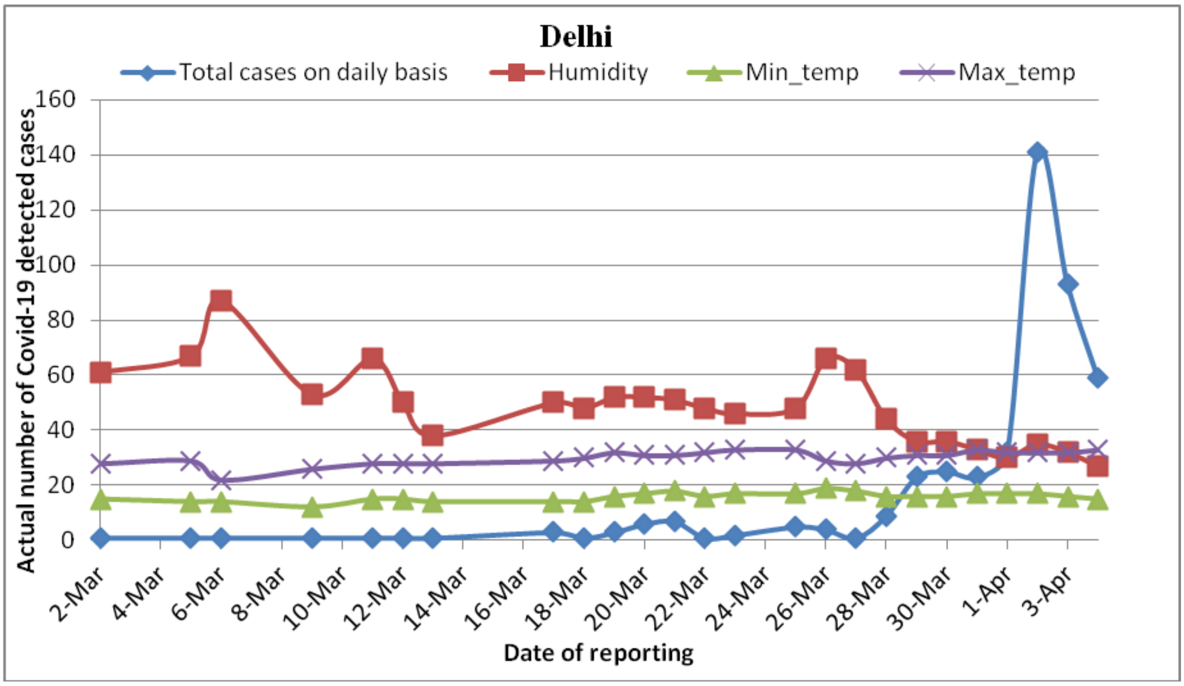
Fig.1. Sates with detected cases of Covid-19

From **Fig.1.**, it is clear that Maharashtra reported the highest number of cases and descending order for 10 most number of Covid-19 cases was Tamil Nadu>Delhi>Kerala>UttarPradesh>Rajasthan>AndhraPradesh>MadhyaPradesh>Karnataka>Gujarat. The Fig. 2 (a) to Fig. 2 (e) shows the variation of Covid-19 cases on the daily basis in different states.



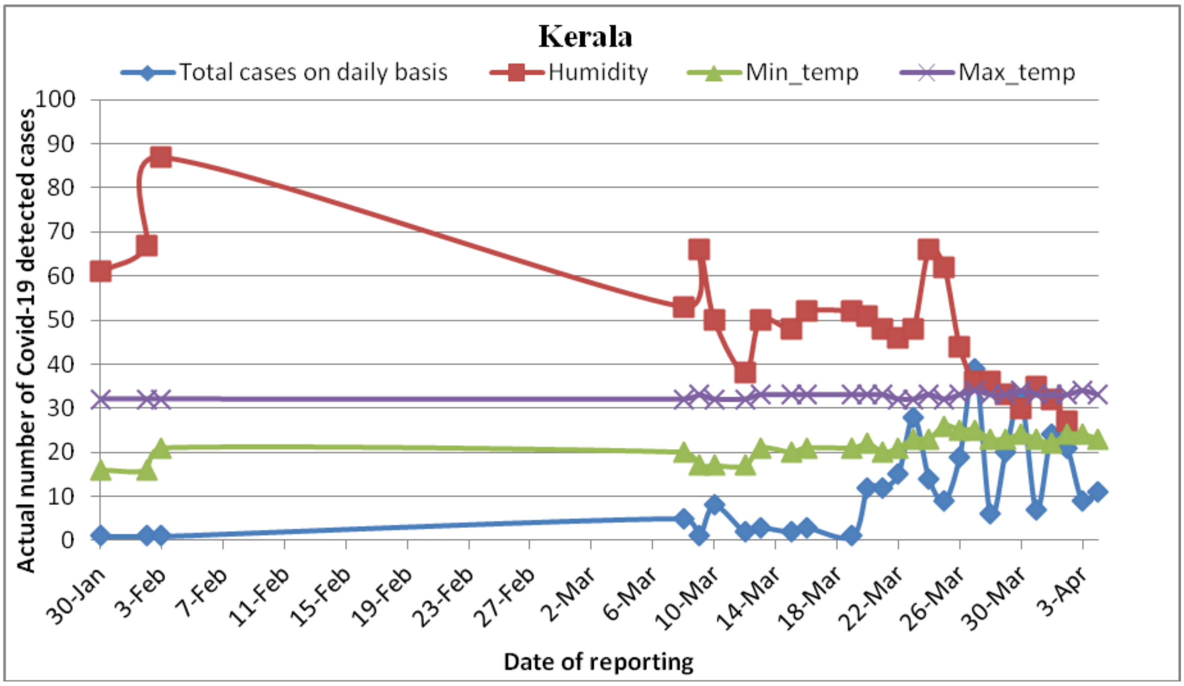
Maharashtra
Total cases on daily basis
Humidity
Min_temp
Max_temp
Actual number of Covid-19 detected cases
0
20
40
60
80
100
120
140
160
9-Mar
11-Mar
13-Mar
15-Mar
17-Mar
19-Mar
21-Mar
23-Mar
25-Mar
27-Mar
29-Mar
31-Mar
2-Apr
4-Apr
Date of reporting

(a)

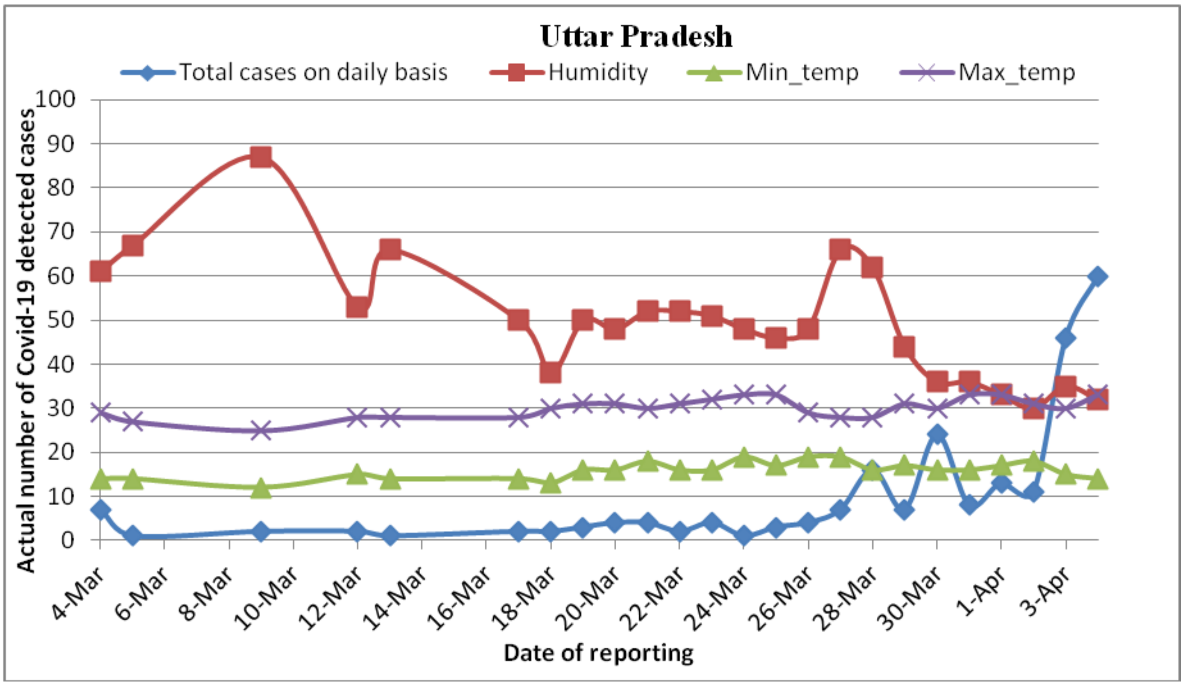


Delhi
Total cases on daily basis
Humidity
Min_temp
Max_temp
Actual number of Covid-19 detected cases
0
20
40
60
80
100
120
140
160
2-Mar
4-Mar
6-Mar
8-Mar
10-Mar
12-Mar
14-Mar
16-Mar
18-Mar
20-Mar
22-Mar
24-Mar
26-Mar
28-Mar
30-Mar
1-Apr
3-Apr
Date of reporting

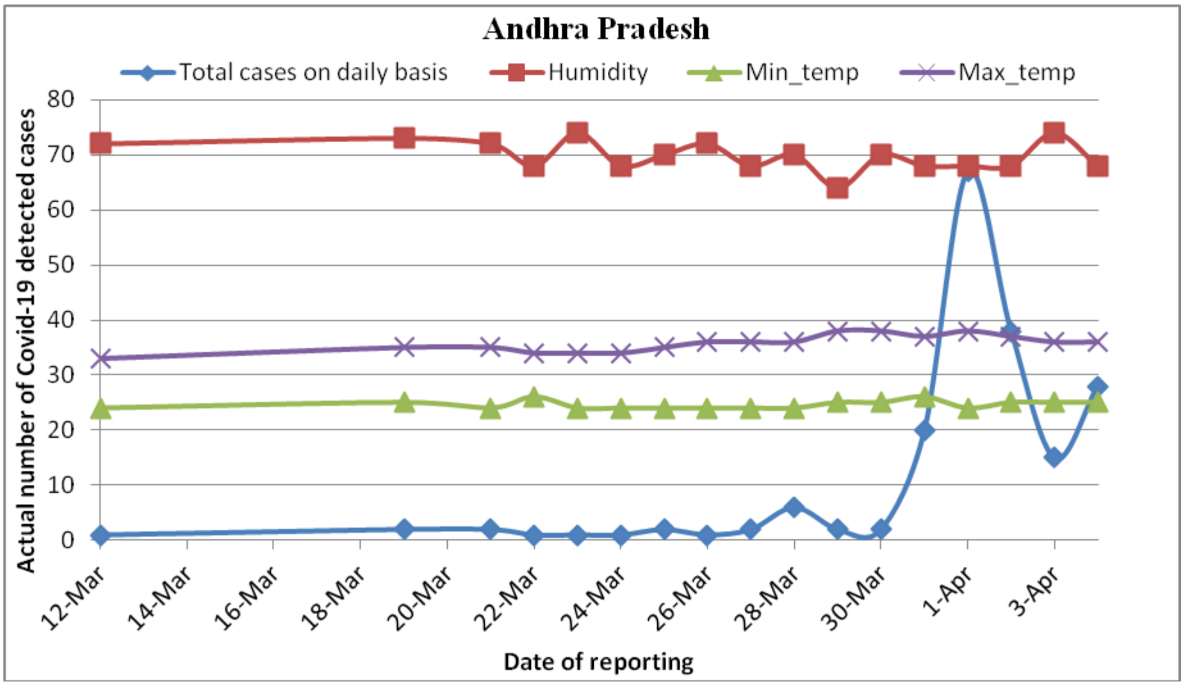
(b)


Kerala
Total cases on daily basis
Humidity
Min_temp
Max_temp
Actual number of Covid-19 detected cases
100
90
80
70
60
50
40
30
20
10
0
30-Jan
3-Feb
7-Feb
11-Feb
15-Feb
19-Feb
23-Feb
27-Feb
2-Mar
6-Mar
10-Mar
14-Mar
18-Mar
22-Mar
26-Mar
30-Mar
3-Apr
Date of reporting

(c)


Uttar Pradesh
Total cases on daily basis
Humidity
Min_temp
Max_temp
Actual number of Covid-19 detected cases
100
90
80
70
60
50
40
30
20
10
0
4-Mar
6-Mar
8-Mar
10-Mar
12-Mar
14-Mar
16-Mar
18-Mar
20-Mar
22-Mar
24-Mar
26-Mar
28-Mar
30-Mar
1-Apr
3-Apr
Date of reporting

(d)



(e)

Fig. 2. (a) to (e) Time series for Covid-19 detected cases in Indian states

2.2. Methodology

In this study, artificial neural networks had been used to predict the number of Covid-19 detected cases in different states of India. The artificial intelligence (AI) based model was used so as to exploit its capability of modeling and understanding of the complex non-linear relationships which exists in the environment and are difficult to be comprehended in simple mathematical terms.

2.2.1. Artificial Neural Network (ANN)

ANNs are data driven models whose working is analogous to working of the human brain. The human brain network is represented in ANN through architecture with several connections so as to optimize and solve a problem. The back propagated neural network was first proposed by the scientists led by Rumelhart and McClelland in 1986 (Li et al., 2020). The neural model can have variable number of inputs and outputs in input and output layer. In these models, the connections between each input and hidden layer and hidden layer to output layer is through a connection termed as weights. These weights are adjusted during training and once optimization is done, the derived topology is used for prediction. The neural models can be used for curve fitting, pattern recognition, clustering and time series analysis. These have been used in wide environmental problems like DO prediction (Ye at al., 2020), PM prediction and exposure (Shuang et al,2020, Photphanloet and Lipikorn, 2020) and many more.

2.2.1.1. Neural architecture

Artificial neural model has broadly two types of architecture –feedforward and feedback networks. Feedforward or multilayer model contains one input and one output layer with variable hidden layers in its architecture. The neurons in middle layer i.e. hidden layer are fixed by multiple trial and error instances so that the topology of neural model can be fixed. In this study, a feed-forward back-propagated neural model was constructed with Levenberg-Marquardt (LM) learning algorithm and number of neurons was varied in hidden layer to optimize the topology. LM method has been known to show the most efficient convergence while training with the back-propagation training process because it works by coordinating between first-order optimization method (steepest-descent method) with stable but slow convergence and second-order optimization method (Gauss-Newton Method) with the reverse characteristics (Chen et al, 2005).

While using the error back propagation (EBP) algorithm, F(w) which is the performance index needs to be minimized and is the sum of the squared errors between the target output and the network's simulated output. F(w) is defined as, Eq. (1) and Eq. (2).

$$F(w) = e^T e \tag{1}$$

where, **w** = [w_1, w_2,...............w_N] represents all the weights in network.

e = error vector containing the error for whole training examples.

When LM is used for the training then the weights increment is done as follows:

$$\Delta w = \frac{1}{[J^T J + \mu I]} J^T + J^T e \qquad (2)$$

where, J = Jacobian Matrix

μ = Learning rate

2.2.1.2. Data for neural model

For this study, the data of detected Covid-19 patients was taken from the Ministry of Health and Family Welfare, Government of India website and John Hopkins University Coronavirus Resource Center repository (John Hopkins, 2020). The log of daily reported cases from different States and Union Territories (UT's) were used to prepare chronological series and was also taken from https://www.kaggle.com/datasets website. The data of different state's relative humidity and minimum and maximum temperature was taken from India Meteorological Department and also from Global Forecast System Web service. The population density data for different states was from Census of India, 2011. For capturing the geography into the model the latitudes and longitudes of states were used. The total data consisted of 367 points with 7 inputs and 1 output. The data was randomly divided for training, validation and testing of neural model. The statistics for ten most number of states is shown in Table 1.

Table 1 Statistical Parameters for Environmental Variables for the states with the most number of cases till 4 April, 2020

Variable	States	Relative Humidity (%)	Minimum Temperature (°C)	Maximum Temperature (°C)	Total Cases on daily basis
Parameter	Maharashtra				
Min		19.00	16.00	29.00	2
Max		86.00	26.00	38.00	145
Average		50.07	21.41	33.63	24
SD		23.02	2.77	2.16	32
CV		45.97	12.92	6.43	137
Correlation		0.02	0.42	0.22	1
	Tamil Nadu				
Min		41.00	23.00	32.00	1
Max		65.00	26.00	37.00	110
Average		54.28	24.61	34.44	27
SD		5.84	0.83	1.01	37
CV		10.76	3.36	2.94	137
Correlation		-0.39	-0.03	0.70	1
	Delhi				
Min		27.00	12.00	22.00	1
Max		87.00	19.00	33.00	141
Average		48.72	15.80	30.04	18
SD		13.83	1.57	2.55	33
CV		28.38	9.97	8.50	185
Correlation		-0.54	0.19	0.39	1
	Kerala				

Min		42.00	23.00	32.00	1
Max		62.00	28.00	34.00	39
Average		55.07	26.00	32.78	11
SD		5.35	1.09	0.63	10
CV		9.71	4.19	1.92	90
Correlation		0.24	0.24	0.45	1
	Uttar Pradesh				
Min		14.00	12.00	25.00	1
Max		81.00	19.00	33.00	60
Average		34.75	15.88	30.08	10
SD		15.76	1.88	2.14	14
CV		45.35	11.83	7.11	146
Correlation		-0.30	-0.13	0.26	1
	Rajasthan				
Min		19.00	15.00	25.00	1
Max		76.00	22.00	35.00	46
Average		39.24	18.76	31.43	10
SD		14.04	1.87	3.00	11
CV		35.79	9.99	9.55	114
Correlation		-0.48	0.18	0.50	1
	Andhra Pradesh				
Min		64.00	24.00	33.00	1

Max		74.00	26.00	38.00	67
Average		25.00	24.59	35.76	11
SD		0.00	0.69	1.48	18
CV		0.00	2.81	4.13	157
Correlation		-0.27	0.08	0.52	1
	Madhya Pradesh				
Min		17.00	17.00	25.00	1
Max		72.00	22.00	36.00	47
Average		28.77	19.92	34.15	14
SD		14.58	1.59	2.96	13
CV		50.69	7.99	8.66	94
Correlation		-0.30	0.10	0.30	1
	Karnataka				
Min		15.00	19.00	33.00	1
Max		51.00	24.00	36.00	17
Average		27.38	21.00	34.71	7
SD		9.39	1.35	0.98	5
CV		34.31	6.41	2.83	71
Correlation		-0.43	-0.01	0.36	1
	Gujarat				
Min		12.00	19.00	31.00	1
Max		57.00	25.00	39.00	13
Average		24.94	21.59	36.29	6

SD		11.14	1.57	2.19	4
CV		44.66	7.29	6.03	56
Correlation		-0.19	-0.03	0.25	1

From Table 1, it was clear that across different states, different environmental variables were differently related to the number of Covid-19 cases and hence for India as a whole based on traditional statistical analysis none of the environment variable can be attributed to the number of cases and hence ANN was used to understand the effect across the country to understand about these variables.

2.2.1.3. Input and Output for neural model

The total inputs taken were 7 which include demographic, environmental and time variable. The inputs selected are given in Table 2 and were selected so as to understand the effect of environmental factors like Relative Humidity (%), Maximum temperature (°C) and Minimum temperature (°C) on the number of Covid-19 patients daily across India from 30 January, 20 to 4 April, 20 along with demographic factors like location (latitude and longitude) and population density. The environmental was of importance as from January to April in India different states experience different temperature and weather. The statistical parameters for environmental and demographic parameters are represented in Table 3.

Table 2 Time, demographic and environmental variables for the study

	Time	Demographic	Environmental

Inputs	Date on which case was detected	Latitude and Longitude, Population density	Relative Humidity, Maximum temperature Minimum temperature
Output	Total Covid-19 detected cases in the different States and UT's		

Table 3 Statistical Parameters for Environmental and Demographic Inputs and Output for whole Indian dataset till 4 April, 2020

Variable	**Population density (per km^2)**	**Relative Humidity (%)**	**Minimum Temperature (°C)**	**Maximum Temperature (°C)**	**Total Cases at different locations on daily basis**
Parameter					
Min	17.00	12.00	-4.00	11.00	1.00
Max	11320.00	91.00	28.00	39.00	145.00
Average	1429.23	45.02	19.74	32.24	9.98
SD	3016.77	17.21	4.62	4.17	18.45
CV	211.08	38.23	23.38	12.93	184.77

The neural architecture with combination of inputs and outputs used for predicting Covid-19 cases is shown in Fig.3.

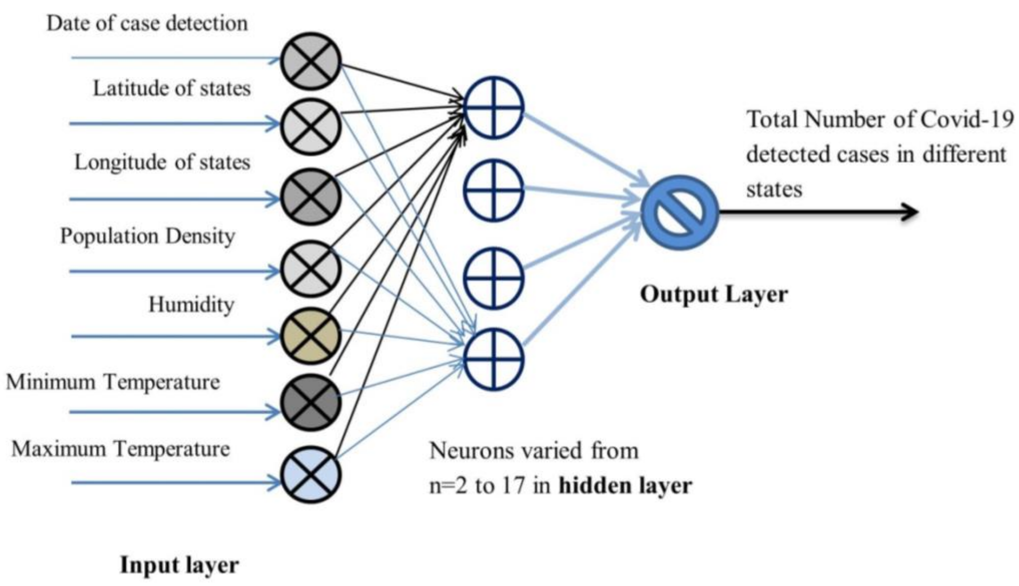


Fig.3. Neural Architecture used in the study

2.2.1.4 Training, testing, validation and activation function

After preparing the matrix of inputs as [367,7] and output matrix of [367,1], 70% (257 samples) data was randomly divided for training, 15% (55 samples) for validation and 15% (55 samples) for testing. The training of neural network was done to optimize the connections i.e. weights and biases, to achieve an optimized architecture which can be used for testing. The supervised training was done in the study with combinations of inputs and output. The testing of neural model was done on unseen data i.e. only inputs are given to the network, to know the model capability for prediction of results.

In the topology of neural networks, inputs are made to pass through activation function, tan-sigmoid was used between input and hidden layer and linear transfer function between hidden layer and output layer. To achieve optimal neural model, these functions can be changed and different combination of activation and transfer function can be used. The hyberbolic tangent sigmoid function is a non-linear activation function and output value is between -1 to

1. These functions are sometimes continuous and differentiable or can be piece-wise continuous and differentiable (ReLU-Rectified Linear Unit).

3. Results and Discussions

3.1. Derived architecture of neural model

In the present study, for predicting the Covid-19 cases in different states and UT's of India, the neural model was constructed and was optimized by fixing the number of neurons in hidden layer. Therefore, for this task neurons were varied from 2 to 17 in hidden layer and root mean square error (RMSE) during training and testing was calculated. The instance at which, the RMSE during training was minimum and correlation (R) values for testing samples was high, the number of neurons in hidden layer were selected. Therefore, for this study the optimized neurons selected for hidden layer were 10 and the final topology obtained was 7-10-1. The performance of architecturally selected neural model with variation in neurons for hidden layer is shown in Fig.4.

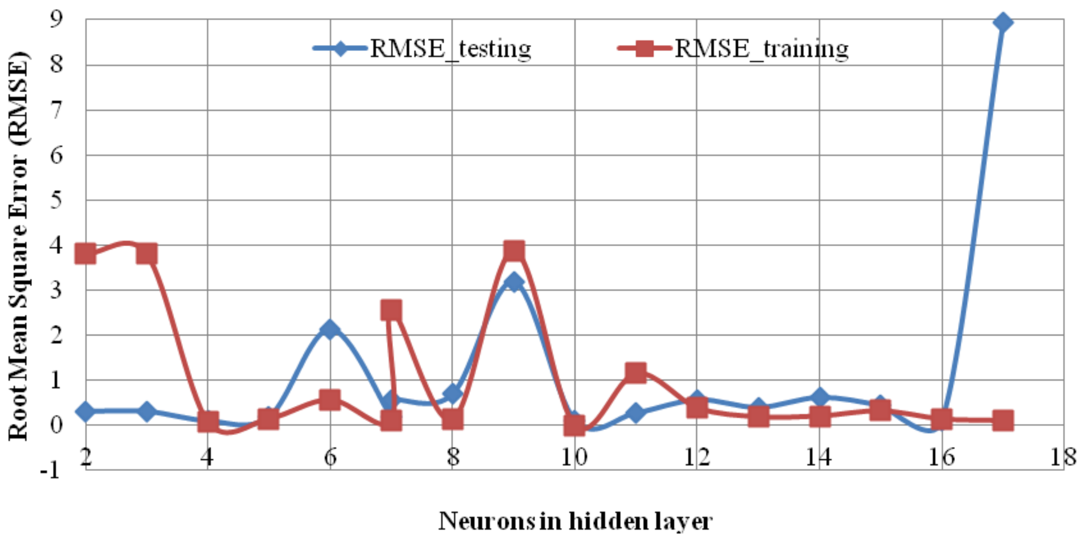


Fig.4. RMSE for different number of neurons in hidden layer

3.2. Performance of model

For assessing the performance of optimized neural model (i) 'Mean absolute error (MAE)',(ii) 'Root Mean Square Error(RMSE)', iii) 'Correlation factor (CF)' (iv) 'co-efficient of correlation (r)' and (v) 'Co-efficient of efficiency (E)' were calculated to estimate and assess the performance of model on trained data and tested data . The values of MAE, RMSE, CF, r and E obtained for training and testing part are given in Table 4 and were calculated using equations (3) to (7)

$$RMSE = \left[\frac{\sum_{i=1}^{N}(C_m - C_p)^2}{N}\right]^{1/2} \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(C_m - C_p)| \tag{4}$$

$$CF = 1 - \left[\frac{\sum_{i=1}^{N}(C_m - C_p)^2}{\sum_{i=1}^{N}(C_m)^2}\right] \tag{5}$$

$$r = \frac{\sum_{i=1}^{N}(C_p - \overline{C_p})(C_m - \overline{C_m})}{\sqrt{\sum_{i=1}^{N}(C_p - \overline{C_p})^2}\sqrt{\sum_{i=1}^{N}(C_m - \overline{C_m})^2}} \tag{6}$$

$$E = 1 - \frac{\sum_{i=1}^{N}(C_m - C_p)^2}{\sum_{i=1}^{N}(C_m - \overline{C_p})^2} \tag{7}$$

Where, C_m = actual Covid-19 cases, C_p = predicted Covid-19 cases, $\overline{C_p}$ = mean of predicted cases and $\overline{C_m}$ = mean of actual cases.

Table 4 Performance of neural models for predicting Covid-19 cases

	MAE	**RMSE**	**CF**	**r**	**E**
BPNN					
Training	5.4534	6.77×10^{-04}	0.8218	0.8736	0.9999
Validation	8.5817	1.085	0.6346	0.7405	0.9986

Testing	5.7308	0.1134	0.6874	0.7861	0.9999

3.2.1. Performance during training

The optimized neural model was trained with 70% of total data, i.e. 257 randomly selected data points and performance of model is shown in Fig.5.

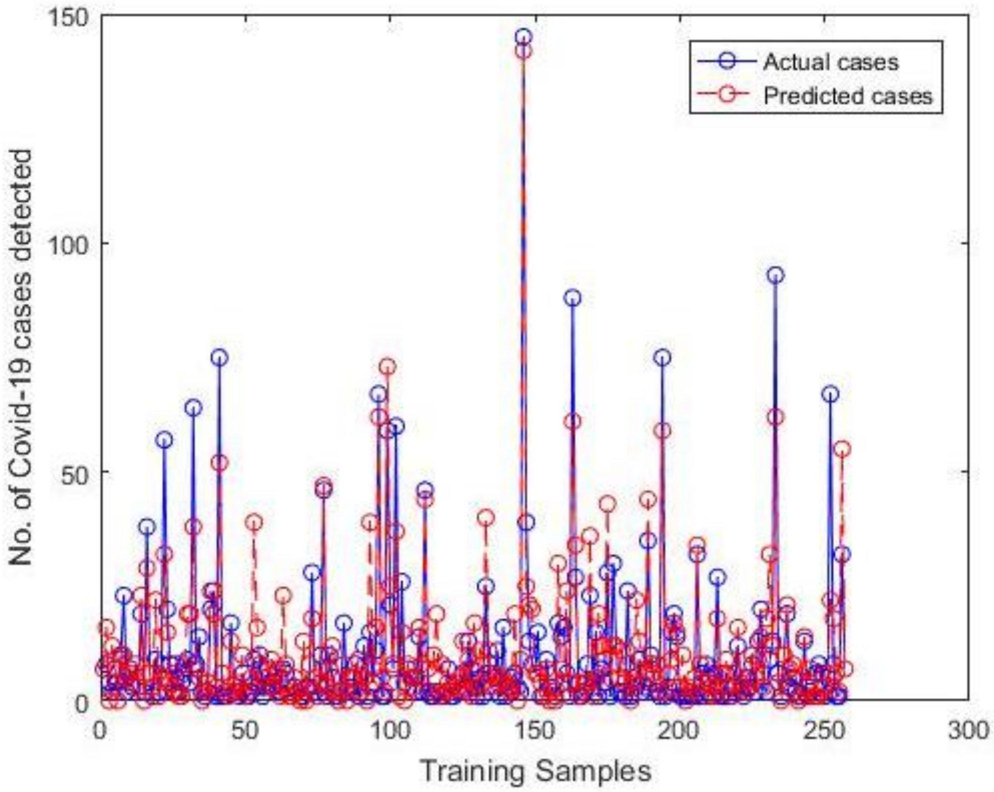


Fig.5. Performance of model during training

3.2.2. Performance during testing

The model was tested on 15% of data and on total 55 data points selected randomly and behavior of the model during testing is shown in Fig. 6.

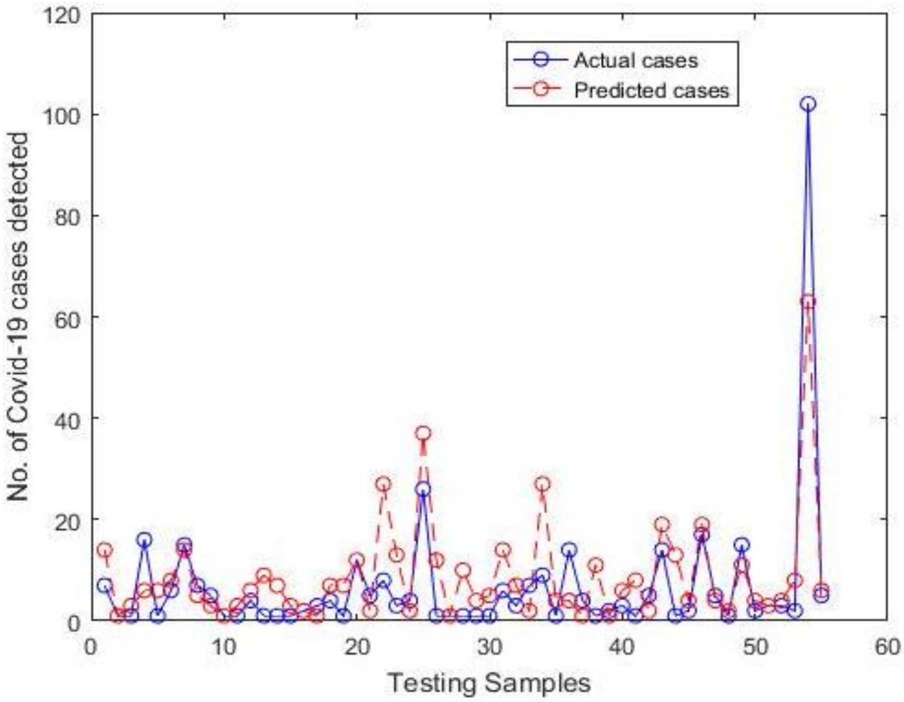


Fig.6. Performance of the model during testing

From Fig.5 and Fig.6 it could be inferred that the neural model was able to predict the number of Covid-19 cases closely on randomly selected samples. These types of models can be used where demographic and environmental factors need to be studied with greater variability as simple statistical models could not capture the dynamics of processes.

3.3. Sensitivity analysis

To bring out the effect of individual input variable which were grouped under demographic, environmental and time for the number of Covid-19 cases in different states across India, the sensitivity analysis was done as per Garson in 1991. The updated final weights of optimized neural model with topology of 7-10-1 were used to calculate the relative effect of each variable over output.

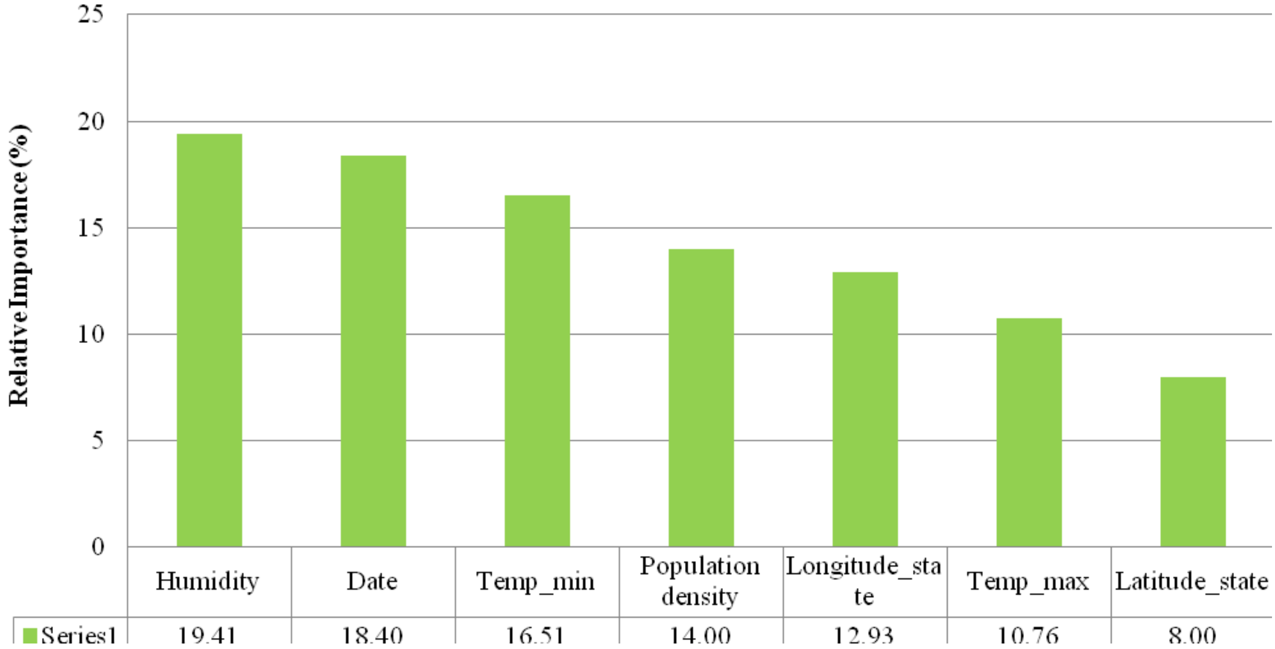


Fig.7. Relative Importance of each variable

From, Fig. 7 it is clear that humidity was one of the environmental factor which was contributing to the number of Covid-19 cases in India from 30 January, 20 to 4 April, 20. Also minimum temperature was contributing more to the number of Covid-19 cases when compared to maximum temperature which means if in coming days, minimum temperature of individual state's decreases and humidity increases, then the number of Covid-19 cases may increase but since it is highly contagion virus, solely environmental factors cannot be leveraged upon for limiting the Covid0-19 cases. It is also highlighted that population density i.e. the demographic factor was also one of the variables that is contributing to Covid-19 cases and hence government guidelines on social distancing and other hygienic norms should be followed to reduce this effect.

4. Conclusions

In this study, an epidemic Covid-19 which started from Wuhan, China and now (during writing of this paper) prevailing across the world was discussed in Indian context since the day of its first reported case. In the study environmental and demographic factors were used to understand the effect of these on the number of Covid-19 cases in different states and UT's of India. The sensitivity analysis of environmental and demographic parameters showed that humidity and minimum temperature has larger contribution to number of cases as compared to other parameters used in the study. In such case, Maharashtra with rising humidity and also due to influence of other parameters, in coming days there might be chances of increased number of cases. Other state like Delhi and Uttar Pradesh which experiences summers from March, public during this time should avoid the use of air conditioner at very low temperature as minimum temperature in the study showed 16.51% effect compared to 10.76% of maximum temperature. Population density of Indian states was also one of the contributing factors and hence government guidelines regarding social distancing and personal hygiene should be followed to reduce this effect. Though, pandemic like situation cannot be only attributed to only environmental and demographic factors because behavior of virus at different conditions is different and its effect on human is a function of many complexities of human body itself. Therefore, public should avoid minimum temperatures and also follow social distancing and hygiene to reduce the effect. The study was till 4 April, 2020 when total Covid-19 cases were 3393 in India and hence more extended analysis of this pandemic combined with clinical variables using AI based model can be done to understand more of this virus and situation across country.

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