Probable Forecasting of Epidemic COVID-19 in Using COCUDE Model

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Abstract

INTRODUCTION: The world has been struck due to the dangerous human threat called Corona Virus Disease 2019. This research work proposes a methodology to encounter the future infection rate, curing rate, and decease rate.

OBJECTIVES: This uses the artificial intelligence algorithm to design and develop the proposed confirmed, cured, deceased (COCUDE) model.

METHODS: A nonlinear auto-regressive model has been developed with several iterations to design the proposed COCUDE model. The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Correlated Akaike Information criterion (AICc) metrics are analyzed to check the stationary and quality for the proposed COCUDE model.

RESULTS: The prediction results are evaluated by the performance error metrics such as mean square error (MSE) and root mean square error (RMSE), in which the errors are lower for the proposed model. Thus, the prediction results indicate the proposed COCUDE model might accurately predict future COVID-19 infection rates with reduced errors.

CONCLUSION: It might support the corresponding authorities to take precautious action on the required necessities for the medical and clinical infrastructures and equipment.

Keywords: COVID-19, future prediction, infection rate, COCUDE model, decease rate

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1. Introduction

The year 2020 makes a historical entry to the world not because of its fancy number but because of the major human infectious threat called the novel Corona Virus Disease 2019 (COVID-19). Even though the COVID-19 virus was found during late November 2019 at the Chinese city Wuhan in the Hubei province, it became a deadly spreading disease throughout the world in 2020 [1, 2]. Still May 2020, no proven medicine or vaccine was found to break the transmission of the infections from the COVID-19 virus. However, few precautious potential therapeutic treatments are being given to infected patients to improve their immune system.

Apart from these, the source wherefrom coronavirus came is not yet scientifically proven. Although few reported that the source of COVID-19 infection is coming from wild animals, especially from bats and pangolin, but it is not yet confirmed. Further, the COVID-19 virus spreads even with the infected human's physical touch to humans, from their used objects, and places. Based on various reports from across the globe, the incubation period is 3-14 days for the COVID-19 virus [2, 3].

The COVID-19 virus is spreading rapidly, and its infection severity to humans as well as to pet animals is very much higher. In countries throughout the world, the mortality rate due to the COVID-19 virus infection is climbing dangerously. The major spreading method of COVID-19 is from the droplets of coughing, sneezing, and talking of the infected humans to the normal uninfected human. Likewise, the novel coronavirus is being widely spread by humans to human contact.

As the infected humans are moving to the various cities and countries around the world, the spreading is rising at an increasing pace. In such a way, from the Hubei province of Wuhan city in China, it is transmitted to the global public



and makes the global pandemic situation. A much needed instantaneous action should be taken to reduce the speed of the spread of COVID-19 worldwide [2, 3, 4].

Typically, being a few days to a week, the COVID-19 infected human would not have any infection symptoms. During or after a week, the COVID-19 symptoms start from mild cough, fever with respiratory problems, and pneumonia symptoms. Based on the individual's immune system, COVID-19 infections affect the normal functions of humans' vital organs and might lead to death. Most of the COVID-19 infected human is admitted to the hospital with mild respiratory problems. Commonly, people with pre-existing chronic disease, weak immune system, and old age humans are targeted for the COVID-19 infection. As well as the decease rate from those patients is much higher than other patients [2, 5].

2. Related Work

Owing to the outbreak of the COVID-19 virus infection to the global public, during 11th March 2020, the world health organization (WHO) had declared it as a pandemic. Even several countries had implemented strict rules to secure public health, namely, lockdown, quarantine, social distancing, etc. But the virus infection and decease rate are marginally higher. Various virology, medical, and clinical research developments are going on around the world. Besides, at this time, much essential research should be concentrated on the prediction of the COVID-19 infections among the global public [1, 2].

As the number of infected cases increases, the essential infrastructures, medical facilities, innovative technologies, diagnostic models, communications, informatics techniques, and advanced equipment required for the future days must be made available. It includes the required number of beds, medicines, ventilation, testing kits for the patients and PPE kit, gloves, N-95 masks, and other safety equipment for the physicians and caretakers. An organized plan should be prepared for developing such medical materials and other essentials. It might support the clinical industry to properly and calmly serve the infected patients [2, 6, 7].

Ghosh et al. (2020) had developed logistic and exponential models to forecast the number of infections for 30 days for a few Indian states. The daily infection rate was considered in this article [22] in order to measure the infection rate. The R-square value for each state was analyzed using logistic and exponential models. A prognostic system modeling technique was developed to forecast the COVID-19 spreading in India by Rafiq et al. (2020). The proposed model was analyzed with the historical data, and the spreading for 30-days has been forecasted for the ten most affected states of India. It was shown that this model predicts the spreading with high accuracy [23].

Therefore, to forecast the spreads and risk of infections, an appropriate optimal methodology and mathematical modeling is much needed to challenge and control the spreads of the coronavirus and safeguard public health. Such that, this research work proposes a confirmed, cured, deceased (COCUDE) model to predict the future COVID-19 infection rate for the public in the state of Tamilnadu, India [5].

As the origin of COVID-19 is China, the infection to humans in India must be spread through the infected foreign traveler [8, 9]. Specifically, as this research focuses on the Tamilnadu state of India, the possibility the people are being infected by the COVID-19 transmission from travelers from outside the state. Apparently, they are spreading the infection to other regions of the state [5]. Therefore, this research focuses on predicting the number of COVID-19 infected, cured, and decease cases using the COCUDE model based on the dataset available from the Ministry of Health, Tamil Nadu, India.

3. Related Work

The proposed COCUDE model and its algorithm are extensively explained in this section to predict the future infection rates of COVID-19.

In epidemiology, the mathematical models are utilized for the extensive analysis of infectious diseases. The welldefined epidemic mathematical model gives the analysis of qualitative as well as quantitative information of the infectious diseases. Further, the vital importance of the epidemic mathematical model is the probable estimation of spread and decease rate of infectious diseases. The epidemic mathematical model also strongly influences hospital emergency planning and risk management, infection control measures, health-economic related aspects, and decision-making [10]. Typically, the epidemic mathematical model facilitates the estimations and predictions of infectious diseases by using complex computational modeling techniques [11, 12].

3.1. COCUDE Model

The proposed COCUDE uses the artificial intelligencebased machine learning methodology in order to predict future COVID-19 scenario. Artificial intelligence is a technique intended to mimic the human brain by artificiality connected neuron nodes with several computations in order to arrive a solution or to make the decision for the problem. Machine learning is a kind of artificial neural network. Typically, machine learning is a self-adaptive learning algorithm, in which it increasingly analyses and processes the given problem or dataset and facilitates the solution based on its experience [25]. Such that, the machine learning incorporates multi-level neurons of an artificial neural network algorithm for its computations.

In the proposed methodology, the machine learning algorithm utilizes the aspects of the SEIR (Susceptible-Exposed-Infected-Recovered) model and decease rate in





Fig. 1. Block diagram of the proposed COCUDE model

order to assess and estimate the epidemic trends [13, 14, 15]. The proposed model is developed considering 1) the COVID-19 infection spreads from an infected human to other humans, 2) normal deaths are not considered for the decease rate prediction, 3) the COVID-19 dataset for the proposed methodology is retrieved from the Department of Health and Family Welfare, Government of Tamil Nadu, 4) the training dataset for COCUDE model is taken from the date of the first infection in the state of Tamilnadu, India to 20th June 2020 [16, 17].

3.2 COCUDE Model Formulation

In this proposed COCUDE model, a nonlinear artificial neural network NARX (Nonlinear Auto-Regressive model with exogenous input) model is employed to predict each CO, CU, and DE models. The NARX neural network is a kind of dynamic recurrent neural network, in which the NARX is working with multi feedback connection of hidden layers for predictions. The NARX neural network model has been applied in several prediction applications of nonlinear processes. The following NARX equation is employed for the proposed COCUDE model.

Where CO denotes the confirmed model, CU denotes the cured model, DE represents the deceased model, 't' is the time with respect to inputs, 'n' is the number of training samples, and 'm' is the number of delays. The equation (1) is employed for future prediction confirmed cases (CO)

based on the cured cases (CU) and deceased (DE) cases. In order to train the CO model, the CU and DE models are given as the input to the NARX model. As per the given equation (2), the future prediction of cured cases (CU) is supported by the inputs of confirmed (CO) cases and deceased cases (DE). Such that, the CU model gives future predictions based on the CO and DE model.

Similarly, equation (3) is adopted for future prediction of deceased cases (CO) based on the confirmed cases (CO) and cured (CU) cases. In order to train the DE model, the CO and CU models are given as the input to the NARX model. So that, the COCUDE model is supported by the NARX neural network algorithm for the future prediction of the COVID-19 confirmed cases, cured cases, and deceased cases.

Figure.1 depicts the proposed COCUDE model using the machine learning algorithm. In the proposed COCUDE model, the metadata is collected from the repository [16, 17]. Then, the outliers and missing data are compromised by pre-processing imputation using mean/median values. The pre-processed dataset has been taken for the training process using the machine learning algorithm. The COCUDE model then predicts the future prediction using the training dataset and validates the predicted dataset with the testing dataset.

3.3 Performance metrics

To estimate the stationary of the predicted dataset, it assessed with the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Correlated Akaike Information criterion (AICc) metrics [18].

The lowest values of the AIC and BIC metrics correspond to the better stationary model. Further, the predicted COVID-19 dataset has been evaluated with the performance error metrics for the accuracy evaluation. The performance error metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean



Absolute Error (MAE) are computed for the prediction results [19, 20, 21,24].

Mean Squared Error (MSE): The MSE is calculated using the equation (4). It is the average of the squared difference between predicted speed results (P_i) and targets (T_i) [24].

MSE(T, P) =
$$\frac{1}{n} \sum_{i=1}^{n} (T_i - P_i)^2$$
(4)

Root Mean Squared Error (RMSE): The RMSE is computed using the equation (5). It is the square root of the average of squared differences between predicted and actual mobility values [24].

RMSE (T, P) =
$$\sqrt{\frac{1}{n} \sum_{i=1}^{n} (T_i - P_i)^2}$$
(5)

Mean Absolute Error (MAE): The MAE is computed using the equation (6). It is the average of the absolute differences between prediction and actual observation [24].

MAE (T, P) =
$$\frac{1}{n} \sum_{i=1}^{n} |T_i - P_i|$$
(6)

Moreover, the predicted future COVID-19 dataset has been analyzed with precision rate. The proposed COCUDE model took the three types of outcomes of COVID-19, such as infection confirmed cases, cured/recovered cases, and decease cases for predicting corresponding future rates.

4. Performance Evaluation and Discussions

The proposed COCUDE model is trained, tested, validated, and its evaluation results are summarized in this section.

4.1 Results Analysis of CO model

Table.1 presents the results of the AIC, BIC, and AICc metrics. The COCUDE model has been iterated ten items on each neuron; among that, the lowest AIC iterations are finalized for each neuron. The number neuron 6 has the lowest AIC values. Such that the neuron 6 has the lowest AIC, BIC, and AICc values as 1380.5, 1385.5, and 1380.6, respectively. Its values are the lowest as compared to other neuron's stationary metrics. Therefore its corresponding neuron 6's dataset has been taken for the future prediction of the CO model.

Table.2 gives the performance error metrics such as MSE, RMSE, and MAE metrics resulting from the CO model. Similar to the stationary (AIC, BIC, and AICc) evaluation results, the neuron 6 has the lowest error values as compared to the results of other neurons. Neuron 6 produces the lowest errors as 1.2054, 1.0979, and 1.0693 for the MSE, RMSE, and MAE metrics, respectively, for the CO model.

Figure 2 depicts the results of the proposed CO model for the future 90 days from 30th July 2020. The results indicate the prediction of future infections in the state of Tamilnadu, India. The predicted results are validated with the actual official dataset, and the CO model results had produced lower error values, as shown in Table.2. Since the MSE of the CO model is lower (1.2054) in Figure.2, we can see that the actual and prediction cases are more or less similar as the overlapped line. In Figure.2, from 176th day to 205th day, the predicted cases majorly match with the actual cases. Based on the obtained results using the proposed CO model, we can say that most probably, the actual and prediction cases are similar.

4.2 Results Analysis of CU model

Table.3 presents the stationary metrics results such as AIC, BIC, and AICc for the CU model. The CU model has been iterated ten items on each neuron; among that the lowest AIC iterations are finalized for each neuron. The number

Criterion/ Neurons	AIC	BIC	AICc
2	1469.6	1477.6	1469.9
4	1483	1490.5	1483.3
6	1380. 5	1385.5	1380.6
8	1423.2	1425.7	1423.3
10	1425.5	1430.5	1425.6
12	1580.2	1585.3	1580.4
14	1539.7	1544.7	1539.8
16	1520.2	1525.2	1520.3
18	1492.1	1497.2	1492.3
20	1450.5	1455.5	1450.6

Table.1 Results of AIC, BIC, and AICc Metrics for CO model

Table.2 Performance Error Metrics resulted by CO model

Metrics/			
Neurons	MSE	RMSE	MAE
2	3.0678	1.7515	1.6886
4	1.5083	1.2281	1.0957
6	1.2054	1.0979	1.0693
8	1.6661	1.2908	1.2377
10	1.5575	2.4259	2.4088
12	3.518	1.8756	1.8016
14	2.9307	1.7119	1.6932
16	6.4948	2.5485	2.4928
18	4.6072	2.1464	1.9652
20	2.3903	1.546	1.4190

neuron 6 has the lowest AIC values. Such that the neuron



6 has the lowest AIC, BIC, and AICc values as 1479.258, 1486.791, and 1479.534, respectively. Its values are the lowest as compared to other neuron's stationary metrics. Therefore its corresponding neuron 6's dataset has been taken for the future prediction of the CU model.

can able see that the actual and prediction cases are more or less similar as the overlapped line. In Figure.3, from 188th day to 211th day, the predicted cases majorly match with the actual cases. Based on the obtained results using the proposed CU model, we can say that most probably, the



Fig.2. Future Predicted COVID-19 Curing rate by CO model

Table.4 gives the performance error metrics such as MSE, RMSE, and MAE metrics resulted from the CU model. The neuron 6 has the lowest error values compared to the results of other neurons, as similar to the neuron 6's lowest AIC, BIC, and AICc evaluation results. The neuron 6 produces the lowest errors as 1.1093, 1.0532, and 1.0322 for the MSE, RMSE, and MAE metrics, respectively for the CU model.

Figure 3 depicts the results of the proposed CU model for the future 90 days from 30th July 2020. The results indicate the prediction of future infections in the state of Tamilnadu, India. The predicted results are validated with the actual official dataset, and the CU model results had

Table.3 Results of	AIC,	BIC,	and	AICc	Metrics	for	CU
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	model	model					
Criterion/ Neurons	AIC	BIC	AICc				
2	1742.149	1749.682	1742.425				
4	1527.528	1535.061	1527.804				
6	1479.258	1486.791	1479.534				
8	1666.517	1674.049	1666.793				
10	1801.991	1809.524	1802.267				
12	1608.141	1615.673	1608.417				
14	1534.959	1542.492	1535.235				
16	1841.013	1848.546	1841.289				
18	1791.097	1798.63	1791.373				
20	1814.488	1822.021	1814.764				

produced lower error values, as shown in Table.4. Since the MSE of the CU model is lower (1.1093) in Figure.3, we

actual and prediction cases are similar.

4.3 Results Analysis of the DE model

Table.5 presents the stationary metrics results such as AIC, BIC, and AICc for the DE model. The DE model has been iterated ten items on each neuron; among that the lowest AIC iterations are finalized for each neuron. The number neuron 12 has the lowest AIC values. Such that the neuron 12 has the lowest AIC, BIC, and AICc values as 585.7667, 593.2993, and 586.0426, respectively. Its values are the

Metrics/			
Neurons	MSE	RMSE	MAE
2	6.7617	2.6003	2.5389
4	7.9903	2.8267	2.7624
6	1.1093	1.0532	1.0322
8	3.6793	1.9182	1.8653
10	6.7274	2.5937	2.639
12	1.1752	1.0841	1.0823
14	4.1006	2.0167	2.0038
16	3.3806	1.8386	1.7888
18	1.3845	1.1767	1.1232
20	3.6452	1.9092	1.8513

Table.4 Performance Error Metrics resulted by CU

lowest as compared to other neuron's stationary metrics.



Therefore its corresponding neuron 12's dataset has been taken for the future prediction of the DE model.





Fig. 3. Future Predicted COVID-19 Curing rate by CU model

Table.6 gives the performance error metrics such as MSE, RMSE, and MAE metrics resulted from the DE model. The neuron 12 has the lowest error values compared to the results of other neurons, as similar to the neuron 12's lowest AIC, BIC, and AICc evaluation results. The neuron 12 produces the lowest errors as 3.4151, 1.8480, and 1.7925 for the MSE, RMSE, and MAE metrics, respectively for the DE model.

Figure 4 depicts the results of the proposed DE model for the future 90 days from 30th July 2020. The results indicate the prediction of future infections in the state of Tamilnadu, India. The predicted results are validated with

Criterion/ Neurons	AIC	BIC	AICc
2	595.592	599.1246	594.8678
4	707.7984	712.8201	707.9347
6	743.8817	751.4143	744.1576
8	635.7356	643.2682	636.0114
10	727.1973	734.7299	727.4732
12	585.7667	593.2993	586.0426
14	714.9297	722.4622	715.2055
16	661.058	668.5906	661.3338
18	696.2258	703.7584	696.5016
20	687.5292	692.5509	687.6655

the actual official dataset, and the DE model results had

able see that the actual and prediction cases are more or less similar as the overlapped line. In Figure.4, during 197th day to 231th day, the predicted cases majorly match with the actual cases. Based on the obtained results using the proposed DE model, we can probably say that the actual and prediction cases are similar.

4.4 Recommendations and limitations of the COCUDE model

The future prediction results of the COVID-19 using the COCUDE model is analyzed by using Table.7 and Table.8.

Table.6 Performance Error Metrics resulted by DE model					
Metrics/Neurons	MSE	RMSE	MAE		
2	4.0340	2.0085	1.9684		
4	4.1325	2.0328	2.9889		
6	4.286	2.0702	2.147		
8	4.7965	2.1901	2.0969		
10	4.8489	2.2020	2.1658		
12	3.4151	1.8480	1.7925		
14	7.1387	2.6718	2.5672		
16	5.6801	2.3833	2.3125		
18	4.1346	2.0337	1.9865		
20	9.4947	3.0813	3.0175		



Table.7 summarizes the AIC, BIC, and AICc metrics for the COCUDE model. In Table.7, neuron six had given the lowest AIC, BIC, and AICc metrics as 1380. 5, 1385.5, and only. In the future, this work will be extended to evaluate for major infected states of India. Further, this work does not consider, re-infection of COVID-19 to the same



Fig. 4. Future Predicted COVID-19 Decease rate by DE model

1380.6 respectively for the CO model; for the CU model, its values are 1479.258, 1486.791, and 1479.534 respectively for neuron 6. Similarly, neuron 12 had given the lowest AIC, BIC, and AICc metrics as 585.7667, patients. The survivability factor after recovering from COVID-19 and few more influencing factors on the COVID-19 are not evaluated in this work.

Model	Criterion/Neurons	AIC	BIC	AICc
CO	6	1380. 5	1385.5	1380.6
CU	6	1479.258	1486.791	1479.534
DE	12	585.7667	593.2993	586.0426

Table 7 AIC BIC and AICc Metrics for COCUDE model

l able.8	Table.8 Performance Error Metrics resulted by COCUDE model					
Model	Metrics/Neurons	MSE	RMSE	MAE		
СО	6	1.2054	1.0979	1.0693		
CU	6	1.1093	1.0532	1.0322		
DE	12	3.4151	1.8480	1.7925		

593.2993, and 586.0426, respectively, for the DE model using the artificial neural network algorithm.

Table.8 summarizes the MSE, RMSE, and MAE metrics for the COCUDE model. In Table.7, neuron six had given the lowest MSE, RMSE, and MAE metrics as 1.2054, 1.0979, and 1.0693, respectively, for the CO model; for the CU model, its values are 1.1093, 1.0532, and 1.0322, respectively for the neuron 6. Similarly, the neuron 12 had given the lowest MSE, RMSE, and MAE metrics as 3.4151, 1.8480, and 1.7925, respectively, for the DE model using artificial neural network algorithm.

However, the proposed COCUDE prediction model is applied and evaluated for the state of Tamilnadu in India

5. Conclusion

This research work focused on predicting the future COVID-19 population in the state of Tamilnadu, India, using artificial neural network-based machine learning algorithms. The proposed COCUDE model has been trained and testing using the given official dataset. The predicted dataset of the presented COCUDE model has been tested, and it gives the lowest error metric values. The presented CO and CU model had produced the lowest MSE error metrics values as 1380.5 and 1479.258, respectively,



for neuron 6. Also, neuron six had outperformed these for these two models as compared to neurons. Further, the neuron 6 of the CO and CU model gives the lowest AIC values as 1.2054 and 1.1093, respectively, with the highest stationary and quality. Similarly, for the DE model, the neuron 12 had offers the lowest MSE metrics with 3.4151 as well as the lowest AIC value with 585.7667 as compared to other neurons by employing the artificial neural network with the NARX algorithm. Therefore, the proposed COCUDE model predicts the precise future infection cases, cured cases, and decease cases. Such that the results of the proposed COCUDE model might more helpful for respective authorities to plan future any necessities because of the COVID-19 pandemic. Future work will concentrate on evaluating the proposed COCUDE model for all other states of India. Moreover, evaluating the survivability factor after recovering from COVID-19 and other influencing factors of the COVID-19 will be investigated.

Compliance with Ethical Standards:

Conflicts of interest: Nil Research involving human participants and/or animals: Nil Informed consent: NA

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