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Covid-19 Prediction Modeling Using Bidirectional Gated Recurrent Unit Network Model

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Abstract: Artificial Neural Networks (ANN) are Non-linear models can solve many complex and sophisticated real world problems. Deep Learning (DL) based forecasting mechanism has a significant role to enhance the future course of action in numerous domains. A variant Recurrent Neural Networks are being effectively applied to handle the problems concerned with prediction. In this paper, a Bidirectional Gated Recurrent Unit (BGRU) Neural Network model has been proposed to predict the total number of Confirmed, Deaths and Cured cases on SARS-CoV-2 (COVID-19) pandemic. Our model performance is determined by Mean Absolute Percentage Error (MAPE), R^2 score, $R^2_{Adjusted}$ score and Root Mean Square Error (RMSE). Finally, the BGRU is contrasted with

Machine Learning Methods such as simple Linear Regression (LR), Least Absolute Shrinkage Selection Operator (LASSO), Support Vector Regression (SVR) and simple Exponential Smoothing (ES). The findings show that BGRU outperforms among the existing Techniques.

Keywords: COVID-19; Prediction; Deep Learning; Regression; Mean Absolute Percentage Error(MAPE)

I. Introduction

Time series data Predication or Forecasting, in which future data is estimated using several methods such as statistical methods, Machine Learning, Neural Network models,and Hybrid Algorithms. Data from Time series can be univariate or multivariate and few examples are Daily Electrical Energy Load, Temperature, Air Pollution, Renewable Energy Generation and viral Diseases pandemic. Predicting such type of data in advance helps the society to take preventive measures and safety precautions to monitor the situation in advance. Past several decades world is threatened from several viral Diseases [1] such as Ebola, Influenza, MERS-CoV, SARS and Zika. At Present viral Disease SARS-CoV-2(COVID-19) has been recognized as a Global Hazard, it was first identified in Wuhan, China in December 2019.Corona virus Disease occurs through airborne transmission and SARS-COV2 has a long incubation period compared other viral Diseases. COVID-19 has severe effects on the respiratory system and other organs [2], which can ultimately lead to death. As per World Health Organization (WHO), COVID-19[3] infected cases are 12768 307(0.17%) and deaths are 566654(0.007%) reported as of 13th July 2020. To comprehend the pandemic of viral diseases, several Machine Learning (ML) and statistical Techniques have been tendered. Current decade Deep Learning (DL) models are predominating in forecasting of viral diseases because of Non linear learning behavior and automatic extraction of relationship among the parameters. Future estimation of the viral diseases indirectly helps the society and Government to acquire the necessary course of action. Following section presents a quick literature survey on future findings of viral Diseases using several types of Machine Learning (ML) and Deep Neural Networks Models.

II. Related Work

In recent years, Deep Learning models are widely using to learn complex real world problems. ParulArora, Himanshu Kumar and BijayaketanPangrahi [4] study reported a Descriptive case investigation of India COVID-19 predictive analysis using Deep Learning models.The Model yields Mean Absolute Percentage Error less than 3% for daily prediction and less than 8% for weekly prediction. Recently, Nanning Zheng et al. [5] presented Hybrid model using Artificial Intelligence to investigate the COVID-19 in china.The Authors showed Mean Absolute Percentage Error (MAPE) for next six days in Wuhan, Beijing, Shanghai, and countrywide is 0.52%, 0.38%, 0.05%, and 0.86%, respectively. Vinay Kumar Reddy Chimmula and Lei Zhang [6] developed Long Short Term Memory(LSTM) network to forecast the future COVID-19 cases and also compared transmission rates of Canada with Italy and USA. In [7], reported predicting the spread of COVID-19 in India and effectiveness of preventive measures using LSTM and curve fitting. The Model determines the number of positive cases and recovered cases and it shows better accuracy within a certain range. There are lots of studiesperformed for the forecast of corona virus using Machine Learning Methods [8] and Susceptible–Infectious–Recovered (SIR) [9] model.Machine Learning Algorithms obtain 10-day future forecast of total Infected and Death cases. The SIR Machine Learning Algorithm predicts the COVID-19 outbreak in mainland china and brings uncertainty in prediction due to too many unknown parameters. Aishwarya Kumar, Puneeth Kumar G and AnkitaSrivastava[10] have presented the study report on Modern Technologies to fight against corona virus crisis at different scales, prediction outcome and disease tracking. Another review [11] emphasized various Neural Network models and hybrid models for Time Series prediction. Some Researchers have used Hybrid Techniques, particularly in COVID-19 forecasting [12] and dengue disease prediction [13]. ZeynepCeylan [14] developed conventional autoregressive using integrated and moving Average (ARIMA) model for predicting the COVID-19 prevalence in Italy, Spain and France. In [15] study shows prediction model on SARS-Cov-2 pandemic in Wuhan after lock down.The model shows SIR model performance better than (Susceptible–Exposed–Infectious–Recovered (SEIR) Domenico B et al. [16] study performed COVID-19 pandemic using simple Auto Regressive Moving Average (ARIMA) model.There are ample of work performed for investigating the different diseases and other sequential datausing Neural Network form Hybrid Techniques such as forecast of the SARS epidemic [17], model of HIV incidence [18], Exchange Rate Prediction [19] and prediction of financial sequential data[20].In this research work, we proposed Bidirectional Gated Recurrent Neural Network pattern, which is organized into six sections. Section I presents Introduction, section II describes related work, section III contains Materials and Methods, section IV describes Methodology, section V contains the Results.

III. Materials and Methods

Dataset

The dataset utilized in this research work has been obtained from Github covid19india, a world largest community of Data Science practitioners [21].The datasetcase_time_series consists of cumulative Daily summary of all Indian states, which incorporates a total Confirmed, Deaths and Recovered. In this inquiry, we have considered the dataset from 30th January, 2020 to 11thAugust, 2021.The sample of data files used in our study are displayed in Table 1, Table 2 and Table 3.

Table1.COVID-19 Cumulative Confirmation Cases

Date	Number of
2020-01-30	1
2020-02-02	2
2020-02-03	3
………….	…………
2021-08-09	31997024
2021-08-10	32035400
2021-08-11	32076986

Table2.COVID-19 Cumulative Deaths

Date	Number of Deaths
2020-01-30	0
2020-02-02	0
2020-02-03	0
……………	…………..
2021-08-09	428715
2021-08-10	429211
2021-08-11	429702

Table3. COVID-19 Cumulative Cured

Date	Number of Cured
2020-01-30	0
2020-02-02	0
2020-02-03	0
………..	………………
2021-08-09	31173387
2021-08-10	31213484
2021-08-11	31252611

Bidirectional Gated Recurrent Unit (BGRU) Model:

Deep Learning (DL) based Recurrent Neural Network process the time series samples through the sequence of values and maintains state of the Information. The Recurrent Neural network takes a sequence of vectors as input and current state then combine them to obtain the output.

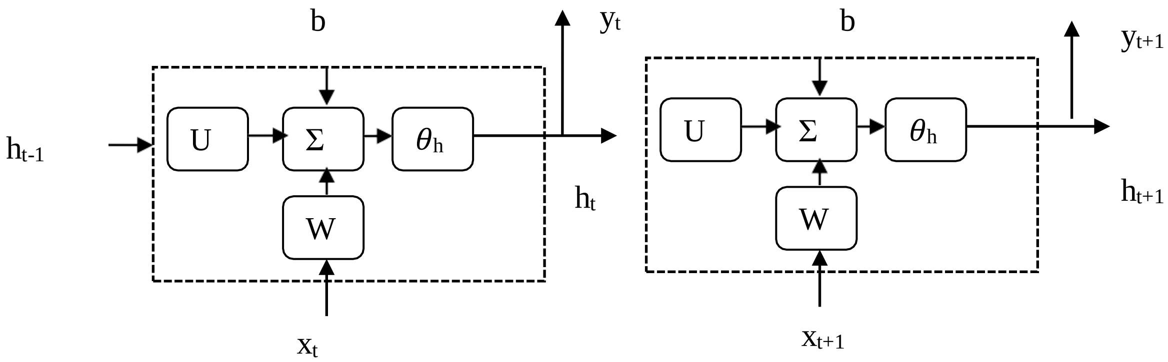

Figure.1.Structure of Recurrent Neural Network (RNN)

$$h_t = \theta_h(W * x_t + U * h_{t-1} + b) \qquad (1)$$

where h_{t-1} and h_t are the previous and current state of RNN, $x_t$andy_t are the input and output of RNN,θ_h is the Tanh activation function and U,W and b are the weights of state, input and bias respectively. Recurrent Neural Network is simple structure as appeared in Figure1, but it has vanishing gradient problem. So, it doesn't fit for long term sequence prediction. To avoid vanishing gradient problem custom Recurrent Neural Network has developed such as Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU). LSTM can effectively handle long term dependencies and maintains gradient flow. It has three gates, they are Input, forget and output gate. GRU is like LSTM except memory cell and it has only two gates i.e. update and Reset gate. Unlike LSTM, GRU has a simple model requires fewer computation and it can be trained quickly. The studies show that Gated Recurrent network performance is identical to LSTM [22, 23]. GRU structure is appeared in Figure 2. GRU contains update gate indicates which data can be transferred to the next and reset specifies the way previous state data is combined with new data. The formula for the GRU output and state are as follows

$$r_t = \sigma(W_r x_t + U_r h_{(t-1)} + b_r) \qquad (2)$$

$$z_t = \sigma(W_z x_t + U_z h_{(t-1)} + b_z) \qquad (3)$$

$$h'_t = \emptyset_h(W_h x_t + U_h h_{t-1} r_t + b_h) \qquad (4)$$

$$h_t = (1 - z_t)h_{(t-1)} + z_t h'_t \qquad (5)$$

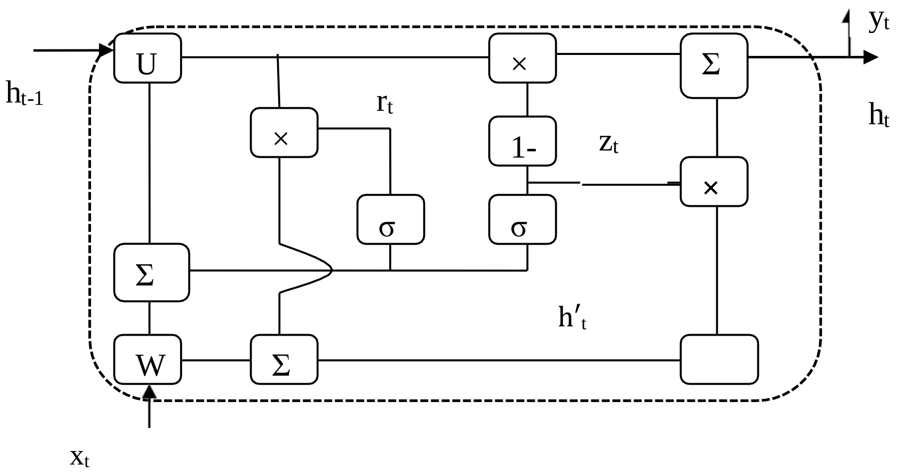

Figure 2. Internal Architecture of Gated Recurrent Unit (GRU)

Where x_t and y_t is the input and output vector. r_t, z_t, $\hat{h}_t$, σ, Θ_h, U and W is reset gate, update gate, current state, sigmoid activation, Tanh activation, weight vectors of state and weight vector of input, respectively. Bidirectional GRU is a usual variant of GRU that has higher performance than regular GRU on certain tasks. In, BGRU has two GRU layers, one layer in chronological order and another layer in antichronological order, and then merge their output. By doing a sequence in both ways, BGRU can catch sequence that may be overlooked by the GRU. BGRU graphical representation as shown in Figure 3

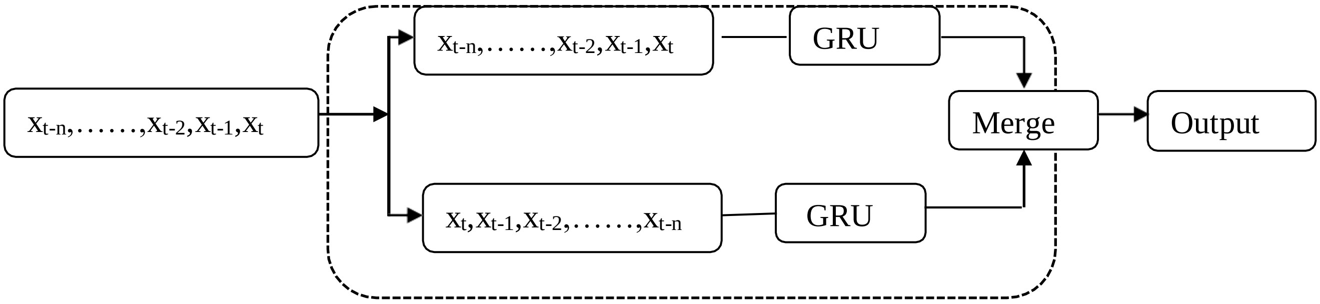

Figure 3.Data processing using BGRU

Performance Metrics:

we examine the outcome of the Model in terms of Mean Absolute Percentage Error (MAPE), R-Squared (R^2)Score, Adjusted R-Squared Score ($R^2_{Adjusted}$) and Root Mean Square Error (RMSE).

a) Mean Absolute Percentage Error (MAPE): MAPE is better reflecting the prediction error [24, 25]. It calculates the contrast between the real data and model prediction on test data, then divided by actual data. Lower MAPE indicates model prediction is close to actual value. It is characterized as follows.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\widehat{y_i}}{y_i}\right|*100 \qquad (6)$$

where n, y_i and $\widehat{y_i}$ is the size, actual data, and prediction data, respectively.

b) R-Squared (R^2) Score: It is regarded as the coefficient of finding, indicates how well data values fit the curve [26, 27]. R^2 score shows that scatteredness of data values around the regression curve. It is normally ranges from 0 to 1. High R^2 score indicates the goodwill of the prediction model. R^2 score can be resolved as:

$$R^2 score = 1 - \left[\frac{\sum_{i=1}^{n}(y_i-\widehat{y_i})^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}\right] \qquad (7)$$

$\bar{y}$is the average of the actual data.

c) Adjusted R-Squared Score (R^2_{Adjusted}): It shows how well independent variables fit the curve. Adjusted R-squared score (R^2_{Adjusted}) decreases, if we had more ineffective independent variables to the model. However, if we had useful independent variables, its value will decrease. R^2_{Adjusted} value is always equal or less than to R- squared value. It can be outlined as:

$$R^2_{adjusted} = 1 - \left[\frac{(1-R^2)(n-1)}{(n-p-1)}\right] \qquad (8)$$

d) Root Mean Square Error (RMSE): It is known as residual, which measures prediction error based on distance from best fit values and actual data. RMSE can be calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2} \qquad (9)$$

IV.Methodology:

Our study has performed on COVID-19 data for future forecasting on cumulative Daily Confirmed, Deaths and recovered cases in the upcoming 30 Days. The Dataset used in this work consists of Day wise time series summary table, which includes the day wise cumulative confirmed cases, Deaths and Recoveries. The proposed work flow has displayed in Figure 4.

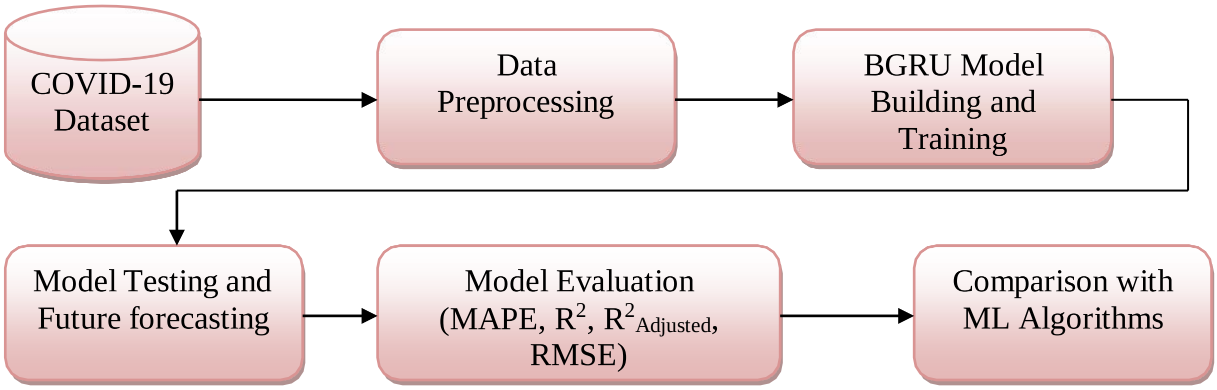

Figure.4.Proposed work flow

Initially COVID-19 Data set is preprocessed, in this total confirmation, death and recovery cases are aggregated Day wise of all states and then data has normalized in the scale of 0 to 1, which is required for smooth convergence of model parameters. After preprocessing 80% of data has utilized during training and the remaining dataset is employed for testing. BGRU network is developed using open source Libraries such as TensorFlow and Keras [28]. BGRU model uses single hidden layer with 5 neurons wrapped inside the Bidirectional wrapper class. It creates two similar layers, each one has 5 neurons and work parallel. These two layers outputs are merged using concatenation mode. The outcome of BGRU is sent through dense layer, which has one neuron for determining the output. In hidden layer, hyperbolic tangent and sigmoid are the functions for activation and recurrent activation function, respectively. Our model prediction is evaluated with various optimization algorithms and epochs as shown in Table 4,5and 6. RMSprop shows low MAPE compared to other optimization algorithms.BGRUwith 100 or 200 epochs gives less MAPE as shown in figure.5 As a result, we use RMSprop optimization Algorithm [29] and trained through 200 epochs. After training, model is verified on test dataset to generate the prediction values and same network parameters are given for future forecasting. Finally model performance is evaluated with MAPE, R^2, $R^2_{Adjusted}$ and RMSE. We are also compared our model with state-of-the-art Machine Learning Techniques that were studied in [8].

Proposed BGRU Model Algorithm:
Step 1: Covid-19 Data set Preprocessing is done using Min-Max Normalization method.
Step 2: Data is splitted into train, validate and target without shuffle.
Step 3: BGRU Network is tuned through the specified parameters such as Number of layers, Neurons, type of activation, Back propagation Algorithm, Numberof epochs and batch size.
Step 4: Model is tested on covid-10 confirmation, cured and deaths data set.
Step 5: Finally BGRU model is evaluated using MAPE, RMSE, R^2,$R^2_{Adjusted}$Parameters.

V. Results and Discussions

Our research attempts to create a method for the predicting the total Daily Confirmed, Deaths and Recovered cases premised on the COVID-19 Indian dataset.

Confirmed cases future prediction:

Our model performs a prediction on test data and predicts the total confirmed cases in the coming thirty days. The BGRU has been evaluated on test data using MAPE, R^2, $R^2_{Adjusted}$ and RMSE. The results of our proposed model compares with Machine Learning Techniques were developed for COVID-19 prediction.Table7. Shows the Quantitative results by MAPE, R^2, $R^2_{Adjusted}$ and RMSE, which gives a comparative analysis of LR, LASSO, SVR, ES and our model BGRU. In accordance with the outcome, BGRU performs better among the models. Our model has MAPE of 0.242%, $R^2$of 0.9994, and $R^2_{Adjusted}$of 0.9994 and RMSE of 82395.It indicates Bidirectional GRU has significant performance in predicting the sequential data. Figure 7, 8,9,10 and 11 show the prediction on test data and future forecast of BGRU, LR, LASSO, SVR and ES, respectively. BGRU model future forecasting shows that approximately 0.96% increase in cumulativeconfirmedcovid-19 cases in India by second week of September 2021.But it may change due to other parameters such as safety measures, vaccination and pandemic awareness.SVR shows poor metrics as compared with other methods.

Table4. Different optimizers MAPE on Confirmed, Deaths and Recovered data

Optimizer	Confirmed	Death	Recovered Cases
Adamax	0.8817	0.6969	0.5748
Adam	1.1182	0.8279	1.0249
Nadam	0.7649	0.5534	0.7025
SGD	22.176	17.3379	22.87
RMSprop	**0.242**	**0.338**	**0.306**
Adadelta	97.49	96.80	97.7965

Table5.MAPE of BGRU for various epochs

MAPE\Epochs	50	100	200	300	400	500
confirmed	2.629	0.242	0.242	0.744	0.744	0.744
Death	2.359	0.338	0.338	0.386	0.386	0.386
Recovered	2.709	0.306	0.306	0.842	0.842	0.842

Table 6. Specifications of BGRU

Hyper parameter	Value
No of layers	3
Number of Neurons in Hidden Layers	[5 5]
Activation and Recurrent Activation	[Tanh, Sigmoid]

Number of Epochs	200
Type of back propagation algorithm	RMSProp
Learning rate	0.001
Dropout	0.05

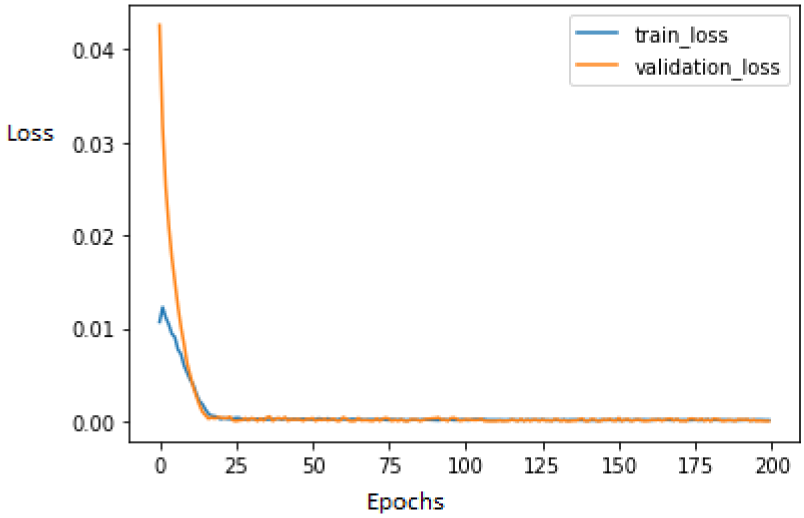

Figure.5. BGRU training and validation loss.

Table 7. Performance metrics on COVID-19 Confirmed test data

Method	MAPE (%)	R^2	$R^2_{Adjusted}$	RMSE
LR	0.489	0.9983	0.9983	145602
LASSO	0.458	0.9985	0.9985	140802
SVR	5.019	0.7846	0.7825	1498248
ES	1.141	0.9898	0.9897	385511
BGRU	**0.242**	**0.9994**	**0.9994**	**82395**

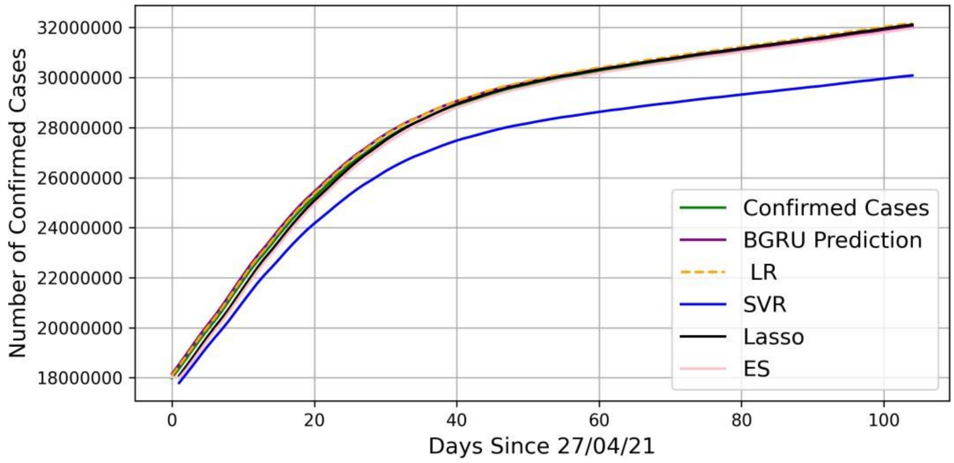

Figure.6 Prediction performance of various models on covid-19 confirmation cases

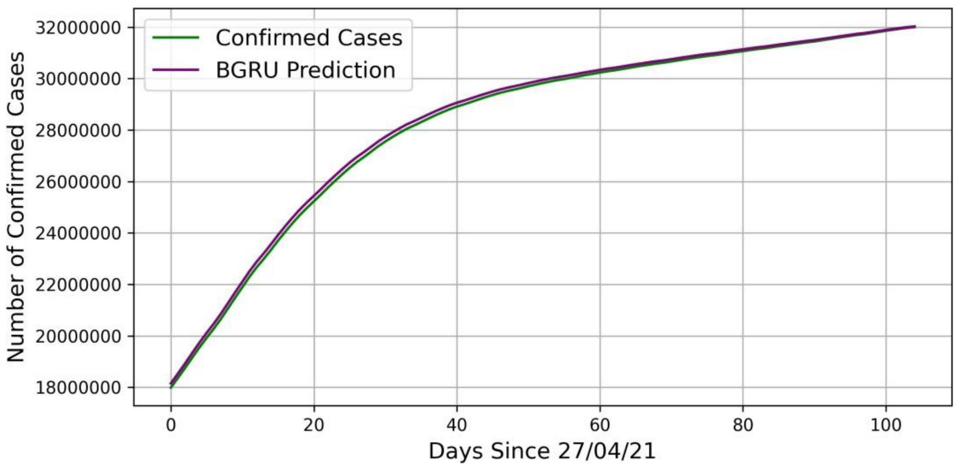

Figure.7. Forecast of COVID-19 confirmed cases using BGRU.

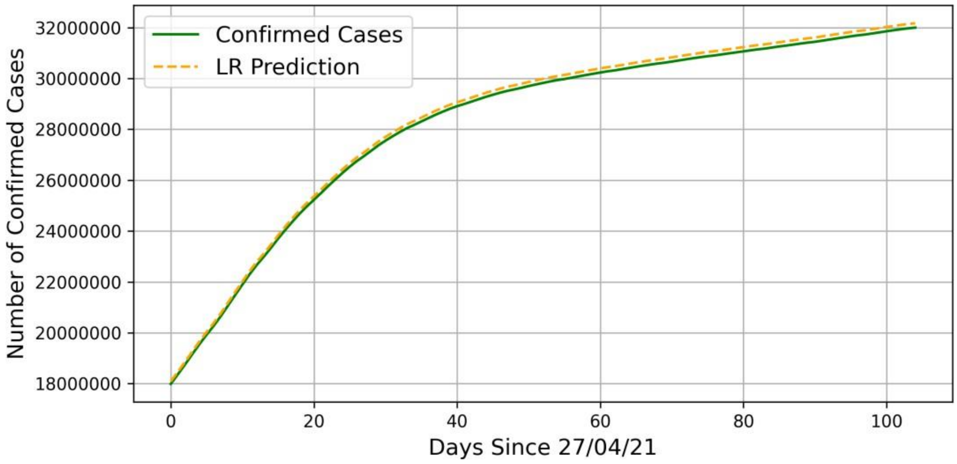

Figure 8. Forecast of COVID-19 confirmed cases using LR.

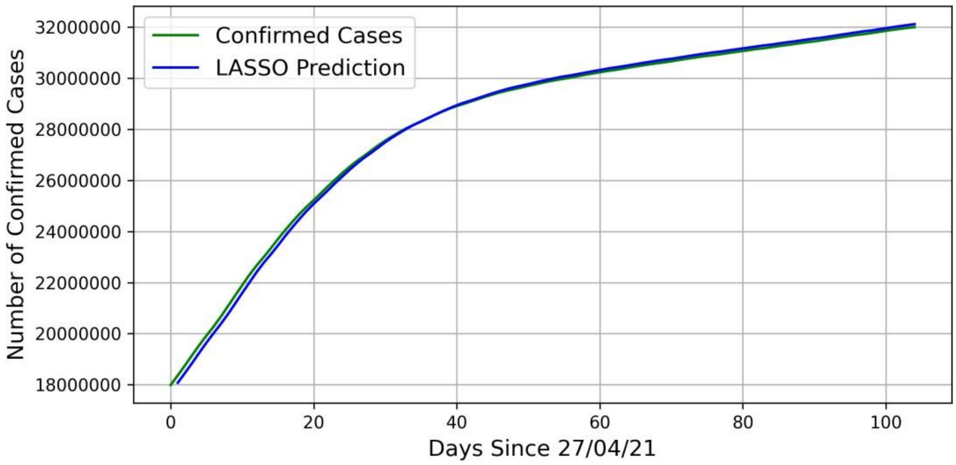

Figure 9. Forecast of COVID-19 confirmed using LASSO.

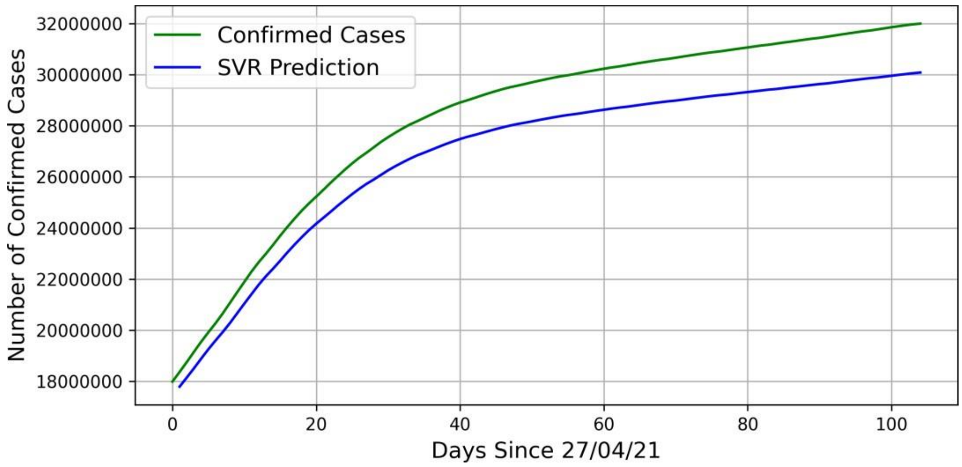

Figure 10. Forecast of COVID-19 confirmed using SVR

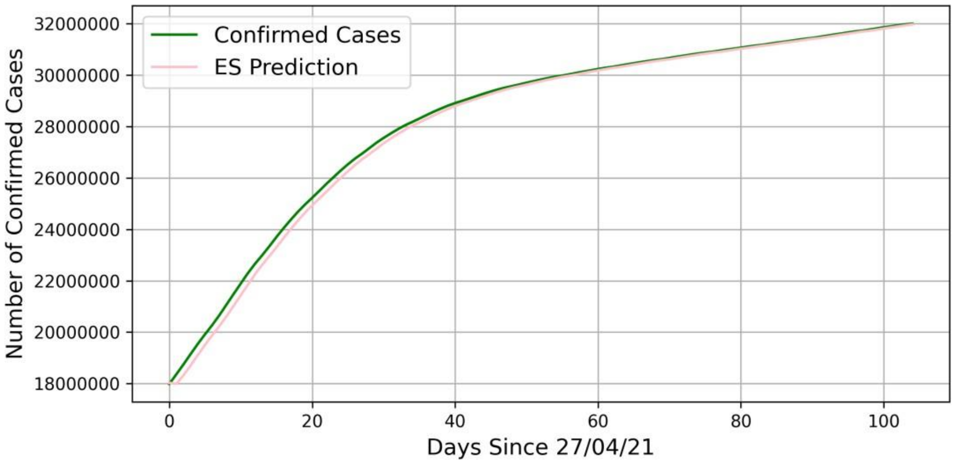

Figure 11. Prediction of COVID-19 confirmed using ES.

Death rate future prediction:

Proposed model attempts to forecast the death rate in the coming 30 days. The model outcome metrics such as MAPE, R^2, $R^2_{Adjusted}$ and RMSE are measured on test dataset. As displayed in Table 8, BGRU has better performance among the models. Our model has MAPE of 0.338%, R^2 of

0.9996, and $R^2_{Adjusted}$ of 0.9996 and RMSE of 1219. Figure 13,14,15,16 and 17 shows the model evaluation on test dataset and future forecast for the BGRU, LR, LASSO, SVR and ES respectively. BGRU model future forecasting shows that approximately 3.17% increase in cumulative death cases in India by the second week of September 2021.Support Vector Regression (SVR) has highest MAPE of 5.505%, R^2 of 0.8549, $R^2_{Adjusted}$ of 0.8535 and high RMSE of 22584.

Table 8. Performance metrics on COVID-19 death rate test data

Method	MAPE (%)	R^2	$R^2_{Adjusted}$	RMSE
LR	0.534	0.9990	0.9990	2075
LASSO	0.561	0.9989	0.9989	2215
SVR	5.505	0.8549	0.8535	22584
ES	1.500	0.9939	0.9938	5510
BGRU	**0.338**	**0.9996**	**0.9996**	**1219**

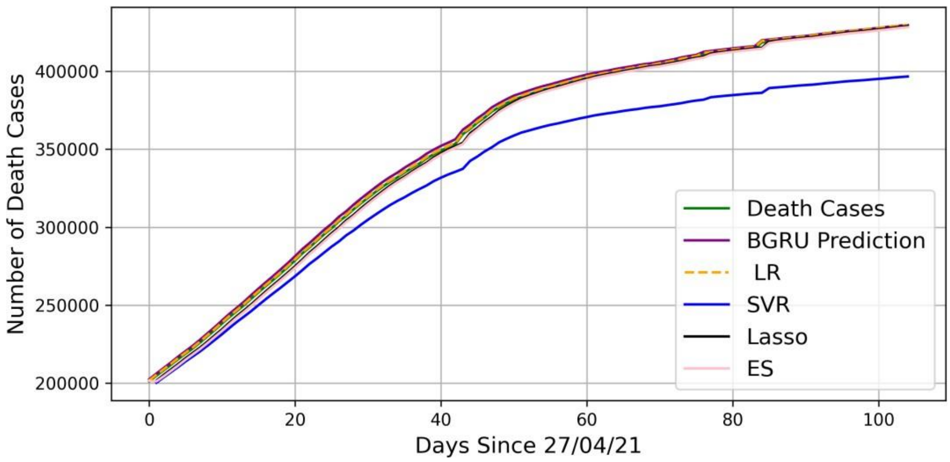

Figure.12 prediction performance of various models on covid-19 deaths

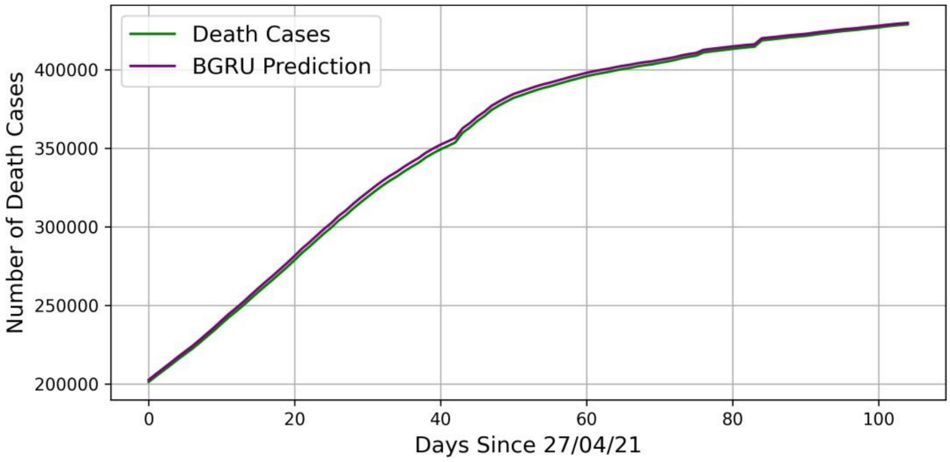

Figure .13 Forecast of COVID-19 death rate using BGRU.

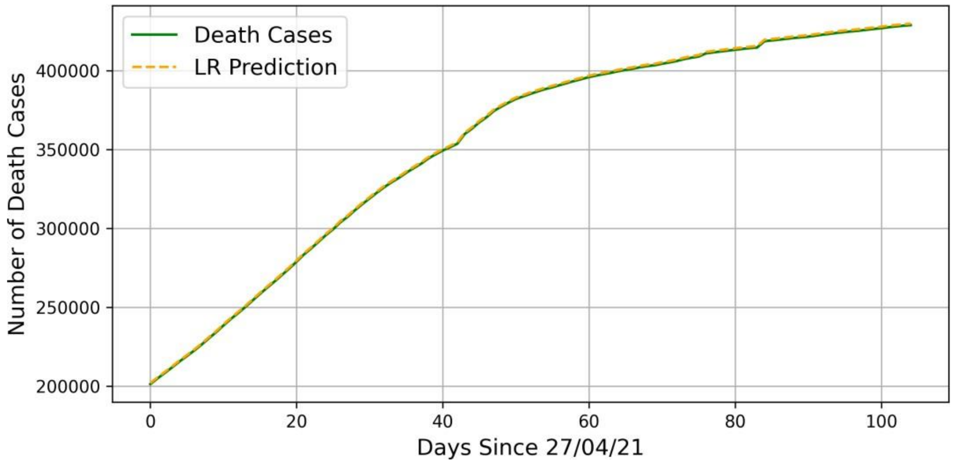

Figure.14 Forecast of COVID-19 death rate using LR.

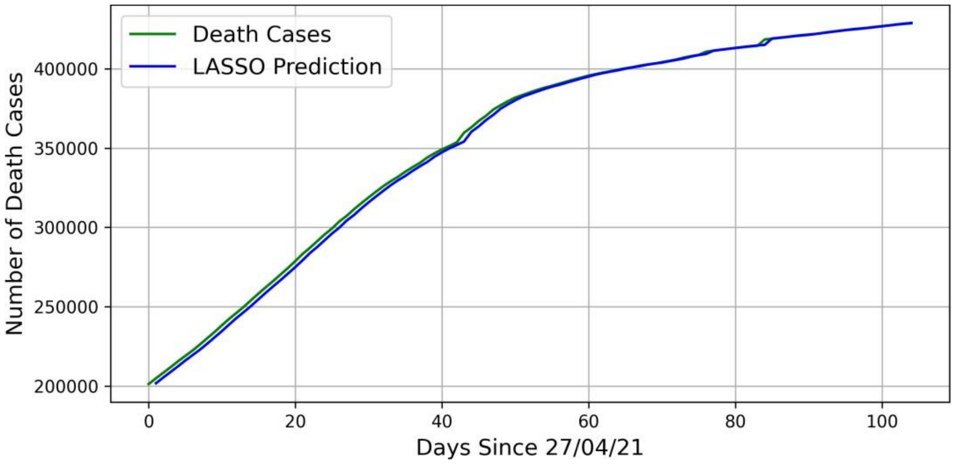

Figure 15. Forecast of COVID-19 death rate using LASSO.

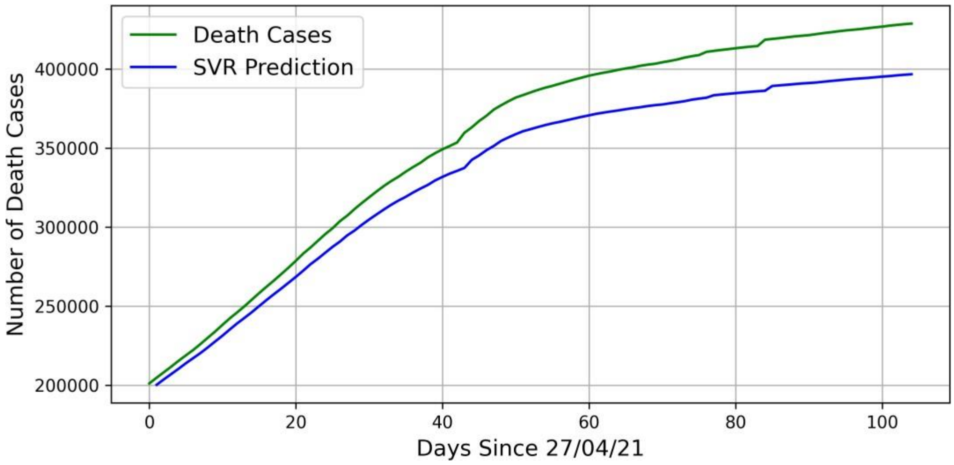

Figure 16. Forecast of COVID-19 death rate using SVR

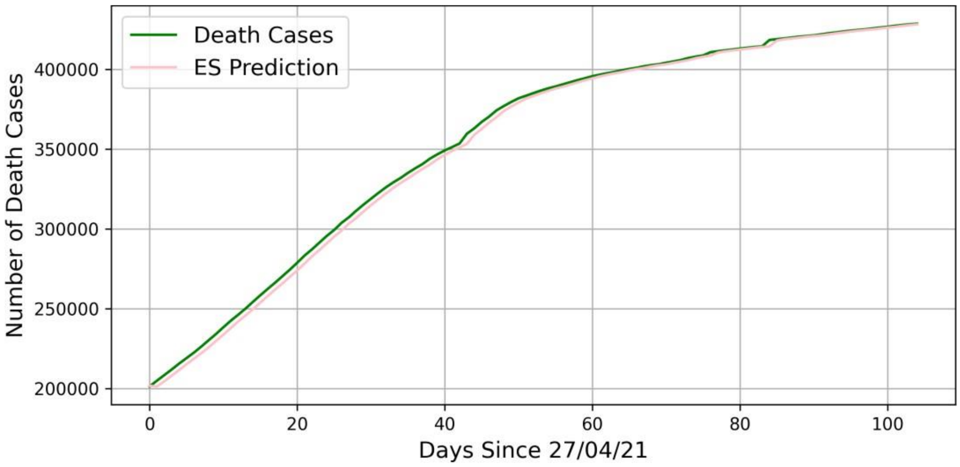

Figure 17. Forecast of COVID-19 death rate using ES.

Recovery rate prediction:

In Cured rate prediction and future forecasting, model shows better outcome with references to metrics as displayed in Table 9. Our model achieved MAPE of 0.306%, R^2 of 0.9995, and $R^2_{Adjusted}$of 0.9995 and RMSE of 94634. Figure 19,20,21,22 and 23 shows the forecast on test dataset and future forecast for of BGRU, LR, LASSO, SVR and ES respectively. Future forecasting represents approximately 1.13% decrease in cured rate in India by second week of September 2021.Particularly, SVR model prediction and future forecasting performance completely distinct from other models. SVR model evaluation metrics are poor among the models.

Table 9. Performance metrics on COVID-19 Cured cases test data

Method	MAPE (%)	R^2	$R^2_{Adjusted}$	RMSE
LR	0.538	0.9989	0.9989	153134
LASSO	0.533	0.9989	0.9989	158807
SVR	4.94	4.94	0.8809	1448105
ES	1.439	0.9925	0.9924	424613
BGRU	**0.306**	**0.9995**	**0.9995**	**94634**

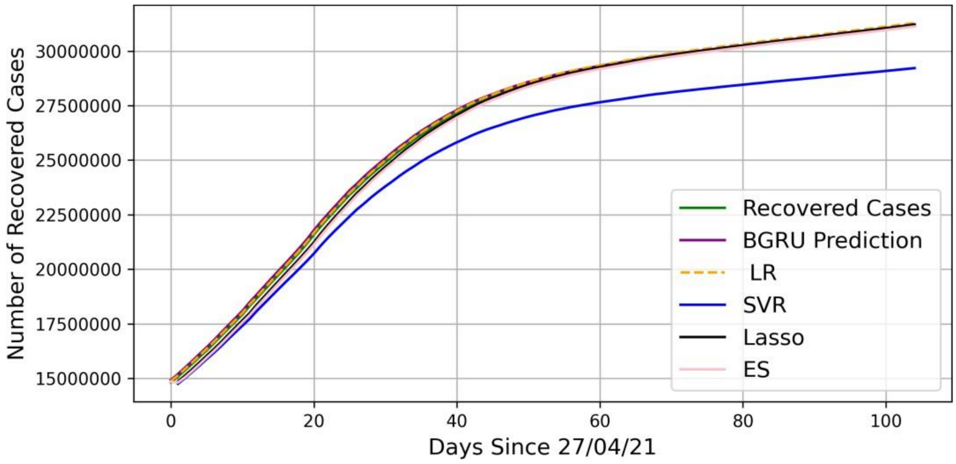

Figure 18. Prediction performance of various models on covid-19 recovered data.

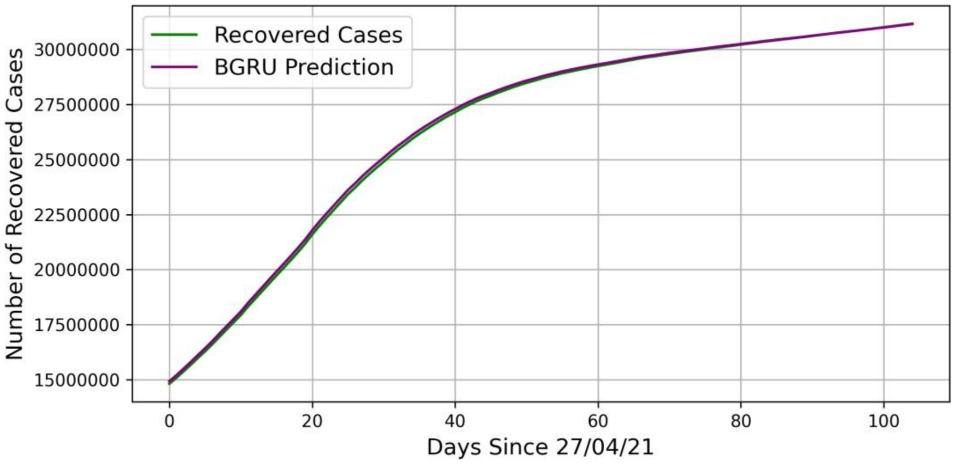

Figure 19. Forecast of COVID-19 cured cases using BGRU.

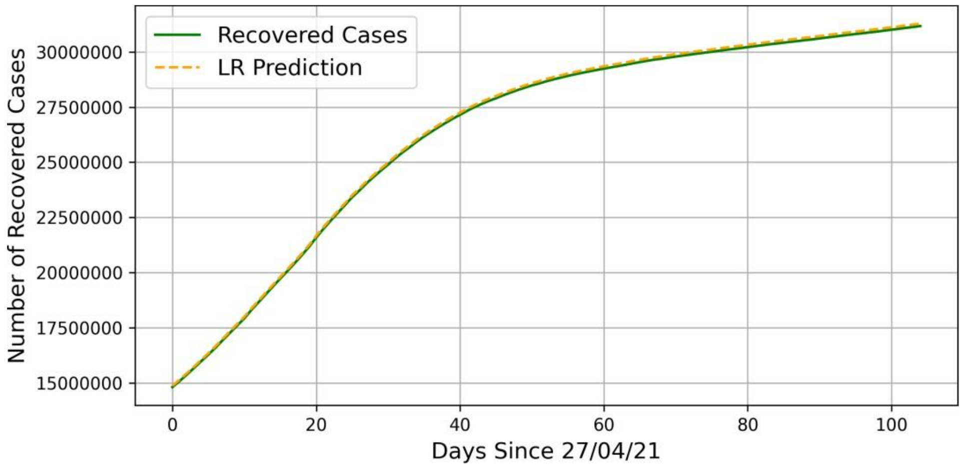

Figure 20. Forecast of COVID-19 cured cases using LR

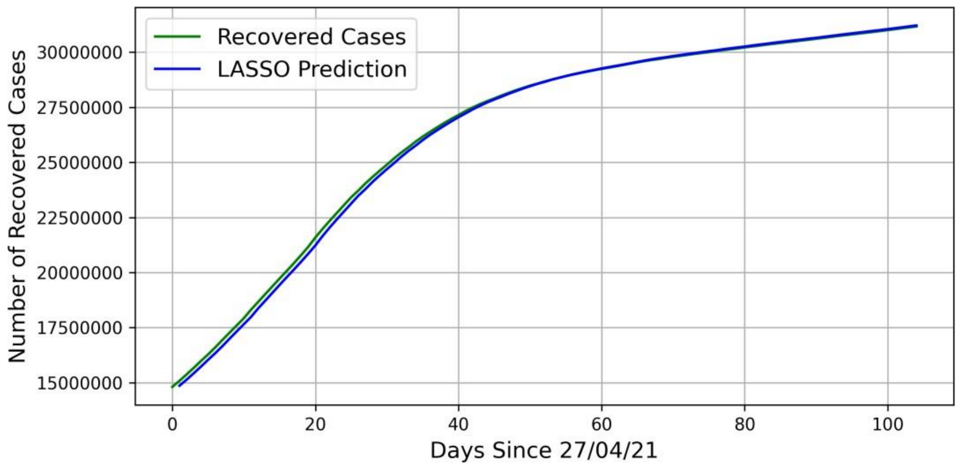

Figure 21. Forecast of COVID-19 cured cases using LASSO

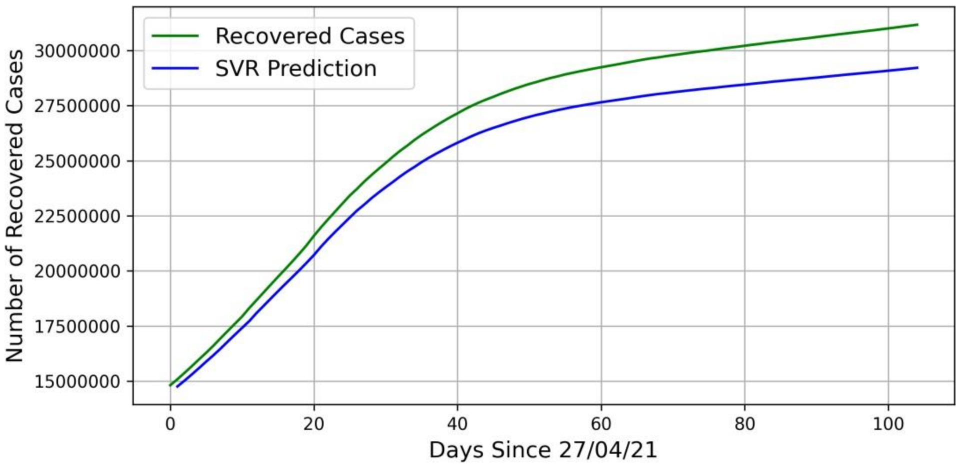

Figure 22. Prediction of COVID-19 cured cases using SVR

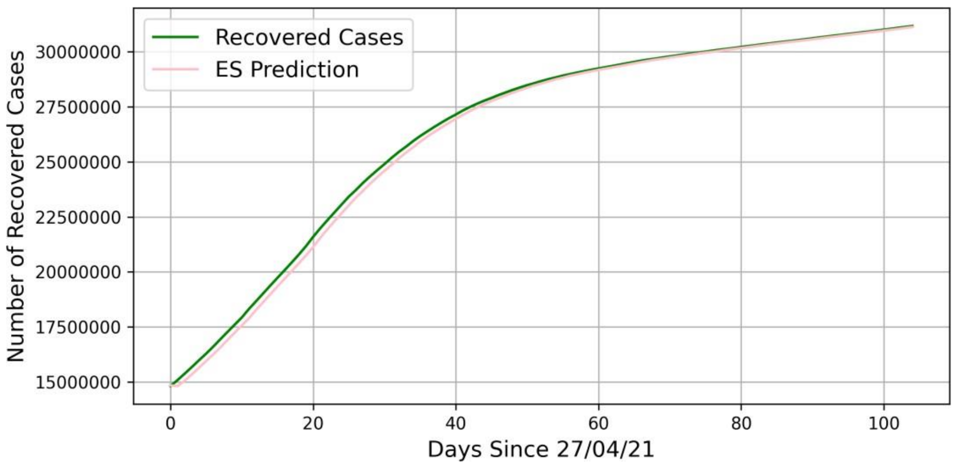

Figure 23. Forecast of COVID-19 cured cases using ES.

VI. Conclusions

In this work, BGRU Neural Network has been put forward for forecasting the threat of COVID-19. The system makes day wise prediction for upcoming days using Neural Networks. The overall outcome proved that BGRU outperforms as compared to Machine Learning Techniques

[8].BGRU produces low metrics in all cases for the forecasting of confirmed rate, death and recovery cases as shown in Table 7, 8 and 9. Support Vector Regression produces lower performs for this cumulative series data set, which is due to incorrect hyper plane. LR and LASSO produce moderately good performance on all datasets. The investigation shows that ES performs average in all situations for the projection of confirmed, deaths and recovery cases. In accordance with the results of our model, cumulative Confirmation increases by 0.96%, Death rate increases by 3.17%and rate of recovery decreases by 1.13% for the coming one month period. Our projections may vary if proper safety measures and potential vaccination achieves fruitful results. We infer that model forecasting as per the current COVID-19 pandemic is correct, which will be useful to realize the upcoming trends. Our study forecasting, it can help the society to take some preventive measures from this pandemic situation. Our work can be extended to Hybrid Algorithms or other Neural Network models to minimize the performance metrics and computation time.

References

[1].Bloom DE and Cadarette D,” Infectious Disease Threats in the Twenty-First Century: Strengthening the Global Response”, the Frontiers in Immunology, vol.10, no.549, pp.1-12, March (2019).

[2].FrancescoDi Gennaro, DamianoPizzol,Claudia Marotta,MarioAntunes, Vincenzo Racalbuto,Nicola Veronese and Lee Smith, “Corona virus Diseases (COVID-19) Current Status and Future Perspectives: A Narrative Review”, International journal of Environmental Research and public health, April (2020), 17, 2690;

[3].Corona virus disease (COVID-19) Situation Report – 175, World Health Organization (WHO), July (2020).

[4].ParulArora, Himanshu Kumar, BijayaKetanPanigrahi, “Prediction and analysis of COVID-19 positive cases using deep learning models:A descriptive case study of India”, Chaos, Solitons and Fractals, vol.139,May (2020).

[5].NanningZheng, , Shaoyi Du , Jianji Wang , He Zhang, Wenting Cui , Zijian Kang, Tao Yang,et.al , “Predicting COVID-19 in China Using Hybrid AI Model,” IEEE Transactions on Cybernetics, March 2020.

[6].Vinay Kumar Reddy Chimmula, Lei Zhang, “Time Series Forecasting of COVID-19 transmission in Canada Using LSTM Networks”, Chaos, Solitons and Fractals, vol.135, May 2020

[7].AnuradhaTomar, Neeraj Gupta, “Prediction for the spread of COVID-19 in India and effectiveness of preventive measures”, Science of the Total Environment, vol.728, August 2020.

[8].FurqanRustam,Aijaz Ahmad Reshi,ArifMehmood.SaleemUllah, ByungWonon, et.al.,”COVID-19 Future Forecasting Using Supervised, Machine Learning Models”,IEEE Access, vol.8,pp-101489-101499, May 2020.

[9].LinhaoZhong, Linmu, Jingli, Jiaying Wang, Zhe Yin, DarongLiu,“Early Prediction of the 2019 Novel Coronavirus Outbreak in the Mainland China Based on Simple Mathematical”, IEEE Access, vol. 8,pp-51761-51769, March 2020.

[10]. Aishwarya Kumar, Puneet Kumar Gupta*, AnkitaSrivastava, “A review of modern technologies for tackling COVID-19 pandemic”, Diabetes &Metabolic Syndrome: Clinical Research & Reviews, vol.14, pp.569-573, May 2020.

[11].Ahmed Tealab, “Time series forecasting using artificial neural networks methodologies: A systematic review”, Future Computing and InformaticsJournal, vol.3, pp.334-340, October 2018.

[12].SabaAI, ElsheikhAH,”Forecasting the prevalence of COVID-19 outbreak in Egypt using nonlinear autoregressive artificial neural networks”, Process SafetyandEnvironmentalProtection, May 2020

[13].TanujitChakraborty, SwarupChattopadhyay, IndrajitGhosh, “Forecasting dengue epidemics Using a hybrid methodology”, Physica A, vol.527, May 2019

[14]. ZeynepCeylan,“Estimation of COVID-19 prevalence in Italy, Spain, and France”, Science of TotalEnvironment, vol.729, April 2020,

[15].Weston C. Roda , Marie B. Varughese , Donglin Han , Michael Y. Li , “Why is it difficult to accurately predict the COVID-19 epidemic?”, Infectious Disease modelling,vol.5,pp.271-281,March 2020.

[16]. D. Benvenuto, M. Giovanetti, L. Vassallo, S. Angeletti, M. Ciccozzi, “Application of the ARIMA model on the COVID-2019 epidemic dataset”, DatainBrief, vol.29, no.105340, Feb.2020.

[17]. Y. Bai and Z. Jin, “Prediction of SARS epidemic by BP neural networks with online prediction strategy,” Chaos, Solitons and Fractals, vol. 26, no. 2, pp. 559–569, 2005.
[18]. Xiaming Li, XianghuiXu, Jie Wang1, Jing Li, ShengQin,JuxiangYuan,”Study on Prediction Model of HIV Incidence Based on GRU Neural NetworkOptimizedbyMHPSO”,IEEE Access, pp. 49574-49583,March 2020.
[19]. Zhang GP, ”Time series forecasting using a hybrid ARIMA and neural network model”,Neurocomputing, vol.50,pp.159-175, 2003.
[20]. M. Khashei, S. R. Hejazi, M. Bijari, "A new hybrid artificial neural networks and fuzzy regression model for time series forecasting", Fuzzy Sets and Systems, Vol. 159, pp.769– 786, 2008.
[21].https://github.com/covid19india/api.(Accessed on 16th Auguest 2021)
[22]. Junyoung C, Caglar G,KyungHyun C and Yoshua B, “Empirical Evaluation of GatedRecurrent Neural Networks on Sequence Modeling”,arXiv: 14124.3555 2014.
[23]. Y. Tang, Y. Huang, Z. Wu, H. Meng, M. Xu, and L. Cai, “Question detection fromacoustic features using recurrent neural network with gated recurrent unit,” ICASSP, IEEE Int. Conf. Acoust. SpeechSignalProcess. - Proc., vol.16, pp. 6125–6129, May 2016.
[24].C. Willmott and K. Matsuura, ``Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance," Climate Res.,vol. 30, no. 1, pp. 79-82, 2005.
[25]. R. Kaundal, A. S. Kapoor, and G. P. Raghava, ``Machine learning techniques in disease forecasting: A case study on rice blast prediction," BMCBioinf., vol. 7, no. 1, p. 485, 2006.
[26]. J. Lupón, H. K. Gaggin, M. de Antonio, M. Domingo, A. Galán, E. Zamora,J. Vila, J. Peña_el, A. Urrutia, E. Ferrer, N. Vallejo, J. L. Januzzi, and A. Bayes-Genis,Biomarker-assist score for reverse remodelling prediction in heart failure: The ST2-R2 Score," Int. J. Cardiol., vol. 184,pp. 337-343, April 2015.
[27]. J.-H. Han and S.-Y.Chi,”Consideration of manufacturing data to apply machine learning methods for predictive manufacturing," in Proc. 8th Int.Conf.Ubiquitous Future Netw. (ICUFN), pp. 109-113 July 2016.

[28]. Scott Zhu, Francois Chollet, Complete guide to using & customizing RNN layers(2019),https://keras.io/guides/ /working_with_rnns/

[29].Qingtao, Fang Liu Yong Li and Denis Sidorov, Air Pollution Forecasting Using a Deep Learning Model Based on 1D Convents and Bidirectional GRU, IEEE Access,vol.7,pp.76690-76698, June 2019.

[30]. Francois C,Deep Learning with python, Manning Publications Co, 2018.

[31].Van Rossum G, Drake FL.,Python 3 Reference Manual.Scotts Valley, CA,CreateS pace, 2009.

[32].Hyndman, R. J. &Athanasopoulos, G. Forecasting: principles and practice(2013)

[33].Qiong Li, Yuchen Fu, Xiaoke Zhou, YunlongXu, A hybrid Support Vector Regression for Time Series Prediction,3rdInternational Conference on Knowledge Discovery and Data Mining(2010), doi:10.1109/WKDD.2010.92

[34]. Amir Farzad, HodaMashayekhi, Hamid Hassanpour, A Comparative Performance Analysis of Different Activation Functions in LSTM Networks for Classification,Neural computing & Applications(Springer,2017),doi:10.1007/s00521-017-3210-6

[35].Samsudin R, Shabri A, Saddi P, A Comparision of Time Series forecasting using Support Vector Machine and Artificial Neural Network Model., Journal of Applied Science,ANSI(2010).

[36].MengyangWang,Hui Wang, Jiao Wang, Hongwei Liu, Rui Lu, TongqingDuan,Xiaowen Gong, SiyuanFeng, Yuanyuan Liu, Zhuang Cui, Changping Li*, Jun Ma, A novel model for malaria prediction based on ensemble algorithms,PLOS ONE(2019), doi.org/10.1371/journal.pone.0226910

[37].Zhang X, Liu Y, Yang M, Zhang T, Young AA, et al. (2013) Comparative Study of Four Time Series Methods in Forecasting Typhoid Fever incidence in China. PLOS ONE 8(5):e63116.doi:10.1371/ journal.pone.0063116

[38].MahmoodAkhtar, Moritz U. G. Kraemer, and Lauren M. Gardner, A dynamic neural network model for predicting risk of Zika in real time, BMC Medicine 2019.

[39].Jason Brownlee, Long Short Term Memory Networks with Python: Develop Sequence Prediction Models with Deep Learning (2017).

[40].LizhenWu,Chun Kong, XiaohongHao, and Wei Chen, A Short-Term Load Forecasting Method Based on GRU-CNN Hybrid Neural Network Model, Hindwai Publisher(2020), Volume 2020, doi.org/10.1155/2020/1428104.

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