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COVID-19 in Bangladesh: A Deeper Outlook into The Forecast with Prediction of Upcoming Per Day Cases Using Time Series

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Abstract

A global pandemic on March 11th of 2020, which was initially renowned by the World Health Organization (WHO) revealed the coronavirus (the COVID-19 epidemic). Coronavirus was flown in –December 2019 in Wuhan, Hubei region in China. Currently, the situation is enlarged by the infection in more than 200 countries all over the world. In this situation it was rising into huge forms in Bangladesh too. Modulated with a public dataset delivered by the IEDCR health authority, we have produced a sustainable prognostic method of COVID-19 outbreak in Bangladesh using a deep learning model. Throughout the research, we forecasted up to 30 days in which per day actual prediction was confirmed, death and recoveries number of people. Furthermore, we illustrated that long short-term memory (LSTM) demands the actual output trends among time series data analysis with a controversial study that exceeds random forest (RF) regression and support vector regression (SVR), which both are machine learning (ML) models. The current COVID-19 outbreak in Bangladesh has been considered in this paper. Here, a well-known recurrent neural network (RNN) model in order to referred by the LSTM network that has forecasted COVID-19 cases on per day infected scenario of Bangladesh from May 15th of 2020 till June 15th of 2020. Added with a comparative study that drives into the LSTM, SVR, RF regression which is processed by the RMSE transmission rate. In all respects, in Bangladesh the gravity of COVID-19 has become excessive nowadays so that depending on this situation public health sectors and common people need to be aware of this situation and also be able to get knowledge of how long self-lockdown will be maintained. So far, to the best of our knowledge LSTM based time series analysis forecasting infectious diseases is a well-done formula.

***Keywords**:* Deep Learning; COVID-19; LSTM; Time Series Forecasting; SVR; RFR; ML; COVID-19 transmission.

1. Introduction

COVİD-19 is a stormy epidemic covered the more than 200 countries. Initially it appeared late December 2019 in

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Wuhan, China [1]. Originally WHO called this respiratory infection as COVİD-19 that spread throughout the body a certain incubation period to be 6.4 days (2-14days) [2-3]. The outbreaks of a novel coronavirus are gradually being published at an exponential rate day by day. Observation of people's health showed flu-like symptoms, together with cough, dyspnea, fatigue and fever [4]. Due to pandemic, millions have been dying, some were endangered in positive cases. Moreover, this attenuation is possible in case of the timely forecast, when confirmed cases are well predicted. Meanwhile, the future situation had led to public health measures in China, but during four-4 months it has enlarged all over the countries and territories [5]. Overall scenario explained the necessity of collecting sample data, however, it is quite impossible to test over the largely populated area. Predicting per day data using time series hotspot problems suggests how the future will go. Nowadays Bangladesh is coming into a red zone where daily affected numbers are rising in high dimensions. Bangladesh's first attempt was affected by this influenza since 7 March 2020 with 3 confirmed cases that have been announced by the Institute of Epidemiology Disease Control & Research (–IEDCR). In the middle the situation was smoothie while other countries were severely infected but the current situation goes opposite. According to the IEDCR report, confirmed cases are increasing as twofold. By this time-series analysis containing the longest sequences needs a mathematical model for the early prediction. In this paper we studied confirmed cases in Bangladesh regions over existing models by deep learning model in LSTM. Throughout our study estimation will help the governments and public health officials forecasting prevention and control strategies. LSTM is an artificial recurrent neural network, which is a potential pattern for time predictions series where data is sequential [6,19]. Treated LSTM on 3 cases of Bangladesh those who have died, recovered, influenced by this epidemic showed maximum prediction relates to forecast model for several benefits moreover abandoned with rough purpose. It is extremely admirable over the discussion to produce output and show graphical representation of the prominent study throughout this epidemic. Entered with a deep learning model most of the biological cases analysed using time series statistical situations [7-9]. In the meantime, a small number of relevant cases was published on COVİD-19. Given the novelty of the subject, a part from the prediction of COVİD-19 not so many measures had been applied to the health sector in Bangladesh so far. Due to an experiment, three cases of epidemic become long-term estimation, then one needs to focus on a short-term estimation to detect the accuracy level growth [10]. Real data based upon biological time series data processed by the recurrent neural network model. All kinds of time series real-world dataset could be suitable for sequential data modelling [11].

To the best of our knowledge, we propagate a deep learning based forecasting method that is applicable for both medical surgery departments and governmental institutions to discover and synthesize as pandemics. At the end of the study LSTM successfully predicted the future epidemic situation over confirmed cases which was real time analysis that IEDCR delivers on public domain in Bangladesh. Overall, from a Bangladesh perspective we elaborate our model with a comparative to speech as they showed other countries [12,18]. According to better forecasting, the model has been trained by severely using death cases, recovery cases and predictive positive cases. The structure of the rest of this paper forecast over the upcoming 30 days in 3 stages along with LSTM deep learning model.

2. Research Review

During this COVID-19 epidemic long day-long advances misery by time series data. Taking up with time series several patterns of data is necessary to researchers owing to prognosis and reveal analysis sections. Current situations fully depending upon study of analysis because of prediction can raise awareness. LSTM estimation offers privilege over time series data with short term and long term sequences. Meanwhile based on time series analysis had been placed by the deep learning analysis. We have discussed this kind of proposals in literature over the section of time series analysis using COVID-19 data moreover simulate their works by the discussions.

Yunlu Wang et al. [13] aimed at twofold perspective that using real time COVID-19 data influenced by the breathing characteristics settled with respiratory patterns. Demand with a comparative study including LSTM. Zifeng Yang et al. [14] reflected by their analysis in China who were infected through the COVID-19 that using LSTM applied over the SARS dataset. Swarna Kamal Paul et al. [15-16] due to this epidemic covered the USA and Italy of dataset from the public domain proposed by the LSTM with exploration of forecasting the next spread of COVID-19. Shuo Feng et al. [17] smoothly described a certain prediction of COVID-19 real time based analysis treated as a SEIR model over LSTM. Among three positive cases of data analysis give future review. Public health making awareness is a necessary duty of all countries in a sense Rahele Kafieh et al. [18] published an impressive controversial approach during the session of COVID-19 in Iran cases about time series analysis revealed by deep learning model contacting LSTM. Seyed Mohammad et al. [19] demonstrated COVID-19 in Iran evaluated RMSE performance on LSTM after that shows what future has come.

Narinder Singh Punn et al. [20] aimed to predict the application of SVM, PR and DNN, RNN, LSTM methods worldwide for confirmation, recovery and death cases. Hamed Jelodar et al. [21] used LSTM RNN which investigates sentiment classification of social comments. LSTM strongly claims that inquiries are significant for public opinion. Yang Yu et al. [22] proposed a ML based transmission simulator(MLCM) to predict COVID-19 asymptomatic dispatch which includes disease progression and control during data-driven. Qiyang Ge et al. [23] applied developed methods to real-time forecasting on confirmed cases across the world and RNN based LSTM for predicting future response time series. Mohamed R. Ibrahim et al. [24] has unveiled a fictional variant LSTM auto-encoder model predicting the expansion of coronavirus for every country around arbitrary with sequential LSTM. Shaoyi Dua et al. [25] predict COVID-19 by hybrid AI model. LSTM can effectively fix constant explosions and disappearance during the training process by introducing the carousel of constant error alone.

3. Methodology

3.1. COVID-19 Dataset Formation

Data on the COVID-19 epidemic in Bangladesh has been collected from IEDCR since March 8 to May 12. Datasets contain daily reports and time-series sequential tables. We have arranged the series table in CSV format. In the ordination of the attributes have chosen Confirmed, Deaths and Recovery rate. The approach will predict next 30 days cases based on the present situation. It's easy to observe the explicative accrual of propaganda that needs to be controlled. Dataset constructed a 70 days of data set which is shown in the graph in COVID-19 cases.

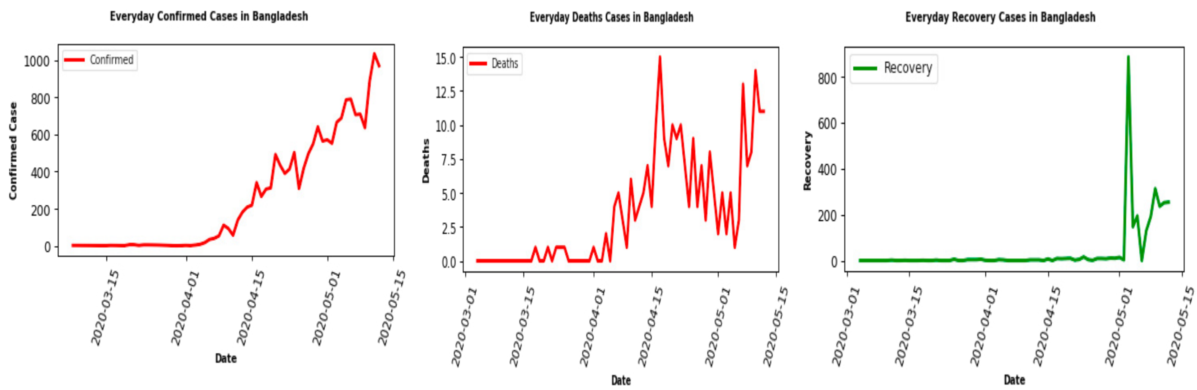

Figure-1: Input Framework for Epidemic status for COVID-19 on Death, Confirmed and Recovery cases.

3.2. LSTM Network Modelling estimation of model parameters

Figure_1 illustrates the input model how easily fed into LSTM by setting the model parameters for the real-time transmission [6,12]. In Table-1 Set with the following parameters where train size and test size divided into 70% and 30% along with batch size 1 and epochs set by the 100. This sequential data needs to split with look-back 1. Pre-Trained the input format that is necessary to LSTM input has to be a picking format. Deep neural network trained on these parameters by Tensorflow.

Optimum selected layout for LSTM

Train Size	Test Size	Look Back	Batch	Epochs	Days to predict
70%	30%	1	1	100	30

Table 1: Optimum selected layout for LSTM

3.3. Training & Testing

Due to progression of Recurrent Neural Network, an important session of training and testing should cover on epidemic analysis [27]. Regarding the test, it was used the area of Bangladesh in all regions, which have been affected by this infection. Three stages of confirmation, recovery and death need labeling corresponding per day cases. On behalf of the scenario, deep learning is implemented by the standard measurement. DNN consists of an existing layer that fits into the model in LSTM. Before preprocess, the data are divided into two parts according to train and test sets and the scores is 70% and 30%. DNN requires Min Max Scaler (feature_range=(-1, 1)) that provides the actual RMSE value. Later on rebuild a reshape train and test set for all RMSE value measurement. RNN proclaimed with 2 hidden layers with input and output layers build by the dense layer.

3.4. Performance Measure Metrics

Time series analysis evaluates the model grabbing some theoretical Metric function as mean squared error (MSE) in which widely known as objective function, another one RMSE computing Function of metrics for simulating the regression learning [6, 20]. Adam optimizer is the RNN optimum value across the prediction much popular [14]. RMSE [28] is the mostly used metric function for LSTM models for future prediction purpose of time series during COVID-19 analysis.

3.5. LSTM Model

Long Short-term Memory is an alternative to a repetitive neural network that can also provide a long-term adherence. LSTM networks can reflect data for a long period of time. It may contain the same or more hidden parts without input and output levels. Every hidden layer structure has three gates- input, output and forget. The interior memory postulate of its cell simply stores the obligatory and relevant reality through these gates. By wasting trivial actuality from the cell region the forget gate tries to increase the utility of the network. It is planned to transfer new data to the cell state of input and output gate passes important information from the memory cell to the output. The output of the previous layer becomes the input of the next layer in Stacked LSTM. By using hidden layers stacked LSTM can gather more actuality. The stacking of hidden layers makes the repetitive model deeper and the features can be learned more rigorously [26].

3.6. LSTM model analysis

Strong representation needs a comparative study. In our model, on LSTM focused maximum cases. During the Dataset of COVID-19 in Bangladesh relevant with long term and short term sequences where it could be extracted from and processed. We trained COVID-19 data from 15 march to 15 may 2020 per day over the thousand cases set by the 1000 parameters. Performance of the model that has represented by the RMSE value. Also adding with min max squared who rule the LSTM. Moreover, Bangladesh COVID-19 study with prediction up to 2 weeks trained by the LSTM [29] gives actual predictions that also compare with other ML models such as Random Forest(RF) [30] and SVR. Figure_2 describes the actual happening in the LSTM hidden layer [26]. LSTM function determines the solution by RMSE and Mean squared error that will produce a loss function by confirmed, death, recovery cases as Table-2. Furthermore, table-2 illustrates the loss error rate graph, which is the present loss history of model LSTM. In graphical scenario each case predicted with 100 epoch set by the boundary of 0 to 1. After that this analysis makes historical predictions among training and test sets using loss rate.

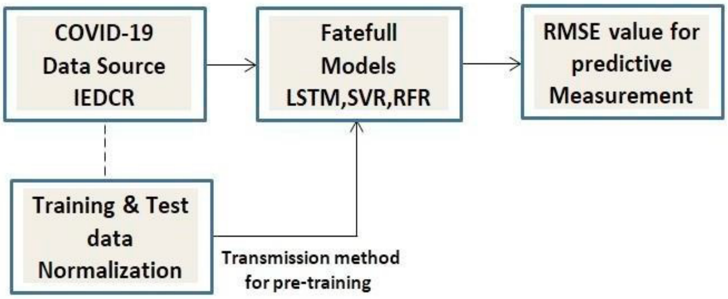

Figure-2: Proposed Method of COVID-19 Forecast.

Model Loss		
Confirmed	**Death**	**Recovery**
0.0230	0.2479	0.0039

Table 2: Loss Function determination of loss error rate with epoch

First attempt to explain loss function low rate table 2 has shown how the confirmed, recovery and death cases reduce from high to low output with 0.0230, 0.2479, 0.0039. Fig_3 illustrates how the plotting curve minimizes output randomly in each epoch also test data reshaped and add with training data. On the basis of contemporary, model loss history for true and predict of trained vs test data further epoch making a debated loss history decreasing loss output which is shown as graphical plotting speaks as same output that generally bow down from high to low.

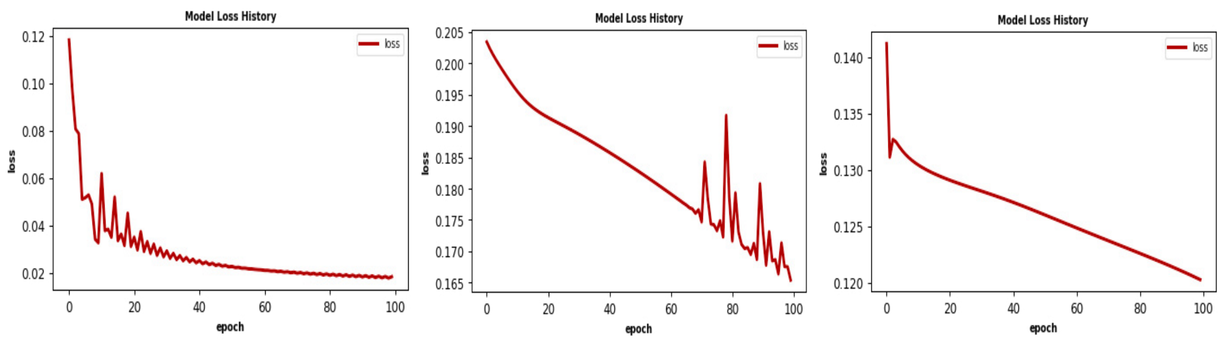

Figure 3. Loss on the train and test sets of LSTM models based on three cases.

4. Results and Discussion

4.1. Future Trajectory of COVID-19 in Bangladesh

In overall view, to provide a forecast on the counting number of 3 infectious cases in Bangladesh is the upcoming situation measure till June 15th of 2020. Considering results in Table-3, excellent performing network LSTM of deep learning model that also compared with other ML models depend on desired RMSE value of train, test and all for future prediction. Fig_4 is the forecast area of the predicted daily increased or decreased of confirmed, death and recovered cases in Bangladesh till May 13th to June 15th of 2020. After that, predicted value compared with real data value plotted by another fig_5 and the last listed time series data of future prediction for raising awareness based on the prediction of what next.

Real time data procedure is quite a complicated situation to handle starting with finding the statistical data as a working file after the reshaping into trained and test data later applied with LSTM then we can visualize the data over graphical representation. Data visualization on graphical representation we have taken per data in Y axis and 3 separate conditions from COVID-19 epidemic on confirmed, death, recovery data in X axis over per day of 1000 cases. We are trying to focus on illustrating the condition below such a simple description.

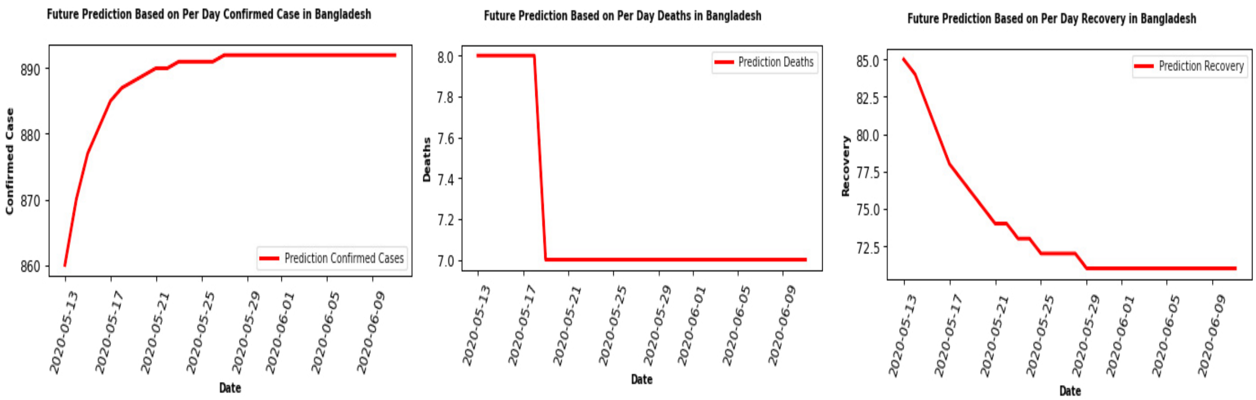

Figure 4: Future Prediction on per day Confirmed, Recovery, Death Cases.

Figure 4 plotted the data over 3 cases and visually represent the starting situation in Bangladesh on March 2020. Initially, critical condition level is low after that curve started to rise affected in positive cases. In case we describe the graph as we can see on 13th May confirmed cases 860 in the middle 29th May increase by 890 after that 9th June it will go constant. Second graph shows for death cases on 13th may found 8 deaths in the middle, death cases found low by 7 on 29th May at last 9th June situation remain the same. Now come to the recovery graphical plot with a different view in 13 May recovery rate is 85 in the middle, 25th may recovery case bow down and after that 9th June recovery rate below 71. In figure 4 all graphical situations remain the same, no positive reflection in that case, future prediction necessary to raise awareness about health risk.

Figure 5 plotted the data over 3 cases and visually representing from the figure 4 that replies infected and death rate tremendously increase besides that recovery rate is poor till 15th June of 2020 in which critical condition level is low After that curve started to rise affected in positive cases. In case we describe the graph as we can see on 13th May confirmed cases 500 in the middle 29th May increase by 800 to 850 after that 9th June it will go constant. Next graph shows for death a zigzag plotting cases on 13th may found 6 deaths in the middle, death cases found low by 7 on 29th may at last 9th June situation remain the same. Now come to the recovery graphical plot with a different view in 13 may recovery rate is 140 in the middle, 29th may recovery case bow down below 60 and after that 9th June recovery rate around 60. In figure 5 all graphical situations remain the same but the number of prediction cases increase but There has no positive reflection in that case figure-4 to figure-5 has been necessary to further future prediction due to time series analysis predict accurately no longer than two weeks. Therefore, double prediction may check the previous prediction in which remain the same of existing output.

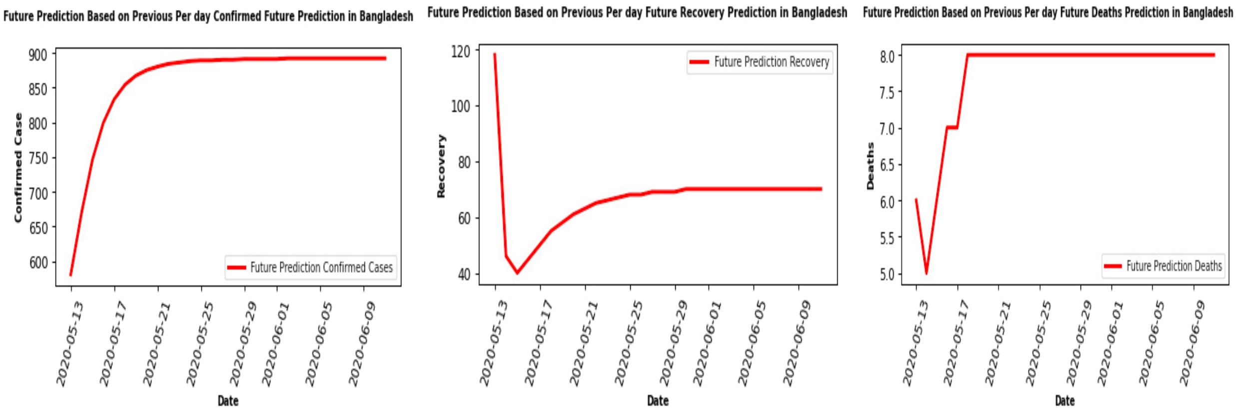

Figure 5: Further Prediction on Previous per day Confirmed, Recovery, Death Cases.

Figure 6 plotted the data over 3 cases where visually represented future prediction based on per day showing the graph trajectory where green trajectory of prediction in more than 2 weeks is the actual curve in which means the total output of all trajectories. The starting situation in Bangladesh on march 2020 critical condition level is low after that curve started to rise in positive cases. In case we describe the graph as we can see 15th march confirmed cases prediction simulated by the actual death is null in the middle, first may actual prediction being affected over 600 and 15th June more than 15 days are prediction increase by the 800 people would be confirmed cases.
Coming to the next death cases prediction simulated by the actual death 15th March was null, in the middle, first may actual prediction being die over 10 also predicted per day 10 to 12 and 15th June over 2 weeks is prediction will increase by the per day death may 12 people will be death cases. After that if we present recovery cases there is no outstanding positive impact. In future up to 15 June recovery cases will be decreased by 200 per day.

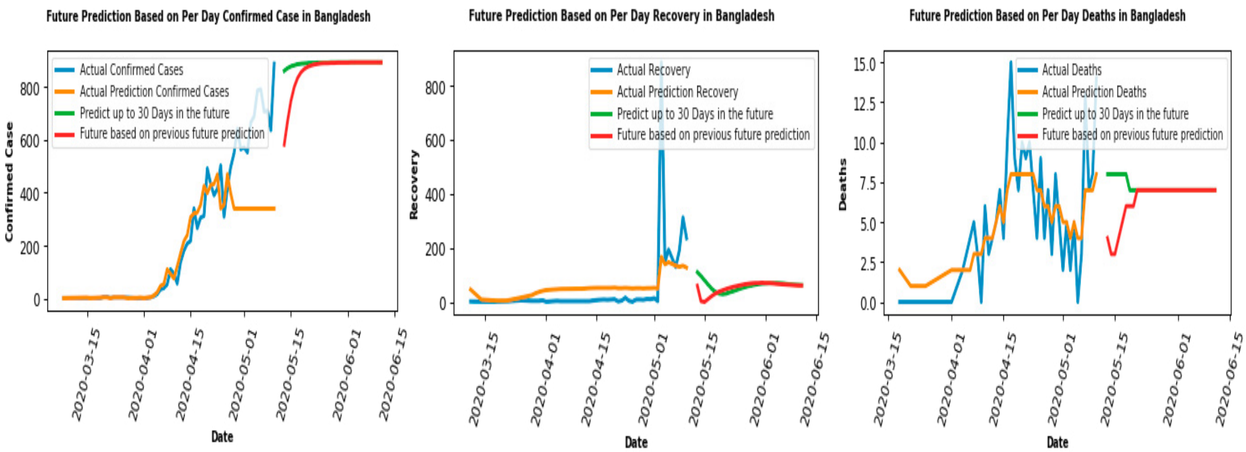

Figure 6: Number of infections up to two weeks in Bangladesh as of 15 June 2020
in COVİD-19 epidemic future predictive analysis using LSTM.

To the best of our knowledge, in Figure-7 that has proclaimed a comparative study that is measure the output how far accurate between the actual output of our LSTM prediction based model till 9th of June and the next 15th June to 15th of July scenario of Bangladesh Covid-19. Especially, graph has showed the after June of 2020 next scenario in which daily confirmed, death and recovery rate is too high situation will bow down. In that case, our model estimation so much true instead we have analysis by the previous figures where figure states that upcoming days in Bangladesh infected cases increase rapidly but recovery cases very low and everyday scenario of death cases also very high which is lagging very negatively. This comparison relates the prediction of model give actual measurement of COVID-19.

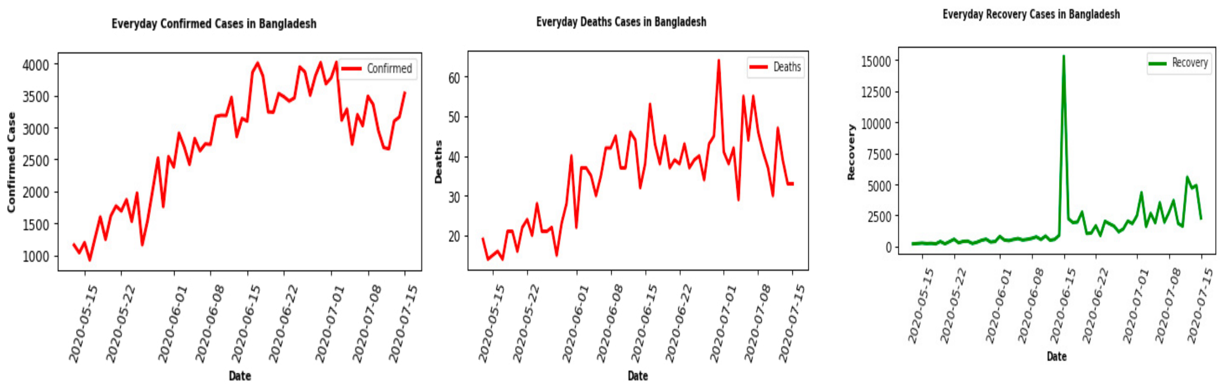

Figure 7: Comparative scenario of between model prediction and next June of 2020 to July affected per day situation

4.2. Optimal Model Selection

According to COVID-19 real time analysis best for LSTM in deep learning method [6,14,18]. Although we evaluate the performance of models we've approached three types of models based on deep analysis. In these three models trained by the per day confirmed, death, recovery cased. Comparative study as followed by the RF regression model and SVR model [26,18]. Table-3 assumed the RMSE value which through we proved LSTM is the optimum solution. Coded by the MAPE metric to analyze different models and percentages of error on real value remain safe greater than Mean Absolute Error. Here, we calculate the RMSE value for LSTM, SVR, RF regression on train, test and all RMSE values are high comparatively only LSTM evaluation RMSE value is accurate.

In a sense, we should say LSTM is perfect fitted of real time analysis [31]. Long-term sequences to short-term sequences generate a strong visualization. Convolutional network which have hidden layer with input, dense and output layer committed their proof a faithful model with high performance on time series analysis [32].

RMSE

Model	Train Accuracy			Test Accuracy			All Accuracy		
	Confirmed	Death	Recovery	Confirmed	Death	Recovery	Confirmed	Death	Recovery
LSTM	53.14	2.54	27.15	274.86	4.18	330.28	65.83	2.95	163.21
RFR	200.65	6.48	9.27	680.36	8.09	336.73	184.21	3.28	170.15
SVR	150.29	8.45	7.16	650.33	9.91	304.12	166.15	4.73	215.08

Table 3: Comparative Results on prediction of LSTM, RFR, SVR

5. Conclusion & Future Works

In this article has been accomplished by the proposing forecast model where whole country will get information due to the pandemic of Covid-19 in Bangladesh. Throughout, the full approach we have studied about the time series analysis by the taking of patient data from IEDCR healthcare in Bangladesh and this is the relevant source of data. During the procedure using LSTM model for making future estimation we had taken three cases that is confirmed, death and recovery cases. In the section of methodology, we try to forecast up to 30 days upcoming scenario plotted with graphical visualization that has conflict the situation over three different cases. Time series analysis effectively been proposed the output where upcoming Bangladesh scenario in two or three weeks going to badly fall down. Confirmed and death cases will remain high and recovery cases will recover very poorly. Particularly, time series analysis approach we had made a comparative analysis by the RMSE rate among the LSTM, RF regression and SVR models. Lastly, predicted output checked by the current two weeks of data and the situation is the quite similar to the predicted output.

Furthermore, the study of Covid-19 need lots of advancement in future. Tropically, more data influence system will remain highly efficient. Eventually, so many types of idea have related to Covid-19 that will applicable by the time series analysis in next.

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