



Time series forecasting of COVID-19 transmission in Asia Pacific countries using deep neural networks

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Abstract

The novel human coronavirus disease COVID-19 has become the fifth documented pandemic since the 1918 flu pandemic. COVID-19 was first reported in Wuhan, China, and subsequently spread worldwide. Almost all of the countries of the world are facing this natural challenge. We present forecasting models to estimate and predict COVID-19 outbreak in Asia Pacific countries, particularly Pakistan, Afghanistan, India, and Bangladesh. We have utilized the latest deep learning techniques such as Long Short Term Memory networks (LSTM), Recurrent Neural Network (RNN), and Gated Recurrent Units (GRU) to quantify the intensity of pandemic for the near future. We consider the time variable and data non-linearity when employing neural networks. Each model's salient features have been evaluated to foresee the number of COVID-19 cases in the next 10 days. The forecasting performance of employed deep learning models shown up to July 01, 2020, is more than 90% accurate, which shows the reliability of the proposed study. We hope that the present comparative analysis will provide an accurate picture of pandemic spread to the government officials so that they can take appropriate mitigation measures.

Keywords COVID-19 · Convolutional neural networks · LSTM · RNN · GRU

1 Introduction

At the beginning of December 2019, the extremely intense syndrome coronavirus (COVID-19) detected in the Chinese

city Wuhan caused the episode of a new coronavirus illness and China turned into the epicenter of this disease [28]. Fever, breathlessness, and dry cough are the known symptoms of this transferable disease [26]. Meanwhile, due to human traveling, the malady has spread more than 206 nations or regions of the world, ultimately the USA and Europe have emerged as new focal points [6, 43]. The World Health Organization announced this disease as a pandemic disease on the 11th of March 2020 [50].

After World War II, the COVID-19 has been considered as the major crisis for the world's economy and health [7]. On the 17th of May, the confirmed patients of COVID-19 were 4799266 whereas 316520 people lost their lives due to this pandemic [51]. These figures surpassed the records of two carnivorous epidemics (SARS-CoV and MERS-CoV). Since there is no medical treatment/vaccine of coronavirus, different nations have adopted different measures to control this epidemic. Strict lockdown, partial lockdown, closure of all educational institutes, and dismissal of all types of flights are the most common in all. On January 23, 2020, the Local administration of Wuhan imposed a strict lockdown, followed by many neighboring cities soon after [17]. They suspended all types of public transport and advised the citizens to stay at home.

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Due to the unavailability of the proper cure for this malady, keeping up social distancing is the best way to decrease COVID-19 transmission from one person to another [10]. Ultimately the other countries also followed the Chinese model of lockdown curfews and quarantines. On March 9, 2020, the Government of Italy forced a national quarantine due to the exponential increase in COVID-19 patients. Furthermore, they confined the movement of citizens except for medical emergency and supply of necessary goods and services. The similar measures were taken by Argentina (March 19, 2020 [4]), Spain (March 14, 2020 [31]), the USA (various states from March 19, 2020 [12]), South Africa (March 26, 2020 [11]), the UK (March 23, 2020 [45]) and numerous different countries.

After China, Iran became the epicenter of this disease in Asia. Consistently, several Pakistani citizens travel to Iran to perform religious activities. On February 23, 2020, as the number of Corona patients began to rise, Pakistan shuts its border with Iran [49], but hundreds of Pakistanis somehow managed to return, either by diverting through Afghanistan to Pakistan or by any other way. The first two cases of COVID-19, from Karachi and Islamabad each, were confirmed by the Government of Pakistan officials on 26 February. Both cases have recent travel history to Iran. To forestall the infection spread to other people, the Government decided to isolate the visitors on their arrival from Iran in Taftan, a town in Baluchistan near the Pak-Iran border [19, 37].

Such a tempestuous situation of epidemic outbreaks raised several general questions: will coronavirus persists until the discovery of its vaccine or it will automatically be abolished after a certain period? How much time does the medical scientist need to prepare its proper medicine/vaccine? How many people will be affected by this epidemic? What could be the death/recovery rate among the affected patients? Does it vary in different age groups and regions of the world? If Yes, then what could be the possible reasons? To what extent is the lockdown policy effective to reduce the spread? What are the side effects of lockdown and how long is it affordable for different countries?

Usually, medical predictions are not precise while their unreliability is underestimated [29, 30]. Since the number of cases to be investigated can be estimated single-handedly, therefore the prediction of the future of pandemics and epidemics is not an easy task [40]. Regardless of the inaccuracies related to medical forecasting, still these are important by portraying a picture of the present circumstances to the public so that a comprehensive preparation can be made for the future challenges. The uncertain circumstances of the epidemic forced the scientists and data analysts to proposed COVID-19 spreading models to predict its intensity shortly [1, 3, 18, 32, 33, 38, 52]. Similarly, some optimization

techniques [36] can also help to optimize such models and leads to more optimal results.

In recent weeks, numerous studies on COVID-19 have been reported, but they lack the specific measures such as:

- Most current studies are country-specific rather than comparative research for some regions with particular algorithms [8].
- They also lack the time variable when taking COVID-19 data into account. Many studies are based on linear knowledge and are not linear [48].
- Some studies have considered observational studies models which can only be initialized based on hypotheses [48].
- In this work, we have developed a forecasting model of COVID-19 outbreak in Asia pacific countries particularly Pakistan, Afghanistan, India, and Bangladesh employing state of the art deep learning models such as LSTM, RNN, and GRU.
- We assessed the key features of each model to predict the possible number of COVID-19 cases in the next 10 days.
- The comparative study of these four countries will help the higher authorities to prepare for the necessary actions that need to be taken based on our model predictions. Summary of COVID-19 since 01-22-2020 to 06-21-2020 in Pakistan, India, Afghanistan and Bangladesh is presented in Figs. 1, 2, 3 and 4.

The remaining sections are organized is as: related work along with the systematic summary table is presented in Section 2. Where Section 3 elaborated four deep learning models used for the time series forecasting. Empirical

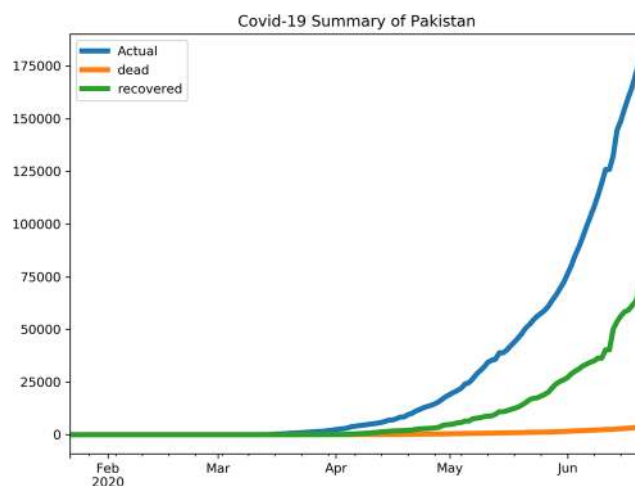


Fig. 1 Summary of COVID-19 since 01-22-2020 to 06-21-2020 in Pakistan

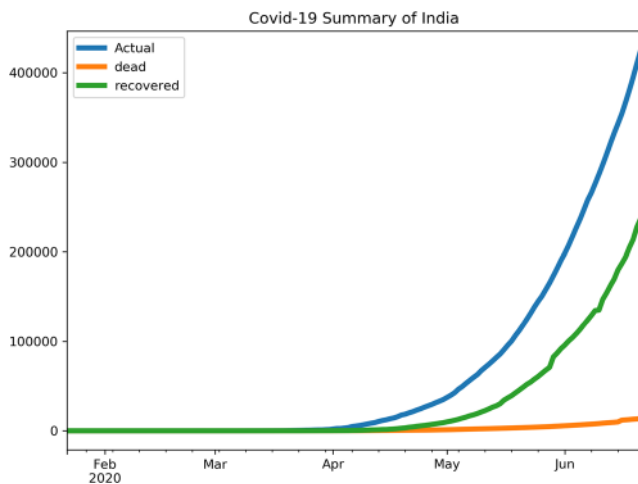


Fig. 2 Summary of COVID-19 since 01-22-2020 to 06-21-2020 in India

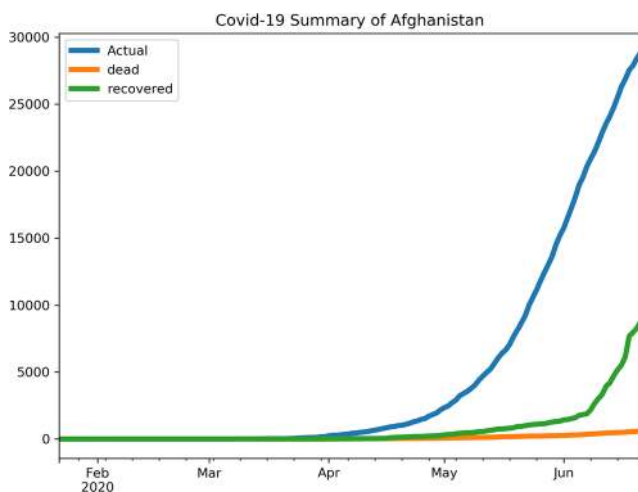


Fig. 3 Summary of COVID-19 since 01-22-2020 to 06-21-2020 in Afghanistan

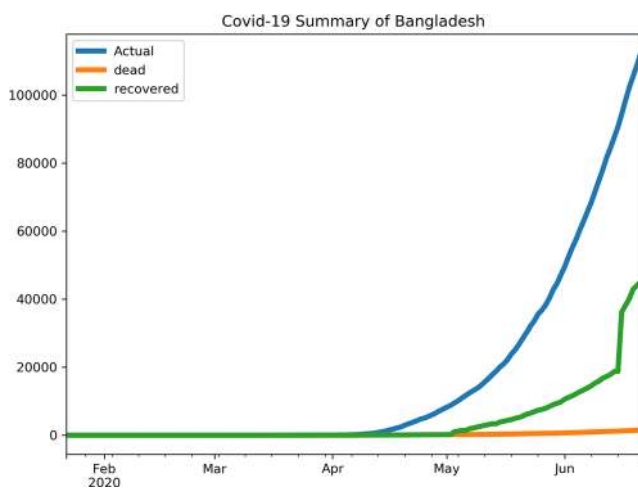


Fig. 4 Summary of COVID-19 since 01-22-2020 to 06-21-2020 in Bangladesh

results obtained after experiments and their analysis is done in Section 4. The study is concluded in Section 5.

2 Related work

The author employed a flower pollination algorithm and Salp Swarm Algorithm to forecast the number of COVID-19 patients in the next ten days. A. Remuzzi and G. Remuzzi provides a comprehensive analysis of COVID-19 present and expected future situation in Italy [38]. Perc et al. [32] developed a basic iteration technique that only requires the daily values of affirmed cases of COVID-19 as input. The method considers anticipated recoveries and deaths and determines the maximum allowed daily growth rates that lead away from exponential increase toward stable and declining numbers. The estimates show that daily growth rates must be kept at least below 5% if we want to see plateaus any time soon. In [52] a segmented Poisson model is presented to examine the information available for the COVID-19 outbreaks in the six Western countries Italy, Canada, Germany, the UK, France, and the USA. Some similar studies have been proposed in [23, 34, 46].

The temporal dynamics of the COVID-19 outbreak, from 22-01-2020 to 15-03-2020, in China, Italy and France were analyzed by Fanelli and Piazza [18]. In [33] an efficient model for the prediction of COVID-19, in the time window Feb 1, 2020, to March 11, 2020, is proposed. The authors divide the prediction time window in 4 rounds of ten days each. It is found that the second and third sets of forecasts that ranges from 11/02/2020 to 01/03/2020 came very close to the original cases. Cleo Anastassopoulou et al. [3] presents Data-based analysis and prediction of the coronavirus disease epidemic. They used publicly available epidemiological data for Hubei, China, from 11-01-2020 to 10-02-2020 and give assessments of the main epidemiological parameters. Another forecasting model of the COVID-19 outbreak is presented in [1].

In the study [42], two kinds of datasets have been revealed, i.e., huge information got from World Health Organization/National databases and information from an online networking correspondence. Gauging of a pandemic should be possible dependent on different boundaries, for example, the effect of natural components, the brooding period, the effect of isolation, age, sex, and some more. These methods and boundaries utilized for anticipating are broadly concentrated in their work. Be that as it may, determining strategies accompany their arrangement of difficulties (specialized and conventional). Their investigation examines these difficulties and gives a lot of proposals to the individuals who are right now battling the worldwide COVID-19 pandemic (Table 1).

Table 1 Latest studies on COVID-19 time series analysis

	Ref	Dataset	Methods	Region	Limitations
1	[21]	Self-gathered	Data mining (PNN+cf)	China	Detection of only suspected cases
2	[20]	CCDCP	Composite Monte-Carlo (CMC)	China	Focused on recommendation only
3	[5]	WHO	Logistic inference	Hybrid countries	Detection of only death cases
4	[22]	WHO	Modified auto encoders (MAE)	China + Hybrid countries	Measuring impact in qualitative way
5	[24]	DATA S-013	Gompertz model + Bertalanffy model	China	Detection of only death cases
6	[27]	ICD	Weibull equation and Hill equation	Github	Considered infection rate only
7	[16]	ICD	Charlson Comorbidity	Github	Measure risk rate

3 Methods and models

3.1 Deep learning

Deep learning neural networks methods have emerged as a promising technique for automatically learning arbitrary complex mappings from inputs to outputs [35]. They support multiple inputs and outputs. These techniques are robust to noise, non-linear, multivariate inputs, and multi-step forecast [2, 36, 53].

3.2 Recurrent neural network

The recurrent neural network (RNN) is a well-known neural network in which the outcome of the preceding step takes as input into the ongoing step [41, 53]. It is an extension of traditional neural networks. It is well-known that the inputs and outputs do not depend upon each other in conventional neural networks, but in cases where the next word of a sentence has to be predicted, the previous words are essential and therefore the previous words must be saved. This is how RNN came into being, which resolved this problem by using a hidden layer. The hidden state is the leading aspect of RNN is the hidden state, in which some sequence data is stored. The present and the recent past are the input sources of RNN networks, which together determine how they react to new data. RNN has a “memory” that stores all information about what has been computed [41, 44]. It employs the same parameters for every input because it does the same job for all inputs or hidden layers to generate the results. This decreases the complexity of parameters, unlike other neural networks.

Let $(x_1, x_2, x_3, \dots, x_T)$ be the given sequence of inputs and φ is a non-linear mapping. Then,

$$[h_t = \begin{cases} \varphi(h_{t-1}, x_t), & \text{if } t \neq 0 \\ 0 & \text{if } t = 0 \end{cases} \quad (1)$$

Conventionally, the update of the hidden state h_t at time t can be implemented as;

$$h_t = g(Wx_t + Uh_{t-1}) \quad (2)$$

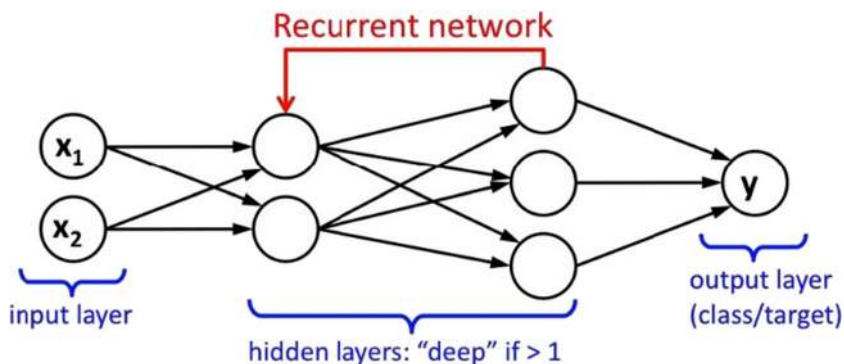
where g denotes smooth and bounded mapping just like a hyperbolic tangent map. RNN keeps track of all information over time. It is also useful in time series forecasting because it remembers all previous inputs. The basic architecture of RNN with 2 input neurons and 5 hidden neurons is presented in Fig. 5.

3.3 LSTM networks for time series modeling

Much of the real-world datasets are temporal in nature. Because of its typical features, there are various unresolved issues with broad-spectrum applications. Time series (TS) data is the information gathered over regular time intervals such that every data point is evenly spaced over time. Time series analysis is most productive when utilized in transient estimating. It is the method of predicting future patterns/trends of a certain event with temporal characteristics. To forecast the transmission of coronavirus, it can be productive if provided information has temporal components and it is different from conventional regression schemes. A time series information may be divided into trend, error, and seasonality.

If a repetition in a specific pattern is found at regular intervals of time, then a trend in time series is said to be

Fig. 5 Basic architecture of RNN with 2 input neurons and 5 hidden neurons [39]



observed. This repetition evolves due to external factors like mandatory social distancing, lockdown/quarantines. There is no seasonality or trend in numerous real-world scenarios. After assessing the time series nature, numerous prediction techniques must be applied in certain TS.

The given time series is divided into two segments, stationary and non-stationary. If the series is independent of time components, then it is called stationary time series. In this series, seasonality effects, trend, mean, and variances remain constant over time. Stationary time series is easy to examine and lead to meaningful prediction. A time series data is called non-stationary if seasonality effects, trend, Mean, standard deviation, and variances in it vary with the variation in time.

We have utilized ADF (Augmented Dickey-Fuller) analysis [13] on the input information of COVID-19 to decide whether it falls in a stationary or non-stationary category. The Augmented Dickey-Fuller test is the fundamental unit root analysis to note the effect of patterns observed in the input data. A parameter, namely P scores of the test is used to present the outcomes of ADF analysis. A P score of less than 5% leads to the rejection of the null hypothesis, that is, a unit root is absent and ultimately the series is stationary. If one acquires the value of P larger than 5% then it means that the unit root is present in the input information, and hence, the series is non-stationary.

Before start looking at the structure of the model, it is important to explain the LSTM network’s internal system and major motives behind utilizing it instead of conventional Recurrent Neural Networks. The limitations of conventional time series prediction methods are controlled through Recurrent LSTM networks by adjusting non-linearities of the given dataset and provides outstanding outcomes on temporal information. Every block of LSTM works at a distinct time step and forwards its output to the upcoming block until the last LSTM block produces the sequential output. To the best of our knowledge, RNNs with blocks are effective systems to assemble a time TS model. The memory blocks are the basic component of LSTM networks.

They memorize network parameters for long periods to combat vanishing gradients. It is important to mention that the in LSTM memory blocks and the differential storage networks of digital systems have a similar structure. Gates in LSTM assist to process the data using activation mapping (sigmoid) and output lies in the interval $[0, 1]$. Since we have to ignore negative values and allow only positive scores to the next gate to obtain a transparent out, therefore we utilize sigmoid activation mapping. The following equations represent all three gates of LSTM networks;

$$\Gamma_t = \text{sigmoid}(\Phi_\Gamma [\mu_{t-1}, v_t] + \beta_\Gamma) \tag{3}$$

$$\Psi_t = \text{sigmoid}(\Phi_\Psi [\mu_{t-1}, v_t] + \beta_\Psi) \tag{4}$$

$$\Omega_t = \text{sigmoid}(\Phi_\Omega [\mu_{t-1}, v_t] + \beta_\Omega) \tag{5}$$

Where: Γ_t = input gate mapping

Ψ_t = forget gate mapping

Ω_t = output gate mapping

Φ_X = neurons coefficients gate X

μ_{t-1} = preceding time step outcomes

v_t = input to the present mapping at time t

β_Ω = neurons bias at gate X

In Eq. (3), the input gate provides the data which must be saved in the cell state. The forget gate activation output based data is acquired from Eq. (4). For the output gate, the Eq. (5) merges the cell form data and the forget gate output

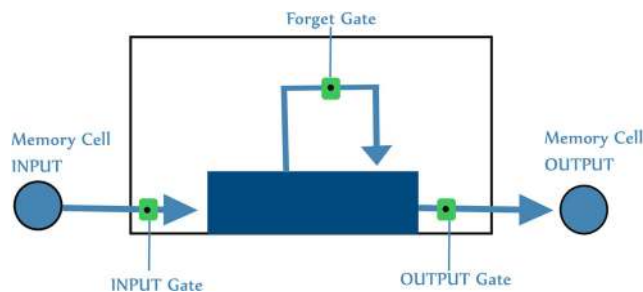


Fig. 6 The graphical representation of LSTM block

Fig. 7 LSTM network architecture

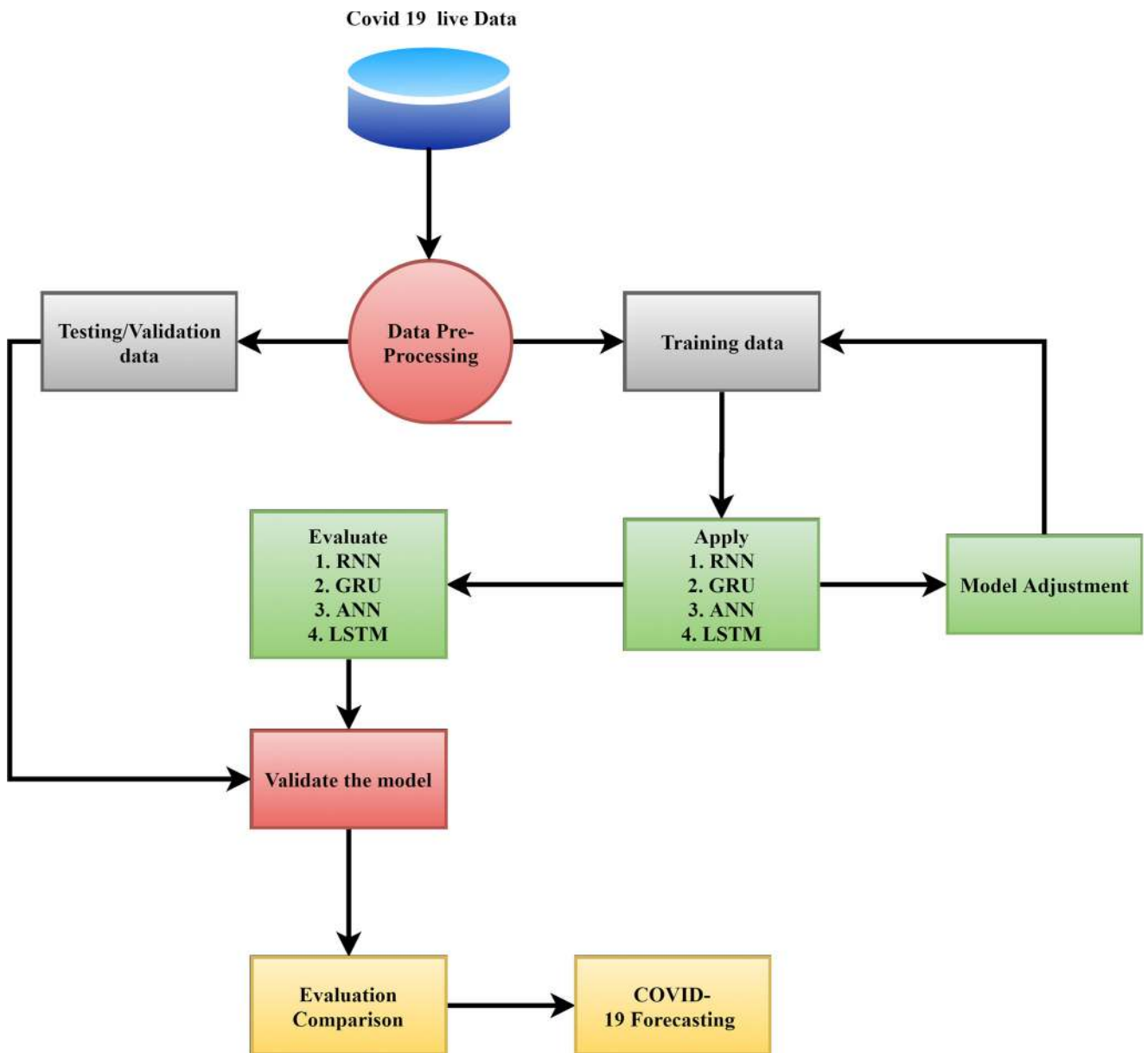
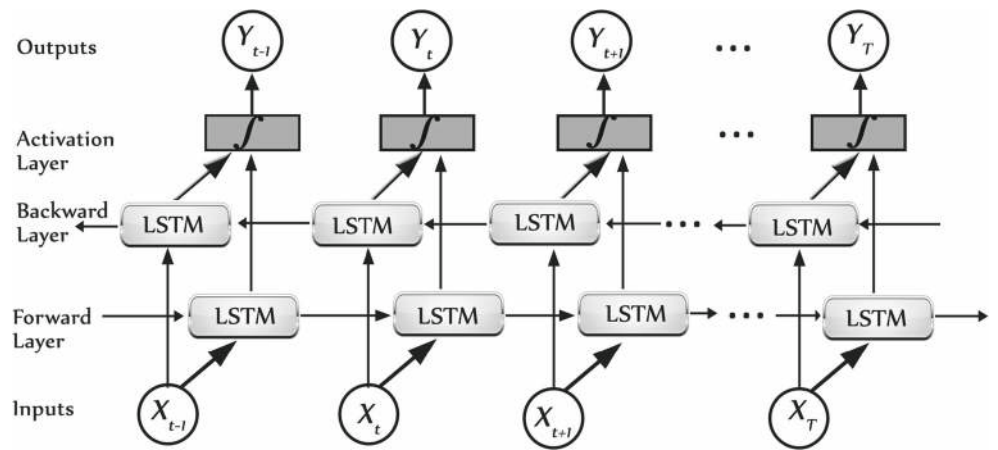


Fig. 8 Object process diagram of COVID-19 comparative analysis

at the time step to generate the output. Figure 6 shows the graphical representation of the LSTM block utilized in this work. The motivation for developing self-loops is to design a system that allows the sharing of weights or gradients for a long period. It is helpful to model deep networks where gradient disappearance is an incessant problem. By modifying weights like self-looped gates, the time scale can be adjusted to identify the dynamically evolving parameters. With the techniques mentioned above, LSTMs achieve excellent findings in [25]. Figure 7 shows the network architecture utilized in this paper (Fig. 8).

3.4 Gated recurrent unit

Gated recurrent units (GRUs) is an upgraded version of standard RNN, introduced by Cho et al. in 2014 [14]. It makes each recurrent unit to adaptively capture dependencies across various time steps. The GRU, like LSTM, has a forget gate to regulate the information flow however with fewer parameters as compared to LSTM since it does not possess separate memory cells. The network architecture of GRU is visualized in Fig. 9.

Let h_{t-1}^j and \bar{h}_j^t denote previous and candidate activations respectively, then activation h_t^j of the GRU at time t can be calculated by the following formula:

$$h_t^j = z_t^j \bar{h}_j^t + h_{t-1}^j (1 - z_t^j) \tag{6}$$

where z_t^j is an update gate that determines how much the unit updates its content or activation. The following equation is used to find the value of update gate z_t^j

$$z_t^j = (U_z h_{t-1} + W_z x_t) \sigma \tag{7}$$

The process of calculating the linear sum between the current state and the recently calculated state is the same in both GRU and LSTM units. However, GRU does not have

an appropriate system in place to control the extent to which its condition is exposed, it rather discloses the entire state each time.

The candidate activation or Current Memory Gate \bar{h}_j^t can be computed as;

$$\bar{h}_j^t = \tanh \left(U \left(r_t \odot h_{t-1} \right) + W x_t \right)^j \tag{8}$$

Where r_t denotes the reset gate and \odot is Hadamard product. The reset gate r_t can be calculated in a similar way to \bar{h}_j^t ; that is,

$$r_t = \sigma \left(W x_t + U_r h_{t-1} \right)^j \tag{9}$$

The working capability of GRU and LSTM in certain natural language processing tasks, speech signal modeling, and polyphonic music modeling is found to be identical. However, the performance of GRUs is better on certain smaller and less common data sets.

In [47] G. Weiss et al. have shown that the LSTM is strictly stronger than the GRU because it can easily count indefinitely unlike GRU. Thus, the GRU does not learn simple languages that can be read by the LSTM.

4 Results and discussion

The object process diagram of COVID-19 comparative analysis for proposed frameworks is presented in Fig. 8. The dataset is preprocessed to maintain the time variable at a single column from the starting date of COVID-19 to the current data used in the study. For merging several attributes, we employed inner joins and other concatenation approaches used to pre-process the datasets [9, 10]. After that, the data is passed to the deep learning models i.e RNN, LSTM, ANN, and GRU for training purposes. The evaluation is then performed before hyperparameters adjustment.

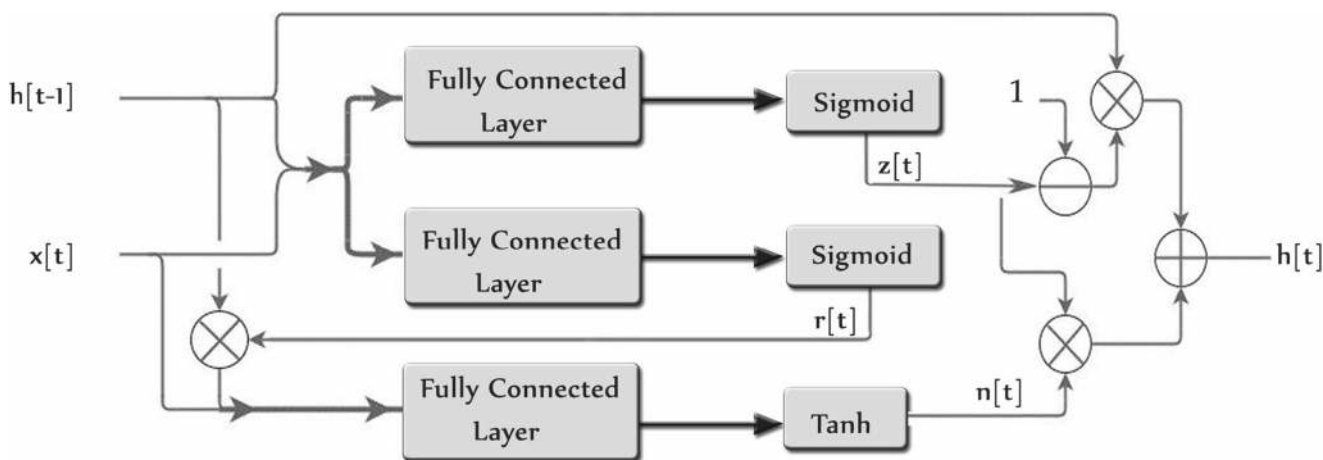


Fig. 9 The network architecture of GRU

4.1 Dataset

The methods utilized in this research are dependent on the live data guide and are entirely divergent from prior examinations. The outcome of our method time series forecasting will assist the targeted countries to proceed further to eliminate the current COVID-19 pandemic. The data set used for the training and testing of deep learning models are taken from the standard WHO website which is organized and publicly available at [15]. We trained RNN, LSTM, and GRU with COVID-19 cases from 01-22-2020 until 06-21-2020. As mentioned earlier, we only consider Pakistan, India, Bangladesh, and Afghanistan for the comparative analysis. The proposed framework is enough dynamic in nature as it updates the forecasting results each day from each country considered. It also considers all previous data from Jan 22, 2020, up to the current day to predict the next 10 days number of COVID 19 cases.

4.2 Experimental setup

All experiment is performed on Haier Intel® Core™ i3-4010U CPU machine with the specifications as, 8 GB random access memory, 128 GB solid-state drive, and no graphic card. Famous deep learning packages from python i.e Keras, Tensor flow, Numpy were used to implement LSTM, RNN, GRU, and ANN. The activation function for the input layer was set to Relu with true return time series sequences. Adam optimizer is used in the Last layer. The validation length for the training process was fixed to 10 and the batch size was 1 with Early-stopping epochs criteria. Moreover, the experiment for one model includes a total of 100 epochs with 10 epoch per step.

4.3 Discussion

The comparative analysis of three different forecasting models has been carried out to predict the COVID-19 cases count in the next 10 days to help the Asia Pacific countries to avoid this breakthrough by taking necessary actions in advance. The model includes RNN, LSTM, and GRU comprises deep learning layers to dynamically extract the features from previous knowledge and predict new patterns symmetrically. In the last couple of weeks, with more than 108K COVID-19 cases, Pakistan has crossed the official include in neighboring China, the nation earlier caught by the COVID-19. Authoritatively anticipated figures propose positive cases in Pakistan could arrive at 125K by June 15. Prediction results of the next 10 days about possible COVID-19 cases obtained using RNN in Pakistan are presented in Table 2.

To validate the forecasting predictions obtained using the proposed framework, actual cases of the previous 10

days have been taken with a confirmed number of COVID-19 patients. The minimum and a maximum difference of actual versus predicted has been recorded to validate the performance.

As compared to Pakistan, India got a bit high COVID-19 spread ratio. In the early stage, they were managed to control it by applying sudden and strict curfew. However, as the long stretch of April began, the number of cases began multiplying rapidly and the early achievement began to disentangle. Prediction results of the next 10 days about possible COVID-19 cases obtained using RNN in India are shown in Table 3. Patient in Afghanistan is progressively confronting an always serious danger: The arrival of almost 3M Afghan transient laborers since February from Pakistan and Iran, one of the infection's worldwide focal points. The Afghan well-being service surveyed that the infection has spread to 29 of 34 areas, first because of these mass returns yet now naturally inside networks, as well. Prediction results of the next 10 days about possible COVID-19 cases obtained using RNN in Afghanistan are listed in Table 4.

As compared to Afghanistan, the total confirmed cases of the coronavirus outbreak are higher in Bangladesh since the month of June. But lesser than the total confirm count in Pakistan and India. However, the corresponding ratio of spreading is high then the other small Asian regions. Prediction results of the next 10 days about possible COVID-19 cases obtained using RNN in Bangladesh are elaborated in Table 5. Similarly, Table 6 representing the forecasting results obtained from 22/6/2020 to 1/7/2020 in Pakistan by using the GRU model. In addition, possible total confirms count in India, Afghanistan, and Bangladesh predicted by GRU from 22/6/2020 to 1/7/2020 are shown in Tables 7, 8 and 9.

Lastly, we employed LSTM to check the relation of forecasting prediction with GRU and RNN in terms of better accuracy, minimum range, maximum range, and the corresponding intervals. The empirical results obtained using LSTM with the next 10 COVID-19 cases prediction in Pakistan are recorded in Table 10. Moreover, possible total confirmed counts in India, Afghanistan, and Bangladesh predicted by LSTM from 22/6/2020 to 1/7/2020 are shown in Tables 11, 12 and 13. From Tables 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, and 13, Actual shows the already confirmed cases from 12/06/2020 to 21/06/2020, predicted representing the total number of confirmed cases predicted by the corresponding model in a particular state. Where Min reveals the minimum number of predictive cases and Max displays the maximum number of predictive COVID-19 cases in a particular country from 12/06/2020 to 1/07/2020.

Graphical representation of the next 10 days COVID-19 cases prediction obtained using RNN in Pakistan are exhibited in Fig. 10 Where the visualization curves for

Table 2 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using RNN in Pakistan

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	125933	134226.9	67245.4	201208.3783	0.9
13/6/20	132405	141502.9	74521.46	208484.4302	0.9
14/6/20	144478	149065.2	82083.72	216046.6932	0.9
15/6/20	148921	157161.6	90180.12	224143.0968	0.9
16/6/20	154760	165724.9	98743.38	232706.3555	0.9
17/6/20	160118	174724.1	107742.6	241705.5888	0.9
18/6/20	165062	184141.5	117160	251122.962	0.9
19/6/20	171666	194240.1	127258.6	261221.6122	0.9
20/6/20	176617	204998.9	138017.4	271980.417	0.9
21/6/20	181088	216449.1	149467.6	283430.542	0.9
22/6/20	–	228637.1	161655.7	295618.6308	0.9
23/6/20	–	241231.8	174250.3	308213.2699	0.9
24/6/20	–	254507.6	187526.1	321489.0959	0.9
25/6/20	–	268539.4	201558	335520.9305	0.9
26/6/20	–	283331.8	216350.3	350313.3225	0.9
27/6/20	–	298931.3	231949.8	365912.8102	0.9
28/6/20	–	315386.6	248405.2	382368.1239	0.9
29/6/20	–	332787.3	265805.8	399768.7374	0.9
30/6/20	–	351137.4	284155.9	418118.9142	0.9
1/7/20	–	370486.3	303504.8	437467.8047	0.9

India predicting the next 10 days COVID-19 cases using RNN is visualized in Fig. 11. Figures 14, 15, 16, 17, 18, 19, 20 and 21 representing the line curves of forecasting predictions achieved using GRU and LSTM on the counts of

Pakistan, India, Afghanistan, and Bangladesh respectively. In the X-axis the graphs show the total number of possible COVID-19 cases from minimum to maximum where the Y-axis represents the corresponding dates.

Table 3 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using RNN in India

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	308993	317032.8	223469.6	410596	0.94
13/6/20	320922	330664.3	237101.1	424227.5	0.94
14/6/20	332424	345066.9	251503.7	438630.1	0.94
15/6/20	343091	359935.7	266372.5	453498.9	0.94
16/6/20	354065	375677.2	282114	469240.4	0.94
17/6/20	366946	392240.7	298677.5	485804	0.94
18/6/20	380532	409381.9	315818.6	502945.1	0.94
19/6/20	395048	427891.9	334328.7	521455.1	0.94
20/6/20	410451	447527.2	353964	541090.5	0.94
21/6/20	425282	468183.5	374620.3	561746.7	0.94
22/6/20		490500.4	396937.2	584063.7	0.94
23/6/20	–	512545.6	418982.4	606108.8	0.94
24/6/20	–	535798.4	442235.1	629361.6	0.94
25/6/20	–	560225.1	466661.9	653788.3	0.94
26/6/20	–	585952.8	492389.6	679516	0.94
27/6/20	–	612985.2	519422	706548.4	0.94
28/6/20	–	641345.5	547782.3	734908.8	0.94
29/6/20	–	671192.7	577629.5	764755.9	0.94
30/6/20	–	702482.4	608919.2	796045.6	0.94
1/7/20	–	735230.2	641667	828793.4	0.94

Table 4 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using RNN in Afghanistan

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	23546	24981.77	10513.29	39450.25	0.87
13/6/20	24102	25955.72	11487.24	40424.2	0.87
14/6/20	24766	26969.66	12501.18	41438.14	0.87
15/6/20	25527	28076.02	13607.54	42544.5	0.87
16/6/20	26310	29215.89	14747.42	43684.37	0.87
17/6/20	26874	30386.37	15917.89	44854.85	0.87
18/6/20	27532	31596.84	17128.36	46065.32	0.87
19/6/20	27878	32910.18	18441.7	47378.66	0.87
20/6/20	28424	34315.72	19847.24	48784.2	0.87
21/6/20	28833	35853.4	21384.92	50321.88	0.87
22/6/20	–	37461.69	22993.21	51930.17	0.87
23/6/20	–	38973.29	24504.81	53441.77	0.87
24/6/20	–	40564.4	26095.92	55032.88	0.87
25/6/20	–	42236.78	27768.3	56705.26	0.87
26/6/20	–	43975.14	29506.66	58443.62	0.87
27/6/20	–	45782.14	31313.66	60250.62	0.87
28/6/20	–	47671.29	33202.81	62139.77	0.87
29/6/20	–	49648.07	35179.59	64116.55	0.87
30/6/20	–	51707.58	37239.1	66176.06	0.87
1/7/20	–	53848.19	39379.72	68316.67	0.87

We have used the real-time live uni-variate data set which means the deep learning model only considering date and time to predict the next 10 days cases. Furthermore, we

are monitoring the response from live data which is produced by domain-specific expertise hence, no data business exists.

Table 5 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using RNN in Bangladesh

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	81523	84733.74	61672.11	107795.4	0.94
13/6/20	84379	88212.18	65150.55	111273.8	0.94
14/6/20	87520	91878.88	68817.25	114940.5	0.94
15/6/20	90619	95731.17	72669.55	118792.8	0.94
16/6/20	94481	99730.28	76668.66	122791.9	0.94
17/6/20	98489	103949.4	80887.81	127011.1	0.94
18/6/20	102292	108450.4	85388.76	131512	0.94
19/6/20	105535	113094	90032.37	136155.6	0.94
20/6/20	108775	117859.3	94797.71	140921	0.94
21/6/20	112306	122805	99743.38	145866.6	0.94
22/6/20	–	128139.4	105077.8	151201	0.94
23/6/20	–	133080.8	110019.2	156142.5	0.94
24/6/20	–	138236.6	115175	161298.2	0.94
25/6/20	–	143582.3	120520.7	166644	0.94
26/6/20	–	149114.2	126052.6	172175.8	0.94
27/6/20	–	154838.7	131777	177900.3	0.94
28/6/20	–	160753.9	137692.3	183815.5	0.94
29/6/20	–	166811.9	143750.3	189873.5	0.94
30/6/20	–	173027.7	149966.1	196089.4	0.94
1/7/20	–	179418.8	156357.2	202480.5	0.94

Table 6 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using GRU in Pakistan

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	125933	131041.2	77119.9	184962.4	0.93
13/6/20	132405	138180.1	84258.78	192101.3	0.93
14/6/20	144478	145584.1	91662.79	199505.3	0.93
15/6/20	148921	153412.8	99491.5	207334.1	0.93
16/6/20	154760	161671.8	107750.6	215593.1	0.93
17/6/20	160118	170412.1	116490.9	224333.4	0.93
18/6/20	165062	179714.2	125792.9	233635.4	0.93
19/6/20	171666	189699.5	135778.3	243620.8	0.93
20/6/20	176617	200325.4	146404.2	254246.7	0.93
21/6/20	181088	211648.9	157727.6	265570.2	0.93
22/6/20	–	223692.3	169771	277613.6	0.93
23/6/20	–	236739.3	182818	290660.5	0.93
24/6/20	–	250631.8	196710.6	304553.1	0.93
25/6/20	–	265466.8	211545.6	319388.1	0.93
26/6/20	–	281328.3	227407	335249.6	0.93
27/6/20	–	298306.1	244384.8	352227.4	0.93
28/6/20	–	316509.8	262588.5	370431.1	0.93
29/6/20	–	336041.5	282120.2	389962.8	0.93
30/6/20	–	357000.2	303079	410921.5	0.93
1/7/20	–	379516.4	325595.1	433437.7	0.93

4.4 Performance analysis

The empirical analysis has been done on all the experiments performed to show the achievement of employed models on

different datasets and to co-relate the insights extracted from the results. From Table 2, we obtained 90% accuracy with RNN to predict COVID-19 cases in Pakistan for the next 10 days. We can see that on 12/6/20 there are 12599 actual

Table 7 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using GRU in India

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	308993	332399.6	153263.3	511535.9	0.87
13/6/20	320922	346945.2	167809	526081.5	0.87
14/6/20	332424	363164.4	184028.1	542300.7	0.87
15/6/20	343091	379782.3	200646	558918.6	0.87
16/6/20	354065	397318.8	218182.5	576455.1	0.87
17/6/20	366946	415597.5	236461.2	594733.7	0.87
18/6/20	380532	435098.1	255961.8	614234.4	0.87
19/6/20	395048	456404.1	277267.8	635540.4	0.87
20/6/20	410451	478479	299342.7	657615.3	0.87
21/6/20	425282	502325.6	323189.3	681461.9	0.87
22/6/20	–	526626.5	347490.2	705762.8	0.87
23/6/20	–	549795	370658.8	728931.3	0.87
24/6/20	–	574109.9	394973.6	753246.2	0.87
25/6/20	–	599436.4	420300.2	778572.7	0.87
26/6/20	–	625846.6	446710.3	804982.9	0.87
27/6/20	–	653273.2	474137	832409.5	0.87
28/6/20	–	681790.3	502654	860926.5	0.87
29/6/20	–	711335.3	532199.1	890471.6	0.87
30/6/20	–	741825.9	562689.6	920962.2	0.87
1/7/20	–	773323.6	594187.3	952459.9	0.87

Table 8 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using GRU in Afghanistan

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	23546	21188.31	11263.63	31112.99	0.9
13/6/20	24102	21890.06	11965.37	31814.74	0.9
14/6/20	24766	22503.12	12578.44	32427.8	0.9
15/6/20	25527	23053.19	13128.51	32977.87	0.9
16/6/20	26310	23522.91	13598.22	33447.59	0.9
17/6/20	26874	23986.36	14061.68	33911.05	0.9
18/6/20	27532	24435.55	14510.87	34360.23	0.9
19/6/20	27878	24866.87	14942.19	34791.55	0.9
20/6/20	28424	25249.51	15324.83	35174.19	0.9
21/6/20	28833	25609.63	15684.95	35534.31	0.9
22/6/20	–	25934.89	16010.21	35859.57	0.9
23/6/20	–	26526.83	16602.15	36451.51	0.9
24/6/20	–	27087.14	17162.46	37011.82	0.9
25/6/20	–	27633.92	17709.24	37558.6	0.9
26/6/20	–	28179.17	18254.48	38103.85	0.9
27/6/20	–	28735.86	18811.18	38660.54	0.9
28/6/20	–	29304.86	19380.18	39229.54	0.9
29/6/20	–	29886.31	19961.63	39810.99	0.9
30/6/20	–	30484.62	20559.94	40409.3	0.9
1/7/20	–	31112.54	21187.86	41037.22	0.9

cases in Pakistan but RNN estimated 13422 cases which are a minor difference. Although, RNN estimate 370486 total cases at the beginning of July in Pakistan. Similarly, in Table 3 RNN achieved 94% when predicting cases for

India. There were 308993 total cases on 12/6/20 and the RNN predicts 317032. At the end of 1/7/20, RNN gave the count of 735230 which seems alarming and greater than the total cases in Pakistan.

Table 9 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using GRU in Bangladesh

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	81523	82080.62	54876.2	109285	0.94
13/6/20	84379	86105.54	58901.12	113310	0.94
14/6/20	87520	90281.51	63077.09	117485.9	0.94
15/6/20	90619	94682.98	67478.56	121887.4	0.94
16/6/20	94481	99313.84	72109.42	126518.3	0.94
17/6/20	98489	104227.4	77023.01	131431.8	0.94
18/6/20	102292	109414.7	82210.25	136619.1	0.94
19/6/20	105535	114920	87715.58	142124.4	0.94
20/6/20	108775	120728.4	93523.99	147932.8	0.94
21/6/20	112306	126884.5	99680.08	154088.9	0.94
22/6/20	–	133436.4	106231.9	160640.8	0.94
23/6/20	–	140299.1	113094.6	167503.5	0.94
24/6/20	–	147527.1	120322.6	174731.5	0.94
25/6/20	–	155170.5	127966.1	182374.9	0.94
26/6/20	–	163246.2	136041.8	190450.6	0.94
27/6/20	–	171770.7	144566.3	198975.1	0.94
28/6/20	–	180760.9	153556.5	207965.4	0.94
29/6/20	–	190260.3	163055.9	217464.7	0.94
30/6/20	–	200287.6	173083.1	227492	0.94
1/7/20	–	210879.8	183675.4	238084.3	0.94

Table 10 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using LSTM in Pakistan

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	125933	126551.1	80093.88	173008.4	0.95
13/6/20	132405	133051.9	86594.6	179509.1	0.95
14/6/20	144478	139895.2	93437.96	186352.5	0.95
15/6/20	148921	147356	100898.7	193813.3	0.95
16/6/20	154760	155496.2	109038.9	201953.4	0.95
17/6/20	160118	164387.7	117930.5	210845	0.95
18/6/20	165062	174276.9	127819.7	220734.2	0.95
19/6/20	171666	185305.9	138848.6	231763.1	0.95
20/6/20	176617	197666.2	151209	244123.5	0.95
21/6/20	181088	211557.6	165100.3	258014.9	0.95
22/6/20	–	227421.5	180964.3	273878.8	0.95
23/6/20	–	247040.5	200583.2	293497.8	0.95
24/6/20	–	270386.4	223929.1	316843.7	0.95
25/6/20	–	298734.5	252277.2	345191.8	0.95
26/6/20	–	333906.7	287449.4	380363.9	0.95
27/6/20	–	378636.2	332178.9	425093.5	0.95
28/6/20	–	437217.5	390760.2	483674.8	0.95
29/6/20	–	516609.6	470152.3	563066.9	0.95
30/6/20	–	629117.2	582660	675574.5	0.95
1/7/20	–	797175.6	750718.3	843632.9	0.95

As compared to Pakistan and India, Afghanistan got low accuracy of 87% with RNN (referred to Table 4). On 12/6/20 the actual score was 23546 with the prediction of a total 24981 however, in the end, it leads to the 53848 which

is still better than other Asia Pacific countries (Fig. 12). Likewise, in the case of Bangladesh, RNN shows 94% accuracy in Table 5 with 81523 actual cases and 84773 predicted cases at the beginning (Fig. 13). RNN inferred

Table 11 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using LSTM in India

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	308993	318334.9	197827.6	438842.2	0.92
13/6/20	320922	332589.2	212081.9	453096.5	0.92
14/6/20	332424	347646.9	227139.6	468154.1	0.92
15/6/20	343091	363579.2	243071.9	484086.4	0.92
16/6/20	354065	380415.1	259907.8	500922.4	0.92
17/6/20	366946	398203.8	277696.5	518711.1	0.92
18/6/20	380532	417062.3	296555	537569.5	0.92
19/6/20	395048	437344.8	316837.5	557852.1	0.92
20/6/20	410451	459148	338640.7	579655.3	0.92
21/6/20	425282	482722.8	362215.5	603230.1	0.92
22/6/20	–	508295.9	387788.6	628803.1	0.92
23/6/20	–	535545.1	415037.8	656052.4	0.92
24/6/20	–	565201	444693.8	685708.3	0.92
25/6/20	–	597633.3	477126	718140.6	0.92
26/6/20	–	633260.4	512753.1	753767.7	0.92
27/6/20	–	672634.2	552127	793141.5	0.92
28/6/20	–	716452.1	595944.9	836959.4	0.92
29/6/20	–	765584.7	645077.4	886092	0.92
30/6/20	–	821098	700590.7	941605.3	0.92
1/7/20	–	884364.1	763856.9	1004871	0.92

Table 12 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using LSTM in Afghanistan

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	23546	23920.75	17215.45	30626.06	0.94
13/6/20	24102	24755.13	18049.83	31460.43	0.94
14/6/20	24766	25607.4	18902.09	32312.7	0.94
15/6/20	25527	26477.29	19771.99	33182.59	0.94
16/6/20	26310	27362.41	20657.1	34067.71	0.94
17/6/20	26874	28285.47	21580.17	34990.78	0.94
18/6/20	27532	29240.32	22535.02	35945.63	0.94
19/6/20	27878	30246.39	23541.08	36951.69	0.94
20/6/20	28424	31312.1	24606.8	38017.4	0.94
21/6/20	28833	32433.65	25728.34	39138.95	0.94
22/6/20	–	33615.39	26910.08	40320.69	0.94
23/6/20	–	34843.79	28138.49	41549.09	0.94
24/6/20	–	36141.65	29436.35	42846.96	0.94
25/6/20	–	37517.47	30812.17	44222.77	0.94
26/6/20	–	38982.94	32277.64	45688.24	0.94
27/6/20	–	40551.05	33845.74	47256.35	0.94
28/6/20	–	42236.28	35530.98	48941.58	0.94
29/6/20	–	44053.5	37348.2	50758.81	0.94
30/6/20	–	46016.39	39311.08	52721.69	0.94
1/7/20	–	48152.07	41446.77	54857.37	0.94

the predictions with 179418 cases on the 1/7/20. We can infer that Bangladesh is far away from Pakistan and India in COVID-19 cases but their transmission rate is greater than the one in Afghanistan.

From Table 6, we obtained 93% accuracy with GRU to predict COVID-19 cases in Pakistan for the next 10 days. We can see that on 12/6/20 there are 125939 actual cases in Pakistan but GRU estimated 131041 cases which are a

Table 13 Prediction results (% Accuracy) of next 10 days about possible COVID-19 cases obtained using LSTM in Bangladesh

Date	Actual	Predicted	Min	Max	Model accuracy
12/6/20	81523	82655.52	51790.99	113520.1	0.93
13/6/20	84379	86559.88	55695.34	117424.4	0.93
14/6/20	87520	90682.33	59817.8	121546.9	0.93
15/6/20	90619	95077.71		125942.2	0.93
16/6/20	94481	99750.35	68885.82	130614.9	0.93
17/6/20	98489	104764	73899.47	135628.5	0.93
18/6/20	102292	110161.5	79297	141026.1	0.93
19/6/20	105535	116002.5	85137.94	146867	0.93
20/6/20	108775	122325.2	91460.63	153189.7	0.93
21/6/20	112306	129210.4	98345.86	160074.9	0.93
22/6/20	–	136766.9	105902.4	167631.4	0.93
23/6/20	–	144963.6	114099.1	175828.2	0.93
24/6/20	–	154011.8	123147.2	184876.3	0.93
25/6/20	–	164066.3	133201.8	194930.9	0.93
26/6/20	–	175313	144448.5	206177.6	0.93
27/6/20	–	187980.1	157115.5	218844.6	0.93
28/6/20	–	202371.9	171507.4	233236.4	0.93
29/6/20	–	218877.9	188013.3	249742.4	0.93
30/6/20	–	238003.9	207139.4	268868.4	0.93
1/7/20	–	260427.8	229563.3	291292.4	0.93

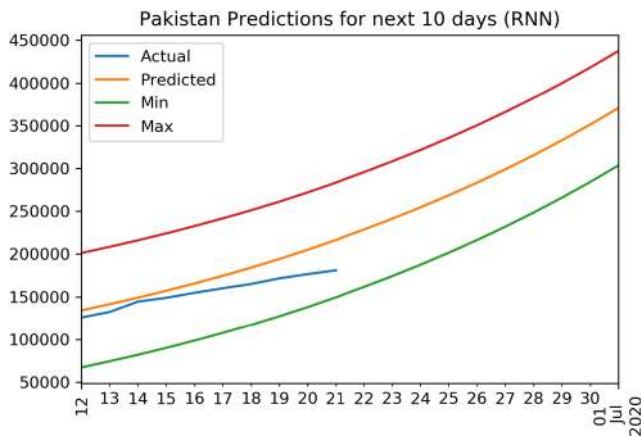


Fig. 10 Graphical representation of next 10 days COVID-19 cases prediction obtained using RNN in Pakistan

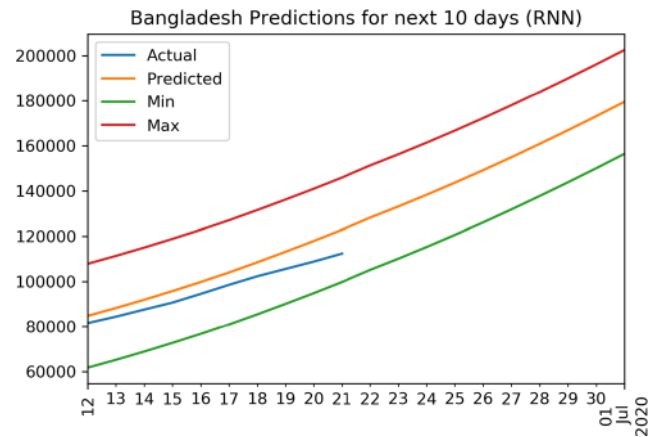


Fig. 13 Graphical representation of next 10 days COVID-19 cases prediction obtained using RNN in Bangladesh

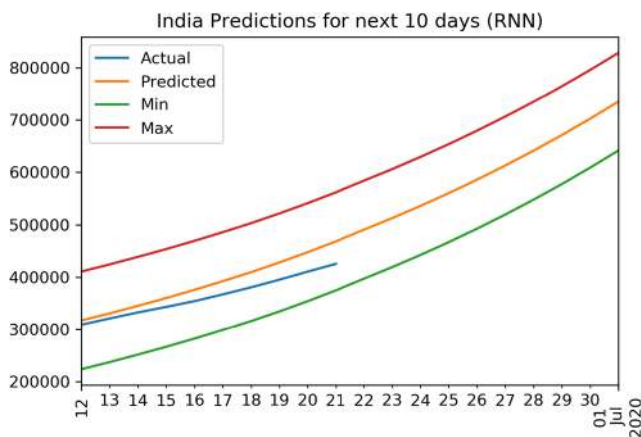


Fig. 11 Graphical representation of next 10 days COVID-19 cases prediction obtained using RNN in India

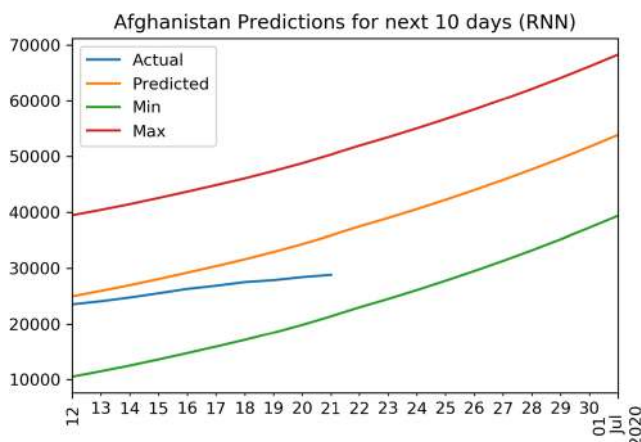


Fig. 12 Graphical representation of next 10 days COVID-19 cases prediction obtained using RNN in Afghanistan

secondary diversity. Although, GRU evaluated 379516 total cases at the beginning of July in Pakistan. Furthermore, in Table 7 GRU scored 87% when predicting cases for India. There were 308993 total cases on 12/6/20 and the GRU predicts 332399. At the end on 1/7/20 GRU delivered the count of 773323 which appears distressing and greater than total cases in Pakistan. Afghanistan got accuracy of 90% with GRU (referred to Table 8). On 12/6/20 the actual score was 23546 with the prediction of a total 21188.31 however in the end it leads to the 31112.54. Besides, in the case of Bangladesh, GRU shows 94% accuracy in Table 9 with 81523 actual cases and 82080 predicted cases at the commencement. GRU inferred the predictions with 210879.8 cases on the 1/7/20.

From Table 10, we reached 95% accuracy with LSTM to predict COVID-19 cases in Pakistan for the next 10 days. We can see that on 12/6/20 there are 12599 actual cases in Pakistan but LSTM predicted 126551.1 cases. It is the

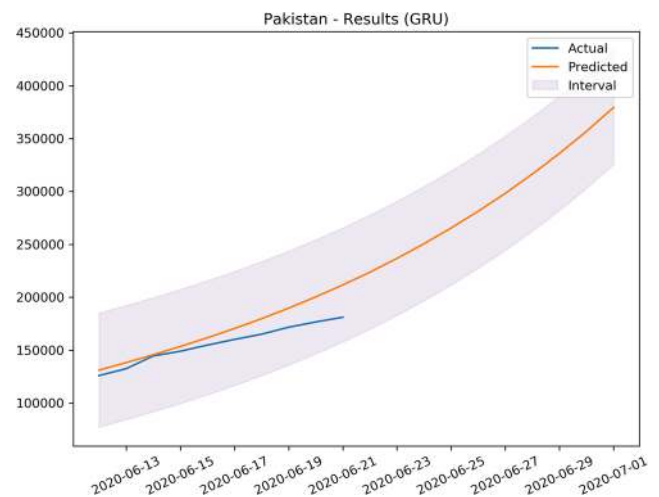


Fig. 14 Graphical representation of next 10 days COVID-19 cases prediction obtained using GRU in Pakistan

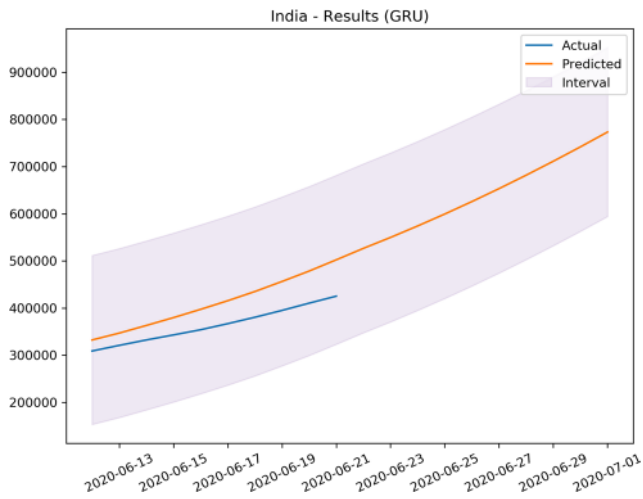


Fig. 15 Graphical representation of next 10 days COVID-19 cases prediction obtained using GRU in India

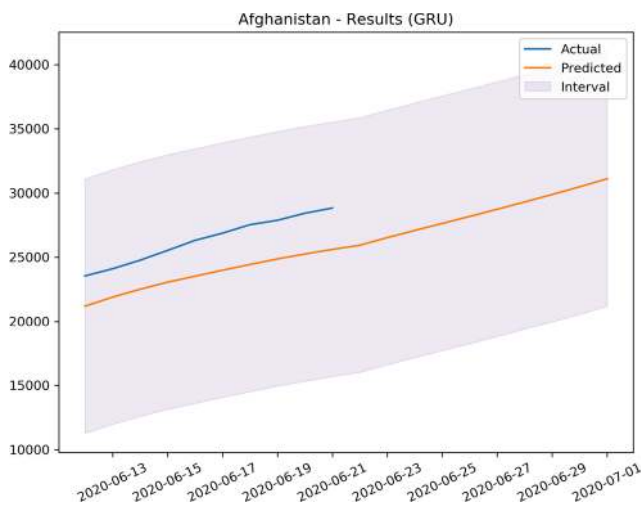


Fig. 16 Graphical representation of next 10 days COVID-19 cases prediction obtained using GRU in Afghanistan

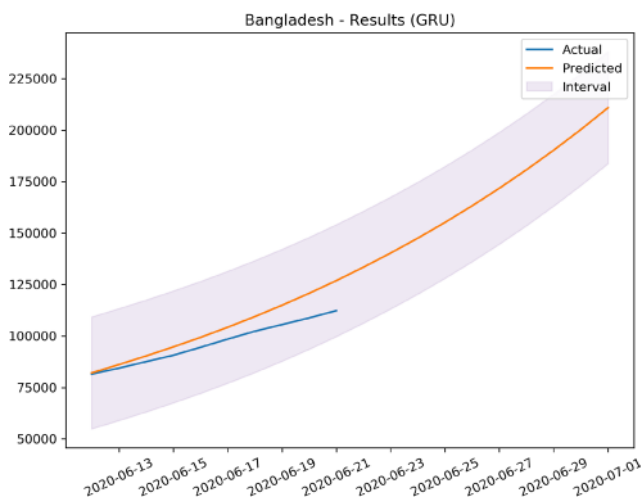


Fig. 17 Graphical representation of next 10 days COVID-19 cases prediction obtained using GRU in Bangladesh

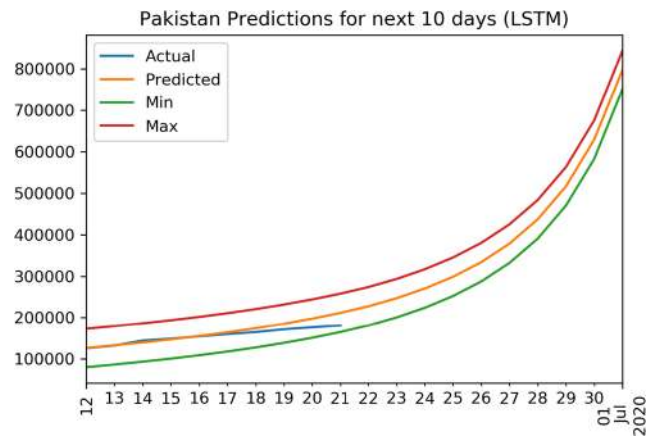


Fig. 18 Graphical representation of next 10 days COVID-19 cases prediction obtained using LSTM in Pakistan

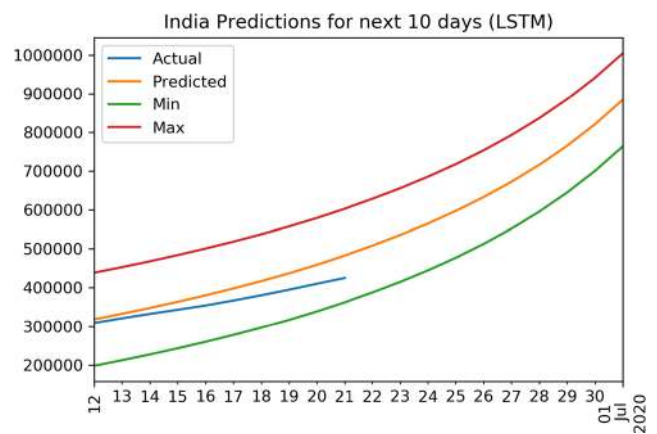


Fig. 19 Graphical representation of next 10 days COVID-19 cases prediction obtained using LSTM in India

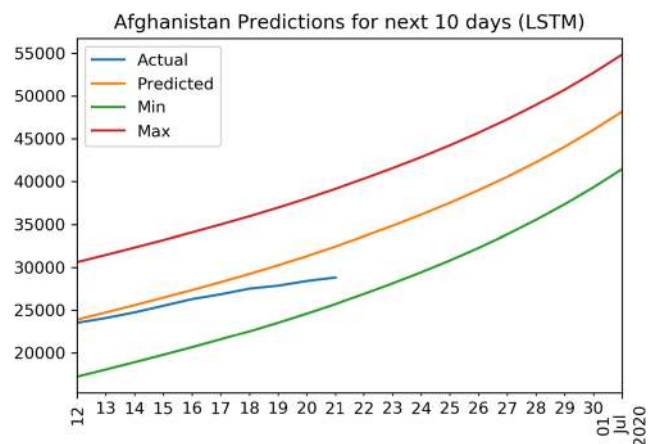


Fig. 20 Graphical representation of next 10 days COVID-19 cases prediction obtained using LSTM in Afghanistan

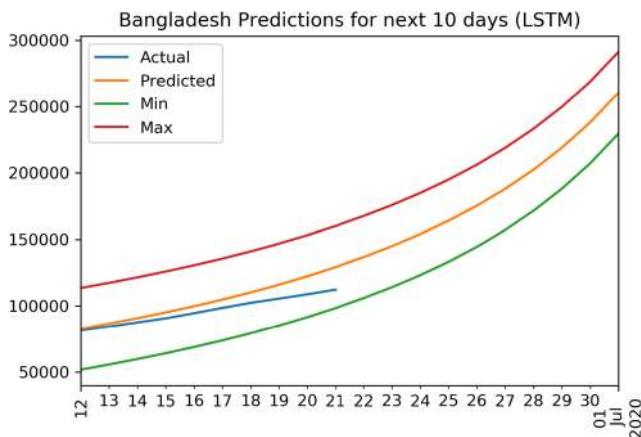


Fig. 21 Graphical representation of next 10 days COVID-19 cases prediction obtained using LSTM in Bangladesh

best accuracy so far we achieved with any other model and other countries. Nevertheless, LSTM rated 797175 total cases at the beginning of July in Pakistan. Thus, in Table 11 LSTM achieved 92% when predicting cases for India. There were 308993 total cases on 12/6/20 and the LSTM predicts 318334.9. At the end of 1/7/20 LSTM proffered the count of 884364. Table 11 and 12 shows the accuracy of 94% and 93% using LSTM for Afghanistan and Bangladesh respectively. After analyzing the trend curves of total count in Asia pacific areas (referred to as Figs. 14, 15, 16, 17, 18, 19, 20 and 21) we can conclude the order of COVID-10 prediction in terms of total cases from higher to lower as India > Pakistan > Bangladesh > Afghanistan.

5 Conclusion

Approximately all of the world's countries face COVID-19 as their natural threat. Better predictive models need to be in place to predict danger in advance. The present study deals with the prediction of the COVID-19 epidemic in Pakistan, Afghanistan, India, and Bangladesh. We used the most recent deep learning algorithms such as LSTM, RNN, and GRU to predict the number of cases of COVID-19 pandemic for the next 10 days. The data set used for the implementation of deep learning techniques is obtained from the official WHO website. The outcomes of our models are very encouraging as one can see the results until July 01, 2020, having a precision rate greater than 90%, which indicates the authenticity of the proposed model. We are closely monitoring the spread of the pandemic in the Gulf and some European countries and planning to conduct an extensive study in our future research.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

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