Impact of Temperature to Predict Covid-19 Transmission in Bangladesh: A Comparative Study by Using Deep Learning

***Abstract*— Coronavirus disease 2019 (COVID-19) has already shaken the world by killing and infecting millions of people worldwide due to the lack of effective vaccines and medicines. Researchers around the world are struggling to find more appropriate solutions to stop this pandemic. Different predictions are made based on the trend data like new cases, deaths, recoveries and etc. So that the government can take better initiatives to stop the outbreak based on the prediction rate. Many studies have been conducted to predict COVID-19 infection; still, there is always room for more research on coronavirus because its variants shift and vary from country to country for various causes. It has been found that previous works were unable to provide enough data to their model to anticipate more accurate results. In Bangladesh, no significant evidence was identified that could explain how temperature affects COVID-19 transmission. So, it is necessary to reevaluate the latest datasets, including more features. This study focuses on how COVID-19 transmission in Bangladesh varies with temperature. Here, we try to predict the upcoming per day new infections using a Deep Learning-based model Long Short Term Memory (LSTM) network for both short and long-term. The model also compared with other country's data, particularly on India, Saudi Arabia, Italy, and Malaysia. The results demonstrate that when using temperature data to predict the short-term, the model's accuracy improves slightly for Bangladesh but differs for other nations, but when using temperature data to predict the long-term, the model's accuracy remains unchanged.**

Index Terms — Covid-19, Deep Learning, Recurrent Neural Network, Long Short Term Memory, Temperature.

I. Introduction

On 7th January 2020 Chinese authorities identified the cause and were temporarily named "2019-n CoV"[1]. The new virus was subsequently named the "COVID-19 virus". In a very short time, people began to get infected with the virus and quickly the virus spread to every corner of the world. Initially, patients with COVID-19 had symptoms of cold, cough, fever, trouble in taking a breath but now there are some new symptoms such as diarrhea, headache, a rash on the skin, or discoloration of fingers, chest pain, and this virus also directly affects human lungs.

A few days later, "the World Health Organization (WHO) declared the outbreak a Public Health Emergency of International Concern on 30 January 2020, and a pandemic on 11 March 2020" [2]**.** Since coronavirus is completely new, there was initially no vaccine for the virus, so developing countries have taken steps to treat coronavirus, such as trying to invent vaccines, lockdown, social distancing, wearing the mask, using hand sanitizer, applying curfew are the most common in all. At the same time, experts are looking at numerous causes of the virus's propagation, such as lockdown, social distancing, temperature, seasonal influence, vaccination, and so on. Now some countries have invented the COVID-19 vaccine and supplying it to others. The rest of the countries are trying to invent or import the COVID-19 vaccine. On 8 March 2020, the first corona patient was identified in Bangladesh. At first, the infection rate was low, but it increased with time. When the infection rate was increasing, the government took various steps. Bangladesh's Globe Pharmaceuticals' COVID -19 Vaccine is in the trial state. The vaccine has been renamed Bangavax[3].

Many research has been done to forecast the COVID-19 cases in Bangladesh using Machine Learning (ML) algorithms. Most of the ML algorithms require a massive amount of data for training. Since the COVID-19 dataset is just a year old, designing reliable forecasting models to train on such a tiny number of data is extremely challenging [4]. On the other hand, we have seen that in the last few years, Deep Learning (DL) is the most successful approach for various predictive tasks. DL networks have gained tremendous popularity among Artificial Intelligence (AI) methodology, especially when contrasted to classic ML methods. In contrast to ML techniques, DL models automate all steps of feature extraction, feature selection, and classification [5]. So , with all that keeping in mind, it is high time to reconsider the fact with the latest datasets and the most promising forecasting models. As per the author's knowledge, no research paper has been reported so far on predicting of COVID-19 upcoming new cases in Bangladesh with the effect of temperature. We hope that this contribution would assist the government, decision-makers, and researchers in taking further actions.

As of now, different ML and DL methods have been applied to predict the COVID-19 transmission. However, it has been impossible to train ML algorithms with sufficient data since the outbreak began. And due to the small dataset, the effect of temperature on COVID-19 transmission in Bangladesh was challenging for the researchers. This study has made progress in this area, but the aim is not to achieve state-of-the-art performance, rather focused on the effect of temperature on COVID-19 transmission rate. In this paper, we propose a DL based Recurrent Neural Network (RNN) architecture Long short-term memory (LSTM) network for predicting the number of patients who may get infected in the upcoming days with COVID-19 in Bangladesh. Besides, we have predicted both the short-term (10 days) and long-term (30 days) infected cases for both with and without temperature. Also, previous works didn't get much data to forecast the COVID-19 transmission.

The LSTM network contains LSTM cells in each layer, followed by activation function and dropout regularization. Each of the LSTM layers handles different specific tasks. When remembering the syntax of the past data is essential to predict the latest one, then the LSTM works the best. To improve the learning capability and increase the accuracy of the LSTM, we need to make strong connections between the hidden neurons by adding more hidden layers and neurons. During the learning process, if RNN dealing long sequence data, then vanishing or exploding gradient manifests as a weakness of the RNN [6].To overcome this problem, Schmidhuber has proposed the LSTM, which contains the gates to capture better the correlation of data with long-term dependencies[7]. The LSTM parameter optimization is especially important for highly complex data that are non-linear and long and depends on the data characteristics. The parameter optimization is done by choosing the number of layers, hidden units. [8]

The DL model used in this study has been evaluated on the COVID-19 dataset, which are publically available and data starting from March 3, 2020, till April 26, 2021. In this study, five impacted country's data is considered: Bangladesh, India, Saudi Arabia, Italy, and Malaysia. We have split the training data and testing data from each country's data. In particular, the selected country's data is divided into two parts, specifically for input training and output training. The best LSTM parameters and hyper-parameters are found by trial and error.

The rest of the paper is organized as: Section 2 describes the related work of COVID-19 prediction. Section 3 presents COVID-19 dataset collections, models design, and then the training and testing process and the prediction accuracy measurement. In section 4, the results are shown with a brief discussion. Lastly, section 5 discusses the conclusion of this paper.

II. Related Work

Time series data has been used to track the COVID-19 epidemic. Researchers are focusing on time series data analysis in most of the predictions. Proper forecasting of the pandemic can raise public awareness. LSTM estimation has a distinct advantage over time-series data with both short and long sequences. Meanwhile, DL analysis has been placed based on time series analysis. We examined such suggestions in the literature in part on time series analysis utilizing COVID-19 data, and we also simulated their work through the discussions.

N.Yudistira proposed a prediction model for anticipating the upcoming pandemics considering the number of confirmed cases, death, recovered, latitude, and longitude. [9]. R. Pal, A. Sekh, S. Kar, et al. used the Bayesian optimization framework to optimize and automatically design country-specific networks to achieve country wise risk prediction of COVID-19 [4]. G. Pinter, I. Felde, A. Mosavi, et al. proposed a hybrid ML approach for COVID-19 prediction in Hungary [10]. M. Alazab, A. Awajan, A. Mesleh, et al. used ML and DL algorithms to predict and detect COVID-19 [11]. N. Zheng, S. Du, et al. proposed a hybrid AI model to predict the COVID-19 in China [12]. Most of the algorithms used DL and ML methods to predict any future task based on past incident data.

M. Rahman et al. used the SIR model to the impact of control strategies on COVID-19 in Bangladesh [13]. M. Khan, A. Hossain proposed the infection trajectory-pathway strategy (ITPS) of COVID-19 Outbreak situations in Bangladesh [14]. A. Chowdhury, K. Hasan, K. Hoque used ANFIS and LSTM algorithms to predict the COVID-19 upcoming 10 day's newly infected cases in Bangladesh. They considered previous days based on 3 scenarios to predict COVID-19 cases.[15]. A. Hridoy, M. Naim, N. Emon, et al. presented data-driven estimation methods to predict the possible number of COVID-19 cases in Bangladesh for the upcoming months [16]. P. Aroraa,, H. Kumar, B. Panigrahi, et al. aims to predict the number of coronavirus positive cases for 32 states and union territories of India. Proposed method gives high accuracy for short-term prediction. Among them, based on errors and various features, bi-directional LSTM gives the best results [22].

In the last few months, we were analyzing and investigating COVID-19 in Bangladesh. We have investigated the COVID-19 in Bangladesh based on DL approaches using two methods. The first method is to predict the COVID-19 new cases in Bangladesh based on DL approaches using temperature data combined with the trend data like new cases, deaths, recovered. The second method of COVID-19 in Bangladesh is based on DL approaches using only the trend data and leaving behind the temperature data. COVID-19 predicting is very challenging because it spreads rapidly. COVID-19 symptoms do not appear immediately, resulting in a rapid spread of it. Thus, it is important to check which method gives accurate forecast results and which don't, during a pandemic in Bangladesh. In this case, the number of new cases, temperature, new tests, new deaths, new recovered, total active are used as parameters or features of the LSTM network. In general, LSTM is utilized to solve RNN difficulties, non-linearity, lengthy sequence, and heterogeneous features are some of them.

III. METHODOLOGY

This methodology section is divided into some subsections to get a better overview of the whole work. Firstly after discussing the data sources and data pre-processing, the following subsections discuss the model and its variations, later subsection describes the training testing mechanism of the dataset, and then some mathematical terms are shown which is used for the model's accuracy measurement.

A. Covid-19 Dataset

The COVID-19 dataset for this research is collected from the publicly available dataset provided by **"**Our World In Data (OWID)**"** [17] and **"**NASA Prediction Of Worldwide Energy Resources**"** [18], which are updating every day. These datasets are available in the format of time series decorated in date, month, and year. And this research is considered the datasets from April 7, 2020, to April 26, 2021 total of 384 days. We collected each day's number of new cases, new deaths, new tests from "OWID" [17]**,** and the recovered cases from "Datahub" [19], and the temperature data from "NASA" [18]**.** Dataset also includes total active cases, which are calculated as follows:

$$\text{Total active cases} = \text{Total cases} - \text{Total deaths} - \text{Total recovered} \qquad (1)$$

This approach will predict the next 10 days for short-term predictions and the next 30 days for long-term predictions. The model was designed considering the previous 5 timesteps to predict the 6th day's new cases. The table below illustrates the input dataset of this study.

TABLE I INPUT FRAMEWORK OF THE MODEL

Date	**New Cases**	**Tempe-rature (Celcius)**	**New Tests**	**New Deaths**	**New Recovered**	**Total Active**
2020-04-07	41.0	37.18	981.0	5.0	0.0	114.0
2020-04-08	54.0	37.64	1097.0	3.0	0.0	165.0
2020-04-09	112.0	35.99	1184.0	1.0	0.0	276.0
2020-04-10	94.0	37.25	649.0	6.0	0.0	364.0
2020-04-11	58.0	36.79	1340.0	3.0	3.0	416.0

B. Data Preprocessing

Preprocessing data is an important aspect of any data analysis or prediction strategy. The data has been filtered to exclude null and empty values, as the data may contain null or empty values, as well as irrelevant data. When it comes to data analysis, there are various phases involved. An illustrated figure of the whole methodology is shown in Fig. 1.

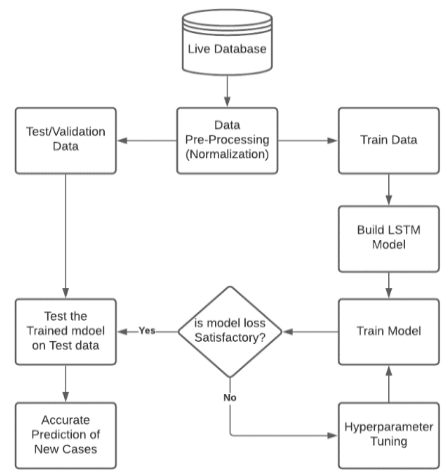


Figure 1: Methodology Diagram

In the case of time series data, normalization is very important for LSTM networks. So, for the input features/variables normalization here, MinMaxScaler is used. MinMaxScaler transforms all the features into the range [0,1] means that the minimum value will be 0, and the maximum value will be 1 for each feature/variable. It is important to transform the training and testing data into the same amount of scale for avoiding scaling problems during the train and test of the model. The MinMaxScaler is defined as follows,

$$Xscaled = (X - Xmin) / (Xmax - Xmin) \qquad (2)$$

Where X is the input training dataset, and Xscaled is the output of the normalized training and testing dataset.

C. Model Details

*(1)*Deep learning

Recently, DL is the most successful approach for the prediction task. This section briefly discusses the core principle of two DL models

RNN and LSTM, which will be used later for the COVID-19 forecasting in Bangladesh.

(2)Recurrent Neural Network(RNN)

In the cases of classification and regression problems, a Deep sequential model is more well structured than traditional models [20]. The special feature of RNN is it's hidden states which store information of the past sequence. In most cases, RNN is used for prediction because they have the ability to analyze the sequential data [21]. The key drawbacks of RNN are the disappearing or expanding gradient problems. RNNs can't solve this problem because they only bind the activation functions of hidden layers from the previous time stage. [7].

(3)Long-short-term-memory (LSTM)

LSTM is a RNN addition that handles long-sequence inputs by using a forgetting mechanism [9]. In the cases when remembering the syntax of the past data is very important for predicting the latest result, then LSTM works the best. Vanishing gradient and exploding gradient are the most disadvantages of RNN. LSTM can overcome RNN problems. Recently, LSTM very much used any prediction, handwriting recognition, speech recognition, and natural language processing (NLP). LSTMs are one of the most effective options for prediction jobs since they estimate future forecasts based on numerous highlighted aspects in the dataset [22]. LSTM was successful in forecasting because of its ability to handle time-dependent datasets. [23]. The main components of LSTM architecture are cell state and three regulators. These regulators are called gates: forget gate, input gate, and output gate. The cell states carry various information via gates. Which information is allowed to enter the cell state that decides these gates. Every gate has its weight. Which information should be kept or forgotten during training is decided by these gates using the RNN learning process. Each gate has its own decision, and these decisions are different from each other. The forget gate determines which information from the previous phase should be retained. The input gate decides which data is required for the current state update. The output gate selects which data is required for the following phase. These gates represented via the following equations:

Input gates: It = sigmoid(Wi[Ht-1,Ct]+bi) (3)

Forget gate: Ft =sigmoid(Wf[Ht-1,Ct]+bf) (4)

Output gate: Ot =sigmoid(Wo[Ht-1,Ct]+bo) (5)

It, Ft and Ot are the input gate, forget gate, and output gate, respectively, in the preceding equations. Wi = Wf = Wo refer respectively to the weight parameters. Ht-1 represents the previous timestamp. Ct represents the current timestamp and bi= bf=bo refers respectively to the BIOS parameters.

The LSTM model used for this research is constructed by two LSTM layers and a Dense layer. The First LSTM layer has 40, and the second LSTM has 136 units of hidden neurons, respectively. And the activation function for both layers is Rectified Linear Unit (RELU), which maps all the values in a range from 0 to any positive numbers. Adam optimizer used and the loss function (LF) used here is Mean Squared Error (MSE). The batch size of 32 and the number of the epoch is 1000 with an Earlystop callback function with patience 500 is applied to build the model. Table II., Table III. and Table IV. give a glance at the model parameters and hyperparameters.

TABLE II

LSTM Layers	Hidden Neurons	Activation Function	Return Sequence
LSTM Layer 1	40	Relu	True
LSTM Layer 2	136	Relu	False

TABLE III.

Optimizer	Loss Function	Batch Size	Epochs
Adam	MSE	32	1000

TABLE IV

Callback	Monitor	Restore best weights	Patience
EarlyStop	Value loss	True	500

D. *Training and Testing*

While predicting the short-term, our test data contains COVID-19 cases from April 17, 2021, to April 26, 2021, we used the rest of the data which is the date from April 07, 2020, to April 16, 2021 (370 days) to train the model. And we used the test data to validate the model in every epoch.

Similarly, for predicting the long-term from the date March 28, 2021, to April 26, 2021, we used the rest of the data from April 07, 2020, to March 27, 2021 (350 days) to train the model and for validation, we used the test data. This approach is the same for all the countries, including Bangladesh also.

In the cases, for experiment with temperature we used temperature as a feature for the input dataset of the model to see the effect of temperature in predicting new infections of the countries.

E. Prediction Accuracy Measurement

Root Mean Squared Error (RMSE) is applied in order to measure the LF of the trained model. And for measuring the prediction performance, Mean Absolute Percentage Error (MAPE) is employed.

RMSE is the measurement of the difference between the actual cases and prediction. And the MAPE is a measure of how accurate a forecast system is. It measures this accuracy as a percentage.

$$\text{RMSE}= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x_\iota})^2} \tag{6}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i-\overline{x_\iota}}{x_i}\right| \times 100\% \tag{7}$$

Here, xi are the original values, $\overline{x_\iota}$ are the corresponding estimation, and n is the total number of samples.

IV. Result and Discussion

The approach taken in this study is different from previous studies. The risk from the virus was reduced significantly for warm places and countries [24]. Although only temperature data alone can not be a potential factor of COVID-19 transmission rate [25]. Temperature is used as a feature in our model for the input dataset to get an overview of the effect of temperature on the accurate prediction of COVID-19 transmission. This approach is divided into four parts; for the first part, we predicted the short-term with temperature and second, we predicted the short-term without temperature. In the third approach, we predicted the long-term with temperature and lastly predicted the long-term without temperature. Our approaches will help the government and researchers to get an idea to be prepared for the next action that needs to be taken. Hence it will help to slow down the infection rate of the country.

Table V. and Table VI. show the result of the comparison of prediction including and excluding the temperature data; in this case, only temperature data has been considered. And the outcome shows that the temperature doesn't really have a good impact on the COVID-19 transmission rate. It only differs from 2 to 3% when adding or removing temperature data from the input dataset.

Here the prediction accuracy is measured by RMSE and MAPE for all countries. For the short-term given in Table V., the accuracy for all the countries is more than 96% to 98%, also Fig. 2. shows the accurate and the predicted results. And for the long-term given in Table VI., the accuracy is more than 93% to 97% and the Fig. 3. Illustrates the accurate and predicted result of the COVID-19 cases. However, for Bangladesh, short-term prediction from the day April 17, 2021, to April 26, 2021, with temperature data gives us a (MAPE=4.5) and the (RMSE=236). And without the temperature data, our model gives (MAPE=5) and (RMSE=218). As the new case's increasing rate is very high, and there is no specific sequence or pattern to recognize and predict the next pattern of the COVID-19 infection. So, it becomes very hard to predict the future COVID-19 new cases. As we may not get the number of cases predicted as same as the actual cases, this model gives a satisfactory result than the previous studies. And also, for a country like Bangladesh, an (MAPE=4.5) or (MAPE=5) is very much satisfactory for this kind of complex and non-linear datasets.

As said before, we have also compared our model with foreign countries, specifically India, Saudi Arabia, Italy, and Malaysia. And the prediction accuracy of those countries is also very much satisfied because their prediction is so close to the real values. These countries have a 2-3% accurate prediction when the temperature was considered in the input dataset.

In Table V., RMSE and MAPE are calculated for short-term prediction. The prediction of five countries Bangladesh, India, Saudi Arabia, Italy, and Malaysia, and their accuracy measured in terms of RMSE and MAPE calculated in two ways short-term with temperature, and short-term without temperature.

The result of this table shows that with temperature the MAPE is in the range of 1.9% to 4.5% for all the countries, and without temperature MAPE range is 2.8% to 5%. The result also shows that the values of RMSE and MAPE remain low when the temperature is used except in India.

TABLE V. PREDICTION ACCURACY IN TERMS OF RMSE AND MAPE OF THE MODEL ON DIFFERENT COUNTRIES BASED ON SHORT TERM (10 DAYS).

Experimented Countries List	Short-term with Temperature		Short-term without Temperature	
	RMSE	MAPE	RMSE	MAPE
Bangladesh	236	4.5	218	5
India	15122	3.7	12999	3.4
Saudi Arabia	24.4	1.9	42	3.6
Italy	353	2.1	506	2.8
Malaysia	113	3.3	173	6

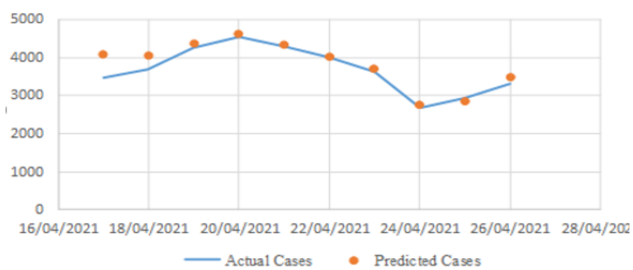
TABLE VI. PREDICTION ACCURACY IN TERMS OF RMSE AND MAPE OF THE MODEL ON DIFFERENT COUNTRIES BASED ON LONG TERM (30 DAYS).

Experimented Countries List	30 days with Temperature		30 days without Temperature	
	RMSE	MAPE	RMSE	MAPE
Bangladesh	651	9.8	680	11.6

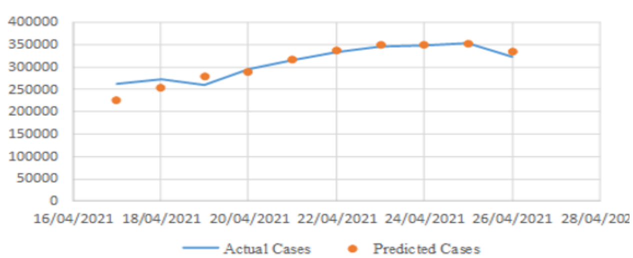
India	10983	6.4	11774	6.5
Saudi Arabia	50	4.6	50	4.5
Italy	1836	9.6	1959	10.0
Malaysia	291	14.4	276	14.4

Similarly for Table VI., here, RMSE and MAPE calculated for long-term prediction. The prediction of five countries Bangladesh, India, Saudi Arabia, Italy, Malaysia, and their accuracy measured in terms of RMSE and MAPE calculated in two ways long-term with temperature and long-term without temperature.

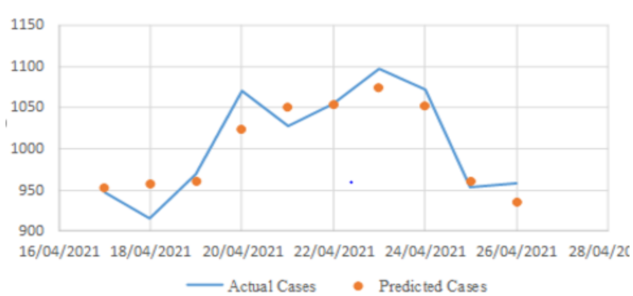
This table results that with temperature the MAPE is in the range of 4.6% to 14.4%, and without temperature, the MAPE range is in 4.5% to 14.4%. Here the MAPE of Bangladesh has changed, but the MAPE of other countries has not changed. In the long-term model, using temperature is almost the same as not using temperature.



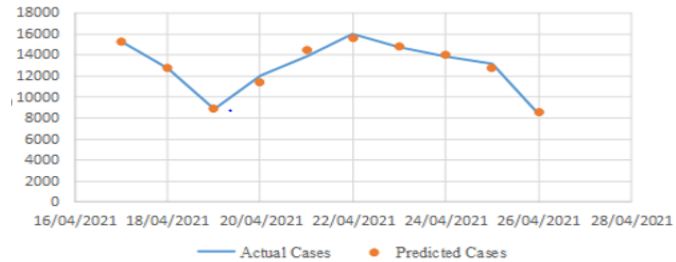
a. COVID-19 new cases short-term prediction in Bangladesh with temperature



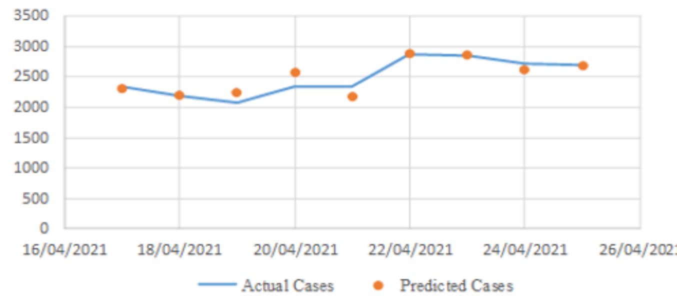
b. COVID-19 new cases short-term prediction in India with temperature



c. COVID-19 new cases short-term prediction in Saudi Arabia with temperature



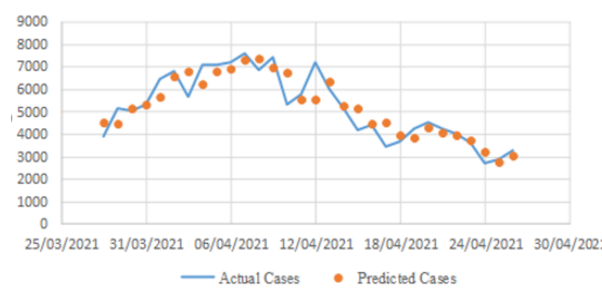
d. COVID-19 new cases short-term prediction in Italy with temperature



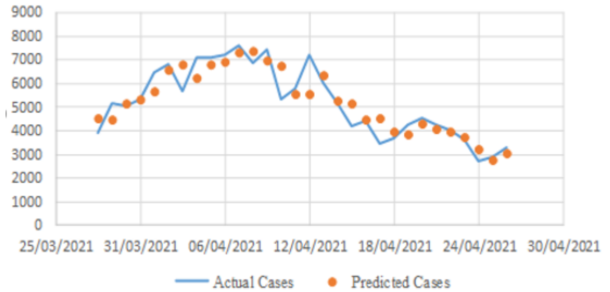
e. COVID-19 new cases short-term prediction in Malaysia with temperature

Figure 2: Actual and predicted COVID-19 new cases(short-term) from 16 April to 26 April considering tempereture data.

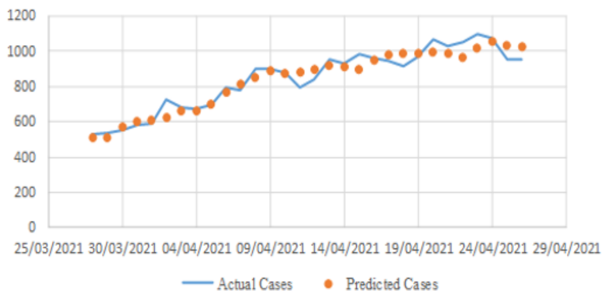
In Figure 2. the short-term prediction with temperature and the actual cases of COVID-19 are shown. Here, the predicted curves are well fitted on the actual curve. The graph of Bangladesh, Saudi Arabia, Italy, and Malaysia shows that after 24 April this country's COVID-19 transmission is going downwards. Whereas, in the case of India, after 25 April the graph is going down. And the predicted curve is also reflecting well the actual curve for all five countries.



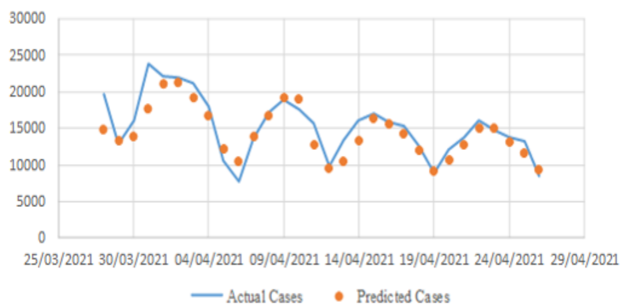
a. COVID-19 new cases long-term prediction in Bangladesh with temperature



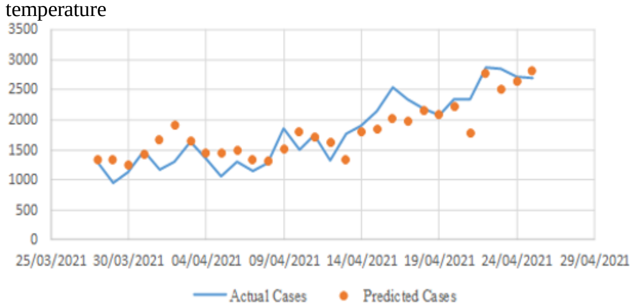
b. COVID-19 new cases long-term prediction in India with temperature



c. COVID-19 new cases long-term prediction in Saudi Arabia with temperature



d. COVID-19 new cases long-term prediction in Italy with temperature



e. COVID-19 new cases long-term prediction in Malaysia with temperature

Figure 3: Actual and predicted COVID-19 new cases(long-term) from 25 March to 25 April considering tempereture data.

In Figure 3. COVID-19 new cases prediction and the actual cases of short-term with temperature of five countries Bangladesh, India, Saudi Arabia, Italy, and Malaysia are shown. And the graph of India shows that the cases are increasing exponentially. In Bangladesh, the cases are very complex and nonlinear and the case count is decreasing at the end of April.

From the results shown above, it is seen that the model's accuracy of prediction for both including and excluding the temperature data is the closest possible value achieved in comparison with the real COVID-19 cases. The prediction accuracy is almost the same for both with and without temperature data for Bangladesh. However, for other countries, MAPE varies 2 to 3%. Our proposed model not only justifies the effectiveness of temperature but also can predict the COVID-19 cases very accurately. This model can predict the short-term and long-term. The experiment with the five countries Bangladesh, India, Saudi Arabia, Italy, and Malaysia got satisfactory results for both the short-term and long-term. So, it is clear that the effect of temperature is negligible in forecasting the upcoming per day's COVID-19 cases.

V CONCLUSION

For more than one year, the COVID-19 pandemic has been a great threat to the whole world. And researchers are trying to find some proper solutions to stop this pandemic or slow down the spread of this disease. Countries including Bangladesh are highly impacted in economical, medical, and agriculture systems by this pandemic. Accurate forecasting of the number of COVID-19 new cases provides suitable information to the governments to overcome the situation with appropriate measures. In this study, a DL based model, which is LSTM, an architecture of RNN, is used to determine the effect of temperature in accurately forecasting the upcoming confirmed cases of five different countries including Bangladesh. The DL model is used because of its capability in processing highly complex and non-linear data. The prediction is done including and excluding the temperature data for both the short-term and long-term for five countries namely Bangladesh, India, Saudi Arabia, Italy, and Malaysia. The performance of the model's prediction has been verified in terms of RMSE and MAPE. The outcome shows that the effect of temperature in forecasting the newly confirmed cases is negligible. The model can be used in predicting coronavirus diseases outbreak accurately. And this study can be further improved by including other factors like vaccination, mask, and sanitizer using rate as features of the model.

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