A Time-Series prediction model using long-short term memory networks for prediction of Covid – 19 data

Gyana Ranjan Patra, Abhishek Das, Mihir Narayan Mohanty

gyana.patra@gmail.com, abhishekdas225@gmail.com, mihir.n.mohanty@gmail.com

Department of Electronics and Communication Engineering,
Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India

Abstract

The recent outbreak of Coronavirus disease 2019 (COVID-19), which gets caused by severe acute respiratory syndrome (SARS) coronavirus 2 (SARS-CoV-2), has been responsible for the deaths of over 3,00,000 people and at the same time has infected over 4.7 million people in the whole world as of mid-May, 2020. There has been more that 1.8 million recoveries during this period too. It becomes imperative for Governments to be aware of the situation and to be able to predict the future number of patients so that readiness in terms of health care and planning of other necessary actions can be maintained. Using the same as a strong motivation, a model for prediction of the number of COVID–19 patients has been developed using the Long-Sort Term Memory (LSTM) network and then employed it for forecasting future cases. The cases of four countries, namely, United States of America, India, Argentina and Brazil are taken into account. The study finds that the LSTM network developed in this paper performs better than two other methods known as Convolutional Neural Network and Nonlinear Auto Regressive Time Series networks and thus can be a useful candidate for prediction of future number of patients of COVID–19.

Keywords: *COVID-19; Coronavirus; Pandemic; LSTM; Trend; Forecast; Epidemic;*

1. Introduction

The recent outbreak of the of 2019-nCov pandemic commenced from December 2019 in Wuhan, China and has been a reason of extreme loss of human lives in the whole world [1, 2]. 2019-nCoV or COVID-19, commonly known as Coronavirus, is a novel highly contagious virus belonging to Coronaviridae family that has been suspected to be transmitted to humans from animals [3]. When infected with this virus the result is mild to severe respiratory problems and sometimes death. As of mid-May there has been 4,721,851 cases of COVID–19 cases with 313,260 deaths [4, 5]. It has spread across more than 200 countries and several water vessels that have been stranded in the seas for months. This strain of coronavirus shows less severe symptoms than the other viruses of the same family such as SARS-CoV (Severe Acute Respiratory Syndrome Corona Virus) and MERS-CoV (Middle East Respiratory Syndrome Corona Virus), resulting in rapid spread of infection amongst human beings [6]. At present the United States of America (USA) and the European Union (EU) countries have been severely affected with this virus [4].

In the present scenario there has been no treatment method or vaccination present, and the only safeguards against this pandemic are social distancing and good hand hygiene. Many countries have employed lock-down to impose the social distancing and reducing community spread that has slowed down the spread. However, this action has resulted in a big economic slow down and can not be the long term solution for this pandemic. Currently, it is a major health crisis around the world and it would not be wrong to say that it is 'an enemy to humanity'. In this circumstance, the only option is preventing the occurrence of infection and preparing our healthcare system for the probable up-comings.

In this scenario it becomes very important to develop computational models those can be used to predict the future number of daily cases and help the policy makers, health care professionals as well as the general public to take up important decisions for fighting with this pandemic.

In this paper, a method using the Long-Sort Term Memory (LSTM) network has been proposed for the prediction of the total number of patients. Using this network prediction of the number of new cases can be achieved and then the policy makers and healthcare professionals can be ready to address the prevailing situations. The performance of the LSTM network has been compared with the Convolutional Neural Network (CNN) and Nonlinear Auto Regressive Time Series (NARTS) networks and fares better than the both.

The rest of the paper is organized as follows. In Section 2 the LSTM network has been explained in detail. In Section 3 the experiments, and the results have been provided. The detailed analysis is provided in the Section 4. The conclusions of the work have been presented in Section 5.

2. LSTM based technique for prediction of COVID-19

The recent methods of deep learning have been successfully employed for many types of prediction applications. The recurrent neural networks (RNN) are effective in these situations as the can extract relevant features from their training samples automatically, feed the activation from the last iteration as input and has self-connection networking capability [7]. RNN has the inherent quality of good data processing and has many a times shown great potential for time series applications as it stores large amount of historical data in its internal state [8]. However, RNN suffers from vanishing and explosion problems which result in high amount of training time. Sometimes the training may fail too. To address these limitations Hochreiter and Schmidhuber designed long short-term memory (LSTM) RNN structure in 1997 [9]. This LSTM network deals with a long-term dependency with the multiplicative gates that regulate the information flow and memory cells in the recurrent hidden layer.

The structure of LSTM consists of four gates i.e. input gate, forget gate, control gate, and output gate which is shown in Fig. 1 [10, 11],

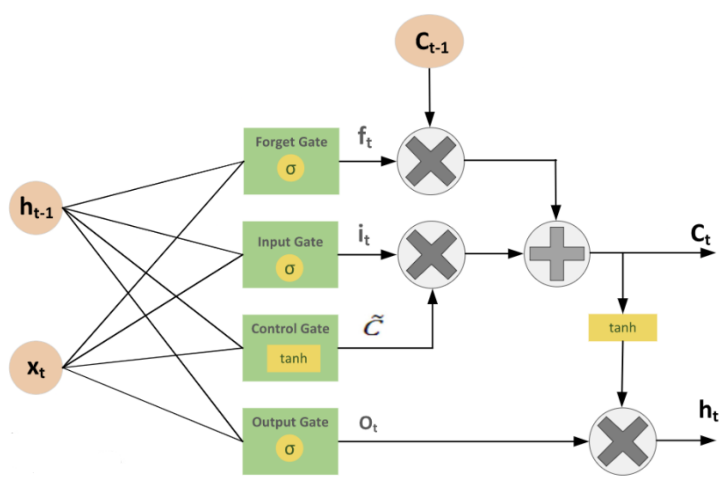

Fig. 1. Structure of the LSTM cell [10, 11]

The input gate is defined as

$$i_t = \sigma(W_i \times [h_{t-1}, x_t] + b_i) \quad \text{Eqn. (1)}$$

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It decides which information can be transferred to the cell. The information from the input of previous memory which is to be neglected is decided by the forget gate and is defined as:

$$f_t = \sigma(W_f \times [h_{t-1}, x_t] + b_f) \quad \text{Eqn. (2)}$$

The update of the cell is controlled by the control gate and is given by the following equations:

$$\tilde{C}_t = \tanh(W_c \times [h_{t-1}, x_t] + b_c) \quad \text{Eqn. (3)}$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

The hidden layer (ht−1) is updated by output layer which is also responsible for updating the output as is given by:

$$o_t = \sigma(W_o \times [h_{t-1}, x_t] + b_o) \quad \text{Eqn. (4)}$$
$$h_t = o_t * \tanh(C_t)$$

In the above equations, $\tanh(\cdot)$ is used to scale the values into range -1 to 1, σ is the activation function which is taken as sigmoid and W are the corresponding weight matrices.

Table 1. Tabulation of different error measures of several countries

Error Measures for USA

Error Measures	LSTM	CNN	NARTS
MAE	**0.057664**	0.152783	0.113625
MSE	**0.003806**	0.025792	0.018734
RMSE	**0.06169**	0.160598	0.136874
MARE	**0.062658**	0.166757	0.124632
MSRE	**0.004456**	0.030665	0.022278
RMSRE	**0.06675**	0.175114	0.149259
MAPE	**6.265796**	16.6757	12.46315
MSPE	**44.5554**	306.6489	222.7822
RMSPE	**6.674983**	17.51139	14.92589

Error Measures for India

Error Measures	LSTM	CNN	NARTS
MAE	**0.036139**	0.059717	0.114536
MSE	**0.001811**	0.005116	0.018147
RMSE	**0.042555**	0.071527	0.13471
MARE	**0.047523**	0.078533	0.14232
MSRE	**0.003137**	0.008978	0.026596
RMSRE	**0.056007**	0.094754	0.163084
MAPE	**4.752264**	7.853276	14.23203
MSPE	**31.36736**	89.78249	265.9636
RMSPE	**5.600657**	9.475362	16.30839

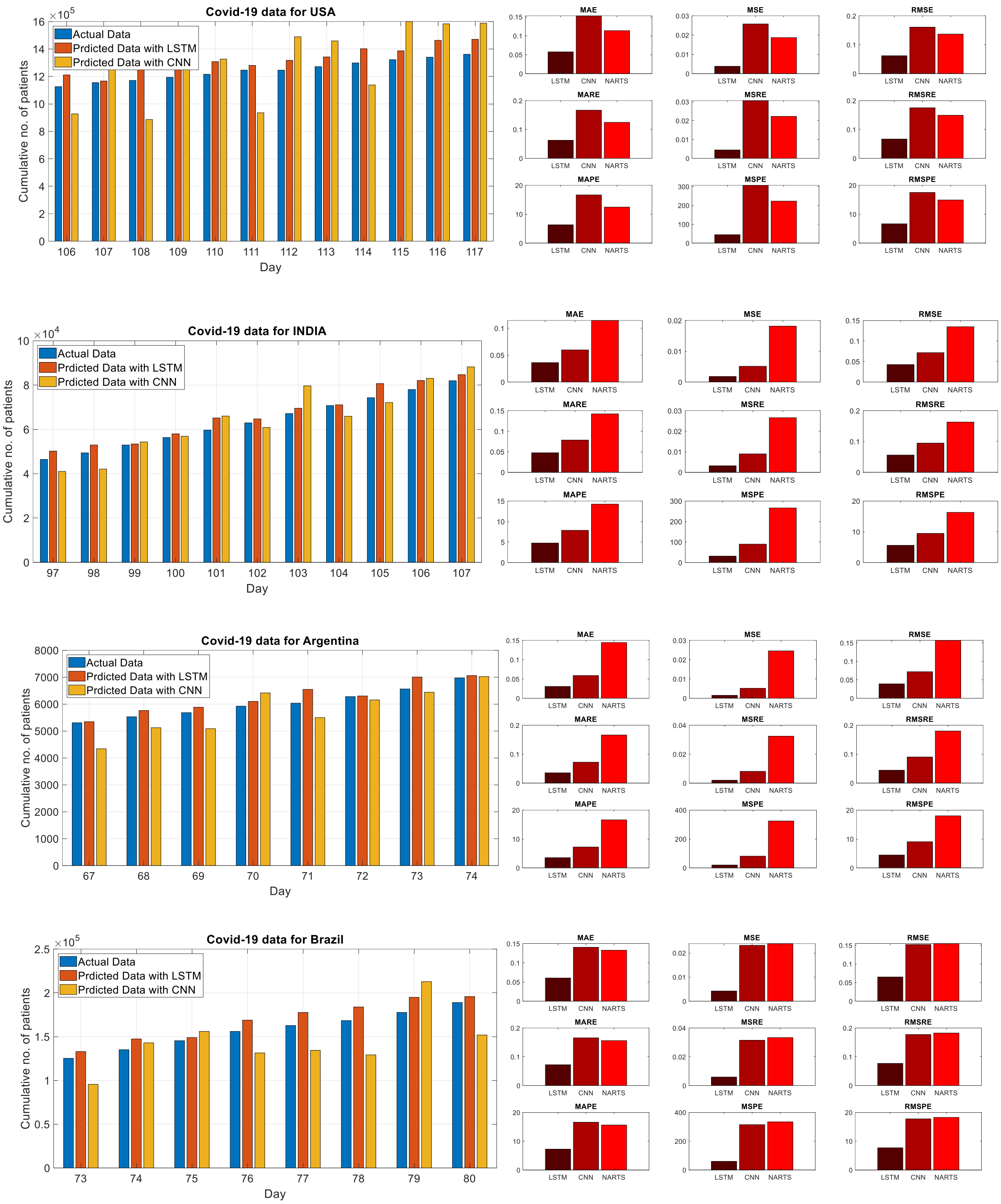
Error Measures for Argentina

Error Measures	LSTM	CNN	NARTS
MAE	**0.030722**	0.058988	0.14446
MSE	**0.001526**	0.005177	0.024558
RMSE	**0.039059**	0.071948	0.156711
MARE	**0.03539**	0.072199	0.166158
MSRE	**0.001986**	0.008135	0.032427
RMSRE	**0.04456**	0.090193	0.180075
MAPE	**3.538994**	7.219939	16.61578
MSPE	**19.85614**	81.34811	324.2689
RMSPE	**4.456022**	9.019319	18.00747

Error Measures for Brazil

Error Measures	LSTM	CNN	NARTS
MAE	**0.060413**	0.140573	0.132668
MSE	**0.004223**	0.023146	0.023856
RMSE	**0.064983**	0.152139	0.154453
MARE	**0.072405**	0.165879	0.156171
MSRE	**0.00594**	0.031505	0.033368
RMSRE	**0.077068**	0.177497	0.18267
MAPE	**7.240477**	16.58792	15.61711
MSPE	**59.39547**	315.0534	333.6836
RMSPE	**7.706846**	17.74974	18.26701

Figure 2. Plot of validation data and different error measures of several countries



3. Results

The data for this study has been collected from the World Health Organization website [12]. A set of four countries, namely, the USA, India, Argentina and Brazil have been chosen to be a part of this study. The Cumulative Number of Cases has been used to study the prediction capabilities of the LSTM network. We have taken 90% of the data of each country for training and the rest 10% are taken for the testing purpose.

The number of hidden layers is chosen to be 400 and the ADAM learning method is used for training. The training was performed in MATLAB with a 5th generation Core i3 machine containing 8 GB RAM and no GPUs. Two other methods were taken into consideration for comparison purposes. They are the Convolutional Neural Network (CNN) and Nonlinear Auto Regressive Time Series (NARTS) networks. These three networks have been trained and validated and the normalized values of different error measures (MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), MARE (Mean Absolute Relative Error), MSRE (Mean Squared Relative Error), RMSRE (Root Mean Squared Relative Error), MAPE (Mean Absolute Percentage Error), MSPE (Mean Squared Percentage Error), RMSPE (Root Mean Squared Percentage Error)) have been found and tabulated in the Table 1. The corresponding plots of validation data and plots of the error measures have been shown in Figure 2.

4. Discussions

The observation from the Table 1 and Figure 2 shows that the LSTM based method outperforms the CNN and the NARTS methods. In almost all parameters LSTM shows better performance than the two competing networks. Thus the LSTM network can be used as a robust model for the forecasting of the COVID–19 cases.

5. Conclusion

In this study, an LSTM network was used to study the forecasting capability using the COVID-19 dataset. Two other models, CNN and NARTS were also used for comparison purposes. The LSTM network outperformed the two competing networks in the nine error measurements by showing a decreasing trend. Thus, the LSTM network can be thought of being used as a good model for prediction of COVID–19 patients.

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