Using AI and ML techniques to Forecast COVID-19 cases with Real-time Data Sets

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Abstract

The spread of COVID-19, namely SARS-CoV-2, has created a disastrous situation around the world causing an unclear future. Machine Learning (ML) and Deep Learning (DL) have a vital role in tracking the disease, predicting the outgrowth of the epidemic, and outlining strategies and policies to control its spread. Despite the inaccuracies of medical forecasts, the numbers of COVID-19 cases forecasts provide us with valuable information for recognizing the present and preparing for the future. This study proposes a time series based deep learning model, specifically the Long Short-Term Memory (LSTM) model. The model will predict the active, confirmed, deaths and recovered cases for 7 days ahead for Egypt and Saudi Arabia based on real-time data. The Egypt prediction model achieves Mean Absolute Percentage Error (MAPE) of 3.26150, a Root Mean Square Error (RMSE) of 0.0144, a Mean Square Error (MSE) of 0.0002, and a Mean Absolute Error (MAE) of 0.0092. While the Saudi prediction model obtains a MAPE of 5.0553, a RMSE of 0.0170, a MSE of 0.0002, and a MAE of 0.0150.

Keywords: Communication, Covid-19, Deep Learning, Forecasting, Data Analysis, Artificial Intelligence, Real Time, Machine Learning.

1. Introduction

Wuhan, China, has become the center of a pneumonia outbreak of uncertain cause in December 2019, eventually termed coronavirus disease 2019 (COVID19), sometimes known as SARS-CoV-2, and formally named COVID-19 by the World Health Organization (WHO) [26] which drew widespread attention not just in China but also abroad.[16] According to WHO announcement, the COVID-19 outbreak resulted in 559,694 deaths worldwide and 10,509,505 confirmed cases on July 9, 2020. The COVID-19 epidemic and its future unfolding trends are currently a hot topic of research due to its prevalence and potential damage.
Consequently, research on the COVID-19 pandemic and its progress trends is an important topic at present. The COVID-19 outbreak is causing panic in the community due to financial problems and governments' inability to make critical decisions. In attempt to reduce the infection from spreading, many governments have implemented social distancing, maintaining one-meter distances between people, refraining from hugging and handshakes, isolating the infected, putting

them on quarantine, and closing schools and malls. There has been a reduction in the spread of the disease due to these measures [14].
As a response to COVID-19's global emergency in the research community, researchers in artificial intelligence (AI) used Deep Learning (DL) and Machine Learning (ML) methodologies to a wide range of COVID-19-related applications, including detecting and classifying the cases, predicting outbreaks, tracking transmission patterns, developing effective medications, predicting mortality rates, assessing the severity of the disease, and predicting COVID19 prevalence. AI mimics the intellectual processes of humans in a wide range of environments.
As part of AI, ML uses statistical models for forecasting future outcomes using data samples (also known as instances) without the need-to-know prior details or to develop explicit programs [27]. In DL, artificial neural networks are used to classify or detect raw data by analyzing the raw data in a defined array of possibilities and then shaping that raw data in a useful way. Considering the COVID-19 pandemic, DL has important implications for medical research. Policy makers, scientists, and researchers are interested in COVID-19 forecasting as it could be utilized to implement effective preventive actions and create effective plans to head off the dissemination of COVID-19 [1]. AI has the potential to be a panacea and is crucial in detecting early Corona virus infections. The goal of this research is to build a COVID-19 prediction model based on DL techniques to contribute to the present humanitarian situation. For the next seven days, a prediction is made for the COVID-19's four most significant variables: the number of new confirmed, death, recovered, active cases. The prominent features of the methodology are summarized in terms of highlights as follows:

- The model utilized a real-time dataset provided by Johns Hopkins.
- The algorithm is a DL: LSTM, which proposed to predict the COVID-19 confirmed, deaths, recovered, and active cases for two countries.
- Performance of the model is assessed using four performance measurement: RMSE, MAE, MAPE and MSE.

The remainder of the article is arranged as follows: Section1 discussing the materials and methods used in the research like dataset and the evaluation metrics, Section2 explaining the employed methodology to forecast the next week's confirmed, deaths, recovered, and active cases of coronavirus, Finally, the result will be discussed.

2. Literature Review

COVID-19 cases are increasing continuously globally, so the health care system in countries is being burdened by it. Several mathematical and statistical methods have been employed to forecast additional resources to prevent the epidemic. To predict COVID-19 outbreaks, most statistical techniques rely on autoregressive integrated moving average (ARIMA) models [5].

In the field of health care systems, there are also common statistical versions that utilize artificial intelligence (AI) as the basis for learning and educating the COVID-19 dataset of Hubei Province, China to forecast epidemic trends and peaks [28]. These methods can often fail to adequately fit the real data and their accuracy in predicting the spread of COVID-19 is very low.

To improve the performance of statistical methods, machine learning (ML) models have been used throughout many fields of study, such as power technology [24], psychology [11], energy engineering, technology [29], psychology [29], and is used for early forecasting and real-time data distribution. As in this study [6] they pretend that ML is best known for its forecasting capabilities. Additionally, there was a latest proposal for an ML approach comply with a classification group called Infection Size Recognizing Aware Random Forest (iSARF) that highlights lung fields and infection size.

In recent years, ML techniques have been used in predicting a variety of diseases, such as coronary artery disease [15], cardiovascular disease prediction [2], and breast cancer prediction [3].

Specifically, on the use of ML on COVID-19, this study [18] concentrates on forecasting confirmed COVID-19 cases live, while the other study [9] specializes in tracking COVID-19 outbreaks and early response.

As well, this study [20] also shows how machine-learning models can forecast the number of recently infected cases, mortality rates, and recovery rates over the following 10 days, which is currently thought to be a potential threat to civilization. In particular, the least absolute shrinkage and selection operator (LASSO), linear regression (LR), the support vector machine (SVM), and the exponential smoothing (ES)forecasting techniques were used. ES has the best performance among the models used, followed by LR and LASSO, while SVM has the lowest performance. The study's findings indicate that these techniques offer a potential approach to employ in the present COVID-19 pandemic scenario.

Similar findings were found in the [25], where the least square support vector machine (LS-SVM) model outperformed the autoregressive integrated moving average (ARIMA) model in terms of accuracy. This result focuses on the five countries with the highest incidence of this disease to model and predicts confirmed cases one month in advance.

Furthermore, to ML, the application of DL algorithms is crucial for the study and forecasting of massive epidemic data patterns. [19]. As COVID-19 being a time series data and having dynamic behavior, it should be dealt by using sequential models such DL models. As in this research [12] they estimate COVID-19 cumulative confirmed cases using DL based convolutional neural network (CNN) model. As well in [4] they analyze the prediction of COVID-19 confirmed, released negative, and death cases utilizing long short-term memory (LSTM) and a gated recurrent neural network (GRU).

Additionally, the study [23], forecasted COVID-19 time-series data in 10 countries disrupted by COVID-19 using SVR (support vector regression), LSTM, BiLSTM, and GRU (Gated recurrent units). According on COVID19 data that is accessible until June 27, 2020, BiLSTM offers improved performance.

In addition, this research [13] attempted to predict COVID-19 occurrences for the upcoming week using four models (ANN, ARIMA, CNN and LSTM). It has been determined that deep learning outperforms ARIMA by a wide error margin. Nevertheless, 1-dimensional CNN slightly outperforms the other two deep learning models, then the ANN, and LSTM comes in third with superior results compared to ARIMA.

On other hand of the utilized technique, the majority of recent studies focus on a single nation rather than doing comparative study across many areas, as mentioned in [7]. Therefore, the authors in [7] instead of concentrating on just one nation, the study dealt with the forecasting of the COVID-19 outbreak across Afghanistan, Pakistan, Bangladesh, and India. The prediction model was used to anticipate the number of COVID19 cases in the upcoming 10 days using deep learning techniques including RNN, GRU, and LSTM. The predictive performance of the utilized deep learning model demonstrated by July 1, 2020, is greater than 90% accurate, demonstrating its effectiveness.

3. Material and Methods

The following section including the novel coronavirus dataset employed, the deep learning algorithm used, and the evaluation metrics utilized in this research.

3.1. Dataset

COVID-19 dataset is taken from the Center for Systems Science and Engineering at Johns Hopkins University due to its 'real-time' availability dataset which is available on [18]. The study applied to two countries which are Egypt and Saudi Arabia. The collected COVID-19 confirmed, deaths, recovery, and active cases dataset ranges from 22 March 2020 until the current time which is 26 September 2021. And for training and testing purposes, 80%-20% utilized respectively.

The single country file contains 550 samples of confirmed and death cases in Saudi Arabia. The sample of the COVID-19 confirmed, deaths, recovered, and active cases dataset used for forecasting the COVID-19 is shown in Fig.1.

Country_Region	Last_Update	Lat	Long_	Confirmed	Deaths	Recovered	Active
Saudi Arabia	2020-03-22 23:45	23.885942	45.079162	511	0	17	494
Saudi Arabia	2020-03-23 23:19:21	23.885942	45.079162	562	0	19	543
Saudi Arabia	2020-03-24 23:37:15	23.885942	45.079162	767	1	28	738
Saudi Arabia	2020-03-25 23:33:04	23.885942	45.079162	900	2	29	869
Saudi Arabia	2020-03-26 23:48:18	23.885942	45.079162	1012	3	33	976
Saudi Arabia	2020-03-27 23:23:03	23.885942	45.079162	1104	3	35	1066
Saudi Arabia	2020-03-28 23:05	23.885942	45.079162	1203	4	37	1162

Figure 1: A Sample of the prediction model dataset

3.2. Deep Learning Algorithm: LSTM

As COVID-19 cases are classified under time series models, the Recurrent Neural Networks (RNNs) are suitable for it. However, despite their advantages, RNNs suffer from a problem known as vanishing gradients. Hochreiter and Schmidhuber [19] introduced LSTM as an advanced version of RNN, which overcomes the limitations of RNN by using hidden layer units, known as memory cells. The input, output, and forget gates are the gates that control memory cells which store network temporal state and control its self-connections [20]. Data is collected and sent to the next state by using the cell state and hidden state. An input, an output, and a forget gate are all used to determine whether data can pass through or not, based on the priority of the data. The equations from 1 to 5 explains how to solve the vanishing gradient problem.

$$i = \sigma\,(X_t W_i + h_{t-1}\, U_i) \qquad (1)$$

$$f = \sigma\,(X_t W_f + \ h_{t-1} U_f) \qquad (2)$$

$$0 = \sigma(X_t W_o + h_{t-1} U_o) \qquad (3)$$

$$C_t = (C_{t-1} \times f) + (i \ \times \ \sigma(X_t W_c + \ h_{t-1}\, U_C)) \quad (4)$$

$$h_t = \sigma\,(C_t) \times O \qquad (5)$$

Where *i* is the input gate, *f* is the forget gate, *o* is the output gate, *c* is the cell state, *h* is the hidden state, *σ* is the Activation function, *W* and *U* are the weight matrix, and *t* is the time.

3.3. Evaluation Metrics

The research evaluates the performance of a DL algorithm which is LSTM using MSE, MAE, RMSE, and MAPE.

MSE is defined as Mean or Average of the square of the difference between actual and estimated values. The MSE equation is presented below in eq.6:

$$MSE = \frac{1}{N} \sum_{i=1}^{n} (Yi \ - \ \hat{Y})^2$$

MAE The MAE measures the average magnitude of the errors in a set of forecasts, without considering their direction. It measures accuracy for continuous variables. The MAE equation is presented below in eq.7:

$$MSE = \frac{1}{N}\sum_{i=1}^{n}|Yi - \hat{Y}|$$

RMSE is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are; RMSE is a measure of how spread out these residuals are. In other words, it tells you how concentrated the data is around the line of best fit. Root means square error is commonly used in climatology, forecasting, and regression analysis to verify experimental results. The RMSE equation is presented below in eq.8:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(Yi - \hat{Y})^2}$$

MAPE is a measure of how accurate a forecast system is. It measures this accuracy as a percentage and can be calculated as the average absolute percent error for each time period minus actual values divided by actual values. The MAPE equation is presented below in eq.9:

$$MAPE = \frac{1}{N}\sum_{i=1}^{n}|\frac{A_t - F_t}{A_t}|$$

4. Research Methodology

In this section, the proposed methodology to build the LSTM model of COVID19 prediction for both Saudi and Egypt will be discussed. The following section describes the work done as shown in Fig.2 to build the proposed COVID-19 prediction model to forecast the confirmed, death active, and recovery cases for the upcoming week. In the first section, the dataset configuration is described.

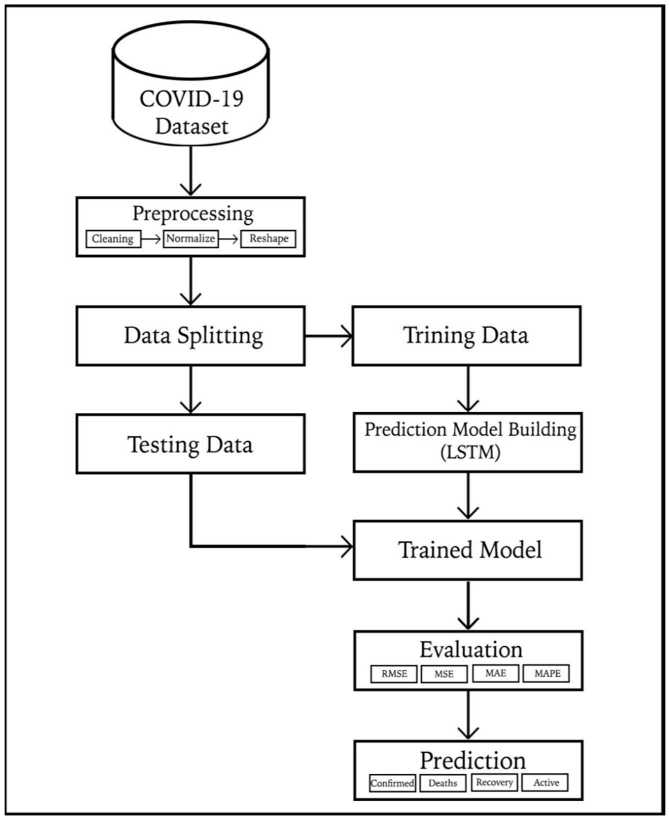


Figure 2: The Proposed real time prediction model

4.1 Dataset Pre-Processing

Initially, COVID-19's real-time data were collected for both Saudi and Egypt. Datasets that have been gathered include daily time series data on active, deaths, confirmed, and recovery cases for Saudi Arabia and Egypt. Several preprocessing techniques were applied to both datasets to build a COVID-19 prediction model. Initially, cleaning of each dataset was applied such as removing irrelevant values and taking care of missing values. In addition, as the datasets consists of a wide range in its value the normalization technique was applied. In the end, as DL models need data to be in a specific form to fit, both datasets were converted to a multidimensional shape

4.2 Model Configuration

A DL-based model was created to predict the COVID-19 cases, called an LSTM, which is appropriate for time-series data. The prediction model predicts the COVID-19 active cases, confirmed cases, deaths, and recoveries for Egypt and Saudi Arabia using a real-time dataset. Fig.3 demonstrates the structure of the LSTM used to develop the COVID-19 prediction model.

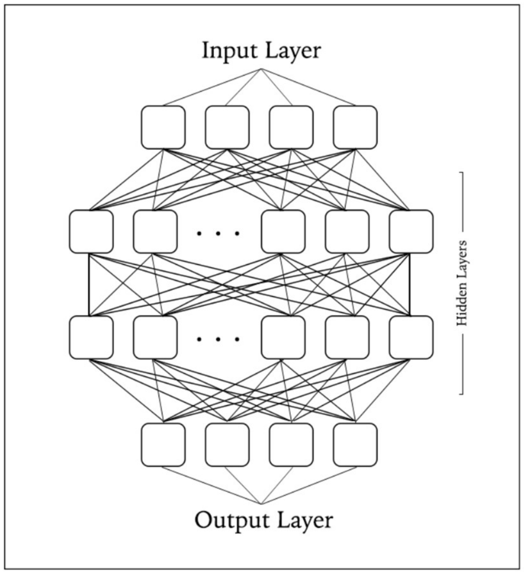


Figure 3: The Structure of the LSTM model

As shown in Fig.3, there is an input layer and two hidden layers, along with one output layer. According to the type of the model which will predict four different cases, the input and the output layer of the LSTM consist of four features. Two hidden layers were used. To reduce overfitting, a regularization function has been added for each hidden layer. Dropouts are used as the regularization function, which drops a random unit of the model. The weights are optimized using the Adam algorithm. The train/test split is the applied method in the training and testing phases, where 80% of the records were utilized for training, and the remaining 20% was used for testing.

The LSTM prediction model was applied to real-time COVID-19 data for one year and half, i.e., from March 23, 2020, to October 10, 2021, using the selected features which are the confirmed, active, deaths, and recovery cases for both Saudi and Egypt. Fig.3 demonstrates the LSTM's employed structure to develop the COVID-19 prediction model for Saudi and Egypt.

The same LSTM COVID-19 prediction model used for Saudi and Egypt. For the structure of the model as shown in Fig.3, there are three layers: an input layer, two hidden layers, and an output layer. Depending on the type of model that will forecast four different cases, the input and the output layer of the LSTM consist of four features.

The difference was on the number of neurons for each model. Two hidden layers were used for both models with 64 neurons and 1000 neurons for each layer in Eygpt model. On other hand for Saudi prediction model, the first layer has 259 while the other has 1000 neurons.

To reduce overfitting, a regularization function has been added for each hidden layer for both models. Dropouts were used as the regularization function, which drops a random unit of the model. The weights were optimized using the Adam algorithm.

The train/test split was the applied method in the training and testing phases, where 80% of the records were utilized for training, and the remaining 20% was used for testing.

Python was used to program the model along with libraries like Keras, Scikit-learn, NumPy, and Pandas. To build the model, we utilized the Keras library and the Scikit-learn libraries, and data preprocessing was conducted using the NumPy and Pandas libraries. To accelerate the training time, the Colab graphics processing unit (GPU) was used. The LSTM prediction model was applied to real-time COVID-19 data for one year and half, i.e., from March 23, 2020, to October 10, 2021, using the selected features which are the confirmed, active, deaths, and recovery cases.

5. Results and Discussion

This section includes the result of the proposed LSTM prediction model to predict COVID-19 Saudi and Egypt cases using a real-time dataset will be discussed in detail using the DL measurement techniques and the difference between the actual and predicted cases.

Country	RMSE	MSE	MAE	MAPE
Saudi Arabia	0.007901	0.0000609	0.0058633	6.3280
Egypt	0.002651	0.000007	0.0016664	4.9376978

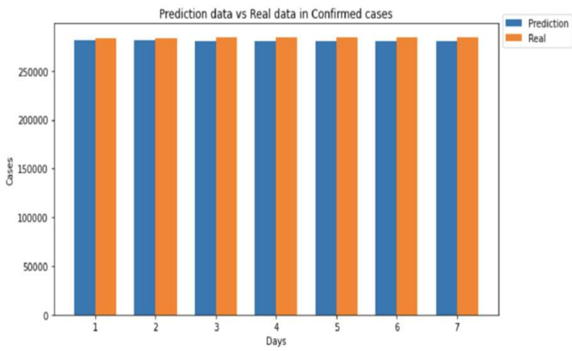
Table 1: Prediction and Training

Country	RMSE	MSE	MAE	MAPE
Saudi Arabia	0.017013	0.0002894	0.0150114	5.0553147
Egypt	0.014464	0.0002092	0.0092198	3.2615096

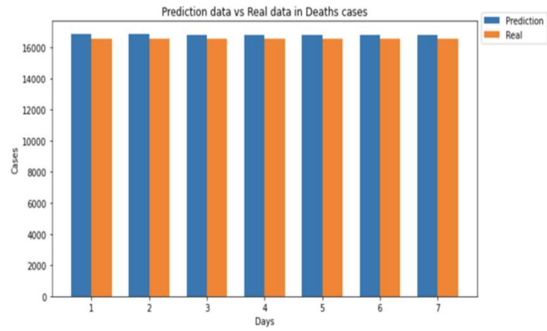
Table 2: Prediction and Testing

First, the model performance was revealed in terms of DL measurement techniques as displayed in Table 1 and Table 2. Table 1 and Table 2 demonstrate the COVID-19 training and testing prediction model results for Saudi Arabia and Egypt. As shown in Table 1 and Table 2, the utilized DL measurement technique was MAE, MSE, RMSE, and MAPE measurement techniques. Egypt outperformed Saudi Arabia in both training and testing phases in model error rate. Specifically, it achieved in training an MAE of 0.0016664, an MSE of 0.000007, an RMSE of 0.002651. And in the testing phase, it achieved an MAE of 0.0092198, an MSE of 0.0002092, and RMSE of 0.014464. In terms of model accuracy of an LSTM algorithm on a particular dataset (MAPE), the LSTM model using the Egypt dataset is better fitting than Saudi Arabia since the MAPE in the training phase equals 4.9376978 and in testing is 3.2615096 unlike the LSTM model using the Saudi Arabia dataset is worse in testing these values.

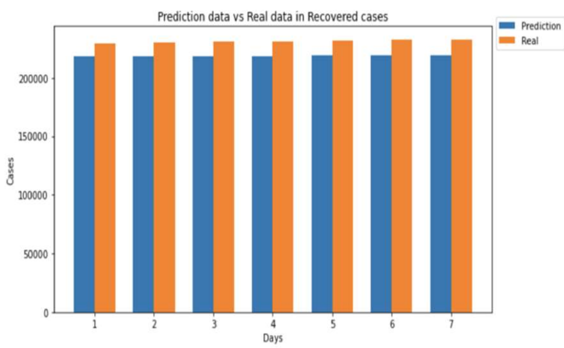
The next phase of revealing the model performance is to visualize the model predicted cases values with actual cases values as shown in Fig4 and Fig5. It shows the cases of Saudi Arabia and Egypt, which are the confirmed (a), deaths (b), active (c), and recovered (d) cases respectively.



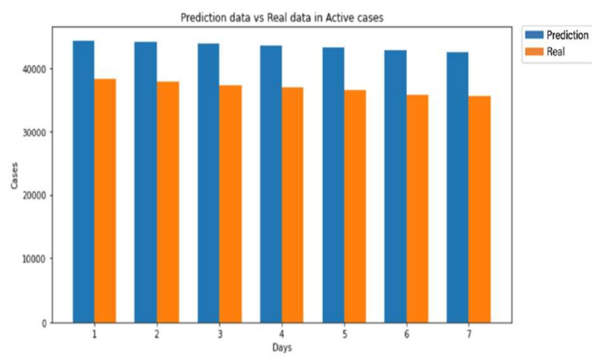
(a) Confirmed Cases



(b) Deaths Cases

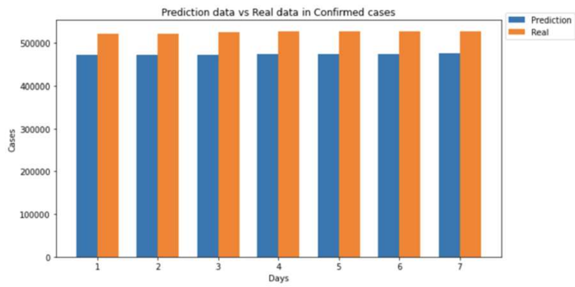


(c) Recovered Cases

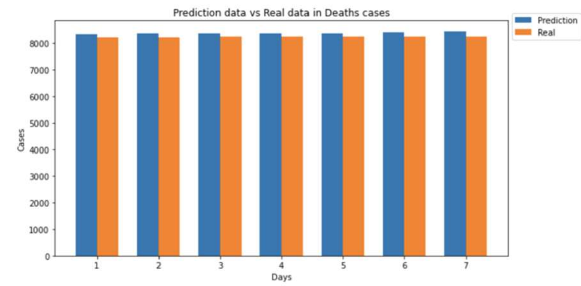


(d) Active Cases

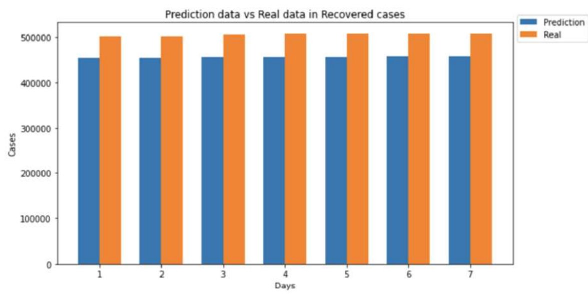
Figure 4: Egypt predicting confirmed(a), deaths(b), recovered(c), and active(d) cases from 22 Mar 2020 until 26 Sep 2021.



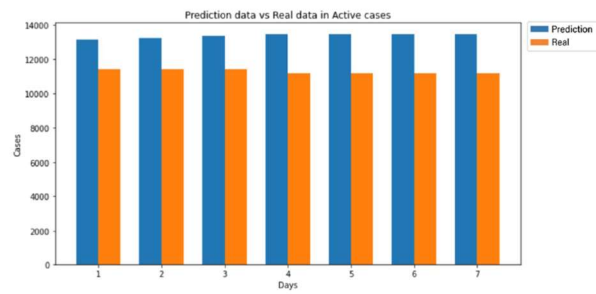
(a) Confirmed Cases



(b) Deaths Cases



(c) Recovered Cases



(d) Active Cases

Figure 5: Saudi predicting confirmed(a), deaths(b), recovered(c), and active(d) cases from 22 Mar 2020 until 26 Sep 2021.

The x-axis represents the number of cases in accordance with a specific day which appears as the y-axis. The blue bar represents the LSTM model case predicted value on a specific day. whereas the orange bar represents the real/actual case value on a specific day. As shown in the Egypt prediction model in Fig4, the model behaves well in all cases there is no obvious variation, especially in confirmed and deaths cases. The model achieved the best point, in death case value where the difference between the actual and predicted 75 cases as shown in Fig.4(b) where the predicted was 288587 and actual was 288637 cases. While in Saudi prediction cases as in Fig.5(b), the model gets the best prediction on death case on day 3 & 4 it was 8,553 and 8,561 compare with a real of 8,237 and 8,249 respectively. In both Egypt and Saudi prediction model the active prediction was the worst.

6. Conclusion

COVID-19 is a global threat that can ignite a massive global crisis. Regardless of the inaccuracies related to medical forecasts, COVID-19 cases number forecasts are still valuable in helping us fully recognize the present situation and prepare for the future. To contribute to controlling the COVID-19 pandemic, this study performed future forecasting on daily COVID-19 confirmed, deaths, active and recovered cases in the upcoming 7 days in Egypt and Saudi Arabia. The model was initially built using the real-time dataset found at Johns Hopkins University's Center for Systems Science and Engineering. The study employed an 80%-20% approach to train and test the model respectively. Different preprocessing techniques were employed such as cleaning and transforming data. A specific configuration to the DL algorithm which is LSTM was applied to produce an accurate prediction result of COVID-19 cases. Moreover, the model performance was revealed in terms of DL measurement techniques and computes the difference between predicted and real values. Finally, in both the training and testing phases, Egypt outperformed Saudi Arabia. The MAE, MSE and RMSE for training were 0.0016664, 0.000007, and 0.002651, accordingly. A MAE of 0.0092198, MSE of 0.0002092, and RMSE of 0.014464 were achieved during the testing phase. The LSTM model based on the Egypt dataset is more accurate in terms of model accuracy on a particular dataset (MAPE) since the MAPE in the training phase is 4.9376978 and in testing is 3.2615096, unlike the LSTM model used with the Saudi Arabia dataset which performs worse in testing. As a result of this research, policymakers will be able to make more informed decisions about the epidemic depending on realistic estimates of its volume. Nevertheless, the research will continue to be enhanced by using the updated dataset and applying the most appropriate machine learning techniques to forecast the future. The real-time dataset will also be expanded to include more countries in the future. Further, one of our main future priorities will be real-time forecasting.

Acknowledgments: We are grateful to Department of Information technology, College of Computing and Deanship of Scientific Research, Qassim University for their undying support in the publication of this study.

References

[1] Abbasimehr, H. & Paki, R. Prediction of COVID-19 confirmed cases combining deep learning methods and Bayesian optimization. Chaos, Solitons Fractals. 142 pp. 110511 (2021).

[2] Anderson, K., Odell, P., Wilson, P. & Kannel, W. Cardiovascular disease risk profiles. American Heart Journal. 121, 293-298 (1991).

[3] Asri, H., Mousannif, H., Al Moatassime, H. & Noel, T. Using machine learning algorithms for breast cancer risk prediction and diagnosis. Procedia Computer Science. 83 pp. 1064-1069 (2016).

[4] Bandyopadhyay, S. & Dutta, S. Machine learning approach for confirmation of covid-19 cases: Positive, negative, death and release. MedRxiv. (2020).

[5] Benvenuto, D., Giovanetti, M., Vassallo, L., Angeletti, S. & Ciccozzi, M. Application of the ARIMA model on the COVID-2019 epidemic dataset. Data In Brief. 29 pp. 105340 (2020).

[6] Bontempi, G., Taieb, S. & Le Borgne, Y. Machine learning strategies for time series forecasting. European Business Intelligence Summer School. pp. 62-77 (2012).

[7] Chimmula, V. & Zhang, L. Time series forecasting of COVID-19 transmission in Canada using LSTM networks. Chaos, Solitons Fractals. 135 pp. 109864 (2020).

[8] Chakraborty, T. & Ghosh, I. Real-time forecasts and risk assessment of novel coronavirus (COVID-19) cases: A data-driven analysis. Chaos, Solitons Fractals. 135 pp. 109850 (2020), https://www.sciencedirect.com/science/article/pii/S0960077920302502.

[9] Grasselli, G., Pesenti, A. & Cecconi, M. Critical care utilization for the COVID-19 outbreak in Lombardy, Italy: early experience and forecast during an emergency response. Jama. 323, 1545-1546 (2020).

[10] Guan, W., Ni, Z., Hu, Y., Liang, W., Ou, C., He, J., Liu, L., Shan, H., Lei, C., Hui, D. & Others Clinical characteristics of coronavirus disease 2019 in China. New England Journal Of Medicine. 382, 1708-1720 (2020).

[11] Hao, B., Li, L., Li, A. & Zhu, T. Predicting mental health status on social media. International Conference On Cross-cultural Design. pp. 101-110 (2013).

[12] Huang, C., Chen, Y., Ma, Y. & Kuo, P. Multiple-input deep convolutional neural network model for covid-19 forecasting in china. MedRxiv. (2020).
[13] Istaiteh, O., Owais, T., Al-Madi, N. & Abu-Soud, S. Machine learning approaches for covid-19 forecasting. 2020 International Conference On Intelligent Data Science Technologies And Applications (IDSTA). pp. 50- 57 (2020).
[14] Kasilingam, D., Sathiya Prabhakaran, S., Rajendran, D., Rajagopal, V., Santhosh Kumar, T. & Soundararaj, A. Exploring the growth of COVID19 cases using exponential modelling across 42 countries and predicting signs of early containment using machine learning. Transboundary And Emerging Diseases. 68, 1001-1018 (2021).
[15] Lapuerta, P., Azen, S. & Labree, L. Use of neural networks in predicting the risk of coronary artery disease. Computers And Biomedical Research. 28, 38-52 (1995).
[16] Nishiura, H., Linton, N. & Akhmetzhanov, A. Serial interval of novel coronavirus (COVID-19) infections. International Journal Of Infectious Diseases. 93 pp. 284-286 (2020).
[17] Organization, W. & Others Naming the coronavirus disease (COVID-19) and the virus that causes it. 2020. (2020).
[18] Petropoulos, F. & Makridakis, S. Forecasting the novel coronavirus COVID-19. PloS One. 15, e0231236 (2020).
[19] Rauf, H., Lali, M., Khan, M., Kadry, S., Alolaiyan, H., Razaq, A. & Irfan, R. Time series forecasting of COVID-19 transmission in Asia Pacific countries using deep neural networks. Personal And Ubiquitous Computing. pp. 1-18 (2021).
[20] Rustam, F., Reshi, A., Mehmood, A., Ullah, S., On, B., Aslam, W. & Choi, G. COVID-19 Future Forecasting Using Supervised Machine Learning Models. IEEE Access. 8 pp. 101489-101499 (2020).
[21] Schmidhuber, J., Hochreiter, S. & Others Long short-term memory. Neural Comput. 9, 1735-1780 (1997).
[22] Shi, F., Xia, L., Shan, F., Song, B., Wu, D., Wei, Y., Yuan, H., Jiang, H., He, Y., Gao, Y. & Others Large-scale screening to distinguish between COVID-19 and community-acquired pneumonia using infection size-aware classification. Physics In Medicine Biology. 66, 065031 (2021).
[23] Shahid, F., Zameer, A. & Muneeb, M. Predictions for COVID-19 with deep learning models of LSTM, GRU and Bi-LSTM. Chaos, Solitons Fractals. 140 pp. 110212 (2020), https://www.sciencedirect.com/science/article/pii/S0960077920306081.
[24] Shahid, F., Zameer, A., Mehmood, A. & Raja, M. A novel wavenets long short term memory paradigm for wind power prediction. Applied Energy. 269 pp. 115098 (2020).
[25] Singh, S., Parmar, K., Makkhan, S., Kaur, J., Peshoria, S. & Kumar, J. Study of ARIMA and least square support vector machine (LS-SVM) models for the prediction of SARS-CoV-2 confirmed cases in the most affected countries. Chaos, Solitons Fractals. 139 pp. 110086 (2020).
[26] WHO. Naming the Coronavirus Disease (Covid-19) and the Virus That Causes it., https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technic%alguidance/ naming-the-coronavirus-disease-(covid-2019)-and-the-virusthat-cau% ses-it, Apr. 1, 2020.
[27] Yadav, M., Perumal, M. & Srinivas, M. Analysis on novel coronavirus (COVID-19) using machine learning methods. Chaos, Solitons Fractals. 139 pp. 110050 (2020).
[28] Yang, Z., Zeng, Z., Wang, K., Wong, S., Liang, W., Zanin, M., Liu, P., Cao, X., Gao, Z., Mai, Z. & Others Modified SEIR and AI prediction of the epidemics trend of COVID-19 in China under public health interventions. Journal Of Thoracic Disease. 12, 165 (2020).
[29] Zameer, A., Majeed, M., Mirza, S., Raja, M., Khan, A. & Mirza, N. Bio-inspired heuristics for layer thickness optimization in multilayer piezoelectric transducer for broadband structures. Soft Computing. 23, 3449-3463 (2019).

[30] Zaremba, W., Sutskever, I. & Vinyals, O. Recurrent neural network regularization. ArXiv Preprint ArXiv:1409.2329. (2014).

[31] Dataset of Center for Systems Science and Engineering at Johns Hopkins University, https://github.com/CSSEGISandData/COVID-19/,31 10 2021.

[32] Khan, N., Aljoaey, H., Tabassum, M., Farzamnia, A., Sharma, T. and Tung, Y.H., 2022. Proposed Model for Secured Data Storage in Decentralized Cloud by Blockchain Ethereum. Electronics, 11(22), p.3686.

[33] Tabassum, M., Perumal, S., Afrouzi, H.N., Kashem, S.B.A. and Hassan, W., 2021. Review on Using Artificial Intelligence Related Deep Learning Techniques in Gaming and Recent Networks. In Deep Learning in Gaming and Animations (pp. 65-90). CRC Press.

[34] Tabassum, M., Perumal, S., Mohanan, S., Suresh, P., Cheriyan, S. and Hassan, W., 2021. IoT, IR 4.0, and AI Technology Usability and Future Trend Demands: Multi-Criteria Decision-Making for Technology Evaluation. In Design methodologies and tools for 5G network development and application (pp. 109-144). IGI Global.