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RESEARCH ARTICLE

Prediction of Covid-19 Cases for Malaysia, Egypt, and USA using Deep Learning Models

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Abstract Forecasting in pandemics and disasters is one of the means that contribute to reducing the damage of this pandemic, and the Corona virus is reportedly the most dangerous pandemic that the entire world is suffering from. As a result, we aim to use a deep learning algorithm to predict confirmed and new cases of Covid-19 in our study. This paper identifies the most essential deep learning techniques. Long short-term memory (LSTM) and gated recurrent unit (GRU) were shown to forecast verified Covid-19 fatalities in Malaysia, Egypt, and the U.S. using time series data from 1 January 2021 to 14 May 2022. The first section of this study examines a comparison of prediction models, while the second section examines how prediction and performance analysis may be enhanced using mean absolute error (MAE), mean absolute error percentage (MAPE), and root mean squared error (RMSE) Metrics. On the basis of the regression curves of two two-layer models, the data were split into training sets of 80% and test sets of 20%. The conclusion is that the outputs of the training model and the original data greatly converged. The findings of the study indicated that, for predicting Covid-19 cases, the GRU model in the three nations is superior than the LSTM model.

Keywords: Covid-19, Deep Learning, Prediction, LSTM, GRU, Malaysia.

Introduction

Forecasting natural catastrophes and pandemics is a vital task for decision-makers in order to establish measures and take action. Corona virus (Covid 19) is a pandemic that abruptly arose in December 2019 in China, notably in Wuhan, where scientists and specialists search in various situations to develop answers or merely lessen the intensity of its threat [1]. The coronavirus has extended to a large variety of nations and harmed the whole global population. Work environments and lives are profoundly affected by the epidemic. In March 4, 2020 until August 1, 2022, the World Health Organization (WHO) registered a global overall 450,147,264 diagnosed cases of COVID 19 [2]. In addition, artificial intelligence is widely used in practice based on deep learning model principles. In the health field, it is widely used to diagnose and predict many diseases such as heart disease, cancer, and diabetes [3]. Forecast models are one approach that aids disclose the direction of this illness, as anticipating the number of verified cases and mortality and the usage of other essential resources, so paying attention to the issue of prediction in such circumstances is important. In order to efficiently and swiftly combat this crisis [4]. It is essential to realise the behaviour of this phenomena, as well as its future direction and outcomes; consequently, the significance of precise scientific prediction, as several econometrics experts from across the world explore for a modelling that simulations the incidence of covid-19. As a consequence of the architecture of the artificial neural network, deep learning has become better at detecting unstructured data patterns such as text, video, and photos. As a result, deep learning has caused a significant shift in industries such as industry, health, energy, and finance. Currently, several sectors are re-evaluating conventional business practices. The Figure 1 shows the classification of deep learning algorithms.

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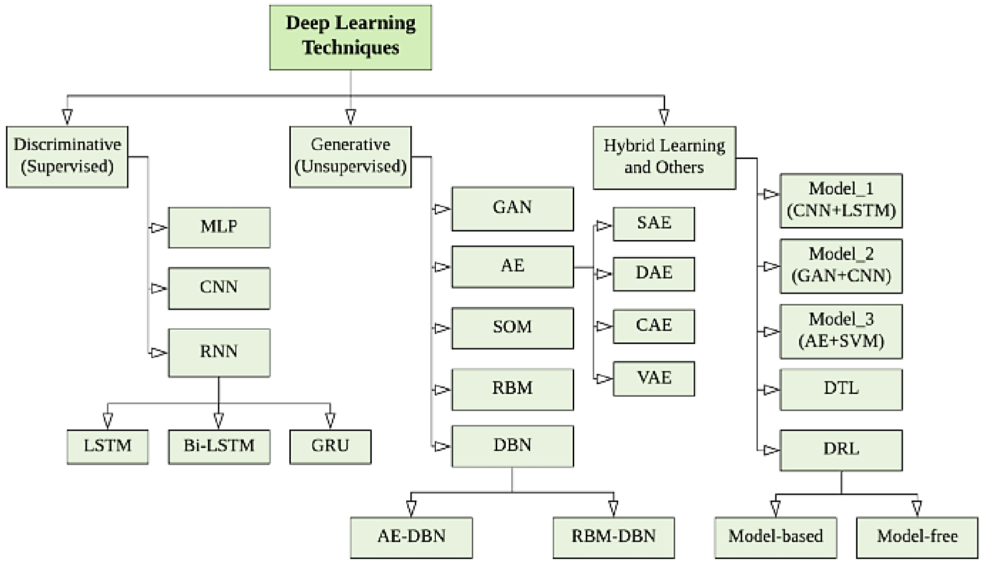

Figure 1. Deep Learning Techniques

The analysis and use of deep learning algorithms in this context, which aspired to detect confirmed and fatal of COVID 19 cases, is crucial to the study of the task of data analysis. In [5] the authors approached to anticipate cases reported of COVID-19 and fatalities the data was collected from June 1, 2020, to November 30, 2020 for three countries namely, Saudi Arabia, Kuwait, and Egypt. LSTM and GRU models were compared using the mean absolute error and square root error. The study showed that the models had a solid prediction performance. In such work, this study utilised LSTM and GRU to forecast confirmed and fatal cases for Malaysia, Egypt, and the United States utilising time series data from January 1, 2021, to May 14, 2022. 80% of dataset used for training, while 20% was for test. By studying existing deep learning methods that are frequently used for predicting Covid-19, eliciting the ideal model, and assessing these models based on their capacity to predict mortality and verified cases for the three nations constituted the contribution of this study. Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Means-Square Error (RMSE) measurements were modified to analyse forecasts of Covid-19 (fatalities and confirmed cases); the objective of evaluating the efficiency of the techniques utilised. The findings demonstrate that the projected values substantially resemble the actual values of Covid-19 instances, and that the employed algorithms perform excellently.

Related Studies

In this section, we examine and show techniques used in deep learning to examine the effects and prevention of COVID-19, various researches and theories have been conducted in this domain in an effort to identify the model that best depicts the behaviour of the problem of new coronavirus infections and more accurately identifies future infections so that proper precautions may be taken. Here the most significant previous literature pertinent to this research: Chimmula and Zhang conducted a study in Canada relied on deep learning (DL) and long-term memory (LSTM) to predict new cases of the Covid-19 virus. The model was trained with data that was extended until March 31, 2020.the results show that Researchers conclude that the incidence of infections in Canada has not reached its peak and is expected to rise soon [6]. ArunKumar *et al*. in [7] The authors have studied the forecast of future deaths and recoveries of Covid-19 in 10 nations using the SVR, RNN, and GRU models, and used Johns Hopkins University's contemporaneous data to determine the total confirmed and predicted cases by area. The aim of the study was a comparison of the presentation of the used algorithms, with the outcomes found that SVR technology has the best performance with an error coefficient of 6.9%.

Moreover, the LSTM algorithm modelled a time series for long-term dependency issues. It achieves more accuracy than a conventional algorithms [8]. It is generally known that COVID-19 case data is dynamic data that fluctuates continually, as the LSTM model can underestimate the MSE parameter error to forecast daily COVID-19 cases with a high level of accuracy. Tian *et al*. (2020) compared three six-state machine learning prediction models, including the hidden Markov chain model (HMM), the Bayesian hierarchical model, and the long-term memory model, in their study (LSTM). In results of the study, show

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that LSTM model had the smallest prediction error rates for four countries. In 2020, Al-Qaness [9] presented his study entitled "Optimization method for predicting confirmed cases of Covid 19 in China". The study author suggests a novel method for estimating future instances of Corona disease. An upgrade, the presented approach Adaptive Neural Fuzzy Inference System (ANFIS) utilizing an improved Flower Pollination Algorithm (FPA) This model was implemented using a dataset from official WHO, which represents confirmed infections in China during 10 days beginning on Jan 21, 2020, and lasting on Feb 18, 2020, to provide predictions for verified infections. On the basis of the measurements of Mean Absolute Relative Error (MARE), Root Mean Squared Relative Error (RMSRE), mean square root of the relative error, and computation of R2, it was construed that the model's outputs were accurate and that it exhibited a high level of performance.

Dairi *et al*. [10] conducted a study analysing deep learning models with a focus on hybrid models such as LSTM, CNN, and GAN-GRU. It is anticipated that hybrid models will play a more significant role in prediction than simple models, for instance supporting vector regression and logistic regression in predicting the future trends of COVID-19. The results demonstrate that hybrid models perform much better at predicting COVID-19 instances, while other deep learning models studied continue to outperform by a small margin. Examples include support vector regression and logistic regression. LSTM-CNN exhibited the highest accurate predictions with a MAPE of 3.718% in the field of time series data prediction, demonstrating that deep learning tools outperform their conventional machine counterparts in all domains. A study was conducted in order to forecast COVID-19 cases using data from Italy, France, Spain, China, Australia, and the United States. This study examined the use of neural network techniques, including such as RNN, VAE, LSTM, BiLSTM, and GRU. According to the study's findings, the LSTM model is better than other models [11].

Furthermore, Shin *et al*. [12] studied the LSTM model, the GRU, and the recurrent neural networks (RNN). The models were evaluated on the basis of criteria for diagnosis and forecasts for Covid patients diagnosed. This study discovered that (RNN) technology is more accurate than LSTM in its predictions. Similarly, a study presented by Azarafza *et al*. [8] utilising RNN, LSTM, and Integrated Seasonal Moving Average (SARIMA) methods to predict COVID-19 cases in Iran. The findings of the study reveal that the LSTM method performed superior good compare with others, where indicated a lower error values when predicting the spread of an illness.There are few researches examining the analyse comparison of deep learning techniques on COVID-19 data, and these models are developed with limited datasets [13]. It is of the greatest priority to forecast severe COVID-19 cases, as well as the dangers of consequences, such as mortality and risk. Therefore, models may be precisely and rapidly programmed from the outset of training when relevant spatial characteristics are extracted from big data sets covering several regions. This paper examined the ability of deep learning algorithms to predict confirmed cases and fatalities using time series data in Malaysia, Egypt, and the United States.

Methodology

In this study, the technique depicted in Figure 2 was utilised, which entails the fundamental procedures for forecasting confirmed cases and mortality for Covid-19 in Malaysia, Egypt, and the USA. Its performance is anticipatory. Lastly, the following coefficients (RMSE, Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are utilised to figure out the best model for predicting Covid-19 instances by utilising the chronological data of the aforementioned countries.

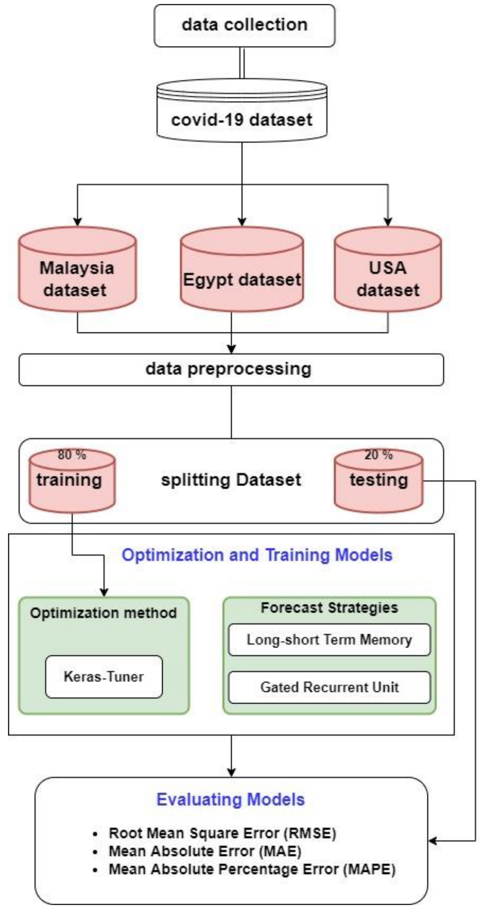

Figure 2. Proposed Model

- ***Data collection***

Date of observation of the dataset in the following format is one of the data attributes utilised YYYY-MM-DD This shows that the country column includes the row data remark, that the cumulative total cases field represents the number of cases reported for each country and the cumulative number of fatalities column represents the number of fatalities per country. In light of this, to evaluate DL models, the data was applied to Malaysia, Egypt, and the United States of America. Study This project's purpose is to estimate the number of deaths cases and confirmed cases in three nations for a period of 499 days, from January 1, 2021 to May 14, 2022, where the dataset used from Kaggle repository [14].

- ***Data pre-processing***

This section describes how time-series data is measured, prepared, and transformed before being used to learn under supervision as follows.

- ***Transforming data into supervised learning***

For the deep learning algorithm, both the input and output are represented as variables. Consequently, its functional linkages are learnt. After the data has been converted, both the input (X) and the output (Y) are identified, which enables the structured data observations to be determined. By implementing the shift() function of the Pandas library, it was possible to go back five days and forecast one day into the future. Apply varied timeframes to the two techniques in order to forecast using them. It provides to flexibility manipulation of both input and output

- ***Scaling data***

The Rectified Linear Unit (RELU), a softmax activation, has been applied in deep learning models as LSTM and GRU. Hence, in order to simplify the procedure, the Python MinMaxScaler library was utilised to get outstanding training and performance for the algorithms that scaled each range using the values 0 and 1.

- ***Data splitting***

According to the studies in [5,15] 80% of the data slipped into the training category and 20% dropped into the testing group. The DL models were trained in a practical method to improve its performance, and the test set was then used to evaluate each model accuracy.

- ***Optimization and training models***

Adjusting the training data or the process of abstract issue description might result in a large improvement, for example, by collecting more data, creating additional data, adjusting the data size, transforming the data, selecting the features, and redefining the problem. In this research, many prediction layers from the Keras-tuner library that are specialized for deep learning models such as long-term memory algorithm (LSTM) and gated recurrent units (GRU) have been employed to get the best outcomes [16]. The number of neurons per buried layer is therefore adjusted between 10 and 500. As the dropout rate for the dropout layer, values between 0.1 and 0.9 are considered. The ADAM optimizer was utilised in the output layer, which comprises of a single neuron [17].

- ***Evaluating the models***

For the purpose of evaluating the performance of the models employed in this work, standard metrics used by several authors, such as, have been applied The Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE); The same metric was followed for this research [5,18]. The techniques are assessed as well as the accuracy of the findings for such LSTM, GRU techniques is determined by three measurements provided in equations 1, 2, and 3, that could be calculated for each as follows.

RMSE is calculated from equation 1 in below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i^{obs} - y_i^{pred})^2} \tag{1}$$

MAE is reached by equation 2 as following :

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i^{obs} - y_i^{pred}\right| \tag{2}$$

The third one is MAPE that can be calculated by equation 3 below:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}}\right| \times 100 \tag{3}$$

y_i^{obs} Represents an actual observation and y_i^{pred} is the forecast value. Nevertheless, the motivation for applying these metrics provides accuracy in the findings achieved when assessing the model's performance, particularly in the field of forecasting for various different types of data, including time series forecasting [18].

Experimental Results and Discussion

In these two subsections, we Describe the tools and accomplishments of a two deep learning methods, LSTM and GRU, further used predict time series data of verified cases and fatalities for Malaysia, Egypt, and USA.

- **Experimental Setups**

In this work, Python v 3 was used along with Jupyter Notebook version 6.7.3 to run the experiment and evaluate the data of the used models. The dataset period is starting from 1st January 2021 to 14th May 2022. It was trained 80%, tested 20%; for both models, compare the outcomes of algorithms in its performance to predict mortality and confirmed cases of covid-19. The two techniques LSTM and GRU with Keras Tuner, Sklearn, and other libraries implemented with different layers to predicting the confirmed and fatals cases of covid-19. In addition, the Keras software suite's Adam optimizer was utilised in this work it is applied due to its high precision and strength in training, as well as its strong accuracy and swift implementation time with deep learning approaches [19].

- **Results of Malaysia**

In this section, the parameters for both models and three countries are presented, and in following section, the findings for every approach are analyzed. In Malaysia, both LSTM and GRU models incorporated the first and second layer parameters. In addition, each layer was comprised of neurons labelled with leaky units; 450 neurons, each with 0.4% dropout, were utilised to forecast verified instances, as shown in Table 1.

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Table 1. A summarization of the most efficient metrics applied in Malaysia's cases

		Confirmed cases		Death cases	
Models	#Layers	Units	dropout	Units	dropout
LSTM	Layer1	450	0.4	360	0.4
	Layer2	[360,470]	[0.4,0.3]	[300,410]	[0.4,0.2]
GRU	Layer1	430	0.4	[440]	0.3
	Layer2	[390,450]	[0.3,0.2]	[450,270]	[0.5,0.4]

For confirmed cases in the region of Malaysia, a simulation with the layer 1 produces high values for RMSE MAPE MAE, with values of 38682.5745, 31858.0556, and 0.8525, respectively. In contrast to the LSTM model, which produces weak values as outputs in the second layer, the following values are generated: 274664.508, 263076.89967, and 6.5304, respectively. The optimal output for LSTM with Layer 1 is 10950.533, followed by 89610.4608 and 2.5147.

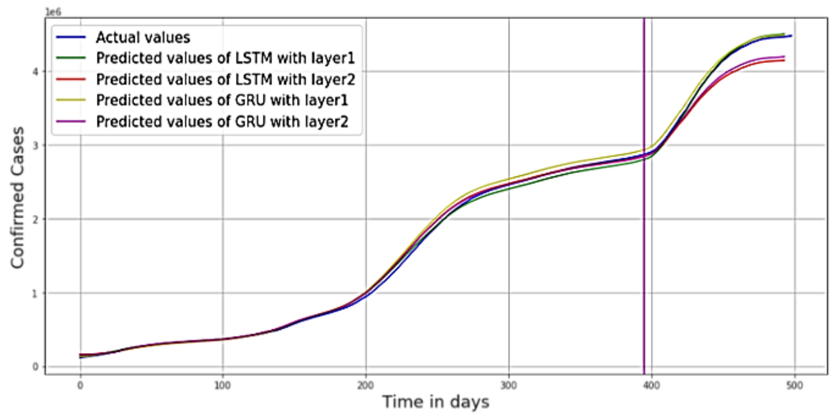

Figure 3. Confirmed cases prediction for LSTM and GRU models in Malaysia

Table 1 depicts a record rise in the prediction of confirmed cases from the beginning of the test, when it was 115.07, to the end, when it was 4.475.87. Even yet, the LSTM and GRU models in the first layer are quite similar to the actual data. While in the second layer we observe a growing disparity between the two models and the actual data. Model using initial layer values comparing the predicted value of 4.512.127 to the actual values of 4.461.13 at the conclusion of the test, which closed with a value of 4.461.13, the prediction is considered to be almost accurate. Figure 3 depicts the numbers obtained from the forecast of confirmed and deaths cases in Malaysia over a period of 494 days. Moreover, the values of the variables match accurately at the beginning of the trial up to 150 days before the expiration date.

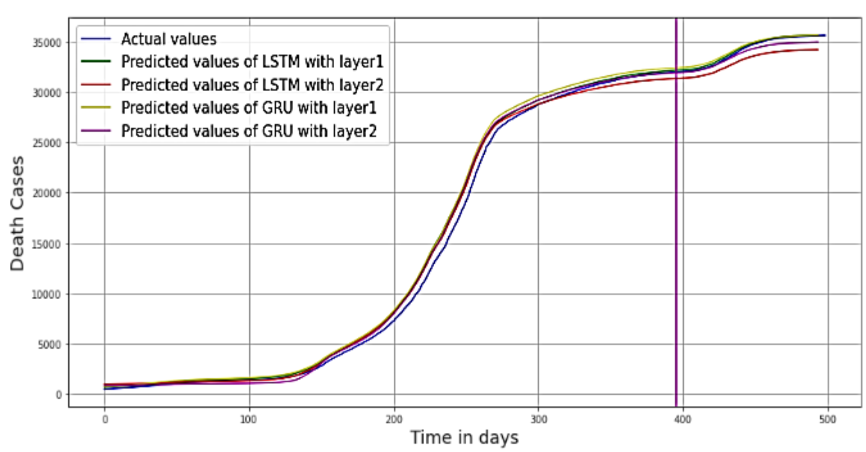

Figure 4. Fatalities cases prediction for LSTM and GRU models in Malaysia

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The Figure 4 show the number of confirmed cases increased less than 1000 at the beginning of the test to 3,538 by the end of the 494-day period. In addition, the result suggests that the variables of the LSTM and GRU models in layer 1 are consistent with the real values, in contrast to the second layer, where the predictions of the two models for the real values deviate significantly. At the ending of the complete test period of 494 days, it is evident that the GRU model with layer1 is near to the genuine values, with a projected value of 35,635 and actual values of 3,558. Lastly, the LSTM model generated layer2 anticipated values that are less correlated than the actual values, which were 34193 versus 3558.

- **Results of Egypt**

This section discusses the outcomes of the experiment performed on the deep learning models LSTM and GRU to predict confirmed cases and fatalities using Egypt-specific data. Initially prediction accuracy is achieved using the long short term memory approach, which combines the input and hidden layers with the output layers. This method was deemed more successful for supplying its parameters to the LSTM and GRU model frameworks. In addition, Table 2 displays the parameters of each model and the two layers used to forecast confirmed cases and death. For Covid 19, where it is noted that 430 neurons and 0.2% of dropout were deployed for the first layer, 390 neurons and 0.5% of dropout were used in the second layer.

Table 2. A summarization of the most efficient measurements applied in Egypt

		Confirmed cases		Death cases	
Models	#Layers	Units	dropout	Units	dropout
LSTM	Layer1	450	0.4	360	0.3
	Layer2	[360,470]	[0.4,0.3]	[300,410]	[0.4,0.4]
GRU	Layer1	430	0.4	[440]	0.3
	Layer2	[390,450]	[0.3,0.2]	[450,270]	[0.5,0.4]

In Figure 5 illustrates the relationship between actual and predicted values for confirmed cases in the State of Egypt during a period of 494 days. The graph reveals that the number of confirmed instances is less than 13947 until it reaches 51564 at the conclusion of the experiment and testing of the two models. At the 200-day point, the data set looks to be highly associated with one another and congruent with actual data, before gradually diverging. Similarly, we could find that the LSTM and GRU models in Layer 2 have an analogous connection to forecast, with the anticipated values of both models deviating greatly from the actual values. GRU model records a strong convergence with the values of 51423 in the layer2 till the conclusion of the test after 494 days, although the actual value is 51564, whereas in the layer 1 the connection between real values and predicted values for GRU model was disparate.

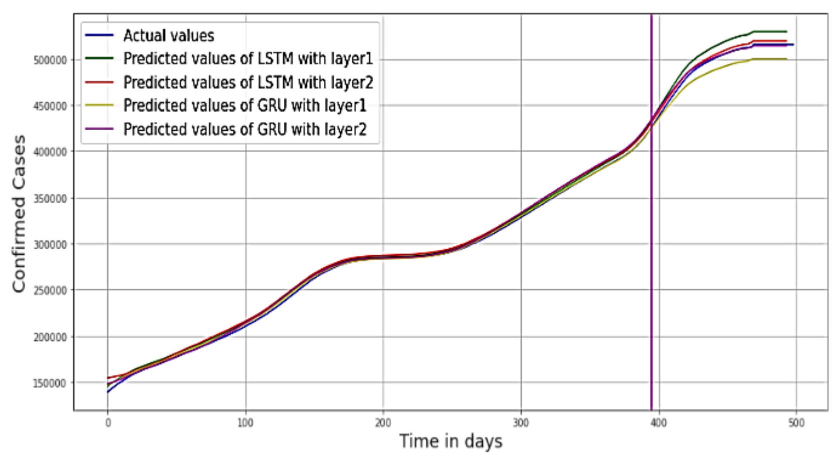

Figure 5. Confirmed cases prediction of LSTM and GRU models in Egypt

In addition, Figure 6 describes the results of the forecast of deaths during a period of 494 days in the State of Egypt, as well as the relationship between actual and predicted numbers. According to the graph, the number of verified instances is less than 76861 before it reaches 24,613 at the conclusion of the trial and testing of the two models.

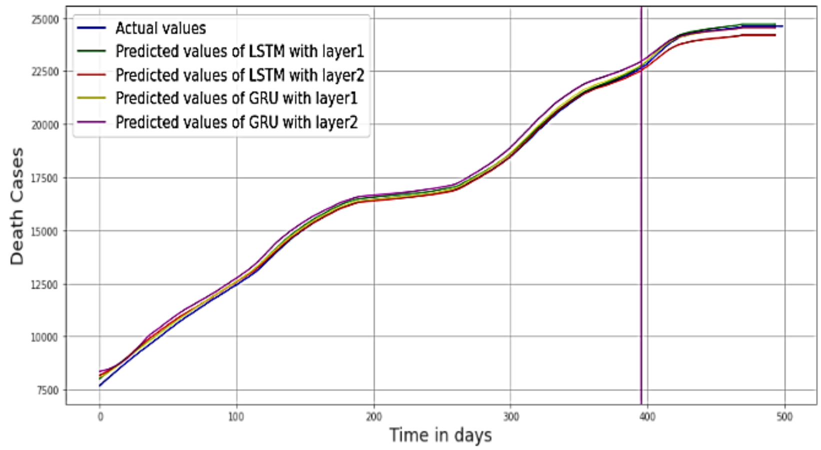

Figure 6. Death cases prediction of LSTM and GRU models in Egypt

At 300 days, the data set looks to be highly connected with one another and congruent with actual data, prior to becoming progressively divergent. Similarly, we observe that the two models in Layer A include a similar connection to forecast, with the two models' expected values differing considerably from the actual values. A model that records a great convergence with values of 24542 in the second layer until the end of the test with a period of 494 days, while the true value is 24613, while in the first layer the relationship was far between the real values and the expected values of the model with the weakest correlation with the real world data; a total of 24,199.

- **Results of USA**

In this section, the prediction results for Covid-19 time-series data employing LSTM and GRU models for confirmed fatal cases of Covid-19 in the United States are presented. The results for confirmed and death cases for covid-19 in the USA are presented in Table 2 below. In terms of the confirmed cases, the highest output values of 232657.58838, 174787.10308, and 0.21631were achieved for RMSE, MAPE, and MSE by GRU with Layer 1. On the hand, the second highest values of 495793.30933, 284517.17255, and 0.66366 were recorded by the LSTM with Layer 1. Meanwhile, for the predicted values of covid-19 deaths in the USA, GRU with Layer 1produced the highest output values for RMSE, MAPE, and MAE at 59.32756, 56.79647, and 0.23378, respectively. Conversely, the lowest values of 20670.26132, 19767.90324, and 1.96574 were recorded by the LSTM with Layer 1 for RMSE, MAPE, and MAE, respectively, while the second strongest scores were achieved by LSTM with Layer 2, producing values of 3226.85814, 2884.93800, and 0.43977, respectively.

Table 3. A summarization of the most efficient parameters used in USA's cases

		Confirmed cases		Death cases	
Models	Layers	Units	dropout	Units	dropout
LSTM	Layer1	220	0.4	500	0.3
	Layer2	[60,160]	[0.2,0.2]	[310,380]	[0.3,0.2]
GRU	Layer1	490	0.4	350	0.3
	Layer2	[390,450]	[0.3,0.2]	[450,270]	[0.5,0.4]

Figure 7 portrays trended actual and forecasted values, for Covid-19 cases in the USA, over a test period of 494 days. Based on the observations of the results, at the initial stage, the predicted value for confirmed case was less than 2,099,731, and then increased to a peak value of 8,420,947 at the time the 494 days elapsed. Additionally, a strong correlation was demonstrated by the predicted output values of LSTM model with Layer 1 and GRU with Layer 1 and the real-world values.

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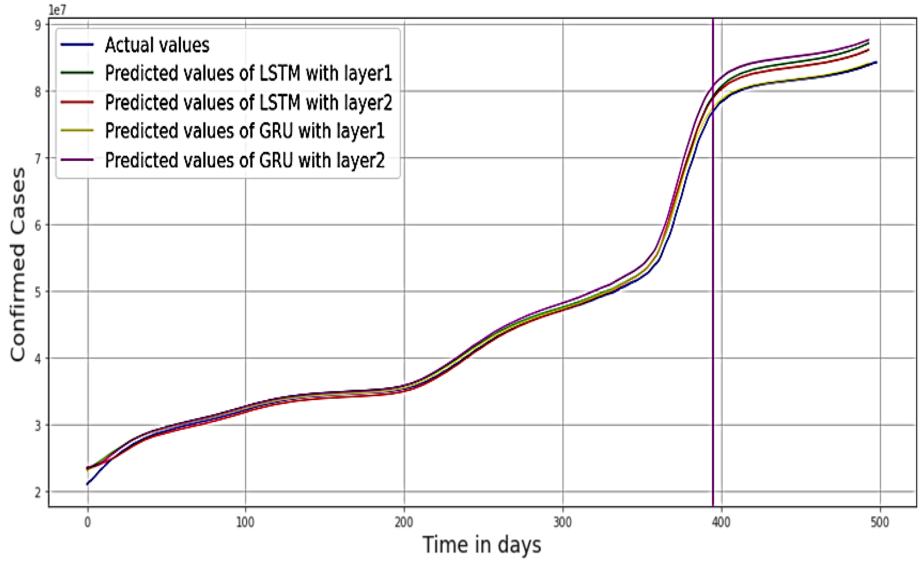

Figure 7. Confirmed cases prediction for LSTM and GRU models in USA.

In contrast, weaker output values were produced by the LSTM with Layer 2. The predicted values produced by the GRU with Layer 1 are closer to the actual values at the end of 494-day testing period. This model produced a predicted value of 8,407,645, compared with real-world values of 8,420,947. On the other hand, GRU with Layer 2 demonstrated the lowest correlation values compared with the actual value.

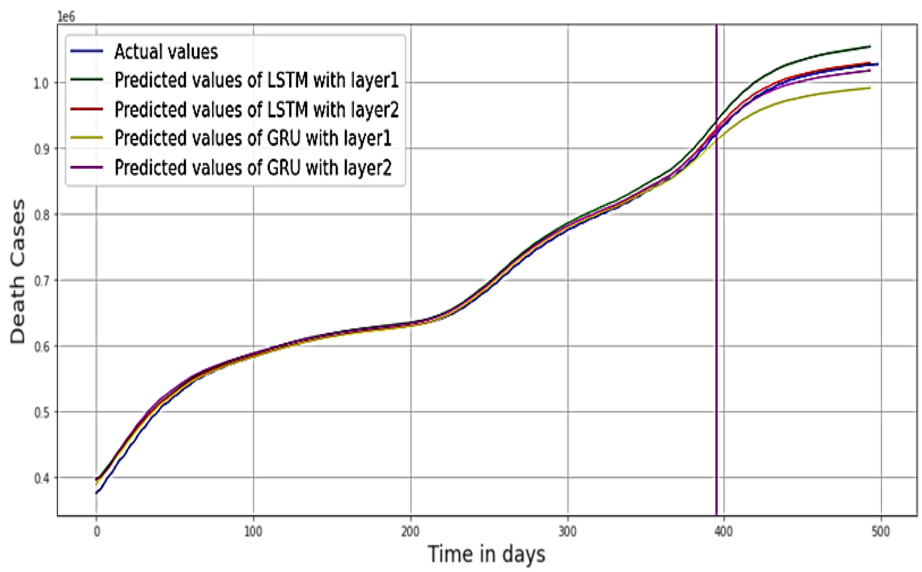

Figure 8. Death cases prediction for LSTM and GRU models in USA

Based on the results produced by the two models, the actual values and predicted values for confirmed covid-19 death cases in the USA for a period of 494 days are presented in Figure 8. It can be seen that at the initial stage, there were less than 375,469 cases, which later increased to 1,025,309 at the peak of the experiment. During the first 200 days, a strong correlation was found between the real-world and predicted data values, while outputs generated by LSTM with Layer 2 and GRU with Layer 1 also share a strong relationship. Meanwhile, the LSTM with Layer 1 demonstrated a weaker correlation between predicted values and real-world values. It was observed that GRU with Layer 1 demonstrated the strongest predicted value of 990,578.

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- **Results Analysis and Comparison**

In an experimental study conducted in three Middle East countries, Omran *et al*. [5] used the LSTM and GRU forecasting frameworks to predict cases for a period of 8 months. The time frame used in their study is different from that used the current study. In their study stronger better performance was recorded by the GRU model, while the best performance was recorded by the LSTM in the current study. In another study carried out by Shahid *et al*. [15] the performance of the LSTM was compared with three other frameworks for the analyses of covid-19 death predictions; the other frameworks used include, SVR, ARIMA, and Bi-LSTM. The efficiency of the models were determined using metrics like RMSE and MAE with result -2.2, 349. On the other hand, in the current study, the use of metrics such as RMSE and MAE were used , and values of 20670.26132 and 19767.90324 were achieved, respectively. From Figure 9, it can be seen that the strongest value of MAPE were achieved by the GRU framework, especially in Malaysia. Overall, the GRU with Layer 1 demonstrated the strongest values for MAE for confirmed death cases at 0.85255 and 0.2864, respectively.

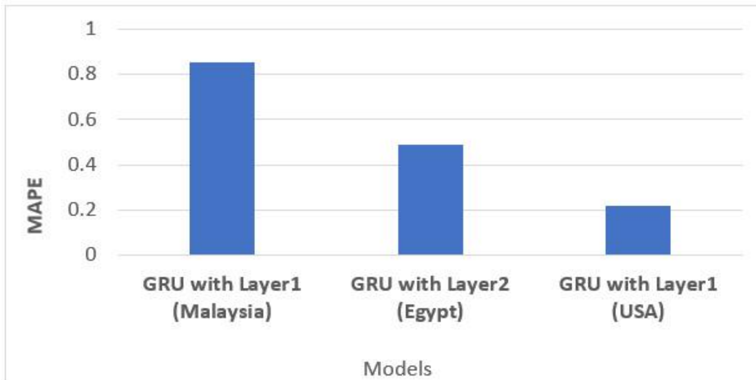

Figure 9. GRU model performance for confirmed cases

Also, for confirmed cases of death, the strongest output values was achieved by GRU model with Layer 2 for MAE, RMSE, in Egypt, with values of 0.48849 and 0.23378, respectively. Meanwhile, in the USA, the strongest outputs for RMSE, MAPE and MAE was achieved by GRU with Layer 1 as presented in Figure 10.

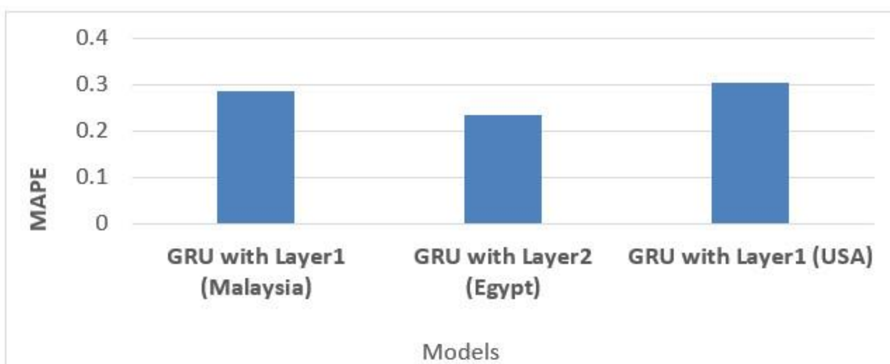

Figure 10. GRU model performance for death cases

Comparing to the recent studies in covid-19 predictions, the study conducted by Dairi *et al*. [9] an LSTM model with three layers, including neuron sizes of (128,64,32) and 200 epochs was designed, and it achieved the highest values of 0.96 and 0.999, thereby rescaling the data through the use of min/max inversion. In this study, the data was rescaled using the min/max function, while the volume of neurons was set at 100 epochs. Lastly, the use of LSTM and GRU was employed in the study alongside a strategy for optimisation so as to differentiate the methods and ascertain the optimal performance of the model for the prediction of COVID-19 cases in the three countries studied within a testing period which started from Finally, the study used LSTM and GRU models with an optimisation strategy to January 1, 2021 and ended in May 14, 2022. Moreover, The LSTM model was used by Indriyani *et al*. [20] for the prediction of daily covid-19 cases in Indonesia from September 2021 until February 2022. The

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parameters which were used in their study include, batch size was 8, 50 epochs, and lookback was 10 days. Meanwhile, in the present study, stronger outputs were produced by the models for the selected metrics at 100 epoch, 50 batch size and 5 days shift back. Consequently, overfitting must be prevented through the maximization of the volume of epochs. Lastly the results derived from this study are evaluated in comparison with other related studies. Based on results of previous studies, covid-19 infections can be predicted using techniques such as support vector machines, linear regression and other statistical tools and techniques. More so, it was observed that related studies less often use complex and hybrid learning models. Nevertheless, sophisticated deep learning models have been employed in predicting covid-19 deaths, and it was found that they exhibited better performance that shallow learning models.

Conclusions

The Corona virus is one of the most worrisome occurrences affecting the political and economic strata of contemporary nations. In this case, the future information is one of the keys to reducing losses and making the right decisions at the right time in order to reduce the risk of the pandemic. Based on our study in which we repeatedly tried to shed light on one of the most important leading methodologies in the field of deep learning. Two models were used LSTM and GRU models to predict confirmed cases of Covid-19 in Egypt, Malaysia, and the United States over a historical data of 499 days. To determine the quality of performance for each model, the true and predicted values of confirmed cases and death were compared using the metrics RMSE, MAE, and MAPE. The results of the study indicate that the model bests in performance when predicting values that are close to the actual values with predicted values for both layers used.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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