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THE POTENTIAL INFLUENCE OF COVID-19 ON THE ARAB WORLD ECONOMY

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ABSTRACT

This paper predicts Coronavirus Disease (COVID-19)'s potential influence on the Arab country's economy by using two predicting models: the Autoregressive Integrated Moving Average (ARIMA) model and Long Short-Term Memory (LSTM) model. The World Bank offers data of the Arab countries' Gross Domestic Product (GDP) over the period 1968-2019. As we show up at the pinnacle of the COVID-19 pandemic, quite possibly the most critical inquiry going up against us is: what is the potential impact of the pandemic on the rate of GDP in Arab countries during the pandemic period? LSTM is recurrent neural networks (RNN), which are competent in understanding temporal dependencies. Therefore, the model based on LSTM achieved a great fit with the real data, which is what made us rely on its results more than the ARIMA model. The results of the LSTM model showed that the COVID-19 pandemic caused a decrease in GDP by approximately 17.22% and 5.41% in 2020 and 2021, respectively, with respect to the real GDP announced by the World Bank. In addition, we trained the LSTM-based model on real data from 1968 to 2020 and predicted the GDP growth rate in the next five years until 2025. Thus, what is certain now is that the Arab world states have to encounter the challenges presented by the current ecosystem. Transition to digital economy is needed, additional volume of data with high-level accuracy is required to improve precise and robust models to attain projections with a reduced amount of margin of error.

JEL Classification: B41, E17, P34

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1. INTRODUCTION

Coronavirus caused a worldwide downturn whose profundity was outperformed simply by the two World Wars and the Great Depression over the previous century and a half (Agarwal et al., 2020). Thus, ensuring world economic stability is an urgent necessity for regulators and economists (Awodumi and Adewuyi, 2020). The quest for stable economic growth is quickly turning into a practical issue among governments, global foundations, and partners interested in investigating the impact of the recent COVID-19 crisis on world economic growth (Awodumi and Adewuyi, 2020). This follows the realization that the pandemic has caused a severe death toll, is tipping millions into extraordinary neediness and is relied upon to dispense enduring scars that push movement and pay well underneath their pre-pandemic pattern for a drawn-out period.

The spread of COVID-19 is anticipated to achieve a broad slowdown of economic activities. As shown by an early assessment of the International Monetary Fund (IMF), the overall economy would diminish by around 3% in 2020. The choking depends on an unmistakably more important size than that of the 2008-2009 Global Financial Crisis. Regardless, in its latest update (June 2020), the IMF reevaluated the assessment to a 4.9% decrease in 2020. The report alludes to the going with clarifications behind the invigorated figure: i) more unmistakable energy in social, isolating activities; ii) lower activity during lockdowns; iii) more great decline in effectiveness among firms that have opened up for business; and iv) more critical vulnerability[1]. The economy-related repercussions will be wide-ranging and uncertain, with different effects on the work markets, creation of supply chains, financial business sectors, and the World Economy (Agarwal et al., 2020). The adverse economic effects may be transmitted by the strength of the social, isolating measures (e.g., lockdowns and related courses of action), its length of execution, and the degree of acquiescence.

Similarly, as with past economic crises, the pandemic is expected to leave long-lasting adverse impacts on the world economic movement and per capita incomes (Zulfigarov and Neuenkirch, 2020; Nejati and Bahmani, 2020; Alfarra and Xiaofeng, 2018). As a result of the recent pandemic, the reduction in energy consumption or the shortage of its supply has severe implications for country income in general and the oil countries in particular because the global economic growth depends heavily on energy-intensive activity (Norouzi et al., 2020; Nejati and Bahmani, 2020).

The COVID-19 pandemic caused dramatic reversals in development and led to a substantial increase in inflation and slow economic growth globally. The GDP of the Arab World at the end of 2019 was (2.81541e+12) USD with a growth of approximately (4.34e+10) USD compared with the GDP (2.77202e+12) USD at the end of 2018. In addition, the growth of gross fixed capital ratio decreased to become (-13%) at the end of 2020. Moreover, as one of the shock ramifications the Arab world trade decreased by approximately 6.6% at the end of 2020. The total trade of the Arab world trade at the end of 2020 was (6.94413e+11) USD compared with (9.13752e+11) USD at the end of 2019. The World Bank offers more details about the Arab world development indicators[2]. In this paper, we focus on studying the impact of the COVID-19 pandemic on the Arab World GDP growth. Thus, to address this inquiry, this exploration utilized the Autoregressive Integrated Moving Average (ARIMA) (Ma et al., 2018; Box et al., 2016) and Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997) models to gauge the Arab global economic growth. The referenced outcomes show that pandemic status significantly affects the Arab world economy. Besides, one of the critical lessons of the recent crisis is that the main objective of reforms to strengthen the global economy is building a foundation for sustainable economic growth depending on the digital economy (Erdmann and Ponzoa, 2021; Solomon and van Klyton, 2020; Alfarra et al., 2017).

The rest of the paper is organized as follows. Section 2 discusses the literature review. In Section 3, we analyze development indicators in the Arab world. Section 4 discusses research methodology. In Section 5, the forecasting results are summarized. Finally, the conclusion and future works are presented in Section 6.

2. LITERATURE REVIEW

Time series forecasting is a major topic in the economic, business, and financial fields. Traditionally, several techniques can be used to effectively predict the next time series delay, such as univariate Autoregressive (AR) (Kurihara, Fukushima, and Finance, 2019), univariate Moving Average (MA), and more notably ARIMA with its numerous differences (Alfarra and Hagag, 2021, Sharma, et al., 2020; Büyükşahin and Ertekin, 2019; Choi, 2018).

Algorithms based on machine learning and deep learning are the emerging approaches for dealing with time series prediction problems. These techniques yield more precise results than conventional regression modeling. It has been stated that artificial Recurrent Neural Networks (RNN) along with memory, such as Gated Recurrent Unit (GRU) and LSTM (Fischer and Krauss, 2018), are exceptional compared to the ARIMA with a substantial margin. However, results from (Siami-Namini and Namin, 2018) showed that the ARIMA model demonstrated its superior precision in forecasting future time series lags. Later the researchers (Siami-Namini, Tavakoli, and Namin, 2019b; Siami-Namini, Tavakoli, and Namin 2019a) illustrated that bidirectional LSTM (BiLSTM) models also give good forecasting results.

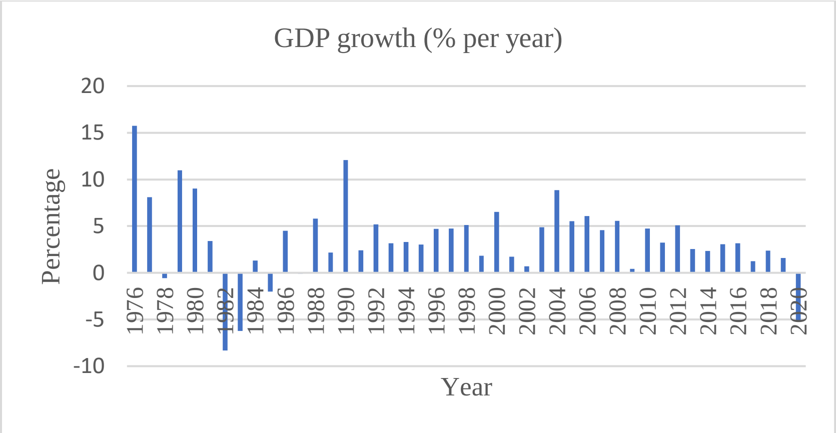
In the previous decade, machine learning has shown prominent improvement in time series forecasts. The research in (Mallqui and Fernandes, 2019) used different machine learning techniques to predict directions. In addition, the researchers in (Papaioannou et al., 2017) developed a trend-following trading strategy to forecast and trade S&P 500 futures contracts. In (Choi, 2018), a hybrid ARIMA-LSTM model has been developed for stock price correlation coefficient prediction. Many authors (Sezer and Ozbayoglu, 2018), (Ghosh, Neufeld, and Sahoo, 2022), and (Singh et al., 2020) have used the standard neural networks to forecast time-series data. Whereas (Xue et al., 2018) and (Borovykh, Bohte, and Oosterlee, 2018) have utilized convolutional neural networks (CNN). Moreover, (Harikrishnan et al., 2021) have investigated the application of different machine learning algorithms to stock price forecasting. (Siami-Namini, Tavakoli, and Namin, 2018) compared LSTM to the ARIMA model. Their empirical results applied to financial data show that LSTM outperforms ARIMA in terms of fewer predictive errors and greater precision.

Empirical results (Qiu, Wang, and Zhou, 2020) used the LSTM method to illustrate the improvement of stock price forecasts when a concentration mechanism is used. (Sharma et al., 2021) noted that for the LSTM and ARIMA models, a significant improvement in the forecasting of share price movements can be achieved by including an analysis of sentiment. Furthermore, the study in (ArunKumar et al., 2022), examined comparative analysis of GRU, LSTM cells, ARIMA, and Seasonal ARIMA (SARIMA) for forecasting COVID-19 trends. They found that the result obtained from deep learning-based models LSTM and GRU outperformed statistical ARIMA and SARIMA models for the time-series data of the countries. We conclude from the literature review that LSTM and ARIMA are considered suitable for the time-series data. Thus, this article proposes two models based on the ARIMA and LSTM for predicting the Arab world's GDP.

3. THE ARAB WORLD ECONOMY OVERVIEW

Devastating shocks have pushed the global economy out of the pre-2019 balance of low inflation and low interest rates in a new context of higher inflation and rising interest rates. Then, a weaker than expected slowdown in China and higher than expected levels of inflation in advanced economies. As activity slowed, so did the three major global economies—the U.S., China, and the Eurozone. The new global environment is one of heightened stress and risk in some countries. Figure 1 illustrates the impact of the COVID-19 pandemic on the Arab world economy. It is also noted that the GDP rate decrease in 2019, 2020 to become (1.58%) and (-5.05%) respectively, compared with (2.36%) in the end of 2018.

FIGURE 1
Arab World GDP Growth Over the Period 1976-2020



As one of the shocks ramifications the Arab world trade decreased approximately 6.85% in the end of 2020. As the total trade of the Arab world trade in the end of 2019 (9.13752e+11) USD. Whereas the total trade decreased to become (6.94413e+11) USD in the end of 2020. Figure 2 reports the trend of the Arab world trade during the period. In addition, Higher inflation has prompted central banks in advanced economies to tighten monetary policy and raise interest rates faster and more vigorously than anticipated. Figure 3 shows the inflation rates during the period 1975-2021.

FIGURE 2
Arab World Trade Over the Period 1960-2020

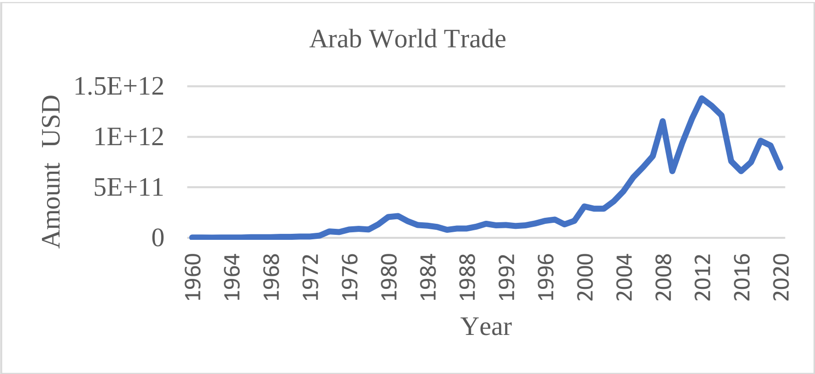
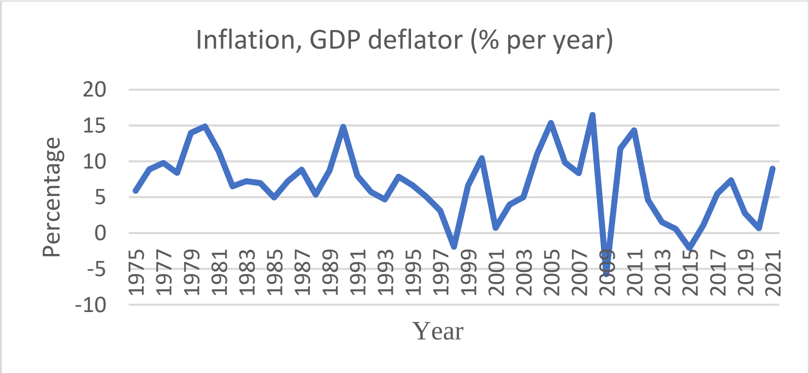


FIGURE 3
The Inflation Rate for Arab World GDP Over
the Period 1975-2021



Moreover, oil and gas are a major source of export earnings and fiscal revenues for the region in general and Gulf Cooperation Council (GCC) in particular. The oil revenue for approximately 13% of the Arab world GDP, which is illustrated in Figure 4.

FIGURE 4
The Oil Revenue Rate from Arab World GDP Over the Period 1970-2019

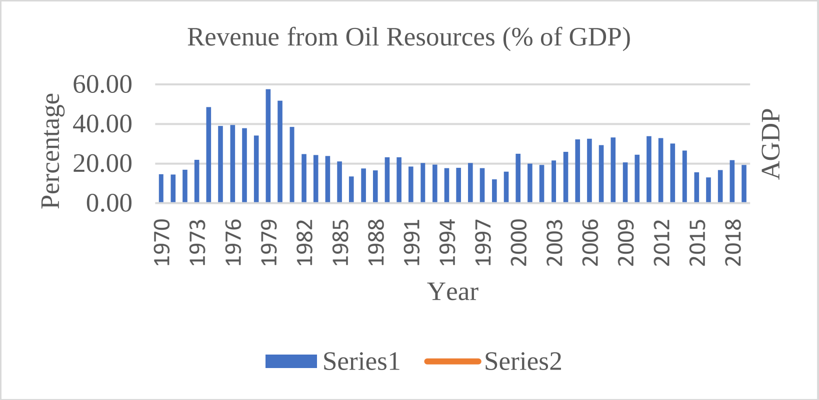


Figure 5 illustrates the capital trend before and after the COVID-19 crisis. It can be seen that the growth of gross fixed capital ratio decreases to become (-13%) in the end of 2020, compared with (7%) in the end of 2019. In addition, Figure 6 displays the increase of unemployment rate to 15% at the end of 2020.

FIGURE 5
Gross Fixed Capital Ratio in the Arab World Over the Period 2001-2020

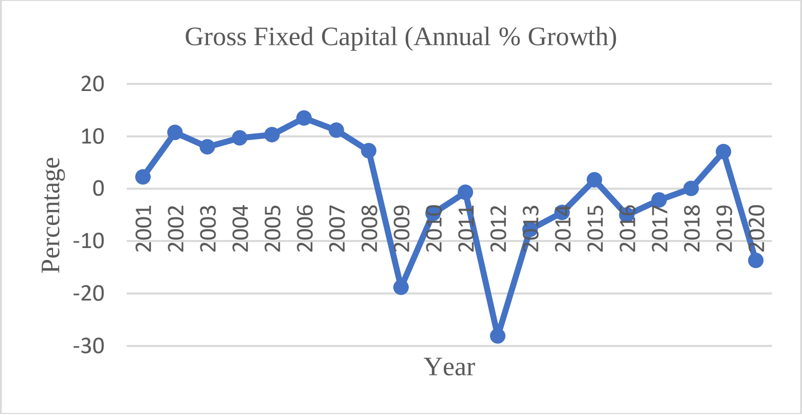
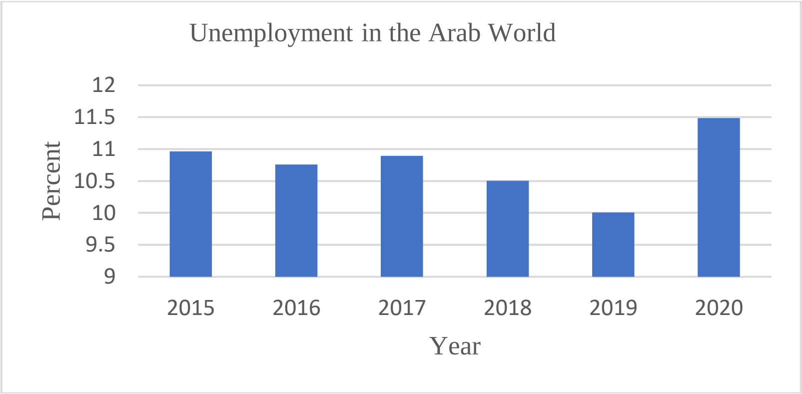


FIGURE 6
Unemployment Indicators in the Arab World Over
the Period 2015-2020



It is too early to know whether the global economy has entirely transitioned to a new balanced situation or whether the changes that have happened will be long lasting or short-lived. What is certain now is that the Arab world countries must confront the challenges posed by the current environment.

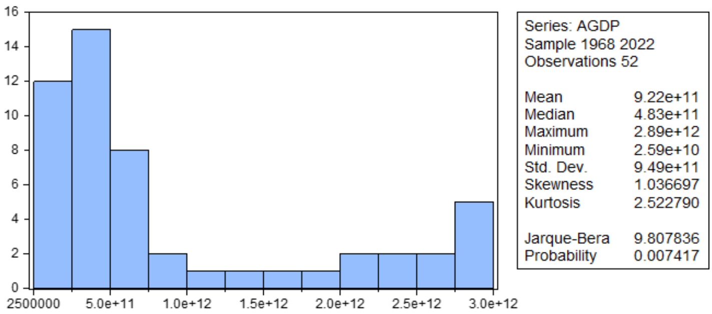
4. METHODOLOGY

4.1 DATA DESCRIPTION

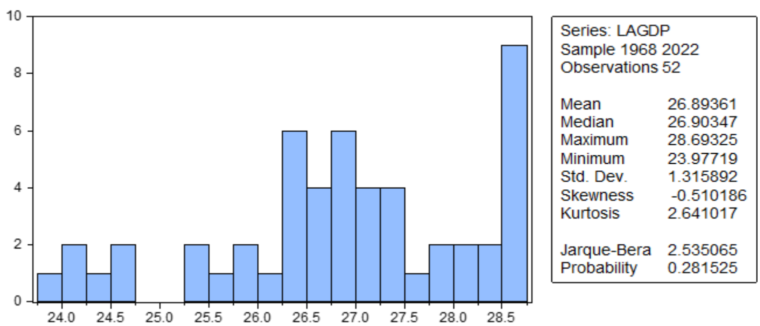
The most essential and primary indicator of general economic matters is the Gross Domestic Product (GDP) to assess the general economic condition. It reflects the country's monetary quality and helps plan and market scale. The World Bank offers GDP information for several nations, including the Arab world over the period 1968-2019[3]. The World Bank provides GDP for the Arab world, which includes 22 countries as follows: Algeria, Bahrain, Comoros, Djibouti, Egypt, Arab Rep. Iraq, Jordan, Kuwait, Lebanon, Libya, Mauritania, Morocco, Oman, Qatar, Saudi Arabia, Somalia, Sudan, Syrian Arab Republic, Tunisia, United Arab Emirates, West Bank and Gaza, and Yemen.

This paper has used the GDP data as a proxy to investigate the impact of COVID-19 on the Arab world economy during the period studied. Figure 7(A) shows that the Jarque – Bera Test: $p < 0.05$; does not follow the normal distribution. In addition, the mean of GDP over the period 1965 to 2019 is 922e+11, moreover the median is 483e+11. Furthermore, the results show that the maximum value is 2.89e+11, and the minimum value is 259e+11, while the standard deviation value is 949e+11, as well as the Skewness value is 1.036697, which is indicates Skewness to right side with Kurtosis factor 2.522790. Figure 7(B) illustrates the AGDP data from 1960 to 2019 after taking the natural logarithm. The Jarque – Bera Test: $p < 0.05$ implying Normal distribution. In addition, the mean of GDP over the period 1965 to 2019 is 26.89361, while the median is 26.90347. Furthermore, the results showed the maximum value is 28.69325, and the minimum value is 23.97719, with standard deviation value of 1.315892, as well as the Skewness value is -0.510186, which is indicates to right side Skewness with Kurtosis factor 2.641017.

FIGURE 7
The AGDP Over the Period 1968-2019
(A) Before Taking the Natural Logarithm



(B) After Taking the Natural Logarithm



4.2 ARIMA MODEL

In econometrics, the ARIMA model is one of the best models for time series analysis (Ma et al., 2018; Box et al., 2016). This model is considered suitable for time-series data to forecast future points in the series. The ARIMA demonstrating approach has three phases; model distinctive evidence, boundary evaluation, and suggest checking of the model (Singh et al., 2018; Box et al., 2016; Zhen-yan, 2012). The autocorrelation function (ACF) and partial autocorrelation (PACF) plots of the differenced series are used to identify the numbers of autoregressive (AR) and/or moving average (MA) terms that are needed. These plots help to identify if all coefficients are significant and all of the patterns have been explained (Singh et al., 2020; Lihua Ma, 2018; Box et al., 2016). A non-seasonal ARIMA model can be summarized by three parameters *p*, *d*, and *q*, which refer to the number of autoregressive terms, nonseasonal differences (i.e., the number of differencing required to make the time series stationary), and moving average terms, respectively. The model with the previous parameters is called ARIMA (*p, d, q*) model (Ma et al., 2018, Box et al., 2016). In addition, all these parameters (i.e., *p, d,* and *q*) are both integrated and non-negative numbers (Ma et al., 2018; Zhen-yan, 2012). Parameter assessment of the properly chosen model is made by most extreme probability, which is a regularly utilized technique for assessment. Finally, the general adequacy of the model is checked so that no further modeling of time series is required. Let $\{y_t\}$ with $t = 1, 2, \ldots, n$ be a classical time series. The ARIMA (*p, d, q*) model is given by the following equation:

$$\Delta^d y_t = \mu + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{1}$$

where Δ^d represents the *d* order difference, μ is constant, $\sum_{i=1}^{p} \emptyset_i y_{t-i}$ is the AR(*p*) model (i.e., lagged values of *y*), and $\sum_{j=1}^{q} \theta_j \varepsilon_{t-j}$ is the MA(*q*) model (i.e., lagged errors).

4.2.1 STATIONARITY TEST

ARIMA Model recommended that the factors utilized in the model must be fixed. The variables associated with our model have the time series attributes. It is seen that the mean of the intrigued factors is not fixed after some time. To make them consistent the regular logarithm was taken. It very well may be seen the conduct of GDP information when taking the characteristic logarithm of the information in Figures 8 and 9. Moreover, Table 1 shows that the ADF = 1.116678 is greater than the critical values of 1%, 5%, and 10% significance levels. Moreover, the p-value is exceeding 0.05. Therefore, the original AGDP sequence is non-stationary. Subsequently, taking the normal logarithm of the AGDP data to exclude it is unstable and obtain the LAGDP sequence. It can be seen that the ADF and p-values are greater than 0.05 (critical value). Which implies the GDP connection cannot reject the null hypothesis. Accordingly, the variance of first-order is accomplished, and a DAGDP succession is found.

The ADF test results for the DAGDP sequence are provided in Table 1. The ADF = -5.113698 less than the critical values and, the p-value = 0.0001< 0.05, which indicates that the series is fixed after changing the logarithmic and taking the variance of the first-order.

FIGURE 8
The AGDP Over the Period 1968-2019

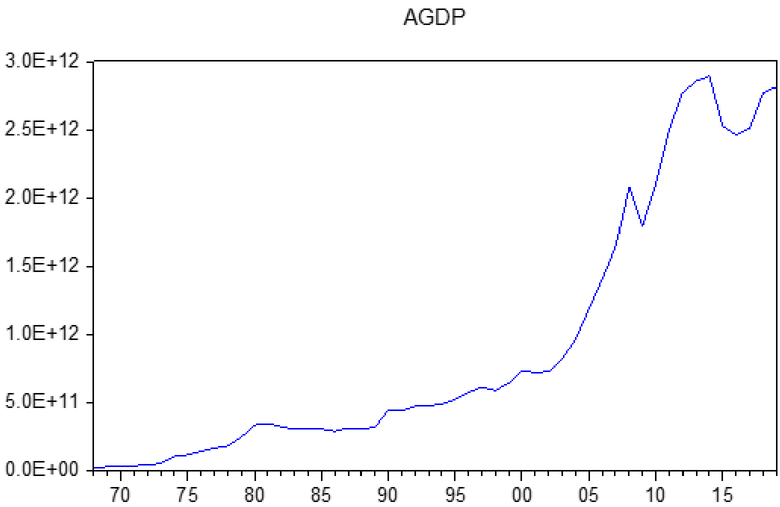


FIGURE 9
The LAGDP Over the Period 1968-2019

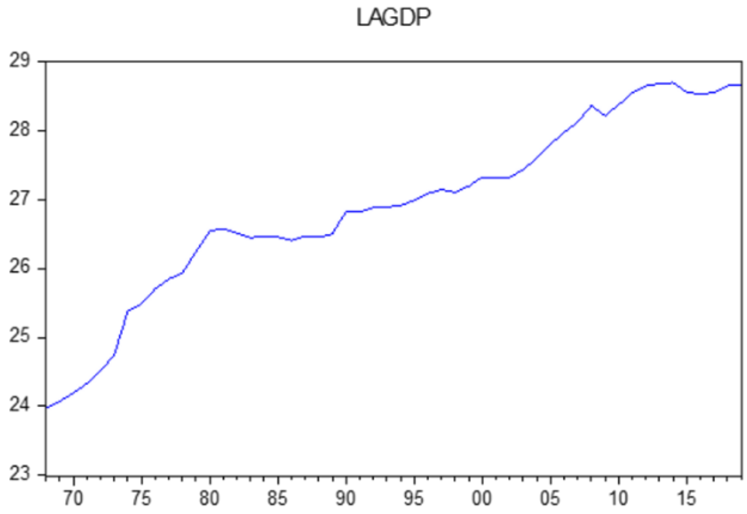


TABLE 1

Unit Root Test

Null Hypothesis: AGDP has a unit root		AGDP Unit Root Test		D(LAGDP) Unit Root Test	
		t-Statistic	Prob.*	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.116678	0.9972	-5.113698	0.0001
Test critical values:	1% level	-3.565430		-3.568308	
	5% level	-2.919952		-2.921175	
	10% level	-2.597905		-2.598551	
*MacKinnon (1996) one-sided p-values.					

4.2.2 MODEL IDENTIFICATION

The autocorrelation coefficient of the LAGDP in Table 2 shows progression is essentially non-zero when the slack demand is one.

TABLE 2
The Best Selected (p, q) Specifications

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |*******	. |*******	1	0.941	0.941	48.730	0.000
. |******|	.*| . |	2	0.876	-0.078	91.831	0.000
. |******|	. | . |	3	0.817	0.017	130.08	0.000
. |***** |	. | . |	4	0.758	-0.040	163.66	0.000
. |***** |	.*| . |	5	0.692	-0.084	192.30	0.000
. |**** |	.*| . |	6	0.608	-0.199	214.88	0.000
. |**** |	.*| . |	7	0.518	-0.107	231.59	0.000
. |*** |	.*| . |	8	0.426	-0.084	243.18	0.000
. |** |	. | . |	9	0.344	0.011	250.90	0.000
. |** |	. |*. |	10	0.279	0.111	256.10	0.000
. |** |	. |*. |	11	0.226	0.089	259.60	0.000
. |*. |	.*| . |	12	0.159	-0.136	261.37	0.000

Besides, the parameter q can be seen as one because the requested lag is more critical than one. The halfway autocorrelation coefficient is nonzero when the slack request is equivalent to one, it is additionally unique according to zero when the lag order is two, along these lines $p = 1$ or $p = 2$ can be assumed. To set up a more rigorous model, the extent of valuations of number of autoregressive terms and moving average terms (i.e., p and q) is properly loose, besides divergent ARIMA (p, d, q) models are demonstrated. Table 3 illustrates the ARIMA test consequences of several p and q parameters and d equal one.

The Akaike info criterion (AIC) and the Schwarz criterion (SC) standards are utilized to decide the best model. Although the convenient ARIMA model is typically chosen based on the result of the AIC and the SC esteem. Reducing the AIC and the SC values are insufficient to choose the best ARIMA model. Following the researchers (Ma et al., 2018; He and Tao, 2018; Zhen-yan, 2012), this work first creates a model with the minimized AIC and SC values. After that, the significance parameter and residual tests were done on the assessment result. The model considered the optimal, if it passes the test. Table 3 reports the model that had success in the tests mentioned above specified via “*”.

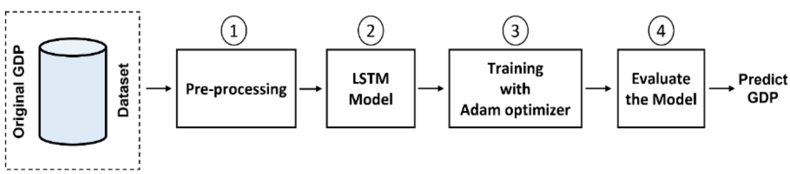
TABLE 3
The Model Results

(*p*, *d*, *q*)	Adjusted R-squared	Akaike info criterion	Schwarz criterion	Standard error of regression
(0,1,1)	0.047704	-1.238153	-1.162395	0.127808
(0,1,2)	0.021562	-1.211072	-1.135314	0.129550
(1,1,0)	0.065128	-1.235668	-1.159187	0.127919
(1,1,1)	0.019286	-1.167252	-1.090035	0.132318
(1,1,2)	0.143862	-1.304699	-1.189978	0.122414
(2,1,0)	0.056157	-1.207171	-1.092450	0.128531
(2,1,1)	0.053341	-1.183284	-1.067458	0.130001
(2,1,2)*	0.244115	-1.408334	-1.292508	0.116165

4.3 LSTM MODEL

Recurrent Neural Network (RNN) with LSTM cells is utilized in this paper. LSTM networks are a state-of-the-art technique for sequence learning, which can capture nonlinear values in the dataset (Yu et al., 2019). The framework of our prediction LSTM-based model is illustrated in Fig. 10. First, data pre-processing is performed. Second, the architecture of the LSTM model is presented. Third, the model was trained and tested based on the Adam optimizer. Finally, forecast GDP for the coming years was made. Each step of the LSTM model is described in the following subsections.

FIGURE 10
A Framework of the Proposed LSTM-based Model



4.3.1 DATA PREPROCESSING

To convert unrepresentative raw feature vectors into a format better suited for downstream estimators, there are several widely used utility functions and transformer classes i.e., scalers, transformers, and normalizers on a dataset. In general, standardizing the data set is advantageous for learning algorithms. Robust scalers or transformers are preferable if there are any outliers in the collection.

To scale each feature's maximum absolute value to one unit, or to a value between a predetermined minimum and maximum value, usually zero and one, we used min-max normalization. This technique converts a value a to $\grave{a}$ in the range of $[max\_new - min\_new]$ as follows:

$$\grave{a} = \frac{a - a_{min}}{a_{max} - a_{min}} \times [max\_new - min\_new] + min\_new; \tag{2}$$

where from min_new to max_new denotes the range of the transformed values. We implemented $min\_new = 0$ and $max\_new = 1$. After that, these transformed values were used as input for the LSTM architecture. Table 4 shows a sample from our data after the min-max normalization.

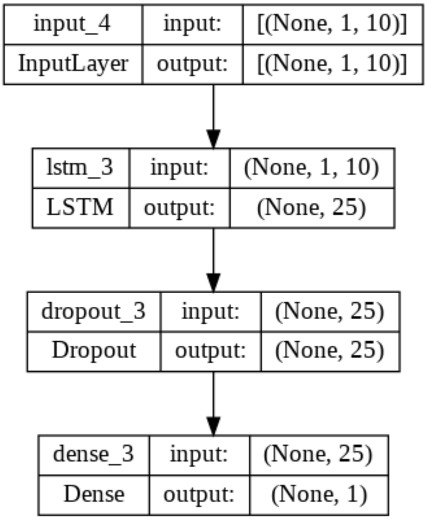
TABLE 4
A Sample of Scaled GDP

GDP without Normalization	Normalized [0, 1]
2.842922e+10	0.00088511
3.201348e+10	0.00213533
3.704523e+10	0.00389044
4.418232e+10	0.00637990

4.3.2 MODEL ARCHITECTURE

The LSTM-based model consists of four layers: 1) input layer with ten observations, 2) LSTM that employs 25 LSTM units, 3) a dropout layer was used. Dropout is a useful method for performing standard layouts using neural networks, and 4) ReLU was employed in the dense layer and the Adam optimizer (Kingma and Ba, 2014) was utilized for gradient-based optimization, and the learning rate was modified by incorporating knowledge from prior observations. Figure 11 shows a simplified architecture of the LSTM-based model.

FIGURE 11
The Architecture of the LSTM-based Model



4.3.3 MODEL TRAINING SPECIFICATION

In the experiment, we performed the train/test holdout validation. The data were split into 90% for training and 10% for testing. The model was trained on 37 records and tested on the remaining 5 as unseen data. The best set of hyper-parameters of LSTM-based model is shown in Table 5. The software environment used to conduct the LSTM-based model was Python 3. All experiments were conducted on the Linux-based Google Colab (an online browser-based platform). The platform provides 12.68 GB of RAM and an Intel(R) Xeon(R) CPU @ 2.20GHz.

TABLE 5
Hyperparameters of the Proposed LSTM-based Model

Hyperparameters	Value
Total trainable parameters	3,626
Learning rate	0.00001
Batch normalization	True
Batch size	16

TABLE 5 *(continued)*

Hyperparameters	Value
Activation function	ReLU
Optimizer	Adam
Epochs	500
Loss function	MSE
Hidden layers	25
Dropout	True (0.1)
Feature scaling	True [0,1]

4.3.4 MODEL EVALUATION

To evaluate the LSTM-based model, Mean Squared Error (MSE) and Mean Absolute Error (MAE) are used. For a sample of n data X, the MSE and MAE for the predicted $\hat{X}$ are calculated as follows.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(X_i - \hat{X}_i\right)^2 \tag{3}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|X_i - \hat{X}_i\right| \tag{4}$$

The results for each model are discussed in the following section.

5. RESULTS AND DISCUSSION

5.1 ARIMA MODEL RESULTS

The assessed consequences of the use ARIMA model as following. The LAGDP sequence is an ARIMA (2, 1, 2) has been shown in Table 6.

TABLE 6
Statistical Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.054324	0.012700	4.277555	0.0001
AR(2)	0.763159	0.072711	10.49582	0.0000
MA(2)	-0.953625	0.021539	-44.27377	0.0000

TABLE 6 *(continued)*

R-squared	0.275610	Mean dependent var	0.091361
Adjusted R-squared	0.244115	S.D. dependent var	0.133613
S.E. of regression	0.116165	Akaike info criterion	-1.408334
Sum squared resid	0.620742	Schwarz criterion	-1.292508
Log likelihood	37.50418	Hannan-Quinn criter.	-1.364390
F-statistic	8.750864	Durbin-Watson stat	1.700697
Prob(F-statistic)	0.000602		
Inverted AR Roots	.87	-.87	
Inverted MA Roots	.98	-.98	

In addition, the Equation (5) illustrates the specified shape of the model. Besides, the *t* values of all the model variables are significant and the probabilities are less than 0.05. Moreover, Equation (6) illustrates the estimated error of regression.

$$\Delta\, LCGDP = 0.0543240983193 + [AR(2) = 0.763158600329, MA(2) = -0.953625457432] \tag{5}$$

$$\hat{\sigma}_a = 0.116165 \tag{6}$$

Figure 12 reports that the model is utilized to suitable the LAGDP information. Genuine information is offered through the inflexible lines, and the superior and inferior dabbed lines orchestrate to fit, values lingering of the model. In addition, Table 7 outlines the AC and PAC results that our model is satisfactory.

FIGURE 12
The LAGDP Sequence: Actual, Fitted, and Residual Series

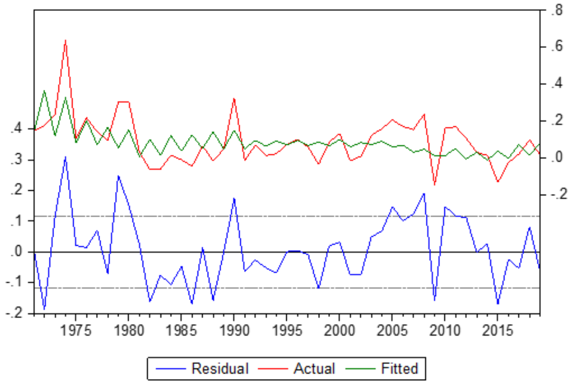
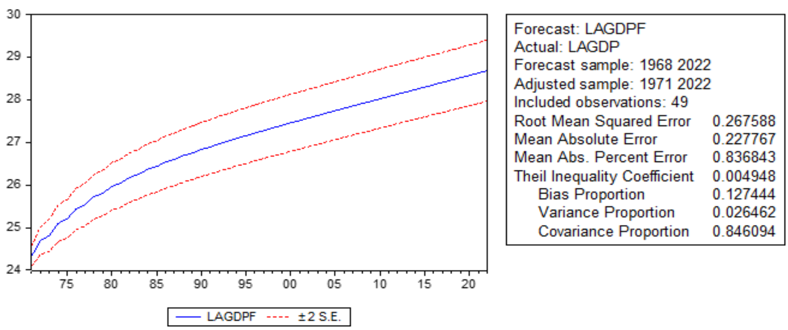


TABLE 7
The Residual Series

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>1</td><td>0.140</td><td>0.140</td><td>1.0225</td><td></td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>2</td><td>0.037</td><td>0.017</td><td>1.0943</td><td></td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>3</td><td>0.030</td><td>0.023</td><td>1.1425</td><td>0.285</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>4</td><td>0.024</td><td>0.017</td><td>1.1750</td><td>0.556</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>5</td><td>0.042</td><td>0.036</td><td>1.2772</td><td>0.735</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>6</td><td>0.181</td><td>0.172</td><td>3.1770</td><td>0.529</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>7</td><td>-0.130</td><td>-0.189</td><td>4.1761</td><td>0.524</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>8</td><td>-0.186</td><td>-0.163</td><td>6.2759</td><td>0.393</td></tr>
<tr><td>**| . |</td><td>**| . |</td><td>9</td><td>-0.244</td><td>-0.220</td><td>10.003</td><td>0.188</td></tr>
<tr><td>. | . |</td><td>. |*. |</td><td>10</td><td>0.030</td><td>0.112</td><td>10.062</td><td>0.261</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>11</td><td>-0.018</td><td>-0.015</td><td>10.084</td><td>0.344</td></tr>
<tr><td>.*| . |</td><td>**| . |</td><td>12</td><td>-0.174</td><td>-0.207</td><td>12.138</td><td>0.276</td></tr>
</table>

Figure 13 delineates the forecast of the Arab world GDP for the ARIMA model. The plot got with the EViews program shows the genuine GDP with strong line and the upper and lower ran line shows the anticipating deviation. The MSE and MAE are 0.071604 and 0.227767, respectively, which are rather large values.

FIGURE 13
LAGDP: Forecast and Actual for the ARIMA Model



5.2 LSTM MODEL RESULTS

The results of MSE and MAE are reported in Table 8. Moreover, the learning curves for training data (i.e., over the period 1968-2014) are shown in Fig. 14. Finally, the actual and predated GDP for the training data is shown in Figure 15. The results demonstrate that the

LSTM-based model has a small MSE and MAE. Therefore, it is suitable to use it in the prediction.

TABLE 8
Evaluation of the Proposed LSTM-Based Model

Metric	Value
Mean Squared Error	0.00072753
Mean Absolute Error	0.02016051

FIGURE 14
The Learning Curves for Training Data Using LSTM-Based Model Over the Period 1968-2014

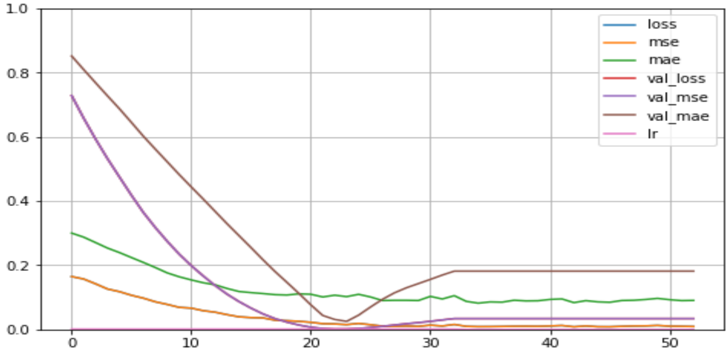
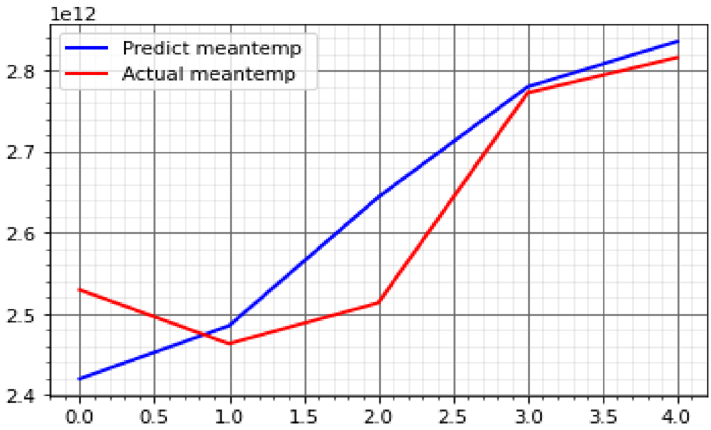


FIGURE 15
The Actual and Predated GDP for the Testing Data
(i.e., Over the period 2015-2019)



5.3 FORECASTING RESULTS AND DISCUSSION

In this subsection, we compare our two models with two prediction models from the literature: LSTM with Random Forest (RF) (Ghosh, Neufeld, and Sahoo, 2022), and GRU (Li et al., 2020) to test the efficacy of the proposed models. The MSE and MAE of the proposed prediction model and related works are listed in Table 9. Our LSTM-based model outperformed all the models and reached the lowest MSE and MAE of 0.000727 and 0.020160, respectively.

TABLE 9
Evaluation of the Prediction Models on the Arab World GDP

Model	MSE	MAE
LSTM+RF (Ghosh, Neufeld, and Sahoo 2022)	0.356997	0.288853
GRU (Li et al. 2020)	0.023869	0.148918
ARIM (our)	0.071604	0.227767
LSTM (our)	0.000727	0.020160

LSTM-based model is more fitted than ARIMA model to the actual data. Therefore, we used LSTM-based model to predict the values that the Arab world GDP was supposed to have in the absence of COVID-19 and compare it with the actual value that appeared in 2020 after the impact of the pandemic. Table 10 reports the GDP of Arab World in USA Dollar over the period from 2018 to 2021 using LSTM-based model. There is a difference of up to 17.22% between the value without the impact of COVID-19 (i.e., LSTM-based model) and with it (i.e., Actual GDP).

TABLE 10
Arab World GDP in USA Dollar (from 2018 to 2021) using LSTM-Based Model

Year	Actual (World Bank)	LSTM	Residual	Present
2018	2.77202e+12	2.77944e+12	7.41530e+09	00.27%
2019	2.81541e+12	2.83525e+12	1.98396e+10	00.70%
2020	2.49625e+12	2.92599e+12	4.29740e+11	17.22%
2021	2.85042e+12	3.00450e+12	1.54080e+11	05.41%

In the final experiment, we train the LSTM-based model with the full data of Arab world GDP over the period 1968-2020, which contains the year of impact of the pandemic 2020. The learning curves for training data (i.e., over the period 1968-2020) are shown in Fig. 16. The MSE and MAE are 0.000000598 and 0.000245, respectively, which indicates the model efficiency. Finally, the prediction of Arab world GDP from 2019 to 2025 is reported in Table 11. Since the model is very similar to the truth, if we consider that the effect of the pandemic, it led to approximately 11.11% decrease in the Arab World GDP. Moreover, the GDP growth rate started increasing again from 2021, and this is what the statistics monitored by the World Bank revealed. Thus, the model reports that the growth rates are 14.22%, 0.10%, 1.85%, 1.24%, and -1.47% for 2021, 2022, 2023, 2024, and 2025, respectively.

FIGURE 16
The Learning Curves for Training Data Using LSTM-Based Model Over the Period 1968-2020

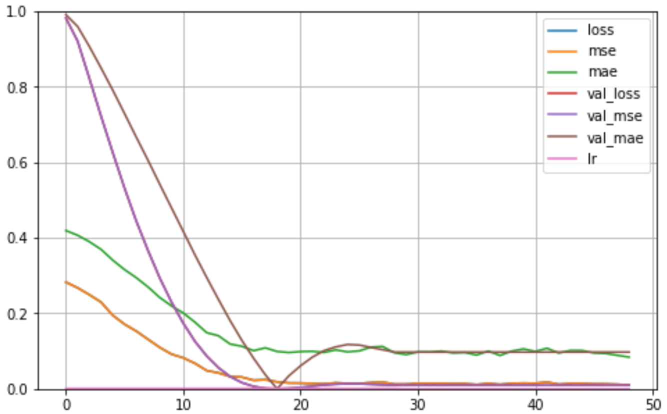


TABLE 11
Arab World GDP Forecast in US Dollar (from 2019 to 2025)

Year	Actual (World Bank)	LSTM	Variation	Growth rate
2019	2.808198e+12	2.808198e+12	-	-
2020	2.496251e+12	2.496251e+12	-3.119470e+11	-11.11%
2021	2.850421e+12	2.851116e+12	3.548650e+11	14.22%

TABLE 11 *(continued)*

Year	Actual (World Bank)	LSTM	Variation	Growth rate
2022	NA	2.854026e+12	2.910000e+09	0.10%
2023	NA	2.906768e+12	5.274200e+10	1.85%
2024	NA	2.942932e+12	3.616400e+10	1.24%
2025	NA	2.899577e+12	-4.335500e+10	-1.47%

6. CONCLUSION

Presently, the novel Coronavirus scourge is yet in progress, forestalling an exhaustive investigation of its full effect. In any case, given preventive steps taken by the Arab world, the main endeavor has been made to assess the economy's probabilities sway in the medium term. This paper's primary contribution is proposing a model for forecasting and examining time frames that authentic patterns are rendered inaccurate because of the recent pandemic. As it was referenced, the pandemic's trend shift phenomena making the entirety of the models created utilizing the historical trends useless. Thus, this paper presented two models for predicting: the statistical Autoregressive Integrated Moving Average (ARIMA) model and the deep learning-based model (i.e., Long Short-Term Memory (LSTM)-based model), which is considered suitable for the time-series data of the countries. The Gross Domestic Product (GDP) data of the Arab countries over the period 1968-2019 is used for evaluating the proposed models.

The results demonstrate that the proposed LSTM-based model outperformed the ARIMA, LSTM with Random Forest (RF) (Ghosh, Neufeld, and Sahoo, 2022), and Gated Recurrent Unit (GRU) (Li et al., 2020) models and reached the lowest Mean Square Error (MSE) and Mean Absolute Error (MAE) of 0.000727 and 0.020160, respectively. The proposed LSTM-based showed that there is a difference of up to 17.22% between the value without the impact of COVID-19 (i.e., LSTM-based model) and with it (i.e., Actual GDP). Moreover, we train the LSTM-based model with the full data of Arab world GDP over the period 1968-2020, which contains the year of pandemic impact 2020. The results predicted that the Arab world GDP growth is approximately 14.22%, 0.10%, 1.85%, 1.24%, and -1.47% for 2021, 2022, 2023, 2024, and 2025, respectively.

The following are some of the limitations of this research: First, there is not finished data to investigate the crisis thoroughly and explore its full range and multi-dimensional effects. Second, the available data size is very small, and the model efficiency will be enhanced with the increase in data size. Third, lack of previous research regarding the economy of the Arab world.

More studies need to be conducted to address the limitations of the proposed models in the future. First, to overcome small-data limitations in GDP prediction, we plan to use in future work surrogate data or merging different datasets. Second, the recent crisis and the closing down of the ventures show the importance of the transition to a digital economy. Finally, the additional volume of data with high-level accuracy is required to improve and develop precise and robust models to attain projections with a reduced amount of margin of error. Moreover, further study can be carried out for improving the model performance.

ENDNOTES

1. World Bank (2020) forecasts a 5.2 percent contraction in global GDP. Similarly, OECD (2020) forecasts a fall in global GDP by 6 percent to 7.6 percent, depending on the emergence of a second wave of COVID-19.
2. https://data.albankaldawli.org/region/arab-world?view=chart , October 2022.
3. https://data.albankaldawli.org/indicator/NY.GDP.MKTP.CD?~locations=1A, October 2022.

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