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RESEARCH ARTICLE - MANAGEMENT

Iraqi Stock Market Prediction Using Artificial Neural Network and Long Short-Term Memory

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Abstract

Stock prediction is one of the most important issues on which the investor relies in building his investment decisions and the financial literature has relied heavily on predicting future events because of its exceptional importance in financial work, after which profit or loss is determined, and since money dealers are eager to profit, the researchers have devoted techniques to forecast as providing the tools to achieve this. The choice of the proper model of time series data affects the precision of the predictions, and stock market data is typically random and turbulent for various industries. To obtain forecast models of stock market data that can accurately portray reality and obtain future forecasts, these models must take all data considerations from linear and none linear trends, different influences, and other data factors, hence the research problem of obtaining a method that gives predictions of Iraq's stock market indicators that are accurate and reliable in stock analysis. In this paper, two models were proposed to predict the Iraqi stock markets index through the use of artificial neural networks (ANN) and a long short-term memory (LSTM) algorithm where Iraqi stock market data were used from 2017 to 2021 and good results were achieved in the prediction where the long short-term memory (LSTM) algorithm reached a mean square error (MSE) rate of as little as 0.0016 while the artificial neural network (ANN) algorithm reached error rate 0.0055.

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Keywords: Stock Market Prediction; ANN; Iraqi Stock Market; LSTM; Deep Learning; Mean Square Error.

1. Introduction

Stock markets play an important role in the development of the national economy, as they provide opportunities to attract financial surpluses and invest them in important development projects, and are also an alternative financial source at a lower cost than resorting to banks for enterprises that aspire to expand their production lines [1]. Due to the high risks of these markets, their performance varies up and down where the wrong decisions lead to heavy losses, and often bankruptcy, hence the importance of integrating market sectors, and predicting their indicators, as they are an important method that helps investors make sound investment decisions to achieve profits and avoid losses [2]. One of the most common investment activities is stock trading on the stock exchange. Investors have devised a variety of stock search methods in the past to help them predict the direction of stock price movements. Predicting and modelling future stock prices based on current news and financial statements is very useful for investors. Investors want to know if the stock will fall or rise within a specified period [3]. Data analysts have devised several analysis methodologies based on current and past financial statements and other information about the company to predict how the company the investor wishes to invest in will perform in the future. Investors use technical analysis to examine and predict the company's future share price using financial balance sheets as well as other statistics that represent the validity of the company's reality [4]. Predicting the direction of the share price is critical for value investors. Predicting the stock market is a difficult challenge because of its volatile nature. Accurate stock forecasting is critical to the development of important trading methods that can help customers buy and sell shares. In general, inventory data suffers from two main issues: noise as well as uncertainty [5].

The emergence of forecast algorithms has undoubtedly changed the stock market. Algorithms make it easy to predict the speed of the change in stock prices in financial markets. In addition, deep learning algorithms have made it much easier for analysts to develop models to predict stock prices. Because of the introduction of deep learning [6], a new model based on previous data can now be built. The basic idea was that by using machine learning and training it on previous data, it is possible to predict the movement of the share price as well as the ratio of movement over a specified period. Over time, this makes investors able to predict the rate of increase in stock prices. On the other hand, it is critical for investors when choosing stocks to look for shares that will increase their value significantly in the future [7].

Nomenclature & Symbols			
LSTM	Long Short-Term Memory	RMSE	Root Mean Squared Error
ANN	Artificial Neural Network	MSLE	Mean Squared Logarithmic Error
MSE	Mean Square Error	Val-MSE	Validation (Val) mean squared error
MLP	Multi-Layer Perceptron	Val-RMSE	Validation Root Mean Squared Error
RNN	Recurrent Neural Networks	Val-MSLE	Validation Mean Squared Logarithmic Error

2. Aim of Research

a. Studying the behaviour of the Iraqi stock market index during the past five years.
b. Identifying common smart prediction models, and comparing them with each other.

The data sets used were collected for a group of the banking sector in the Iraqi stock markets from their official website for the years 2017 to 2021 every week [8].

The article contains the sections arranged as follows: Section three contains the literature review, Sections 4 and 5 are reviewing ANN and LSTM algorithms respectively, while section 6 displays the proposed work in detail. In addition to the above, section 7 shows the experimental results. Lastly, the article's conclusion is expressed in Section 8.

3. Related Work

In this part, the most important previous studies in the field of forecasting and the most important methods and algorithms used will be presented and discussed. It is also the most important finding of previous research. The most common related business on the stock market is:

a. In 2018 [9], researchers (Jain and others) compared the different deep neural network methods used to predict stock prices. Good short-term memory networks, Conv1D-LSTM, and neural bypass networks are some of the networks used related to the problem. Daily stock price data is used to train different neural network models, which contain low, high, closed, and open price values. They were used to predict the value of the closure the next day. Their forecasts are based on the last five days of data. The results of different models are compared with each other. This research presents the Conv1D-LSTM deep neural network, which combines layers of two different technologies - LSTM and CNN - to predict the share price. MAE and MAPE as well as RMSE are used to evaluate model performance. Compared to CNN and LSTM, the Conv1D-LSTM model displays relatively few errors. Conv1D-LSTM has proven effective in predicting stock prices. Depending on the excessive nature of the inventory parameters, different changes may be required.
b. In 2020 [10], Using Adaptive Neuro-Fuzzy Inference System (ANFIS) and fuzzy regression analysis, the goal of this study is to develop a prediction model for the Tehran Stock Exchange Index. This index's behavior is nonlinear and chaotic, which traditional approaches cannot reliably predict. Consequently, utilizing the aforementioned two techniques and identifying three macroeconomic variables such as the exchange rate, inflation rate, and crude oil price as independent variables, we predicted the entire stock index for the following week. The modeling was then conducted utilizing the aforementioned three variables. Based on a comparison of the outcomes, ANFIS performance was superior to fuzzy regression. For the ANFIS output value of 0.021248, the Root Mean Square Error Performance criteria were obtained. The prediction of the following week showed a reduction in error for both tools and ANFIS, with an error value of 0. 007933, resulting in an improvement in the study's performance. Additionally, the model with four inputs was more precise than the model with three inputs. This research is characterized by its concentration on macroeconomic variables, its prediction of the following week's index number, its use of the two tools stated, and its analysis of the models' sensitivity. This study can be utilized by all companies listed on the stock exchange, investors, brokers, as well as individuals and legal entities involved in any aspect of the stock market.
c. In 2020 [11], researcher Bhattacharjec revealed the relationship of common integration between the Indian and U.S. securities market, using the monthly average data of the stock indices of both NSE and NASDAQ for the period from January 2010 to December 2018. Several statistical methods were used, including unit root testing, Johansson's joint integration, and Granger causality, the study findings concluded that the two indicators were not jointly integrated, indicating that there was no long-term balance between the indicators, and the results of the Kranger causal test showed a one-way causal relationship between indicators, extending from NASDAQ to NSE, indicating that NASDAQ can influence NSE.
d. In 2021 [12], shaikh and others stated that the main objective of the article was to predict the share price of any company using advanced machine learning algorithms. The machine learning model is fed through two distinct inputs: human feelings and historical pricing data, and the result is displayed as a graphic with future expectations and labeling (negative or positive neutral). The Recurrent neural network, the Long-Term Memory Model (LSTM), and emotion analysis are used to make the prediction. The machine learning model is then trained using estimated results and a variety of data points. Emotion analysis is a process that takes public feelings from social media and categorizes them.
e. In 2022 [13], researchers (Christy and others) reported that equity and finance experts are always working on this study to predict future stock prices, helping to choose whether to sell or buy shares for a profit. Stock markets encourage investment by pooling resources, allowing companies to increase capital to expand their operations. There are millions of resources available on the stock market. People worry about finding good resources from a range of resources as an investor. Investors will benefit from the proposed share price forecasting model because it will help them price the supplier. The research proposes a unique approach to managing stock market expectations over time based on deep learning.

So the previous studies need large data to increase the accuracy of prediction, and this is what makes it difficult to set up the system.

4. Artificial Neural Network (ANN)

A neural network is a bio-inspired system composed of many neurons, which are single-processing components. The neurons are interconnected via a joint mechanism consisting of a series of weight assignments [14].
Multi-layer perceptron (MLP) is a prevalent technique for regression-type issues. There are three layers in an MLP network: an input layer, an output layer, and a hidden layer. Neuron adds a bias to the input parameters' values after summing them according to their assigned weights.

By using the transfer function, the outputs' values are determined. In the input layer, the number of neurons corresponded to the number of input parameters. Fig. 1 illustrates a typical MLP's architecture [15].

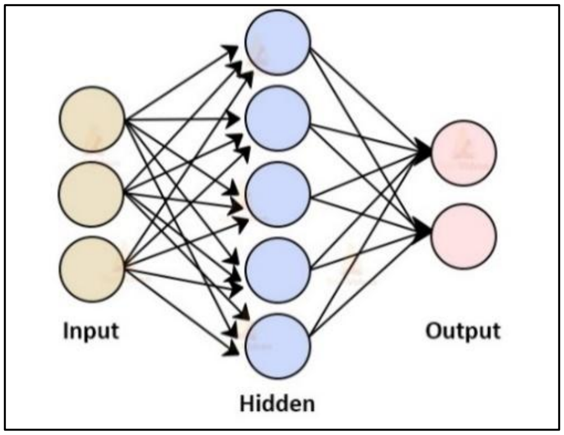

Fig. 1. Artificial Neural Network Structure [15]

5. Long Short-Term Memory (LSTM)

Recurrent neural networks (RNN) are a class of neural networks specifically designed to handle serial data. There are two types of RNNs, one separate-time RNNs and the second RNNs with continuous time [16]. It is designed with a periodic connection structure allowing it to update its current state based on previous cases and current input data. RNNs are usually artificial neural networks consisting of standard repetitive cells. These types of neural networks are known to be very accurate to identify potential conditions. It specializes in processing a series of values such as time series data. Fig. 2 demonstrates the structure of the RNNs algorithm [17].

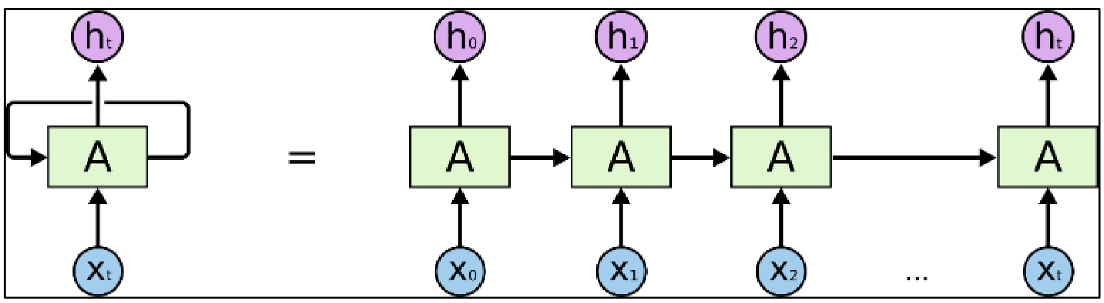

Fig. 2. General structure of RNN algorithm [17]

Moreover, most RNNs can process variable-length sequences. However, RNNs cannot learn long-term dependencies. So, to deal with these long-term dependencies Hochreiter and Schmidhuber proposed in 1997 a solution called Long Short-Term Memory (LSTM) [18].

LSTM is a type of RNN where it can learn and maintain long-term dependencies. LSTM's unique feature is the presence of a memory cell. In LSTM, the addition or deletion of information in the cell is controlled by portals. LSTM contains three types of portals, i.e. forgetfulness, input, and output gates to control the flow of information in the cell. The oblivion portal controls the amount of information to be removed from the previous cell state. The information that will be entered in the cell case is controlled by the input portal. A vector is then created for a filter layer that can be attached to the cell state. The old cell state is then adjusted to a new cell state according to the previous two lines. The output layer chooses information from the cell state to use as outputs [19].

The final LSTM layer in the final time step (n) passes the output (h_n) into a dense layer with a single-output neuron where the final flow (y) is calculated. Equations related to the LSTM cell are represented by the following equations. Fig. 3 shows the overall structure of the LSTM algorithm [20].

$$Forget\ gate = Sigmoid\left(W_f x_t + h_{t-1} + b_f\right)$$
$$Input\ gate = Sigmoid\left(W_f x_t + h_{t-1} + b_f\right)$$
$$C_t = tanh(W_c x_t + h_{t-1} + b_c)$$
$$h_t = C_t \times Sigmoid$$

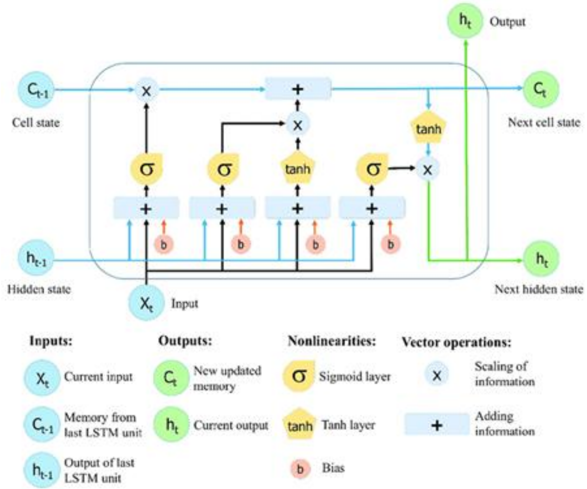

Fig. 3. Long short-term memory node structure [20]

6. Proposed Work

In this paper, two models were proposed to predict the Iraqi stock markets index and then compare the results of each model. The data contains information such as the Index (Market Index), Open (Market Opening Price), High (The highest price reached in the market), Low (Lowest price reached in the market), Close (current closing price), and Adj Close (adjusted closing price). The results were programmed and extracted using Python Tools for Visual Studio, version 16.

6.1. Data Preparation

Data preparation is critical when one wants to acquire some information from data sets to assist in making a forecast. Because the initial data may contain a lot of noise, it's important to reduce it so that it doesn't affect the final output. Furthermore, because some data aspects may be meaningless, this data should ignore when training the data to increase efficiency. In this step, the data is separated into two sections: one for testing purposes and another for training purposes, as well as the data in the five databases has been divided into 70 percent training and 30 percent testing. Fig. 4 illustrates preparation datasets for the training and testing model for the Iraq stock market for years from (2017 to 2021), Table 1 illustrates the datasets.

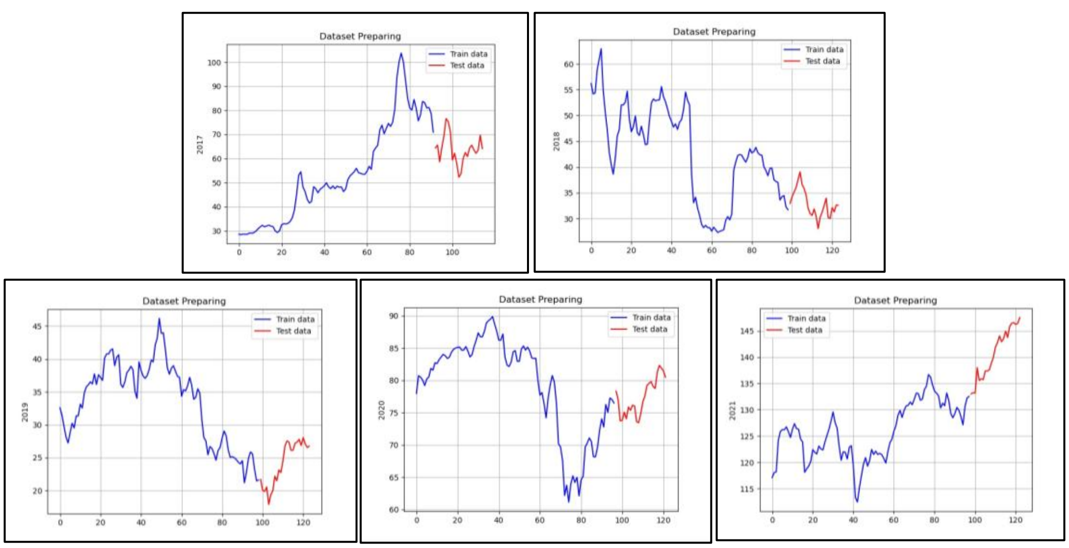

Fig. 4. Datasets preparing

6.2. Artificial Neural Network Model

Despite all the properties listed for neural networks, constructing a neural network for prediction is quite difficult. To construct a prediction model that achieves a sufficient level of performance, it is necessary to examine several key criteria. The structure of the network, including the neurons, number of layers, and connections, is one of the most important aspects. Other considerations include the activation functions of each neuron, the training process, and data normalization, the selection of the training and test sets, and evaluating measurements. In the proposed model, two neural networks, a multilayer Perceptron feed-forward network, and a recurrent network are trained using the backpropagation algorithm. The neural networks input the minimum, maximum, and average values over the previous days. Since we aim to predict the value of the stock share solely based on the stock value history, we forego the use of any other information available about the stock market. Put another way, the proposed approach can be thought of as a time series prediction model. This model employs a three-layer neural network, with neurons in the input layer receiving the minimum, maximum, and average stock price for the preceding d days. There are h neurons in the hidden layer, and each of them has a full connection to the input and output layers. The expected value of stocks is predicted by a single neuron in the output layer.

6.3. Long Short-Term Memory Model

The LSTMs model is generally capable of handling time series data and is therefore a good candidate for stock prediction. LSTMs can learn to adopt the order between items in sequence and are known for their good performance on sequence data sets. To select the best combination of features, the leak-based LSTM model is trained and evaluated with four hidden LSTM layers and 50 units per hidden layer. Each hidden LSTM layer contains a subsequent leak layer and finally, a dense layer is used to connect all neurons followed by the last leak. Leakage is a technique that chooses neurons that will be ignored during training, meaning that their contribution to the activation of neurons downstream is temporarily removed. LSTM is trained on previous data and in turn, predicts stock prices Fig. 5.

Distinguished LSTM is the ability to save data sequences making LSTM a special type of RNNs. Each LSTM node consists mostly of a group of cells responsible for storing passed data flows, and the top line in each cell connects models as a transmission line that delivers data from previous reading to current reading and helps the independence of the model cells to get rid of a filter adding cell values to another. In the end, the neural network layer that forms the cell gates pushes to optimum value by disposing of the data or allowing it to pass.

Table 1. Samples of the dataset from 2017 to 2021

		2017			
Index	**Open**	**High**	**Low**	**Close**	**Adj Close**
Y	X1	X2	X3	X4	X5
662.85	6.4	6.41	6.4	6.4	12371000
684.34	5.35	5.135	5.365	5.19	2838442
659.598	4.882	4.9	4.878	4.895	3178384.1
		2018			
658.21	0.597197802	0.588159341	0.599835165	0.589285714	114878448.4
692.5766667	0.649718954	0.647033613	0.651888889	0.641533147	117824196.5
701.1	0.679434524	0.683690476	0.679404762	0.682410714	99900141.54
		2019			
658.21	1.6875	1.654166667	1.695	1.658333333	10535032.92
692.5766667	2.263916667	2.22975	2.264166667	2.245583333	7837857.242
716.31	2.418848214	2.428583333	2.411535714	2.420857143	17051038.83
		2020			
582.62	5.383333333	5.133333333	5.386666667	5.133333333	5988117.333
564.9	4.32	4.333333333	4.3175	4.325	1546414.333
558.31	3.25	3.2375	3.25125	3.23875	430152.625
		2021			
567.55	4.268	4.271333333	4.276	4.273	1646611.7
564.79	2.949375	2.966875	2.985	2.9875	4988868.875
579.546	4.351	4.373333333	4.340666667	4.363666667	13891445

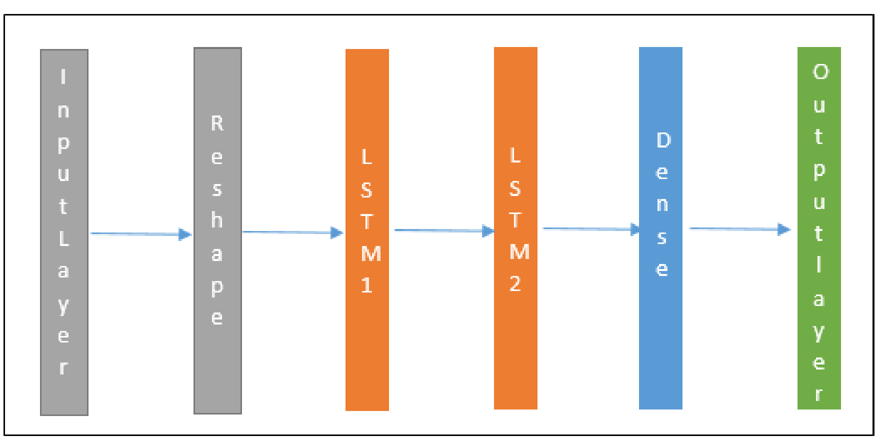

Fig. 5 A proposed LSTM prediction model

7. Experimental Results

Several experiments were conducted on the LSTM model to measure its prediction accuracy.

a. First case: When using the number of 400 iterations to train the ANN model. Fig. 6 illustrate the system's prediction score for five years.
b. Second case: When using the number of 400 iterations to train the LSTM model. Fig. 7 illustrates the system's prediction score for five years.

From previous results, note that the prediction process of a LSTM algorithm is better than ANN algorithm. Table 2 illustrate error measurements for training and prediction for each year.

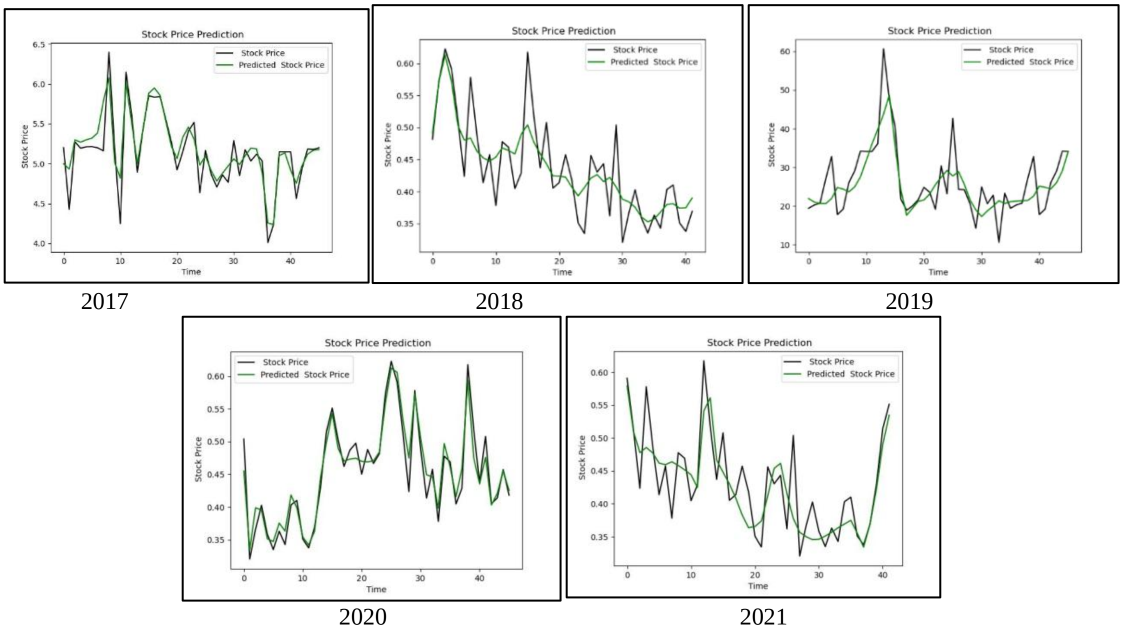

Fig. 7. ANN model prediction results for five years

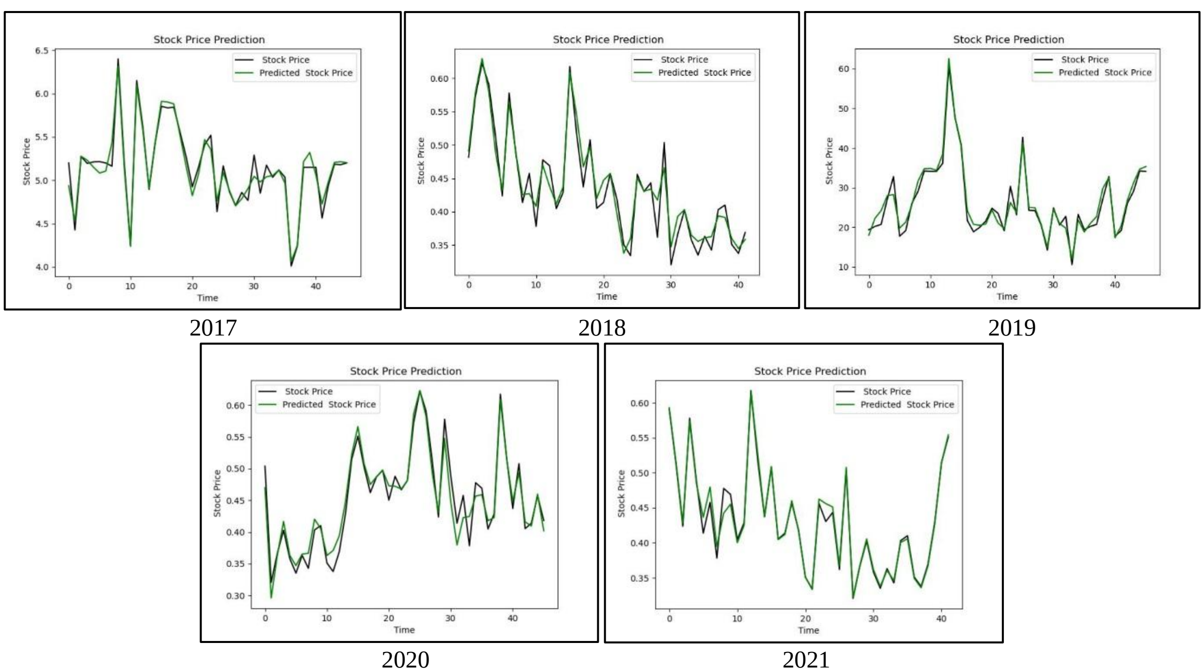

Fig. 9. LSTM model prediction results for five years

From the prediction and data in Table 2 of the long short-term memory (LSTM) algorithm and artificial neural network (ANN) algorithm find that the LSTM algorithm was better in the process of predicting the market index and for all years at iteration 400, so the increase in the number of training iteration affects the accuracy of models and The average of error rate (MSE, RMSE, MSLE, Val-MSE, Val-RMSE, and Val-MSLE) of LSTM algorithm for prediction were (0.00582, 0.0539, 0.00352, 0.00534, 0.05366, and 0.0028). and for ANN algorithm for prediction were (0.0102, 0.07342, 0.00372, 0.00968, 0.07254, and 0.01786).

Table 2. Error rate for each prediction algorithm

iteration	Algorithm	Year	MSE	RMSE	MSLE	Val-MSE	Val-RMSE	Val-MSLE
100	ANN	2017	0.0256	0.2388	0.0128	0.0212	0.2192	0.0108
		2018	0.0400	0.3465	0.0220	0.0421	0.3535	0.0225
		2019	0.0324	0.2226	0.0153	0.0339	0.2247	0.0153
		2020	0.0247	0.2605	0.0130	0.0193	0.2355	0.2187
		2021	0.1218	0.636	0.0181	0.1172	0.6632	0.1704
	LSTM	2017	0.0064	0.1144	0.0028	0.0076	0.1316	0.0032
		2018	0.0245	0.2472	0.0133	0.0215	0.2595	0.0125
		2019	0.0273	0.2091	0.0129	0.0264	0.2112	0.0122
		2020	0.0186	0.2223	0.0095	0.0145	0.2182	0.0095
		2021	0.0576	0.4074	0.0474	0.0456	0.3876	0.0276
200	ANN	2017	0.0128	0.1194	0.0064	0.0106	0.1096	0.0054
		2018	0.0258	0.2079	0.0132	0.0254	0.2121	0.0135
		2019	0.0216	0.1484	0.0102	0.0226	0.1498	0.0102
		2020	0.0137	0.1447	0.0075	0.0107	0.1307	0.1215
		2021	0.0305	0.1599	0.0045	0.02925	0.1657	0.0426
	LSTM	2017	0.0032	0.057	0.0014	0.0038	0.0658	0.0016
		2018	0.0144	0.162	0.0078	0.0129	0.1557	0.0075
		2019	0.0182	0.1394	0.0086	0.0176	0.1408	0.0080
		2020	0.0111	0.1235	0.0055	0.0105	0.0125	0.0052
		2021	0.0144	0.1018	0.0115	0.0114	0.0969	0.0069
400	ANN	2017	0.0064	0.0597	0.0032	0.0053	0.0548	0.0027
		2018	0.0080	0.0693	0.0044	0.0080	0.0707	0.0045
		2019	0.0108	0.0742	0.0051	0.0113	0.0749	0.0051
		2020	0.0055	0.0579	0.0029	0.0043	0.0523	0.0486
		2021	0.0203	0.1060	0.0030	0.0195	0.1100	0.0284
	LSTM	2017	0.0016	0.0285	0.0007	0.0019	0.0329	0.0008
		2018	0.0048	0.0540	0.0026	0.0043	0.0519	0.0025
		2019	0.0091	0.0697	0.0043	0.0088	0.0704	0.0040
		2020	0.0040	0.0494	0.0021	0.0041	0.0485	0.0021
		2021	0.0096	0.0679	0.0079	0.0076	0.0646	0.0046

8. Conclusion

In this study, the results of the prediction of the Iraqi stock markets index were compared using a long short-term memory (LSTM) algorithm and artificial neural network (ANN) algorithm and through practical experiments and the results of each algorithm to predict the Iraqi stock markets index for the five years find that the LSTM algorithm was better in the process of predicting the market index and for all years. Also, note that the increase in the number of training iterations affects the accuracy of models and through practical experiments to increase the number of training iterations for all models conclude that the number of iterations reaches its peak when reaching 400 iterations. It can be tested on other datasets.

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