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CLOSING PRICE PREDICTION OF STOCK LISTED ON THE IRAQ STOCK EXCHANGE USING ANN-LSTM

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ABSTRACT

Financial markets are highly reactive to events and situations, as seen by the very volatile movement of stock values. As a result, investors are having difficulties guessing prices and making investment decisions, especially when statistical techniques have failed to model historical prices. This paper aims to propose an RNNs-based predictive model using the LSTM model for predicting the closing price of four stocks listed on the Iraq Stock Exchange (ISX). The data used are historical closing prices provided from the period of 2/1/2019 to 24/12/2020. Several attempts were conducted to improve model training and minimize the prediction error, as models were evaluated using MSE, RMSE, and R2. The models performed with high accuracy in predicting closing price movement, despite the Intense volatility of time series. The empirical study concluded the possibility of relying on the RNN-LSTM model in predicting close prices at the ISX as well as decisions making upon.

Keywords* : *Stock, LSTM, Prediction, ANN, RNN, ISX

ABSTRAK

Pasar keuangan sangat reaktif terhadap peristiwa dan situasi, seperti yang terlihat dari pergerakan nilai saham yang sangat fluktuatif. Akibatnya, investor mengalami kesulitan menebak harga dan membuat keputusan investasi, terutama ketika teknik statistik gagal memodelkan harga historis. Tulisan ini bertujuan untuk mengusulkan model prediksi berbasis RNNs menggunakan model LSTM untuk memprediksi harga penutupan empat saham yang terdaftar di Bursa Efek Irak (Iraq Stock Exchange). Data yang digunakan adalah harga penutupan historis yang disediakan periode dari 2 Januari 2019 hingga 24 Desember 2020. Beberapa upaya dilakukan untuk meningkatkan pelatihan model dan meminimalkan kesalahan prediksi, karena model dievaluasi menggunakan MSE, RMSE, dan R2. Model memiliki akurasi tinggi dalam memprediksi pergerakan harga penutupan, meskipun volatilitas deret waktu yang intens. Studi empiris menyimpulkan kemungkinan mengandalkan model RNN-LSTM dalam memprediksi harga penutupan di BEI serta pengambilan keputusan.

Kata Kunci* : *Saham, LSTM, Prediksi, ANN, RNN, ISX

INTRODUCTION

In recent years, financial markets have seen significant volatility, particularly with the emergence of the Covid-19 pandemic and the massive damage it caused to various economic sectors, which was reflected in stock prices both negatively and positively. That is what made the risk factor raise, especially since it relates to an uncertain future. The situation of Iraq Stock Exchange (ISX) is not extremely different from other stock markets, despite the lack of international investments and the prevailing nature of local trading of the market. However, Iraq Stock Exchange (ISX) did not immune it to global dangers, as shares had some oscillations especially observed when coincided Covid-19 pandemic with dropping oil prices, which Iraq's economy is heavily reliant on. These rapid fluctuations make investment decisions excessively difficult, prompting investors and financial analysts to hunt for techniques to predict the future. Stock prediction is regarded as a difficult task, with researchers proposing various techniques for predicting stock prices. Statistical models such as Linear Regression (Cakra & Distiawan Trisedya, 2016), Autoregressive and Moving Average (ARIMA) (Ariyo *et.al*, 2014), and (GARCH) models (Franses & Van Dijk, 1996) are among the proposed techniques mentioned. However, previous techniques have been criticized for being inaccurate and having difficulty processing non-linear data. Therefore, modern Artificial Intelligence-based techniques known as "Machine Learning" have recently been proposed, such as Support Vector Regression (SVR) (MS, 2011), Deep Learning Algorithm (Nikou *et.al*, 2019), and Neural Networks. Machine Learning refers to all algorithms that use computers to detect patterns based on provided data (Moghar & Hamiche, 2020), which varies depending on the learning mechanism used to model data.

Long-Short-term Memory (LSTM) network, which is part of Recurrent Neural Networks (RNN), was used in this work. Several similar works of this paper, have been examined in the literature, Tasi & Wang (2009) examined a hybrid model combines Decision trees and Neural networks to forecast the electronic industry stocks price of Taiwan. The findings show that neural network models outperform decision tree models. Abhishek *et.al* (2012) used ANN with Back-Propagation algorithm to predict Microsoft stock price. The findings showed high performance though it was not able to predict stock price precisely, it was able to predict the stock trend. Moghaddam *et.al* (2016) examined the ability of Neural networks to predict the daily NASDAQ exchange rate using several Feed-forward ANNs, which have been trained by Back-propagation algorithm. The study found that ANN is able to predict the trend of NASDAQ exchange rate. Liu *et.al* (2017) developed an analytical model based on merging sentiments of online stock forums and stock market information to predict stock volatility using RNN. They found that the model performs significantly better by merging compared to using RNN only. Jin *et.al* (2019) proposed a predictive model based on deep learning using LSTM considering investors' emotional tendency. They conducted Stock time sequence analysis using empirical mode decomposition (EMD) to reduce the complexity. The empirical study showed that LSTM model improves the prediction accuracy and reduces the time delay. Vijh *et.al* (2020) conducted a comparative study between ANNs and Random forest for predicting the next day closing price of five companies in the operation sector. The findings showed the superiority of ANN comparing RF when tested by MSE, MAPE, and RMSE. Liu *et.al* (2021) studied the impact of Social network information on the accuracy of LSTM model in predicting the close price of the SSE 50 constituent stocks. The empirical findings indicate that the social network variable can significantly improve prediction accuracy. In this paper, we attempt to test LSTM to predict closing prices on the Iraqi Stock Exchange, as this is one of the country's first experiences with financial markets.

The purpose of this work is to obtain a more accurate predictive model than traditional statistical methods. The goal of this work is to assist investors in the Iraqi Stock Exchange in making stock investment decisions by knowing future expectations. For that, we attempted to train predictive models to estimate the closing price trend and predict the next day's price. The sample included four stocks of industrial and banking sectors, both of them listed on Iraq Stock Exchange, for a period from (2 January 2019) to (24 December 2020). Python packages, such as Keras, Sklearn, were used to build the LSTM model. Some Python dependency packages, such as Pandas and Numpy, have also been used to deal with and prepare data provided by Iraq Stock Exchange (ISX).

RESEARCH METHODS

Artificial Neural Networks

Artificial Neural Networks are brain-inspired computational models. They've been used in a variety of fields, including computing, medicine, engineering, economics, and more. Optimization theory was used to construct the artificial neural networks. Artificial Neural Networks, like the human nervous system, are made up of a group of neurons called (processing units) that are linked together by synapses (known as Weights) (Zakaria *et.al*, 2014). In general, artificial neural networks have three layers: input, hidden, and output. The number of neurons in the Input and Output layers is determined by the entered data dimension and target output, respectively.

Concerning the hidden layer, the number of neurons depends on the complexity of the entered data. The hidden layers have transformation functions known as (Activation function), which may include Sigmoid, Tanh, Relu, and others. These functions improve training by processing nonlinear data coming from the input layer (Tharsanee *et.al*, 2021). ANNs learn by computing the error in output values using a specific algorithm that adjusts the weights. Artificial neural networks come in a variety of types. We used recurrent neural networks (RNNs) in this study, specifically the Long short-term memory (LSTM) as mentioned previously.

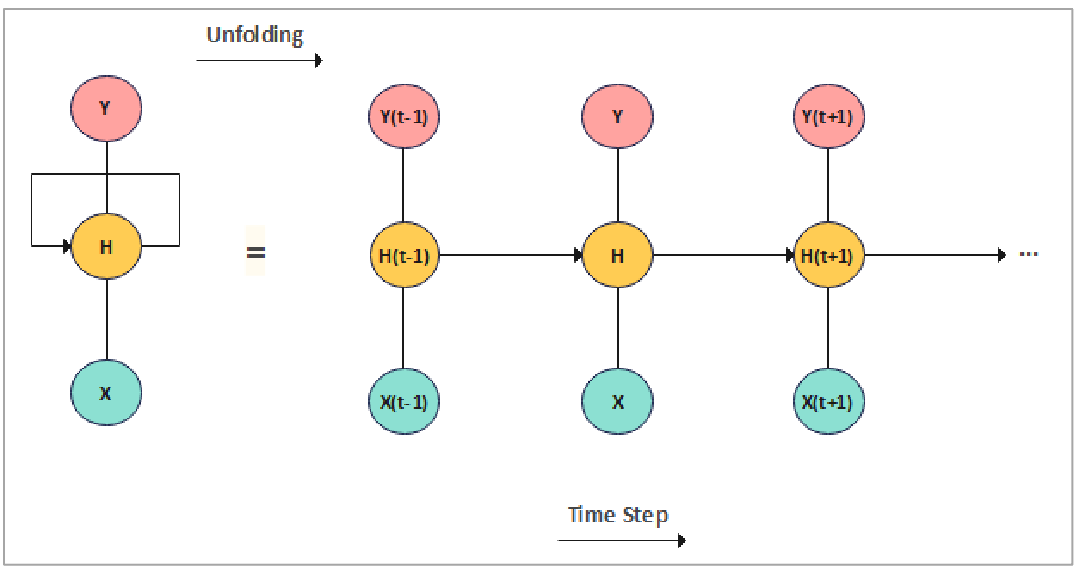
Recurrent Neural Networks (Rnn)

The recurrent neural network (RNN) is a type of artificial neural network that considers the sequence in which the units are connected (Mathur *et.al*, 2019). RNN receives prior output as input into next neurons, allowing it to remember past values (Rather, 2021). According to this context, RNN can be used to predict time series. However, as feedback loops continue, there are some limitations in terms of memory. The inability of RNNs to store memory for a long time due to gradient descent has vanished. (Chen & He, 2018). Given the foregoing, the node at (time t) will receives the output of previous node at (time t-1) in addition to data itself to generate the output at (time t) (Nabipour, Mojtaba and Nayyeri, Pooyan and Jabani, Hamed and Mosavi, Amir and Salwana, 2020). RNN formulas can be described as follow (Lin *et.al*, 1996)

$$\boldsymbol{h_t} = \mathbf{tanh}\,(\boldsymbol{W_t h_t} + \boldsymbol{W_x X_t}) \qquad \textbf{(1)}$$

$$\boldsymbol{y_t} = \boldsymbol{W_y h_t} \qquad \textbf{(2)}$$

Where, xt, ht, yt, and Wh are input, hidden, output vectors and weighting matrix respectively.



Source: *Prepared by researchers based on: Ghosh, A., Bose, S., Maji, G., Debnath, N., & Sen, S. , 2019. Stock price prediction using LSTM on Indian Share Market. In Proceedings of 32nd international conference on (Vol. 63, pp. 101-110).*

Figure 1. Recurrent Neural Networks (RNNs) Chart

Long Short-Term Memory (LSTM)

Due to the limitations of RNNs previously mentioned, Hochreiter & Schmidhuber (Hochreiter, 1997) proposed a modified type of RNN called Long short-term memory (LSTM), which can learn long-term dependencies. LSTM has a large memory and can learn from separate inputs with long time lags (Yadav *et.al*, 2020). Each LSTM node is mostly made up of cells that are in charge of storing passed data streams. The LSTM model consists of three gateways: an input gate that determines whether new input is permitted, a forget gate that discards irrelevant data, and an output gate that determines what data to output. These three gates operate in the (0, 1) range and employ the sigmoid function. The mathematical formulas for these gates are represented by the following equations.

$$\boldsymbol{f^{(t)} = \sigma(W^{fh} \,.\, h^{(t-1)} + W^{fX} \,.\, x^{(t)} + b_f)} \quad \textbf{(3)}$$

f is forget gate, W^{fh} is weight matrix associated with the hidden states, h is hidden state of previous timestamp, W^{fx} is weight matrix associated with the input, $x^{(t)}$ is input of current timestamp, b is bias value.

$$\boldsymbol{i^{(t)} = \sigma(W^{ih} \,.\, h^{(t-1)} + W^{iX} \,.\, x^{(t)} + b_i)} \quad \textbf{(4)}$$

i is input gate, W^{ih} is weight matrix associated with the hidden states, h is hidden state of previous timestamp, W^{ix} is weight matrix associated with the input, $x^{(t)}$ is input of current timestamp, b is bias value.

$$\boldsymbol{g^{(t)} = tanh(W^{gh} \,.\, h^{(t-1)} + W^{gX} \,.\, x^{(t)} + b_i)} \quad \textbf{(5)}$$

$g^{(t)}$ is tanh activation function.

$$\boldsymbol{C_{(t)} = i^{(t)} \,.\, g^{(t)} + f^{(t)} \,.\, C_{(t-1)}} \quad \textbf{(6)}$$

$C_{(t)}$ is cell state of current time stamp, $C_{(t-1)}$ is cell state of previous timestamp.

$$\boldsymbol{o^{(t)} = \sigma(W^{oh} \,.\, h^{(t-1)} + W^{oX} \,.\, x^{(t)} + b_o)} \quad \textbf{(7)}$$

i is input gate, W^{oh} is weight matrix associated with the hidden states, h is hidden state of previous timestamp, W^{ox} is weight matrix associated with the input, $x^{(t)}$ is input of current timestamp, b is bias value.

$$\boldsymbol{h_{(t)} = tanh\left(C_{(t-1)}\right) \,.\, o^{(t)}} \quad \textbf{(8)}$$

$h_{(t)}$ is tanh activation of current timestamp. Figure (2) described LSTM model architecture.

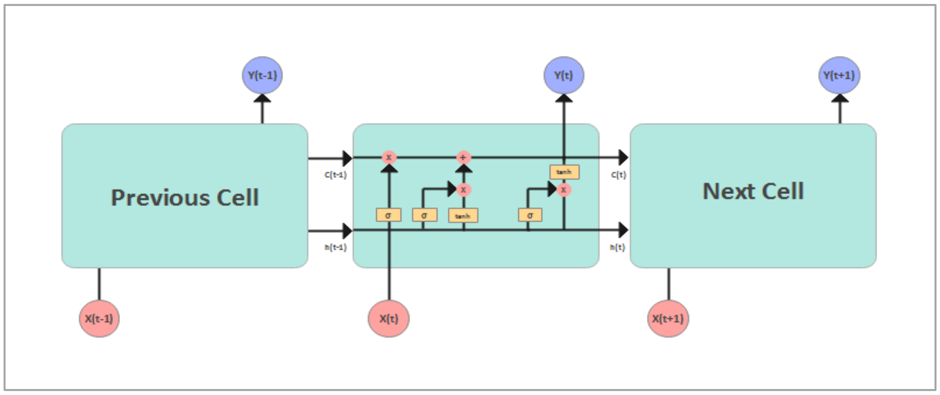


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Figure 2: Long short term memory architecture

Methodology and Data

Description of the Data

The four stocks raw data were acquired from Iraq Stock Exchange (ISX). The data were gathered for a two-year (02/01/2019) to (24/12/2019) as daily indices. Several stock indices are included in the data set, such as Open, Close, High, Low, Volume, Last Close, Average, and Change Rate. Only the closing price is considered in this study. Table (1) displays some statistics of the dataset

Table 1. Closing price statistics

Stock	Observations	Max value	Min value	Average
Baghdad Bank	390	0.50	0.23	0.33
Investment Bank	298	0.30	0.19	0.25
Baghdad Soft Drink Co.	402	4.15	1.91	3.13
Mansour Drugs Co.	362	1.50	0.60	1.00

Source: Processed data by excel, 2022

Proposed Work

In this section, we will discuss the methodology of proposed work for predicting stock closing price of the concerned stock in several stages.

Data Prepration

This phase involves sub-stages to pre-process the raw data: [1] Extracting only the closing price from other features; [2] Missing data have been replaced by the previous day value; [2] Normalizing the dataset in range (0,1) using MinMaxScalar library, to improve the training; [3] Dividing dataset into Training and Testing sets, to evaluate the model later, where the training set was 80%, and testing is the 20% remainder. Table (2) shows dividing dataset based on dates.

Table 2: Dividing dataset into train and test sets

Company	Training Set		Testing Set	
	From	To	From	To
Baghdad Bank	2/1/2019	19/8/2020	20/8/2020	24/12/2020
Investment Bank	2/1/2019	12/8/2020	13/8/2020	24/12/2020
Baghdad Soft Drink Co.	2/1/2019	27/8/2020	31/8/2020	24/12/2020
Mansour Drugs Co.	3/1/2019	6/9/2020	7/9/2020	24/12/2020

Source: Processed data by researchers, 2022

Lstm Model Building

In this stage, we use the Sequential class from the Keras library to structure the LSTM model. The model was built from a sequential input layer, two LSTM layers with (50) neurons with Relu activation function, and a Dense output layer. The models were built using stochastic gradient descent (SGD) and Adamax optimizers.

Training The Model

Several training attempts are made, during which the RNN generates random outputs that are compared to the target values. By adjusting the weights, the back-propagation algorithm reduces errors. The regression loss function was mean squared error (MSE).

Evaluating The Model

At this stage, the model is evaluated by comparing predicted values to test set values. As a result, mean squared error (MSE) and root mean squared error (RMSE) are employed. The lowest score of these measures indicates the model's accuracy.

RESEARCH RESULTS AND DISCUSSION

In this paper, we used two LSTM models to predict the closing price of four ISX-listed stocks from the industrial and banking sectors. Two error metrics, MSE and RMSE, as well as the Coefficient of determination (R2), were used to assess model accuracy. These three measures are widely used to assess the efficacy of Regression models. Below are equations for the performance measures used.

$$MSE = \frac{\sum_{i=1}^{N} e^2}{N} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} e^2}{N}} \qquad (4)$$

$$R^2 = \frac{\sum(\mathbf{y}(\mathbf{i}) - \mu(\mathbf{y}))\mathbf{2}}{\sum(\bar{y}\,(\mathbf{i}) - \mu(\bar{y}))\mathbf{2}} \qquad (5)$$

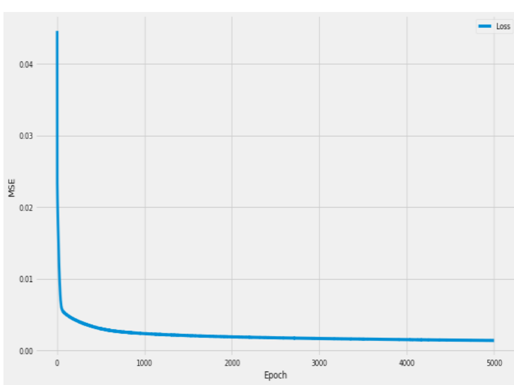
Two optimization algorithms (SGD and Adamax) were applied to the study sample's stock neural network models. Table (3) shows that the SGD algorithm was more accurate for the sample of banks after (5000) training epochs, with very low error measures and a high correlation coefficient between the real and predicted results. The results also show that after (1000) training epochs, the (Adamax) algorithm was more accurate for a sample of industrial companies, with very low error measures and a high correlation coefficient between the real and predicted results. The effectiveness of the LSTM model in predicting the closing price of the tested stocks can thus be determined.

Table 3. The performance of the four models.

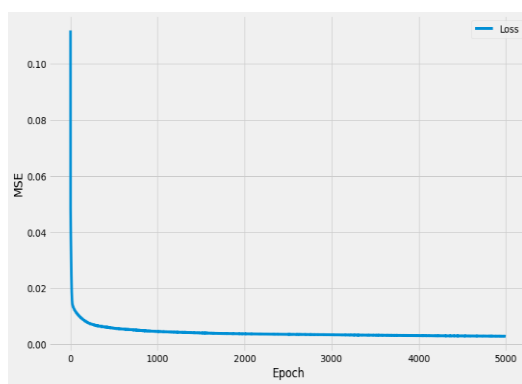
Stock' model	Optimizer	Epochs	MSE	RMSE	R2
Baghdad Bank	SGD	5000	0.00001	0.003	0.90
Investment Bank	SGD	5000	0.000001	0.001	0.94
Baghdad Soft Drink Co.	Adamax	1000	0.0001	0.01	0.99
Mansour Drugs Co.	Adamax	1000	0.0000001	0.0003	0.99

Source: Processed data by python, 2022

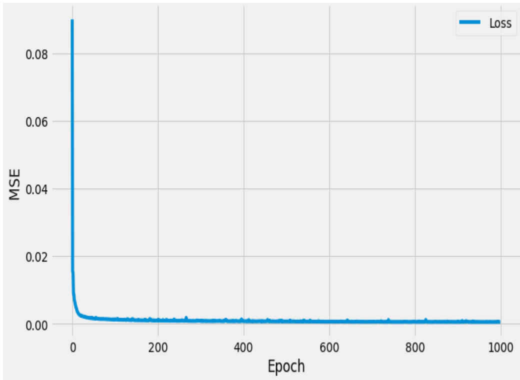
Baghdad Bank



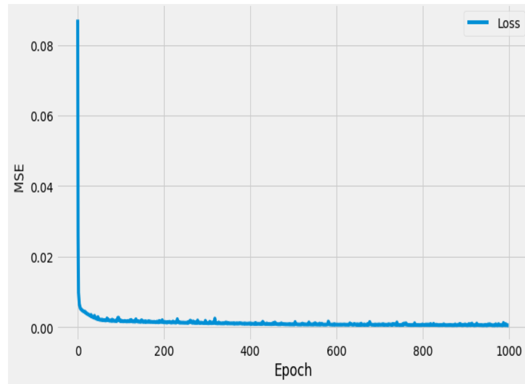
Investment Bank



Baghdad Soft Drink Co.



Mansour Drugs

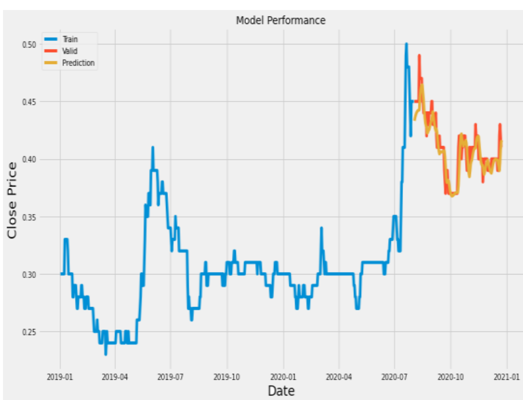


Source: Processed data by python, 2022

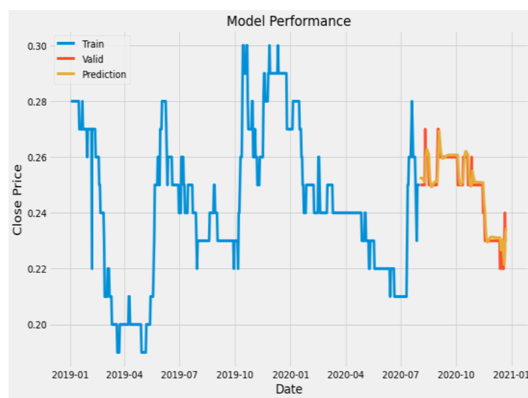
Figure 3: Model performance minimizing errors.

Figure (3) illustrates the decrease in the model's average error in predicting the closing price of the study sample stocks as the number of training periods increases. The practical experience revealed that increasing the number of training epochs, and thus the training duration, improves the accuracy of the neural network models used in the study.

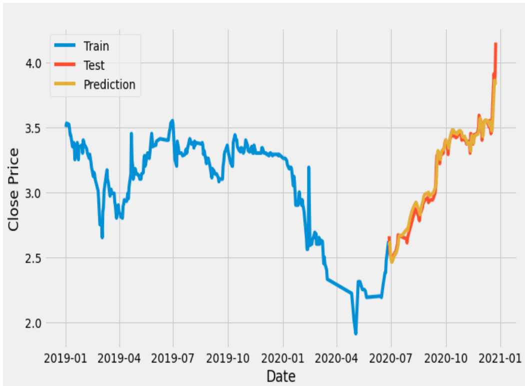
Baghdad Bank



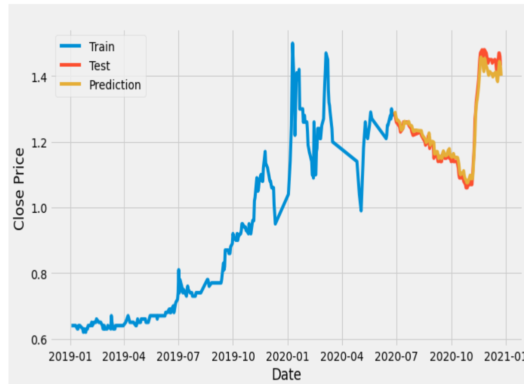
Investment Bank



Baghdad Soft Drink



Mansour Durgs



Source: Processed data by python, 2022.

Figure 4. Stock price prediction for the four models.

Figure (4) illustrates the high accuracy of the four LSTM models tested. The training sample is shown in blue, the test (verification) sample is shown in red, and the predicted value of closing prices is shown in yellow. We can conclude from this that neural networks can model the time series of the study sample stocks despite the presence of significant fluctuations and instability.

CONCLUSION

Stock prices fluctuate significantly, as forecasting future price movements is a challenging task, especially given the inability of statistical techniques to model the stock price movement. This paper proposed an RNN-based predictive model using LSTM to predict the closing price of four stocks listed on the Iraq Stock Exchange's industrial and banking sectors (ISX). Python packages such as Keras and Sklearn are used to build the LSTM models because of their high flexibility and controllability. The empirical results show that the proposed models are accurate, as measured by MSE, RMSE, and R^2. The LSTM models have proven to be reliable in making investment decisions based on them.

RECOMMENDATION

In future work, we will attempt using multivariate to construct a more accurate predictive model, as well as other types of ANNs such as CNN, GRNN, and others.

BIBLIOGRAPHY

Abhishek, K., Khairwa, A., Pratap, T., & Prakash, S. 2012. A stock market prediction model using Artificial Neural Network. 2012 Third International Conference on Computing, Communication and Networking Technologies (ICCCNT'12), 1–5.

Ariyo, A. A., Adewumi, A. O., & Ayo, C. K. 2014. Stock price prediction using the ARIMA model. 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, 106–112.

Cakra, Y. E., & Distiawan Trisedya, B. 2016. Stock price prediction using linear regression based on sentiment analysis. ICACSIS 2015 - 2015 International Conference on Advanced Computer Science and Information Systems, Proceedings, 147–154. https://doi.org/10.1109/ICACSIS.2015.7415179

Chen, S., & He, H. 2018. Stock Prediction Using Convolutional Neural Network. IOP Conference Series: Materials Science and Engineering, 435(1). https://doi.org/10.1088/1757-899X/435/1/012026

Franses, P. H., & Van Dijk, D. %J J. of forecasting. 1996. Forecasting stock market volatility using (non-linear) Garch models. 15(3), 229–235.

Ghosh, A., Bose, S., Maji, G., Debnath, N., & Sen, S. 2019. Stock price prediction using LSTM on Indian Share Market. In Proceedings of 32nd international conference on (Vol. 63, pp. 101-110).

Hochreiter, S. and S. 1997. Long short-term memory. Neural Computation, 9(8), 1735–1780.

Jin, Z., Yang, Y., Liu, Y. %J N. C., & Applications. 2020. Stock closing price prediction based on sentiment analysis and LSTM. 32(13), 9713–9729.

Lin, T., Horne, B. G., Tiiio, P., & Giles, C. L. 1996. Learning Long-Term Dependencies in NARX Recurrent Neural Network. IEEE Transactions on Neural Networks, 7(6), 1329–1338. https://pdfs.semanticscholar.org/f62c/3868ebabb5d84bfcf1c5eae6d72d5fb33125.pdf

Liu, K., Zhou, J., Dong, D. %J J. of B., & Finance, E. 2021. Improving stock price prediction using the long short-term memory model combined with online social networks. 30, 100507.

Liu, Y., Qin, Z., Li, P., & Wan, T. 2017. Stock volatility prediction using recurrent neural networks with sentiment analysis. International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, 192–201.

Mathur, R., Pathak, V., & Bandil, D. 2019. Emerging Trends in Expert Applications and Security. In Emerging Trends in Expert Applications and Security (Vol. 841). Springer Singapore. https://doi.org/10.1007/978-981-13-2285-3

Moghaddam, A. H., Moghaddam, M. H., Esfandyari Finance, M. %J J. of E., & Science, A. 2016. Stock market index prediction using artificial neural network. 21(41), 89–93.

Moghar, A., & Hamiche, M. %J P. C. S. 2020. Stock market prediction using LSTM recurrent neural network. 170, 1168–1173.
MS, V. 2011. Stock price prediction using support vector regression. International Conference on Computing and Communication Systems, 588–597.
Nabipour, Mojtaba and Nayyeri, Pooyan and Jabani, Hamed and Mosavi, Amir and Salwana, E. and others. 2020. Deep learning for stock market prediction. Entropy, 22(8), 840.
Nikou, M., Mansourfar, G., Bagherzadeh Finance, J. %J I. S. in A., & Management. 2019. Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms. 26(4), 164–174.
Rather, A. M. 2021. LSTM-based Deep Learning Model for Stock Prediction and Predictive Optimization Model. EURO Journal on Decision Processes, 9(September), 100001. https://doi.org/10.1016/j.ejdp.2021.100001
Tharsanee, R. M., Soundariya, R. S., Kumar, A. S., Karthiga, M., & Sountharrajan, S. 2021. Deep convolutional neural network–based image classification for COVID-19 diagnosis. Data Science for COVID-19, 117–145. https://doi.org/10.1016/b978-0-12-824536-1.00012-5
Tsai, C. F., & Wang, S. P. 2009. Stock price forecasting by hybrid machine learning techniques. Proceedings of the International Multiconference of Engineers and Computer Scientists, 1(755), 60.
Vijh, M., Chandola, D., Tikkiwal, V. A., & Kumar, A. (2020). Stock Closing Price Prediction using Machine Learning Techniques. Procedia Computer Science, 167, 599–606. https://doi.org/10.1016/j.procs.2020.03.326
Yadav, A., Jha, C. K., & Sharan, A. 2020. Optimizing LSTM for time series prediction in Indian stock market. Procedia Computer Science, 167(2019), 2091–2100. https://doi.org/10.1016/j.procs.2020.03.257
Zakaria, M., Al-Shebany, M., & Sarhan, S. 2014. Artificial neural network: a brief overview. International Journal of Engineering Research and Applications, 4(2), 7–12.