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STOCK CLOSING PRICE PREDICTION OF ISX-LISTED INDUSTRIAL COMPANIES USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Making stock investment decisions is a complex challenge that investors continuously face. When it comes to an uncertain future, making the wrong decision can result in massive losses. The paper aims to develop an artificial neural networks-based model predicting the closing price of top-six traded industrial ISX-listed stocks, which can guide investment decisions. Artificial neural network technology is a recent approach to modeling stock prices on the Iraqi Stock Exchange. The sample consisted of daily indexes ISX-released from (3/3/2019) to (31/3/2019). Matlab 2014b was used to run artificial neural networks using nntool software. Model's performance was evaluated using Mean squared error (MSE), Root mean squared error (RMSE), and R squared. Empirical results demonstrated the ability and efficiency of artificial neural networks to predict closing prices with high accuracy. As a result, we recommended employing Artificial Neural Networks model to predict stock prices and rely on to make decisions.

Keywords : ANN, Stocks, Close Price, Prediction, Investment

ABSTRAK

Membuat keputusan investasi saham merupakan tantangan kompleks yang terus-menerus dihadapi investor. Ketika datang ke masa depan yang tidak pasti, membuat keputusan yang salah dapat mengakibatkan kerugian besar. Makalah ini bertujuan untuk mengembangkan model berbasis jaringan saraf tiruan yang memprediksi harga penutupan enam saham industri yang terdaftar di BEI, yang dapat memandu keputusan investasi. Jaringan saraf tiruan adalah teknologi modern dalam pemodelan harga saham di BEI, yang mengatasi kegagalan model statistik tradisional. Teknologi jaringan saraf tiruan adalah pendekatan terbaru untuk memodelkan harga saham di Bursa Efek Irak. Sampel terdiri dari indeks harian BEI yang dirilis dari (3/3/2019) hingga (31/3/2019). Matlab 2014b digunakan untuk menjalankan jaringan syaraf tiruan menggunakan software nntool. Kinerja model dievaluasi menggunakan Mean squared error (MSE), Root mean squared error (RMSE), dan R kuadrat. Hasil empiris menunjukkan kemampuan dan efisiensi jaringan syaraf tiruan untuk memprediksi harga penutupan dengan akurasi tinggi. Oleh karena itu, kami merekomendasikan penggunaan model Jaringan Syaraf Tiruan untuk memprediksi harga saham serta mengandalkan pengambilan keputusan.

Kata Kunci : ANN, Saham, Harga Penutupan, Prediksi, Investasi

INTRODUCTION

Stocks are the mainstay of the capital markets and the most important investment tools in them. Stock prices in the Iraq Stock Exchange (Iraqi Securities Commission, 2022) are affected by many financial and non-financial influences in a way that is difficult to enumerate, which makes their prices fluctuate instantaneously and continuously. Investing in stocks is one of the most important investment decisions faced by investors. Deciding whether to buy or sell shares is not an easy task as it is related to an uncertain future. Therefore, it has become necessary to make predictions about stock prices in the future, so that the investor can be guided in making his investment decision.

The predictive methods used varied and ranged from simple methods that depend on personal estimates to those that rely on statistical and mathematical methods. The autoregressive model and the moving average (ARIMA) were used in (1987) to predict stock indices (Virtanen & Yli-Olli, 1987), the multiple regression model was also used in (1990) to predict the direction of the market index (Cheng et al., 1990), and the autoregressive conditional heteroskedasticity model was used in (2005) to predict the fluctuations of stock returns (Marcucci, 2005). Despite the results achieved by these methods, they failed to model some time series of stock prices, in addition to requiring the time series to be stable in order to predict them. As a result, there has been an interest in using methods based on machine learning and artificial intelligence as improved methods. Some machine learning techniques were used in 2007 to predict stock prices (Shah, 2007), and the support vector regression model was used in (2013) to predict the direction of price movement (Xia et al., 2013). Artificial neural networks are one of the techniques of artificial intelligence, as its origins go back to (1940) when McCulloch and Pitts developed a computational model of the neural network (Nayak et al., 2001).

Artificial neural networks have been used to solve many problems such as classification, processing, and clustering, in addition to time series prediction such as stock prices. There are several works experimented with ANNs for stocks prediction. Guresen et al (2011) evaluated Multi-layer perceptron neural network (MLP) along with dynamic artificial neural network (DAN2) and GARCH model in stock prediction of NASDAQ index (Guresen et al., 2011). Bing et al (2012) applied Backpropagation neural network to predict the Shanghai stock exchange composite index. The empirical study conducted the Shanghai stock exchange composite index is predictable in the short term (Bing et al., 2012). Yetis et al (2014) used generalized feedforward neural network model to predict NASDAQ index, the results demonstrated good performance (Yetis et al., 2014). Chen et al (2015) evaluated various techniques of machine learning such as LSTM Neural networks, Support vector machine and Genetic algorithm for predicting Chain stock returns. The results proved the power of LSTM in sequence learning for predicting China stock market (Chen et al., 2015). Billah et al (2017) experimented ANN based model with improved Levenberg Marquardt (LM) algorithm comparing with Adaptive Neuro Fuzzy Inference System (ANFIS) to predict the close price. Comparison results showed that LM algorithm can predict the close price with less error than ANFIS (Billah et al., 2017). Hiransha et al (2018) used four architectures of neural networks, i.e MLP, RNN, LSTM, and CNN for predicting the stock price in NSE and NYSE exchanges. The empirical study demonstrated that CNN is outperforming other architectures. The results obtained have been compared with ARIM model, It proved that ANN is outperforming ARIMA model (Hiransha et al., 2018). Teixeira et al (2020) presented a comparative study of five architectures of ANNs, i.e multiple linear regression, Jorden, Elman, Radial basis function, and multilayer perceptron for predicting the six most traded stocks of the Brazilian stock exchange. The results showed that all architectures considered, except RBF, provide suitable reasonable predictions (Mathur et al., 2019). Shahvaroughi et al (2021) experimented ANN based model has been trained using metaheuristic algorithms such as bat algorithm (BA), social spider optimization (SSO), and Genetic algorithm beside ARIMA model to predict stock price indices. The results obtained was compared each other (Farahani & Hajiagha, 2021).

This paper proposes an analytical study to test artificial neural networks' ability to predict closing prices for top-six traded industrial stocks listed on Iraq Stock Exchange (ISX). The main goal of this work is to develop predictive models that can be used to guide investment decisions. The use of neural network technology in forecasting stock prices in the Iraqi Stock Exchange is a recent approach. To achieve that, the paper was organized as follows. Section (2) covered the literature reviews of related works. Section (3) provides a brief knowledge of artificial neural networks. Section (4) presented the methodology and data of this study. Section (5) showed the results and discussion of the experimental study. Finally, Section (6) summarized the conclusion of the study.

Artificial Neural Networks

ANN are one of the machine learning techniques, and their core idea is to try to simulate the biological cells of the human brain and use its working mechanism in a variety of fields. Today, neural networks are used in processing, classification, analysis, and prediction (Ashour, 2018). ANN are considered non-linear statistical data tools. ANN can be used to model the complex relationship between outputs and inputs. The main advantage of ANN is its ability to learn underlying patterns from data, which is something that most traditional methods fail to do (Zhang et al., 1998). There are numerous types of neural networks that are used in prediction. The multilayer perceptron (MLP) is considered in this work. The MLP basic architecture is depicted in Figure (1).

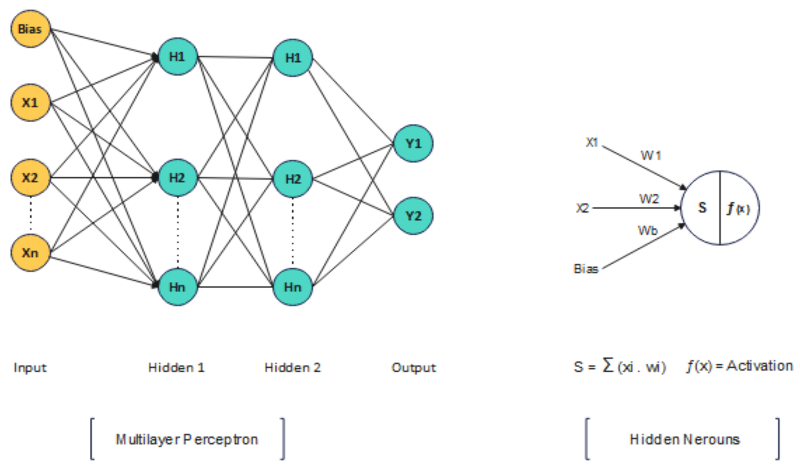


Figure 1. The basic architecture of MLP.

MLP is a feedforward neural network in which data flows unidirectionally from the input layer to the output layer via hidden layers (Bishop, 1995). Weights connect the layers of the neural network together. Perceptrons in the same layer have the same activation function. For the hidden layers in general, it is either a sigmoid or a hyperbolic tangent. Depending on the application, the output layer can be a sigmoid or a linear function (Camacho Olmedo et al., 2018). Because the weighted inputs can be infinite, the activation function's role is to calculate a neuron's response. Thus, after deciding whether or not to activate a neuron, it limits the net input value (Activation Function, 2019). Backpropagation, a generalization of the Least Mean Squared rule, is one of the most well-known learning algorithms used in MLP (Du & Swamy, 2013). Backpropagation is a weight-correction technique that involves propagating errors from one layer to the next, starting with the output layer and working backwards. The backpropagation algorithm is based on the five derived equations known as deriving the gradients (John McGonagle, George Shaikouski, 2022).

- ❖ Partial derivatives

$$\frac{\partial E_d}{\partial w_{ij}^k} = \delta_j^k o_i^{k-1} \tag{1}$$

- ❖ Error of final layer

$$S_1^m = g_o'(a_1^m)(\hat{y}_d - y_d) \tag{2}$$

- ❖ Error of hidden layer

$$S_j^k = g^r(a^k) \sum_{l=1}^{r^{k+1}} w_{jl}^{k+1} \delta_l^{k+1} \tag{3}$$

- ❖ Adding each input-output pair's partial derivatives

$$\frac{\partial E\,(X,\theta)}{\partial w_{ij}^{k}} = \frac{1}{N}\sum_{d=1}^{N}\frac{\partial}{\partial w_{ij}^{k}}\left(\frac{1}{2}\,(\hat{y}_d - y_d)^2\right) = \frac{1}{N}\sum_{d=1}^{N}\frac{\partial E_d}{\partial w_{ij}^{k}} \quad (4)$$

- Weights updating

$$\Delta\partial w_{ij}^{k} = -\alpha\frac{\partial E\,(X,\theta)}{\partial w_{ij}^{k}} \quad (5)$$

The forward propagation and backward propagation processes are repeated repeatedly in the training process of neural networks to minimize the error function (Karazi et al., 2019). Once the minimum error function is reached, the training process stops, and the link weights are generalized between the layers (Chaturvedi, 2017). There are several techniques for conditional stopping of the training process, such as early stopping depending number of epochs. Continuing to train does not always guarantee improved results; in fact, it is more likely that the opposite will occur, as increasing training times can lead to overfitting (Ying, 2019).

RESEARCH METHODS

Raw data were acquired from Iraq stock exchange (ISX) (Iraqi Securities Commission, 2022), representing the historical data of top-six traded industrial ISX-listed stocks from (2/1/2019) to (24/12/2020). The data are some daily indices consists seven independent variables, which are Open, High, Low, Present rate, Last rate, Change rate, and Volume as well. The dependent variable is Close price to be predicted.

Matlab 2014b nntool was used to develop the MLP model (Moler, 2014). By 70 percent, 15 percent, and 15 percent, the data were divided into training, testing, and validation sets, and then normalised for training performance enhancement. Maximum epochs were set to 1000, logistic function was used as activation, mean squared error was used as a performance metric, and Levenberg-Marquardt was used as a training algorithm in MLP. MLP settings can be found in Table 1.

Table 1. MLP model settings

Training Algorithm	TRAINLM (Levenberg-Marquardt)
Transfer Function	TANGENT
Performance Function	MSE
Maximum Epoch	10000

Source: Processed data, 2022

Several attempts have been made to find the best neural network architecture. Experiments have shown that the best architecture includes a single input layer with (8) neurons representing inputs, a single hidden layer with (10) neurons, and a single output representing predicted closing price. The MLP model architecture is depicted in Figure 2.

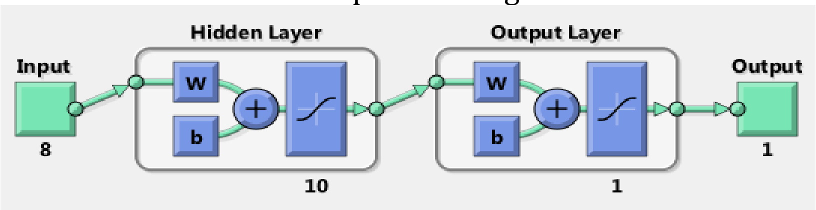


Figure 2. MLP model settings

RESULTS AND DISCUSSION

Some statistical metrics were used to evaluate the performance of predictive models. Mean squared error (MSE), Root mean squared error (RMSE), and R squared (R^2) are applied to the six MLP models. Their formulas are shown below.

$$\boldsymbol{MSE} = \frac{\sum_{i=1}^{N}(O_i - F_i)^2}{N} \tag{3}$$

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(O_i - F_i)^2}{N}} \tag{4}$$

O_i denotes the actual closing price, F_i denotes the predicted closing price, and N denotes the sample.

$$\boldsymbol{R^2} = 1 - \frac{(\sum_{i=1}^{N}(y_i - \hat{y}_i)^2)/N}{(\sum_{i=1}^{N}(\bar{y}_i - \hat{y}_i)^2)/N} \tag{5}$$

Here, N denotes the total number of sample; y_i and $\hat{y}_i$ denote the actual price and predicted price respectively; $\bar{y}_i$ denotes the mean of actual price.

Table (2) shows the results of evaluating the performance of used MLP models for each stock. Although the length of the stock time series varies, the results clearly demonstrated the high accuracy of the models. It is clear from the results that Al-Hilal Co. stock model was the most accurate with (5.64E-06) MSE, (0.002) RMSE, and (0.99) R^2. Chemical & Plastic Co. stock model was the last place in model accuracy with (2.78E-04) MSE, (0.016) RMSE, and (0.99) R^2. In general, the experiment's findings showed that all models were accurate based on the aforementioned measures, with the smaller the error measures (MSE, RMSE), the fewer deviations in the predicted results. (Kristjanpoller et al., 2014). On the other hand, the higher the coefficient of determination (R) (i.e. close to one), indicates the high accuracy of the model, as it shows how much of the variation in a dependent variable is explained by the independent variable (s) (Chicco et al., 2021).

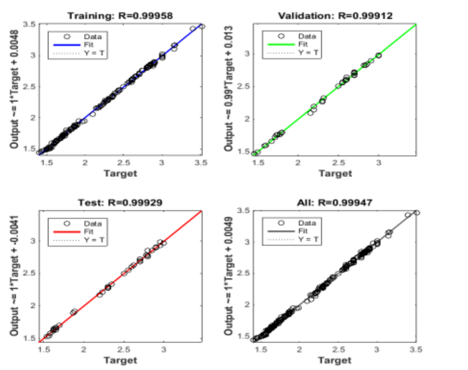
Table 2. Model Performance Analysis

Stock	Observations	MSE	RMSE	R^2
Metallurgical & bicycle Co.	267	2.78E-04	0.016	0.99
Kendiy vaccines Co.	280	4.59E-05	0.006	0.99
Dates packaging & marketing Co.	208	1.97E-05	0.004	0.99
Al-Hilal industry Co.	102	5.64E-06	0.002	0.99
Baghdad soft drinks Co.	402	1.85E-04	0.013	0.99
Chemical and plastic Co.	378	1.17E-04	0.010	0.99

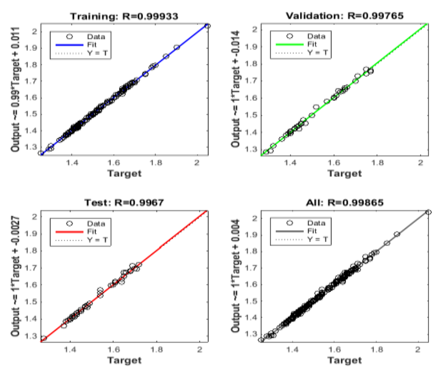
Source: Processed data, 2022

Figure 3 shows the regression curve of the models, as it shows the extent to which the points are located on the regression line, which indicates the high accuracy of the models.

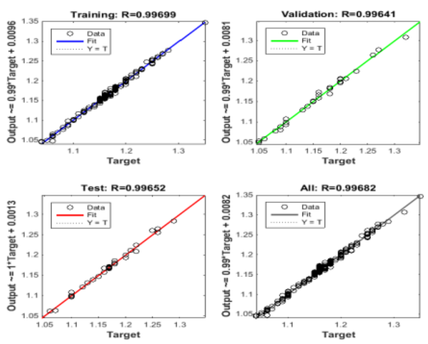
(A) Metallurgical & bicycle industry



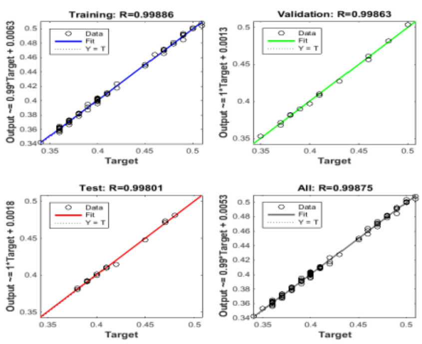
(B) Kendiy vaccines



(C) Dates packaging & marketing



(E) Al-Hillal industry



(E) Baghdad soft drinks

(F) Chemical and plastic industry

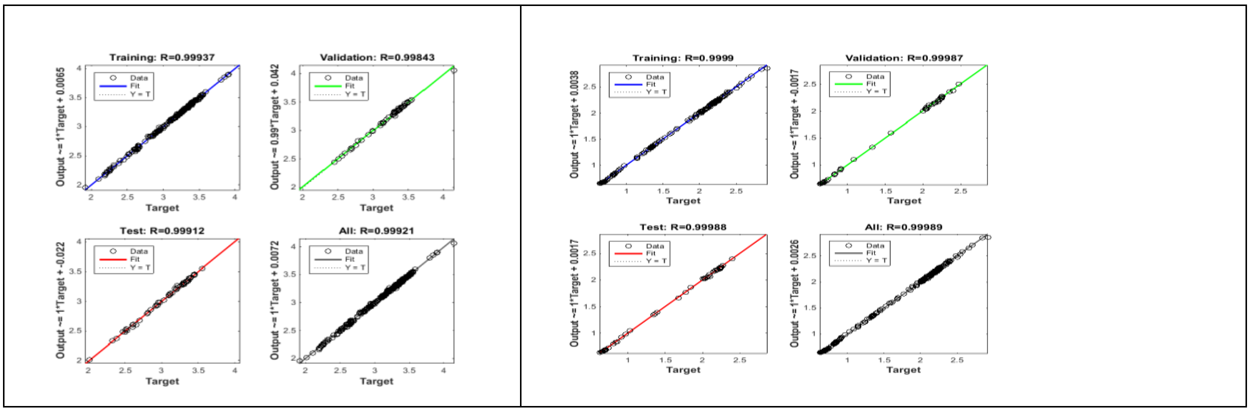
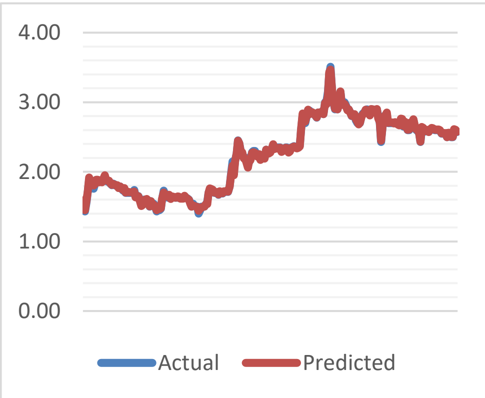
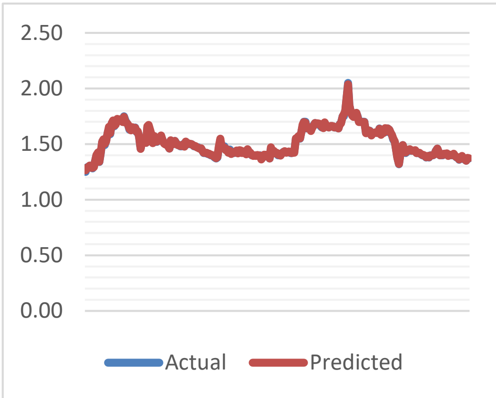


Figure 3. Regression curves of models

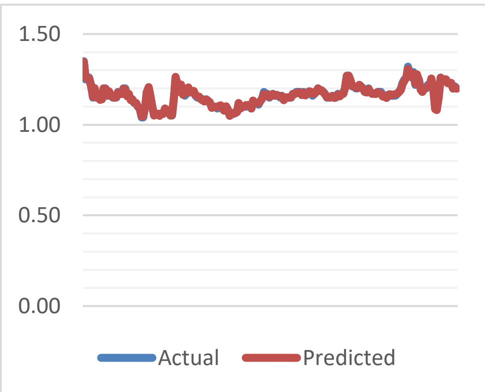
Figure 4 illustrates actual versus predicted closing prices, demonstrating that the results of the artificial neural network model (red trend) are very close to the actual closing prices of the research sample's shares (blue trend). This confirms the results of the accuracy tests, indicating that the predictive models are accurate.



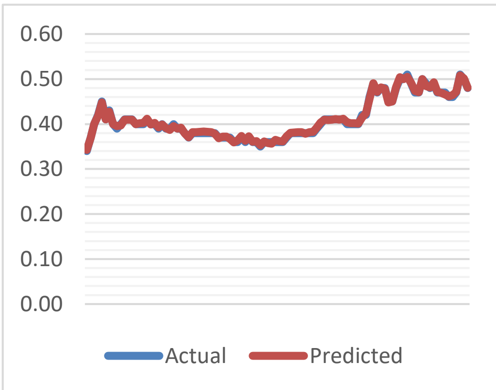
(A) Metallurgical & bicycle industry



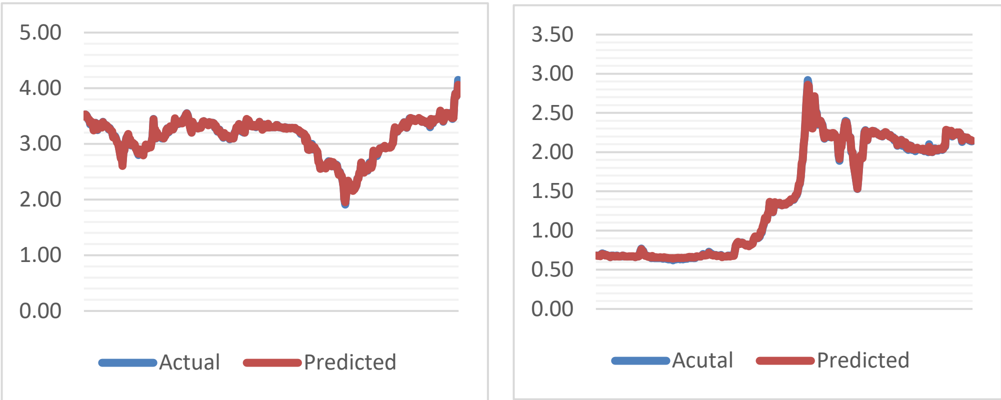
(B) Kendiy vaccines



(C) Dates packaging & marketing



(D) Al-Hillal industry



(E) Baghdad soft drinks (F) Chemical and plastic industry

Figure 4. Comparing predict values and actual values

Based on the previous results, it is clear that the artificial neural network technology is very suitable for predicting the stocks listed on the Iraq Stock Exchange. The findings are unprecedented for stocks traded on the Iraqi Stock Exchange, as previous Iraqi studies using artificial neural network technology failed to predict stock prices (Adnan, 2021).

CONCLUSION

Decision making for investing in stocks is a complex challenge that investors face. As a result, it necessitates making future predictions to serve as a guide. Because of the rapid fluctuations in stock prices, most traditional models fail to predict them. In this paper, we propose an artificial neural network-based model for predicting the closing prices of top-six traded industrial ISX-listed stocks. ANN have the advantage of not requiring any prerequisites for time series stability. Experimentation has shown that increasing the training times improves model accuracy, but not always, as overfitting can occur. The empirical study demonstrated neural networks' high accuracy in time series modelling of closing prices for six stocks. This confirms the feasibility of using neural networks to predict stock prices on the Iraqi Stock Exchange, and thus their use in investment decision making.

RECOMMENDATION

The experiment was restricted to six industrial companies listed on the Iraq Stock Exchange. The researchers suggest that neural network technology be used to predict stock prices, as well as expanding the range of experiments and including other stocks, based on the findings of the experiments.

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