INTERNATIONAL JOURNAL OF RESEARCH IN SOCIAL SCIENCES & HUMANITIES

An International Open-Access Peer Reviewed Referred Journal

Impact Factor: 8.909 E-ISSN : 2249 – 4642 P-ISSN: 2454 - 4671

Estimating Stock Returns Using Artificial Neural Networks: An Experimental Design With An Evidence From Iraq Stock Exchange

***Mohammed H. Adnan, **Prof Mustafa Muneer Isma'eel, PhD**

*Northern Technical University, Mosul, Iraq

**College of Administration and Economics / University of Baghdad

DOI: http://doi.org/10.37648/ijrssh.v11i02.017

Paper Received:

21st April, 2021

Paper Accepted:

30th May, 2021

Paper Received After Correction:

31st May, 2021

Paper Published:

01st June, 2021

How to cite the article: Mohammed H Adnan, Mustafa Muneer Isma'eel, Estimating Stock Returns Using Artificial Neural Networks: An Experimental Design With An Evidence From Iraq Stock Exchange, April-June 2021 Vol 11, Issue 2; 316-334 DOI: http://doi.org/10.37648/ijrssh.v11i02.017

ABSTRACT

The research aims to estimate stock returns using artificial neural networks and to test the performance of the Error Back Propagation network, for its effectiveness and accuracy in predicting the returns of stocks and their potential in the field of financial markets and to rationalize investor decisions. A sample of companies listed on the Iraq Stock Exchange was selected with (38) stock for a time series spanning (120) months for the years (2010_2019). The research found that there is a weakness in the network of Error Back Propagation training and the identification of data patterns of stock returns as individual inputs feeding the network due to the high fluctuation in the rates of returns leads to variation in proportions and in different directions, negatively and positively.

Key words: *stock returns, closing prices, neural networks, Error Back Propagation network.*

INTRODUCTION

The activities of common stock trading are based on expectations of their future returns, which are reflected in the importance of estimating the future returns of stock in order to enable investors make investments decisions in common stocks to achieve the highest possible returns resulting from those investments. Investors are increasingly trying in various classical and modern financial theories and in the presence of financial markets to find effective and efficient methods for estimating future returns of stock.

As investors resort to technical analysis methods of the financial markets concerned with estimating stock indices and their movement using historical data and representing them in graphical forms, as well as basic economic analysis that deals with prominent economic indicators contribute to making investment decisions.

Several recent studies have emerged to use more diverse methods for estimating future returns of stock, including the use of genetic algorithms and fuzzy sets, as well as rough set theory and neural networks in an attempt to obtain more accurate results in estimating future returns of stock. Which called for an effective study the Neural networks in estimating the expected returns of stocks in a simulation of the human mind based on artificial intelligence and machine learning programs to facilitate the task of applying complex methods and models with computer aided.

A study conducted by (Vanstone, 2005) analysis of trading in the Australian stock market using artificial neural networks indicated that trading systems developed using neural networks can be used to provide economically significant returns. To predict the direction of movement of the stock price index using artificial neural networks and vector support machines, the average performance of the artificial neural network model is better than the support vector model.

(Qiu & Akagi, 2016) have studied the application of an artificial neural network to predict return stock revealed that the accuracy of prediction has improved significantly using the traditional BP Error Back Propagation training algorithm. The study (Sorayaei & Gholami, 2016) indicated the effectiveness of the artificial neural network method over the regression method in predicting stock prices in an attempt to provide an effective model for predicting stock prices using artificial neural networks.

in the financial market.Mathen

On the contrary, the study by

(Björklund & Uhlin, 2017) has reached to adifferent results, and it did not reach any evidence that the proposed model can accurately predict artificial neural networks to predict financial time series and improve the portfolio. Johnsson, (2018) agreed that the results showed no evidence of neural network prediction and the superiority of any of the stock indices in verifying whether ANNs outperform the traditional ARCH models.

While studies of hybrid models using the theory of rough set and artificial neural networks, including the study (Si et. al, 2014), indicated that the proposed approach to classification and prediction was feasible and accurate and outperforms other models through the integration of rough set and the Error Back Propagation network. The study (Lei, 2018) agreed that the performance of the prediction model improved and the structure was greatly simplified when using a hybrid prediction model based on reducing the dimensions of conditional features according to the theory of rough set of the stock price trend and forecasting using artificial neural networks.

Rather et. al, (2015) of the repetitive neural network and a hybrid model for forecasting stock returns revealed that the prediction performance of the proposed hybrid prediction model was superior to the recurrent neural network. The study (Waheeb, 2019) confirmed that the use of hybrid models with artificial neural networks achieves a higher accuracy of predicting the time series of the self-regression model of the NARMA moving average by presenting error determinants of the neural networks.

On this basis, interest in the topic of research was preferred in an attempt to apply scientific fields, models, methods and a variety that support the field of business administration, especially the financial field because of its great importance in the field of business and its nature affected by multiple fields of knowledge.

The choice was to use neural networks in estimating the future returns of stocks for a sample of the Iraq Stock Exchange companies and to ensure their accuracy in estimating the results.

The cognitive structure of research contributes to supporting financial thought and improves forecasting processes due to its cognitive properties. Thus, the research seeks to know, apply and explore modern models and methods in financial markets in an attempt to achieve a cognitive advantage in this field as well as support researchers and those interested in the field. Financial markets withthose models.

Based on that, the importance of

research is highlighted in an attempt to help those interested in financial thought and specialists in financial markets in diversifying methods of forecasting future returns of stocks.

In order to achieve the objectives of the research and study its idea the theoretical and experimental level, the research in the first section included a literature review of a set of previous studies in financial thought that included the use of artificial neural networks.

The second section includes the theoretical aspect of the research, the framework of artificial neural networks, the rationale for their use in estimating the returns on stock, and the structure of artificial neural networks.

The third section included a presentation of the research methodology as well as research data and experiment method.

The fourth section deals with the experimental aspect of the research represented in the results of estimating returns using artificial neural networks, as well as a discussion of the results of the research.

The fifth section contains a conclusions that convert the results of quantitative measurement into intellectual content that can be inferred.

NEURAL NETWORKS AND THE RATIONALE FOR THEIR USE TO ESTIMATE STOCK RETURNS

The use of artificial neural networks had its roots in neurobiological studies more than a century ago. For many decades, biologists have speculated on simulating how the human nervous system works (Mehrotra. et. al, 1997). Artificial neural networks are within machine learning science and a subset of artificial intelligence that works on learning by discovering patterns and trends in data that go beyond simple analysis (Johnsson, 2018).

Artificial neural networks have been defined as a computational structure that works in some way to simulate the human mind, and is designed to determine the basic direction of the data and generalize from it, and the artificial neural networkis considered a non-linear statistical data tool. The complex relationship between outputs and inputs can be modeled using artificial neural networks (Hiransha. et.al, 2018).

It is difficult to predict stock market data using traditional time-series analysis of the nature of the stock market and its dense data and major influences, instability, difficulty of regularity, great uncertainty, and hidden relationships, which resembles the behavior of financial time series with random walking (Chang et. al, 2009).

Investors seek to obtain highly accurate forecasts of change in share prices, with the aim of making good decisions and achieving financial returns for stocks, because the main issue in stock market forecasts is one of the priorities of investors. Artificial neural network models provide assistance to investors in this task to achieve greater wealth, which calls for a constant search for this superior system that will yield high returns (Asadi et .al, 2012).

Neural networks have proven to be better effective classifiers than methods based on classical statistical methods in various financial and other fields. It is important for investors to classify investment opportunities in the stock market as acceptable or unacceptable risks, and neural networks provide more accurate assessments (McNelis, 2005).

(Fischer & Krauss, 2018) emphasized that the financial models used to find a relationship between prediction signals for current and future returns are often unable to capture complex non-linear correlations, and on this basis justify the selection of artificial neural networks and their use for the purposes of predicting returns Stock.

The Architecture of Artificial Neural Networks

Artificial neural networks are built in different ways and the architecture of the arti ficial neural network is defined by the way neurons link with each other to form th e network, and the basic units of a neural network are called neurons and links with corresponding weights. Neurons appear in the form of circles containing a numeri cal value, and all neurons are linked together Some are by means of connections th at have a certain weight (Lund & LØvẩs, 2018).

Neural networks consist of a set of layers containing neurons that operate in a parallel manner, and the components of the network structure are illustrated as follows (Panchal & Panchal, 2014; Ramezania et. al, 2019):

1) **The input layer:** The input layer contains many neurons that communicate with the external environment and present a pattern for the neural network.
2) **The hidden layer:** It represents the middle layer between the input and output layer and includes the hidden nodes or hidden neurons that do not exist in the input layer or the output layer. Hidden and activation function within the hidden layer, with the activation function determined according tothe specific requirements of the search problem.
3) **Output Layer:** The output layer of a neural network represents what

outputs actually provided to the environment outside the network architecture and the number of neurons produced should be directly related to the type of work the neural network has to do.

Error Back Propagation Network

The Error Back Propagation algorithm is more reliable for modeling nonlinear dynamic financial market signals and tailoring weights most capable of achieving network targets, based on an estimate of the slope of the sum of the square of error for each layer (Mammadli, 2017). This type of artificial neural network includes one or more feedback loops, which can be in one or several layers, and each neuron whose output returns to the input of all the remaining neurons (Ashour. et. al, 2018). That is, it finds a back way for its outputs to become input again for the purpose of obtaining the best possible results(Ramo, 2019).

The Error Back Propagation network is one of the effective networks for financial forecasting and time series purposes in forecasting future stock prices and saves a lot of effort and time for forecasting in estimating stock returns (Das et. al, 2019). The algorithm of the Error Back Propagation network is being trained in three phases, which are illustrated as follows (Zahedi & Rounagh, 2015):

1) **The forward error propagation stage:** the input signal at this stage moves towards each node of the hidden layer, and the activation value is calculated for each node of the hidden layer, and then those signals are sent to the output layer (Zahedi & Rounagh, 2015). Each node in the hidden layer groups its weighted signal according to the following equation (Ashour et.al, 2018):

$$hj = \frac{2}{(1+\exp(\sum xiwij))} - 1 \quad \text{....(1)}$$

The activation formula is applied to estimate the output of the hidden layer, then the activation values are sent to all nodes in the output layer, and each node in the output layer collects its weighted signal according to the following equation (Ashour et. al, 2018):

$$yk = \frac{2}{1+\exp\,(\sum hjwjk)} - 1 \quad \text{....(2)}$$

2) **The stage of Error Back Propagation:** Each node in the output layer compares the calculated activation value with the actual output value and calculates the error value, and on this basis the error correction factor (Zahedi & Rounagh, 2015). Is calculated by

finding The difference between the activation values or the output values and the target value according to the following equation (Ashour et. al, 2018; Ali & Hassan, 2018):

$$Ek = tk - yk \quad ....(3)$$

The network output is compared to the actual value of the error estimation by means of the equation(Ashour et. al, 2018):

$$\delta k = (tk - yk).f(v) \quad ....(4)$$

Where f (v) is the logistic equation when the nonlinear output node is equal to 1 and the equation is linear, after which the change in the error value is calculated using the following formula (Ashour et. al, 2018):

$$\Delta wjk = a.\delta k.hj \quad ...(5)$$

All nodes in the hidden layer aggregate the referenced input weighted values using the following equation (Ashour et. al, 2018):

$$\Delta j = \delta \sum_j kwjk \quad ...(6)$$

This value is then multiplied by the activation equation to calculate, and then the error value is changed using the following equation (Ashour et.al, 2018):

$$\Delta Vjj = a.\delta j.xi \quad ...(7)$$

3) The weights update stage: The back propagation algorithm adapts theweights of the network at this stage in order to adjust the weights and process the data (Lalithamma & Puttaswamy, 2013: 2), in the output layerby applying the equation (Ashour et. al, 2018):

$$Wik(new) = Wik(old) + \Delta wik \quad ...(8)$$

updating the weight for all nodes in the hidden layer according to the formula (Ashour et. al, 2018):

$$Vij(new) = Vij(old) + \Delta Vij \quad ....(9)$$

The calculation and updating steps of the training process are repeated until the optimum weight is reached, and thus the target outputs are reached Learning (Ramos & Martínez, 2013).

Estimating Stock Returns Using Artificial Neural Networks

Neural networks can deal with multiple application areas including stock market behaviors, basic stock market indicators, GDP, interest rate, gold prices, exchange rates and technical indicators, including closing prices, opening prices, higher prices and lower prices. Using neural networks to help improve prediction processes (Chaigusin, 2011). Stock price indices include indicators (opening and closing prices, highest price and lowest price) for each company traded in the market for a certain period daily, weekly or monthly, thus forming the time series for the share price for a specific period and predicting future stock returns (Zahedi & Rounaghi, 2015).

Designing a neural network that predicts the financial time series requires a carefully thought-out process to select the large number of parameters that must be decided by making eight steps for designing neural networks for financial time series prediction as follows (Björklund & Uhlin, 2017):

1) **Selection of variables (inputs and outputs):** Researchers take into account the selection of the basic and technical factors of the stock markets, and the goal or outputs required may be more sensitive to many inputs or factors, and that all the data available as inputs may not improve the prediction of their results (Chaigusin,2011).
2) **Collecting data:** After determining the required inputs in the first step, the financial asset data as well as the basic data are collected through the financial market database and bulletins, focusing on the indicators and data required as inputs, as well as determining the time horizon for the analysis (Björklund & Uhlin, 2017).
3) **Data preprocessing:** Data is scanned for missing values, and multi-layered neural networks can find patterns or patterns between inputs and outputs without any preprocessing of the data used, and are also suitable for tasks that contain incomplete or incomplete data. Insufficient or ambiguous, however it is recommended to pre-process data when performing actual neural networks, to improve application performance (Chaigusin, 2011).
4) **Training and Test Sets**: The dataset of stock returns is divided into subsets in the design of the first neural networks to train the network in the framework of identifying patterns in the data. The second is a sample test algorithm that will serve as the basis for the decision to choose the grid configuration that provides the best predictive accuracy of the time series (Björklund & Uhlin, 2017).
5) **Structures of neural networks:** The structure of a neural

network refers to how the network is organized, and the components of the network can be divided into three dynamic groups of layers: the input layer, the hidden layers and the output layer, as well as the important design parameter is the activation function that determines how to transform Data between nodes and the choice of this function depends on the form of the required output data (Björklund & Uhlin, 2017).

The basic problem of structuring the neural network model is to determine the number of hidden layers, the number of hidden nodes, the number of output nodes and activation functions, and determine the number of output nodes according to the target or desired output (Chaigusin, 2011).

1) **Neural network training:** Determinants should be provided for the purpose of achieving network goals for a training data set as inputs and outputs associated with supervised learning allowing for the computation of optimal weights between neurons for the network to be able to recognize patterns in the data. Training is carried out to find a set. Weights that reduce the error function (Björklund & Uhlin, 2017).

2) **Evaluation criteria:** Verification problems generally relate to the ability of neural network models to handle data outside of training data and have accurate predictive performance. Validation of neural network models is related to the generalization that is the goal of artificial neural network models (Chaigusin, 2011).

3) **The eighth step, implementation:** the actual implementation of the artificial neural network in order to achieve the desired results from the use of the artificial neural network and achieve the purposes of forecasting the returns of stocks and other financial market indicators. (Björklund & Uhlin, 2017).

METHODOLOGY

The experimental aspect of the research includes the pillars of applying quantitative and experimental analysis of the research. It appeared from the research sample, the nature of the data, the time horizon, and the results of forecasting stock returns using artificial neural networks, and discussing them in comparison with previous studies.

Research Sample and Data

The research data included indicators of monthly stock returns represented by the percentage change in stock prices from historical data bulletins for the Iraq Stock Exchange. The research sample was (38) stock of companies listed on the Iraq Stock Exchange. They were selected according to the stock of companies with the lowest trading stops for the period from January 2010 to December 2019, with a rate of (120) months. The search period amounting two (120) months included interruptions in trading in the stock of companies led to the loss of some values of the closing prices of those stocks as a result of the monthly trading interruptions. The missing value data for stock closing prices were compensated by the double exponential smoothing method using the "Minitab17" program, and then the return on stock of the research sample companies was calculated according to the following formula (Qiu et. al, 2016):

$$y_t = \frac{P_t - P_{t-1}}{P_{t-1}} \qquad \ldots(10)$$

Executing The Process of Estimating Stock Returns

The stock returns were predicted by using the Error Back Propagation network by creating the network training algorithm using the "Matlab12" program. The data set amounting (120) months for the stock sample and for each time series for stocks were divided into 75% to train the network and identify data patterns. The network training data start from January 2010 to June 2017. While the percentage of test data is 25%. From July 2017 to December 2019, for the purpose of testing the network's training on the prediction process and reaching better results to predict stock returns, as recommended by the literature in previous studies. The data were normalized for the input and output when the Error Back Propagation algorithm was programmed to obtain the best results in the prediction process.

RESULTS AND DISCUSSIONS

Table (1) presents the results of estimating stock returns by using the Error Back Propagation network to estimate stock returns for companies, the research sample of 38 stock, as well as the statistical indicators of the process of estimating stock returns. And from it the estimated percentage of return per share and the error coefficient of the prediction process, as well as the best training for the network at the average square error specified for network learning, The results of estimating the stock returns of the research sample companies, respectively, according to their arrangement in Table (1) to (0.159 ,-0.165 , -0.068 ,-0.025 ,0.028 , 0.128 , -

0.262 ,-0.012, -0.023 , -0.1 , 0.08 , -0.001 , 0.02 , -0.045 ,-0.048 , -0.039, 0.1 , -0.016 , 0.202 , 0.024, 0.159 , 0.132 , 0.003 , 0.297 , 0.243 , 0.197 , 0.212 , 0.023 , 0.278, 0.143 ,0.091 , 0.02 , -0.024, -0.094 , 0.2 , -0.054, 0.103, 0.059).

Positive return rates for stock were (23) stock for companies in the research sample in the Iraq Stock Exchange and for various sectors. While the estimated returns of stock in negative proportions (15) stock of the companies in the researchsample in the Iraq Stock Exchange and for various sectors.

It is evident from Table (1) that the highest rate of return on stock estimated according to the network of Error Back Propagation was (0.297) for the stock of *National Chemical & Plastic Industries* and the error coefficient was (0.26). While the best performance rate was at the mean square error (0.65) and the regression coefficient for training the network was (0.58).

While the lowest rate of stock returns was estimated for *Credit Bank of Iraq, stock,* with a negative change rate (-0.262), with an error coefficient (0.22), and at the best performance at an average. The square error is (0.69) and the regression coefficient is (0.54).

Table (1) Results of estimating stock returns using a Error Back Propagation

No	Stock Name	Return	Err	performance	Regression
1	Commercial Bank of Iraq	0.159	0.16	0.69	0.54
2	Bank Of Baghdad	-0.165	0.16	0.85	0.37
3	Iraqi Islamic Bank	-0.068	0.07	0.81	0.42
4	Iraqi Middle East Bank	-0.025	0.14	0.87	0.34
5	Investment Bank of Iraq	0.028	0.10	0.87	0.34
6	National Bank of Iraq	0.128	0.20	0.79	0.44
7	Credit Bank Of Iraq	-0.262	0.22	0.69	0.54
8	Babylon Bank	-0.012	0.12	0.8	0.42
9	Gulf Commercial Bank	-0.023	0.06	0.85	0.37
10	Kurdistan International Bank	-0.1	0.11	0.87	0.33
11	Ashur International Bank	0.08	0.10	0.8	0.42
12	Al-Mansour Bank	-0.001	0.06	0.69	0.54
13	united Bank For Invistment	0.02	0.14	0.89	0.31

14	**Al-Ameen for Insurance**	-0.045	0.10	0.82	0.40
15	**Kharkh Tour Amuzement City**	-0.048	0.07	0.46	0.72
16	**Mamoura Realestate Investment**	-0.039	0.05	0.84	0.38
17	**AL-Nukhba for Construction**	0.1	0.10	0.81	0.42
18	**Iraq Baghdad For General Transportation**	-0.016	0.05	0.85	0.32
19	**Al-Mansour Pharmaceuticals Industries**	0.202	0.19	0.84	0.38
20	**Modern Sewing**	0.024	0.10	0.93	0.24
21	**Iraqi For Tufted Carpets**	0.159	0.16	0.8	0.43
22	**Baghdad for Packing Materials**	0.132	0.13	0.93	0.23
23	**Baghdad Soft Drinks**	0.003	0.05	0.55	0.66
24	**National Chemical &Plastic Industries**	0.297	0.26	0.65	0.58
25	**AL- Kindi of Veterinary Vaccines**	0.243	0.23	0.83	0.39
26	**Iraqi Engineering Works**	0.197	0.19	0.78	0.46
27	**Metallic Industries and Bicycles**	0.212	0.25	0.3	0.83
28	**Ready Made Clothes**	0.023	0.11	0.67	0.56
29	**Babylon Hotel**	0.278	0.24	0.51	0.69
30	**Baghdad Hotel**	0.143	0.14	0.87	0.34
31	**National for Tourist Investment**	0.091	0.08	0.68	0.55
32	**Karbala Hotels**	0.02	0.06	0.84	0.38
33	**Mansour Hotel**	-0.024	0.05	0.46	0.72
34	**Al-Sadeer Hotel**	-0.094	0.10	0.75	0.48
35	**Modern for Animal Production**	0.2	0.25	0.75	0.48
36	**Middle East for Production- Fish**	-0.054	0.07	0.96	0.17
37	**Iraqi Products Marketing Meat**	0.103	0.16	0.35	0.79
38	**Iraqi Agricultural Products**	0.059	0.07	0.86	0.35

The results of the forecast encourage investors to buy stock of companies that are likely to yield positive returns and push them to sell or to avoid investing in stocks that are likely to yield negative returns. This contributes to increasing shareholders' wealth and achieving investment objectives according to the traditional theory of investor behavior towards risk. Researchers use various financial and statistical models and analyzes and forecasting methods, including artificial neural networks, to guide investors' investment decisions. However, most methods and methods of estimating stock returns are not without forecast errors and may include inaccurate forecasting estimates that push investors to make the wrong investment decision. Therefore, the diversity and multiplicity of prediction methods aim to find the model or method that achieves the lowest error rate and provides high accuracy for prediction, and this is what researchers seek in the tests of models and methods in an attempt to develop prediction methods to reach the best possible results.

Despite the normalization of the data when programming the algorithm of the Error Back Propagation network, the statistical results of the error rate (Err), the best network performance (performance) and the level of network learning represented by (Regression) in Table (1) indicate weakness. Training the network on the pattern of the data in question represented by the monthly stock returns for the sample of companies in the Iraq Stock Exchange. This is due to the nature ofthe data, fluctuating between positive and negative values in decimal values of returns.

The validity of the Error Back Propagation network algorithm was validated by using it to predict the pattern of the closing price index for the same time series andfor the same stock. Results better statistical of the network training were achieved for the same time series, although the rate of return per share is calculated according to the percentage change in the closing price index. The nature of the data for closing prices does not contain negative values, which facilitates the prediction process on the artificial neural network.

To make sure of this, we conduct a comparison to test the level of network learning on the stock of the "*Middle East for Production- Fish company*". Because it achieved the worst network training rate (0.17), which represents the worst training of the network for the stock of the research sample and figure. (1) The training rate of the network, according to the company's return to stock index shows:

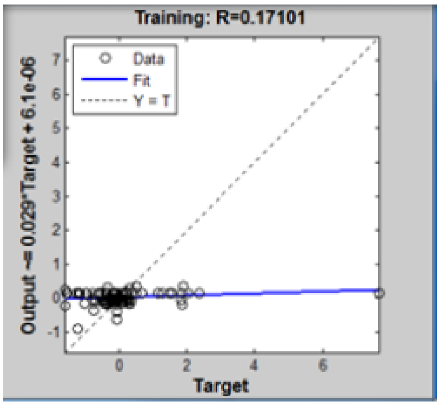

Figure (1) Training rate for network prediction according Stock return index for the Middle East for Production- Fish company

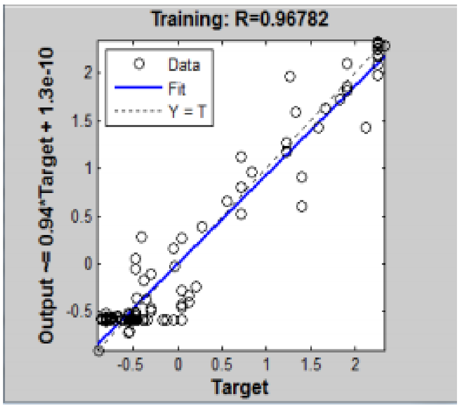

Figure (2) Training rate for network prediction according to the closing price index for Middle East for Production- Fish company

On the contrary, Figure (2) shows a better statistical indicator of the training rate for the same time series to predict the closing price index of (Middle East for Production- Fish) with a training rate of (0.96). This indicates the network's ability to train in the pattern of closing price data better than stock returns data with its decimal fractions.

The results of the research in a study of the effectiveness of using neural networks to predict stock returns are consistent with a study (Björklund & Uhlin, 2017), which showed that artificial neural networks did not reach any evidence that the proposed model of artificial neural networks can accurately predict prediction. Financial time-series and portfolio optimization.

In addition to a study (Johnsson, 2018), whose results revealed that there is no evidence of the superiority of predicting the use of neural networks for stock indicators and verifying whether they outperform the traditional ARCH models in predicting Weekly stock index volatility.

CONCLUSIONS

The research readings in presenting the literature of artificial neural networks and their justifications showed their use to predict stock returns and their role in improving forecasting models, as well as the experimental results obtained after testing the data. The study sample in the Iraq Stock Exchange reached an intellectual product that can be inferred to develop and improve methods of forecasting Stock returns.

Numerous studies by researchers that were used to review the literature on the use of artificial neural networks for the purposes of prediction, stock returns, and time-series estimates, confirm the accuracy and effectiveness of artificial neural network models. Especially when used with hybrid models, the results of forecasting stock returns can be improved. Even when using neural networks alone for financial forecasting purposes, some studies have confirmed their accuracy and effectiveness.

The research showed the failure of neural networks to predict stock returns and identify patterns of data without the use of hybrid models and specific data from stock returns and a sample of companies in the Iraq Stock Exchange.

The weakness of the network of Error Back Propagation was shown to estimate the returns of stock, according to the statistical indicators for evaluating the network.

When comparing the results with the use of inputs that include closing price data for the same stocks and the same time series, the network's ability to predict and have good statistical indicators is evident, in contrast to what the results of forecasting stock returns showed. Which means that the nature of the fluctuating data of the returns of stock, negatively and positively, limits the ability of the network in the process of training and predicting the returns of stock.

Thus, the use of neural networks to predict stock returns can be studied by learning the network and training it on multiple inputs that affect stock returns, or by using hybrid models that help the artificial neural network improve the prediction process in stock returns.

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