Prediction of Iraqi Stock Exchange using Optimized Based-Neural Network

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Abstract

Stock market prediction is an interesting financial topic that has attracted the attention of researchers for the last years. This paper aims at improving the prediction of the Iraq-Stock-Exchange (ISX) using a developed method of feedforward Neural-Networks based on the Quasi-Newton optimization approach. The proposed method reduces the error factor depending on the Jacobian vector and Lagrange multiplier. This improvement has led to accelerating convergence during the learning process. A sample of companies listed on ISX was selected. This includes twenty-six banks for the years from 2010 to 2020. To evaluate the proposed model, the research findings are compared with other standard prediction techniques. It was found that the developed research model outperformed other prediction techniques according to the accuracy and root-mean-secured-error measures.

Keywords

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1. Introduction

The stock market (SM) analysis is a hot area of research for scholars and inventors. This is because the stock market prediction price still represents an issue in the financial time series that needs to be addressed [1]. SM is an effective part of any country's economy. It plays a significant role in the industry and this, in turn, affects the country's economic growth. SM is a public place where companies are allowed to trade money through the sale or purchase of shares and stocks after determining the price agreed upon in advance [1]. Because the connection between inputs and outputs is variable, nonlinear, and volatile, the estimation of stock market future values has become a hard task. Choosing a suitable training and prediction method is also still a very critical problem [2,3].

The SM prediction is a process of concluding the future value of a stock's company based on its historical data. Two ways can be followed to meet this aim. First, the fundamental analysis must be determined by mathematical data of a particular company [4]. Second, technical analysis can be conducted by Technical Indicators (TIs) and machine learning. Numerical factors such as daily ups and downs, the volume of stock, tendency pointers, the highest and lowest prices of a day, directories, simple moving average, etc. can be used. Previous literature has attempted to discover some accurate arithmetic models that can allocate these inputs to predict the desirable outputs [5]. There are many examples of these models. However, the neural network technique has been widely adopted.

Neural Network (NN) has been used in several different areas such as financial forecasting, signal processing, and pattern recognition. It has been widely used due to its successful classification and regression in SM predictions [6]. However, NN algorithms may fail to predict SM precisely. This is because stuck is in local minima, which can generally use the learning rate to avoid this problem. On the other hand, choosing the incorrect value of the learning rate can lead to another problem. If the value of the learning rate is large, the overshooting problem will appear, whereas if its value is small, the convergence speed will be very slow [7].

Based on this discussion, other several methods are available to address such issues in which the Quasi-Newton optimization approach is one of them. This approach depends on the second derivative to avoid falling into local minima. Moreover, learning parameters can be automatically adapted [8].

The key motivations of this research are: (1) Predicting stock market is a very complex task, (2) Where and how people can invest their money is a problem that many individuals face, and (3) The stock market affects the economy of the country [9]. According to these motivations, this research sought to achieve many objectives. First, find out the hidden patterns that may affect the stock market using machine learning algorithms. Second, building a forecasting model that can consistently predict the future value of stocks with greater accuracy. It is expected that this can lead to better business decisions and earn money. Third, it is clear that the SM data are huge, chaotic, non-linear, dynamic, non-stationary, noisy in behaviours, and have a low correlation between attributes and the target of prediction. Such issues are also addressed in this research. Finally, another objective is building an organized SM dataset for Iraq.

To meet the research objectives mentioned above, this research improves the convergence speed in the training of standard Multilayer Perceptron NNs (MLP-NN) that use the Back-Propagation (BP) algorithm, by using the Quasi-Newton method instead of Gradient Descent. Accordingly, this study designs a new prediction model, which can predict the closing price of the stocks as well as giving a decision to sell, buy, or wait for stocks and produce high accuracy in a reasonable time.

The rest of this paper is organized as follows. Section two reviews related work on various data mining techniques of stock market prediction. Section three discusses the proposed research methodology to build the classification model. In section four, the proposed system is explained. Section five reports and discusses the research findings. Finally, section six concludes the key findings of this research.

2. Related work

A review of current techniques is accomplished here for stock market prediction using machine learning and technical analysis.

In [10], the authors reviewed most and the latest papers on SM forecasting using machine learning. The relevant papers are divided into several groups in terms of relevant datasets, inputs, pre-processing methods, techniques and methodologies, prediction methods, and evaluation criteria. The most prominent and widely used

methods are NNs. The researchers also presented the limitations of most technologies used to predict SM. It was indicated that NNs have poor learning on data patterns or their performance may be unexpected or inconsistent due to the complexity of stock exchange data.

As such, the researchers present here some of the previous literature that attempts to improve or outperform NNs for forecasting SM.

In [11], the authors evaluated and compared Long-Short Term Memory LSTM deep learning architectures specifically Stacked and Bidirectional LSTM with shallow NNs and unidirectional LSTM for long-term and short-term prediction of SM. The results showed that both Bidirectional LSTM and Stacked LSTM networks performed better in short-term price prediction than long-term forecasting results. The outcomes also showed that deep learning is better than shallow NNs in predicting SM.

In [12], the authors designed a new stock price prediction system based on a random forest model that predicts both the movement of the stock price and the rate of growth (or decline) at intervals within predefined forecast periods in the China Market. The historical data of each stock was cut into multiple Clips with a predetermined prediction length. This process was done by using a sliding window method. Then, the unsupervised heuristic algorithm was utilized to classify the shapes that appear in the close prices of these Clips into four main classes which are Down, Up, Flat, and Unknown. The results showed an improvement in the forecasting of market volatility as well as better accuracy and return per trade.

According to Hiransha et al. (2018) [13], a group of four kinds of NNs named LSTM, Convolutional Neural Network (CNN), Recurrent Neural Networks (RNN), and Multi-Layer Perceptron (MLP) was implemented. Two stock markets were taken to check the performance of the price prediction. From National Stock Exchange (NSE) market, the collected dataset includes three various sectors: IT, Automobile, and Banking, whereas from the market of the New York Stock Exchange (NYSE), the Petroleum and Finance sectors were selected. The obtained results were compared with the Auto-Regressive Integrated Moving Average (ARIMA) model. It was observed that NNs are superior to the current linear model ARIMA.

In [14], the authors proposed a model based on the integration of NNs with Fuzzy logic ANFIS. The Amman Stock Exchange (ASE) index prices data were used in this research. Different models were compared in which Relative Strength Index RSI, Stochastic Oscillator OS, Moving Average Convergence/Divergence MACD,

and On Balance Volume (OBV) as input indicators were used in this research. The results proved the enormous capabilities of NN and fuzzy logic architecture such as ANFIS to implement time series forecasting as a task for forecasting the direction of stock prices in the ASE.

In [15], the authors used Ant Colony Optimization (ACO) to train the NN instead of the Gradient Descent optimization in predicting stock prices in the Nigerian Stock Exchange. The ACO was also compared with three other algorithms which were Moving Average, Price Momentum Oscillator, and Stochastic. The research findings reached the superiority of the ACO method in accuracy over the other methods implemented.

In [16], the authors evaluated and compared a hybrid model consisted of merging NN technology with Grey Wolf Optimization (NN-GWO) and a standard NN. These models have been applied to the Bombay Stock Exchange dataset in a period time from 2005 to 2018. After using different evaluation error measures, the results showed that the hybrid NN-GWO model is better than the traditional NN model.

In [17], the authors proposed a prediction model based on artificial NNs to predict stock returns for thirty-eight companies listed on the Iraq Stock Exchange during the period from 2010 to 2019. After training the network using the BP algorithm, they found a weakness in its performance and its inability to distinguish between stock returns data patterns when it was used as individual inputs to the network. The reason was that return rates had a large fluctuation, which led to a discrepancy in proportions in different directions, positively and negatively.

In [18], the authors applied the ARIMA model to predict the Iraq Stock Exchange Index. Statistical methods were also used such as arithmetic average, percentage change, T-test, scatter plot, Q plot, and the autocorrelation coefficient. The research dataset consisted of 102 companies listed in ISX. These companies were divided into seven sectors Communications, Banks, Insurance, Industry, Services, Agriculture, and Hotels. The study period was from 1/1/2019 to 12/31/2019. It was found that the model was very good for predicting Iraq Stock Exchange Index with accuracy and reliability level equal to (95%).

In [19], the authors applied an adaptive fuzzy-neuro model to fifty-eight companies listed on the Dubai Financial Market and Abu Dhabi Securities Exchange for the period between 2014 and 2018. After examining four predictors: Return On Equity (ROE), P0ofit Margin (PM), Return On Asset (ROA), and Earning Per Share (EPS), the results showed that ROE was the most significant predictor and ROA was the least.

Table 1 briefly explains the techniques and methods, stock exchange data, periods, and evaluation metrics used in the previously reviewed literature. This leads to the conclusion that most of the earlier studies attempted to build a single model of prediction, either for classification or regression purposes. In this study, however, the proposed model aims at predicting the real price of the stock (regression) as well as providing a decision to buy, wait, or sell (classification).

3. The research methodology

3.1. Stock markets hypothesis

Several important hypotheses of a market should be suggested in any prediction system.

• Efficient Markets Hypothesis

The efficient Market Hypothesis (EMH) confirms that market efficiency operations involve all related pieces of evidence, and it causes all available information to be absorbed at any given time. Moreover, the theory of market efficiency Fama can produce three levels: weak, semi-strong, and strong [20]. These levels refer to the information set used in the statement "prices reflect all available information". The weak EMH assumes that weak stock prices already incorporate all historical data prices. The semi-strong level reflects current available public information and all historical data prices. The efficient strong market hypothesis is supposed to include private information that is hidden within the stock price. According to EMH principles, by including both public and private historical information and the current price, it is impossible to regularly outperform the market [20].

• Random Walk Theory

This theory defines the perception to predict the price differently. Stock prices are inconsistent in this approach in which they are based on other features, although they have the same distribution.

Thus, past movements or trends in asset prices cannot be used to predict future behaviour. Overall, the random walk theoretical basis hypothesis of the theory looks like the semi-strong efficient market in which public information is supposed to reach everyone [21]. This theory says that the costumer's natural behaviour of the market and the most possible one is a random walk, which would suggest that the predictions are not possible.

• Analysis Philosophies

Research currently revealed that the market prices do not follow the principle of random behaviour and predicting the financial market is possible [22]. In the analysis philosophy world, there are two major trading philosophies. The philosophy of fundamental analysis is determined by the mathematical data of a company. It may include sales data, the financial status of the company, import-export volume, audit reports, strength and investment of the company, plant capacity, the competition, terminal balance slips, and production indexes [23]. On the other hand, the technical analysis philosophy predicts future prices by using historical time series data. The favourite idea investors tend to follow the preceding investor behaviour. Therefore, technical analyses are based on this idea. Comparing volumes and historical prices average actions with the current volume and price can complete profitable opportunities. Technical analysis also generates TIs such as Moving Averages, Relative Strength, Rate of Change Index, Moving Average Convergence Divergence, Commodity Channel Index, etc. These indicators have helped traders to determine if the assets are oversold or purchase, or if the trend is weak or strong. Recently, TIs have been widely used in prediction systems as input based on machine learning techniques. This technique knows how to identify data complex patterns and predict prices and trends in the future [23].

• Financial Forecasting

Many machine learning techniques depend on numerical information about the market indexes and stocks which are utilized for markets forecasting. In this study, the researchers employed computational intelligence techniques such as (Artificial Neural Networks, K-Nearest Neighbour, Decision Tree, and Naive Bayes).

3.2. Stock market prediction techniques

• Decision Tree

Decision Tree (DT) is a common classification technique that depends on creating a structure similar to a tree. Their results are very interpretable because they generate rules which are easy to understand. Yet, the outcomes have to be represented in categorical data. As such, DT is less efficient for prediction when the features are numerical [24].

Table 1
Comparison of machine learning algorithms and techniques in financial stock price prediction.

References	Prediction Techniques	Stocks/Index	Data	Period time	Accuracy (%)	RMSE (%)
Althelaya et al. (2018) [11]	MLP, LSTM, Stacked LSTM (SLSTM), Bidirectional LSTM (BLSTM)	S&P 500	Historical daily stock prices (closing price)	01/01/2010 to 30/11/2017	N/A	Short-term: SLSTM: 0.01248 MLP: 0.03875 BLSTM: 0.00947 LSTM: 0.01582 Long-term: SLSTM: 0.06637 MLP: 0.09369 BLSTM: 0.06055 LSTM: 0.08371
Zhang et al. (2018) [12]	unsupervised heuristic algorithm and Random forest (RF), SVM, ANN, k-NN	Shenzhen Growth Enterprise Market in China	prices and technical indices	January 25, 2010, to October 1, 2016.	RF: 72.2 SVM: 61.5 ANN: 57.0 k-NN: 43.9	N/A
Hiransha et al. (2018) [13]	ARIMA, RNN, LSTM, CNN, MLP	National Stock Exchange (NSE) of India and New York Stock Exchange (NYSE).	day-wise closing price	NSE: 1 JAN 1996 TO 2015 June 30 NYSE: 3rd January 2011 to 30th December 2016	N/A	ARIMA: 19.64 RNN: 5.40 LSTM: 4.88 CNN: 4.05 MLP: 3.85
Mohammad et al. (2018) [14]	ANN, ANFIS, Wavelet ANFIS	Amman Stock Exchange (ASE)	Index of Banking Sector	2000–2014	N/A	ANN: 0.0614 ANFIS: 0.0098 ANFIS with wavelet: 0.0721
Ahmed et al. (2019) [15]	Ant colony optimization (ACO), Price Momentum Oscillator (PMO), Stochastic (St.), Moving Average (MA)	Nigerian stock exchange	Historical daily stock prices (closing price)	100 days	ACO: 0.812500 PMO: 0.677778 St.: 0.791667 MA:0.516854	N/A
Sahoo and Mohanty (2020) [16]	ANN and grey wolf optimization (GWO), ANN	Bombay Stock Exchange (BSE)	Historical daily stock prices (closing price)	25 August 2004 to 24 October 2018	N/A	ANN: 0.539518 GWO: 0.534562
Adnan et al. (2021) [17]	ANN	Iraq Stock Exchange (ISX)	Historical daily stock prices (stock return)	2010 to 2019	N/A	0.65
Azzam et al. (2021) [18]	integrated regression model of moving averages (ARIMA)	Iraq Stock Exchange (ISX)	ISX60	(1/1/2019) to (1/31/2019)	95%	N/A
Elfadil et al. (2021) [19]	ANN, Fuzzy logic	Abu Dhabi Securities Exchange and the Dubai Financial Market	Historical daily stock prices (closing price)	2014–2018	N/A	1.56

● **K-Nearest Neighbour**

Many machine learning methods use the concept of the lazy learning algorithm. This is the simplest one because it does not need any model in training. The model is built in which classification or prediction is required [25]. Therefore, KNN is one of the lazy learning types which predicts classes of the entity based on the K the nearest training instances in feature space. The classification of the KNN entity can be done by collecting the majority votes for its neighbours. However, determining the correct value of K in this method is considered a problem.

● **Naive Bayes**

The Naive Bayes Classifier is one of the unpretentious probabilistic models which depends on the Bayes rule along with a powerful assumption of independence. It involves simplifying the assumption of conditional independence. Meaning, class (negative or positive), and words are conditionally independent of each other. For its simplicity, this model is named "naive". The accuracy of the classification is not greatly affected by this assumption, but it makes the classification algorithms fast and applicable to the problem [26].

● **Multilayer Perceptron**

The multi-layer Perceptron (MLP) method is composed of neurons that have differentiable functions [27]. The network involves one or more hidden layers. They consume a high degree of connectivity which is determined by synaptic weights to analyse a large part of the difficulty of these networks as a non-linearity and high connectivity of their neurons.

Fig. 1 depicts that there are three main layers in the MLP-NNs. The input layer (1, 2.,. …, n) is the first layer that inserts a signal to feed the network nodes. The hidden layer (1, 2, …, h) is the second layer, whereas the output layer (1, 2 …,0) is the third one. The complete calculations of the system are done in the hidden layer. The results for that network are obtained from the third layer.

In addition, the network contains bias nodes (b_{hidd}) and (b_{out}). These are linked with the hidden layer and output layer respectively. Moreover, the network contains synaptic weight values $W_{in,hidd}$ which is the assigned among the hidden layer and input layer of that network, whereas $W_{hi, out}$ is the synaptic weight values assigned among the output layer and a hidden layer of the network. A supervised learning method called the
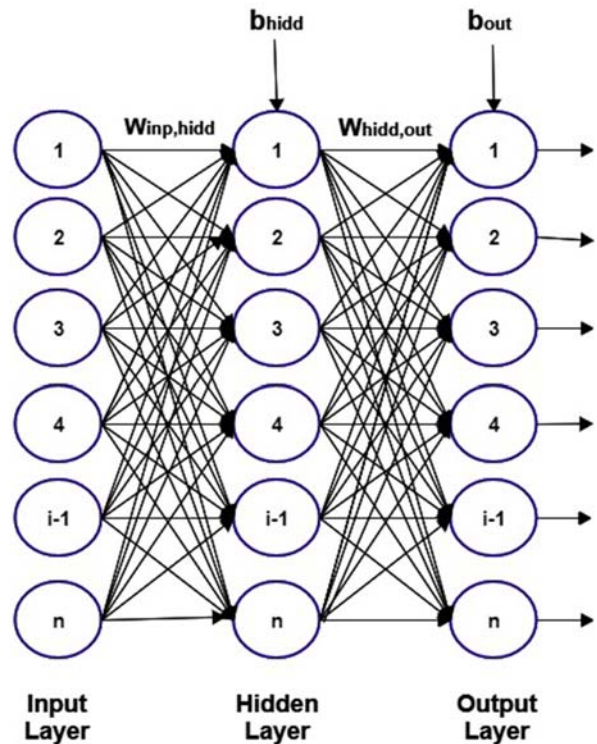

Fig. 1. The multilayer perceptron network [28].

BP algorithm is often used to train MLP. The overall network error was controlled and reduced by adjusting these weight values [28]. In this present study, the error is the average squared error among network simulated output and original output.

3.3. Optimization method

● **Gradient Descent**

Gradient Descent is an optimization algorithm that depends on the first derivative to find the local optimum solution for a differentiable function *f*: It simply follows the steepest descent from the current point by applying recursive steps in the opposite direction of the function gradient at the current point [29].

● **Newton's Method**

Newton's method requires explicit storage and computation of the Hessian matrix (H) and it attempts to find the point x, which is achieved based on the equation $f'(x) = 0$ by approximating the function (*f'*) to a linear function (q) and then explicitly solving the root of this function. The root of the q doesn't need to be the same as the root of *f'*, but it may be a good guess.
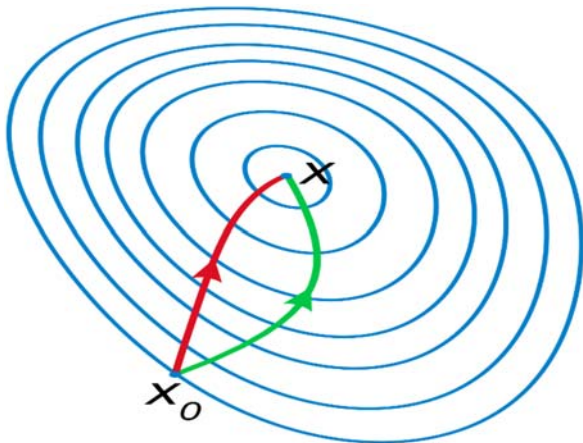
Fig. 2. A comparison of GD and Newton's method [31].

Although Newton's method uses the approximation of the first derivative f', it explicitly calculates the second derivative f'' (the curvature of f), so it needs higher requirements. In return, however, it will increase the speed of convergence [30].

Fig. 2 shows a comparison between Newton's method (red) and GD (green) to minimize a function. Newton's method uses the second derivative (curvature information) to make the path to the goal more directed [31].

● **Quasi-Newton Methods**

The main idea that underlies the Quasi-Newton method uses a symmetric positive definite matrix called B (approximate the Hessian matrix or the reverse of the Hessian matrix). This is instead of the Hessian matrix because the evaluation of this matrix is expensive and sometimes it is not available. Matrix B can be appeared regardless of the matrix used. It is a definite positive symmetric. A suitable matrix update is performed in each iteration and will obtain the same result for the search [32]. Therefore, the update of matrix B is a key issue. The variable metric method was considered as one of the most famous methods which are named the "Broyden-Fletcher-Goldfarb-Shanno" (BFGS) algorithm, in which a rank two modification of the old B was utilized. Of course, there are numerous other update methods, but reports have proven that the BFGS method works better with the imprecise streak search. Thus, in practice, this method is preferred [33]. Finally, the only variation between the Newton method and the Quasi-Newton method concerns H and B.

3.4. Methods of evaluation and testing

● **Performance Metrics**

In this study, two methods are used to evaluate the prediction models which are Accuracy (ACC), and Root Mean Squared Error (RMSE). ACC is the number of accurate predictions that are divided by the entire number of completed predictions by the model [33] as shown in Equation (1).

$$ACC = \frac{f11 + f00}{f11 + f00 + f01 + f10} \tag{1}$$

True Positive (f11): is the number of records from class one that are correctly predicted as class one.
True Negative (f00): is the number of records from class two that correctly are predicted as class two.
False Positive (f01): is the number of records from class two that are incorrectly predicted as class one.
False Negative (f10): is the number of records from class one that is incorrectly predicted as class two.
RMSE is a regularly used measure of the differences between actual values and predicted values by a model [34] as illustrated in Equation (2).

$$RMSR = \sqrt{\frac{1}{n}\sum_{k=0}^{n}(P_k - A_k)^2} \tag{2}$$

P = predicted value of k.
A = actual value of k.

● **Cross-Validation (CV)**

The original data in this method were divided into K equal subsets where each record or subset uses the K−1 of times for training and exactly once for testing. The total error was calculated by aggregating the errors founded through all k runs divided on k as the average across runs [35].

4. The proposed model

Fig. 3 depicts the architecture of the proposed model for SM prediction to understand its ease and quick performance.

The complete description of the proposed model is along with these subsections:

4.1. Stock market dataset

4.1.1. Background of ISX

The Baghdad Stock Exchange (BSX) was established in 1991 by the Iraqi government which started and shared trades for the period from 1992 to 2003.
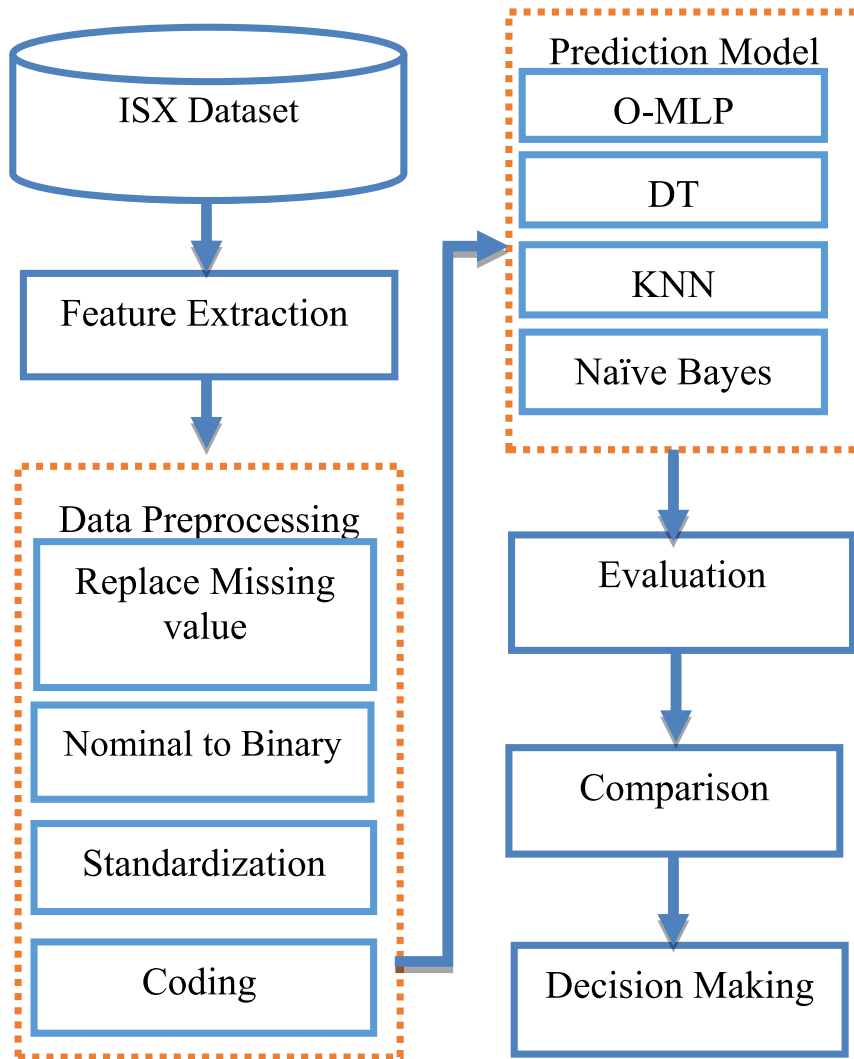
Fig. 3. The proposed system.

This market is managed by the Ministry of Finance in Iraq. Therefore, it is considered as a governmental market which indicates that it is a part of the Iraqi government policy. This market becomes more attractive in the last years where about 113 listed Iraqi companies are distributed between the private sector and the mixed private-public sector [36].

BSX reaches more than seventeen million dollars as an annual average. On March 19, 2003, the Iraqi government decided to close this market before the start of the war operations of the international coalition against the Iraqi regime [34].

The Iraq Stock Exchange (ISX) was established and the governors according to order (74) known as the Stock Exchange Law formed the Board of Directors of the Iraqi Stock Exchange. The market started its activity in trading operations in June 2004 under the direct supervision of the Securities Commission in Iraq [reference]. This is an independent institution that was formed as a self-regulating organization which is similar to the New York Stock Exchange, owned by fifty or so members of the brokerage (Annual reports of the Iraq Stock Exchange, 2004–2020) [37].

During this study on global stock markets, including ISX and their impact on the economy of the country, it was noticed that there was no organized dataset for the stock market in Iraq. Yet, just daily and weekly-scattered reports were founded, although trading in the stock market of Iraq began in 2004 and it included more than a hundred companies under eight sectors namely, Banks, Communications, Investment, Insurance, Services, Agriculture, Industry, and Hotels [38].

For this reason, a regular Benchmark for one of the large sectors was created, which is the bank's sector as a case study, where the main reason for choosing the banking sector in this study is due to the high volume of trading, as the banking sector represents 78% of the total trading volume of the ISX in the last ten years (see Fig. 4).

4.1.2. Dataset

This study relies on an experimental test with a set of historical data from twenty-six stocks (banks) in the banking sector as illustrated in Table 2. The period time for the study started from 1-1-2010 to 3-15-2020 for all banks. As for the number of instances, it is ranged from 69 to 1000 according to the number of daily trading. If the number of daily trading is more than 1000, the last 1000 days are chosen as shown in Table 1. Historical data are continuously collected daily (Open, Low, High, Close, Volume, Adj_Close). Fig. 5 shows the closing price of the stocks of the banking sector during the study period.

Feature extraction

Extracting traditional features from the stock market dataset was performed first. This includes:

- Date: the trading day of the work.
- Open: Stock's Opening Price for a specific day.
- Low: It represents the lowest value of the stock price during the day.
- High: It represents the highest value of the stock price during the day
- Close: A closing stock's price on any given day.

Table 2
Number of trading in the bank sector.

Company Name	Symbol	No. of Trading
Ashur International Bank	BASH	1335
Babylon Bank	BBAY	1789
Bank Of Baghdad	BBOB	2221
Cihan Bank for Islamic Investment and Finance	BCIH	94
Trade Bank Of Iraq	BCOI	2042
Dijlah & Furat Bank for Development and Investment	BDFD	482
Dar Al Salam Investment Bank	BDSI	1336
Economy Bank for Investment & Finance	BEFI	566
Elaf Islamic Bank	BELF	498
Gulf Commercial Bank	BGUC	2005
Iraqi Investment Bank	BIBI	2050
Iraqi Islamic Bank	BIIB	1473
Iraqi the Middle East Investment	BIME	1958
International Islamic Bank	BINT	69
Kurdistan International Bank	BKUI	1143
Al-Ataa Islamic Bank	BLAD	119
Mosul Bank for Development & Investment	BMFI	1631
Mansour bank for investment	BMNS	1796
National Islamic Bank - Iraq	BNAI	209
National Bank of Iraq	BNOI	1361
North Bank	BNOR	1226
Credit Bank of Iraq	BROI	1816
Sumer Commercial Bank	BSUC	1179
Trans Iraq Bank	BTRI	99
United Bank for Investment in Iraq	BUND	1925
Iraqi Union Bank	BUOI	730

- Volume: Volume of Stock trades (buy/sell).
- Adj. Close: It represents the closing stock's price for a specific trading day. The adjusted closing price is regularly used when investigative historical yields or performing an exhaustive analysis on historical returns.

4.2. Pre-processing stage

In this stage, the data was processed and prepared for the prediction step. Linear regression (LR) was employed to replace the missing values with the existing adjacent prices based on Equations (3)−(5).

$$Slop_t = \frac{\sum_{r=t-n}^{t}(D_r - SMA_D(n) \cdot (P_C - SMA_{P_C}(n))}{\sum_{r=t-n}^{t}(D_r - SMA_{D_r}(n))^2} \quad (3)$$

$$Intercept_t = SMA_{P_C}(n) - slope_t * SMA_{D_t}(n) \quad (4)$$

$$LR_t = Slop_t * P_C(t) + Intercept_t \quad (5)$$

Furthermore, the nominal features were converted into binary features. The class attribute was calculated using
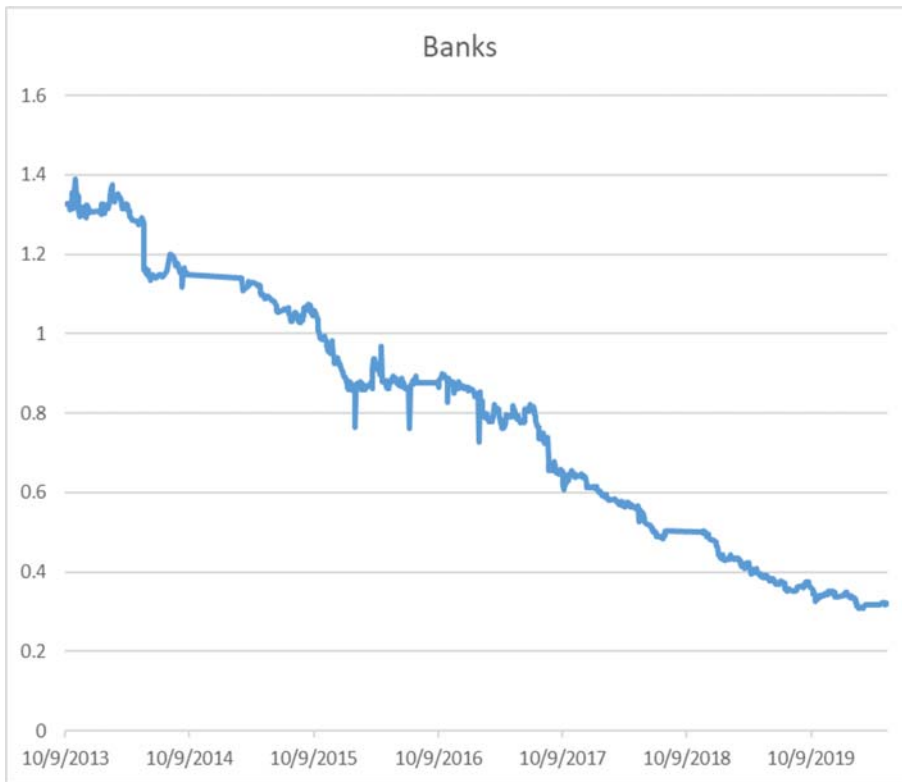

Fig. 4. The trading volume of ISX.

Fig. 5. Close price of the banking sector.

two different equations. First, if the current data point of close price minus the previous data point of the close price is positive, it is represented by a 'buy', whereas if it is negative, it is represented by a 'sell'. Otherwise, it is represented by a 'hold'. Second, a traditional percentage gain is required before classifying a point as 'buy'. If at least 1% gain was wanted once a day from the previous day's close, then it is classified as 'buy', otherwise it is classified as 'sell'. Equations from 6 to 9 illustrate the calculation and generation of the class attribute (Ci).

$$Ci = \Delta \; close \; price \tag{6}$$

$$C_i = \begin{cases} X & if \; close_i > close_{i-1} \\ 0 & if \; close_i = close_{i-1} \\ -1 & if \; close_i < close_{i-1} \end{cases} \tag{7}$$

$$X = \begin{cases} 1 & if \; gain_i \geq 1 \\ -1 \; otherwize \end{cases} \tag{8}$$

$$gain_i = \frac{close_i - close_{i-1}}{close_i} * 100 \tag{9}$$

where i from 1 to total historical data.

Finally, all features were Standardize by using Equation (10).

$$X_{ij}{}' = \frac{X_{ij} - M_j}{SD_j} \tag{10}$$

where:

X_{ij} = data point in row i and column j.

M_j = the mean of column j.

SD_j = standard deviation of column j.

$X_{ij}{}'$ = new data point in row i and column j has a mean of 0 and a standard deviation of 1.

4.3. Prediction model

In this paper, three popular prediction techniques were used for comparison with the proposed prediction model. First, the C4.5 decision tree algorithm was applied to classify future closing prices, which was extended to the (id3) algorithm. This algorithm deals with numerical features > IT uses gain ratio measure to determine the best split. Second, the K-Nearest-Neighbours method was also applied to classify future closing prices. In this study, after trying, it was found that K equals three was the best value to achieve high accuracy of prediction. Third, the Naive Bayes algorithm was applied to classify future SM prices.

The proposed model was based on a developed prediction model. This was performed through Optimize Multilayer Perceptron (OMLP) NNs trained using BP algorithm with one hidden layer by minimizing the given loss function (Squared Error) using Quasi-Newton method based on projected gradients instead of using standard Gradient Descent.

Two neurons were determined in the hidden layer as well as bias. The penalization on the size of the weight equals 0.01 and the value of tolerance equals 1.0E-6. In addition, an approximate sigmoid function version of the logistic function was used as an activation function for the hidden layer to improve the speed of execution time. The sigmoid function was used in the output layer for classifying the direction of stocks. Finally, accuracy and RMSE were employed to evaluate the proposed model and compare the proposed model findings with C4.5, KNN, and Naive Bayes techniques.

The optimization model consists of many steps as shown in Algorithm 1. It contributes to reducing the error by making the loss function (the curvature of f) softer and thus making the convergence faster.

Algorithm 1.
Input: Array $(Q_{vk}) = O_{2vk}$ ()
Output: Array of final weights.
Begin
Definition symbols:
W: vector of all weight in NNs
CF: Converges Factor
Step1: *Initialization.*
 - k=0- Ridge = 0.01
 - Get initial variable values W_k
 - Calculate the Jacobian (gradient) vector G_k using W_k
 - Initialize a symmetric positive definite matrix B_k.
Step2: *If g_k converges to 0, then STOP.*
Step3: *Find the search direction expressed according to:*
 - $d_k= -B_k^{-1}g_k$
Step 4: *Search for α using a line search and set $W_{k+1}= W_k + \alpha d_k$.*
Step5:
 - Calculate the gradient vector G_{k+1} using W_{k+1}.
$G_{k+1}= G_i + Ridge * W_{K+1}$
 - Set $\Delta W_k= W_{k+1} - W_k$ and $\Delta G_k= G_{k+1}$
 - G_k.- The BFGS update is:

$$B_{k+1} = B_k + \frac{\Delta G_k \Delta G_k^T}{\Delta G_k^T \Delta W_k} - \frac{B_k \Delta W_k \Delta W_k^T B_k}{\Delta W_k^T B_k \Delta W_k}$$

Step 6: *Set k=k+1. Go to 2.*
End.

Table 3
Comparative accuracy for the first 13 banks.

Banks	J48	Naive Bayes	KNN	OMLP
BIME	82.10%	59.90%	82.30%	98.70%
BNOR	74.50%	47.30%	65.30%	93.20%
BLAD	73.11%	63.03%	68.91%	96.64%
BUND	82.60%	67.10%	74.60%	98.40%
BMNS	81.10%	71.20%	82.40%	99.20%
BMFI	83.80%	58.60%	80.90%	99.30%
BELF	74.50%	31.93%	70.68%	96.79%
BCIH	98.94%	79.79%	95.74%	94.68%
BDSI	68.80%	47.20%	61.30%	87.80%
BDFD	67.22%	39.42%	62.86%	92.12%
BSUC	90.60%	84.20%	91.90%	93.10%
BTRI	96.97%	46.46%	94.95%	91.92%
BKUI	72.40%	57.10%	69.70%	94.40%

Table 4
Comparative accuracy for the second 13 banks.

Banks	J48	Naive Bayes	KNN	OMLP
BASH	81%	56.50%	80.40%	99.30%
BNOI	88.60%	32.40%	75.90%	93.80%
BCOI	91.80%	58.80%	84.80%	99.10%
BINT	92.75%	85.51%	92.75%	92.75%
BIIB	77.10%	53.60%	73.20%	92.50%
BNAI	82.30%	44.98%	76.08%	95.69%
BBAY	78.10%	52.80%	77.50%	98.40%
BBOB	73.70%	46%	55.60%	98.50%
BUOI	73.70%	32.47%	63.84%	91.10%
BIBI	80.50%	52%	70.60%	92.40%
BEFI	62.01%	32.51%	48.94%	90.46%
BROI	80.30%	53.80%	80.30%	98.70%
BGUC	85.10%	74.70%	78.80%	97.10%

Table 5
Comparative RMSE for the first 13 banks.

Banks	J48	Naive Bayes	KNN	OMLP
BIME	0.2872	0.4801	0.3266	0.0909
BNOR	0.3371	0.5027	0.481	0.1832
BLAD	0.3873	0.4844	0.4553	0.1794
BUND	0.2732	0.3975	0.4115	0.1136
BMNS	0.2857	0.3534	0.3425	0.0779
BMFI	0.2746	0.4414	0.3568	0.0762
BELF	0.3616	0.6258	0.4421	0.1391
BCIH	0.0847	0.3399	0.1684	0.1743
BDSI	0.3805	0.4807	0.5079	0.2482
BDFD	0.4219	0.631	0.4976	0.2116
BSUC	0.2242	0.3042	0.2338	0.1762
BTRI	0.147	0.588	0.1835	0.2195
BKUI	0.3615	0.4935	0.4494	0.1661

Table 6
Comparative RMSE for the second 13 banks.

Banks	J48	Naive Bayes	KNN	OMLP
BASH	0.2958	0.4324	0.3307	0.0784
BNOI	0.2578	0.5444	0.3759	0.1664
BCOI	0.211	0.4736	0.2793	0.0767
BINT	0.2074	0.3112	0.2198	0.2043
BIIB	0.3127	0.445	0.4041	0.1776
BNAI	0.278	0.5319	0.3831	0.1645
BBAY	0.3233	0.5131	0.3724	0.0973
BBOB	0.3455	0.5178	0.5379	0.1077
BUOI	0.3709	0.5937	0.4652	0.195
BIBI	0.2926	0.4439	0.4187	0.1808
BEFI	0.4308	0.6575	0.5597	0.2343
BROI	0.3005	0.5042	0.4227	0.0953
BGUC	0.2647	0.344	0.3578	0.1207

5. Experimental and result

The OMLP, DT, KNN, and Naive Bayes were tested with 10-fold Cross-Validation (CV) to compare the variation of prediction on the same points of view. The accuracy outcomes of these methods were summarized in Tables 3 and 4 and the comparable parameters of Root Mean Squared Error were summarized in Tables 4 and 5.

From Tables 2 and 3, it can be shown that the average percentage of accuracy is 95.23% for the proposed model where V is much higher than the other
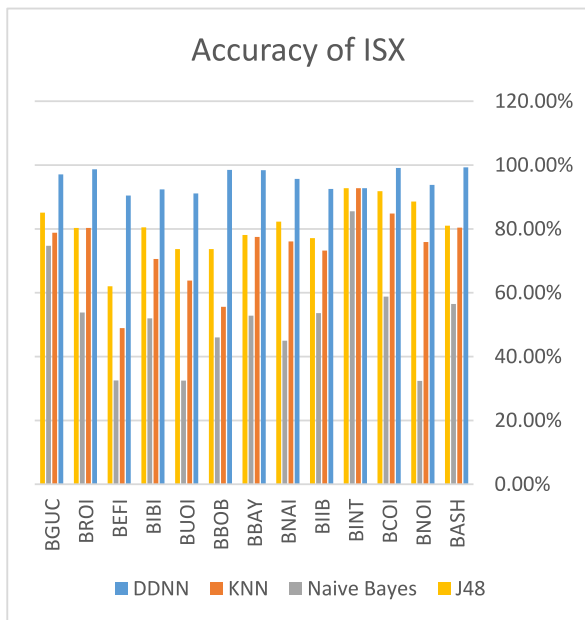

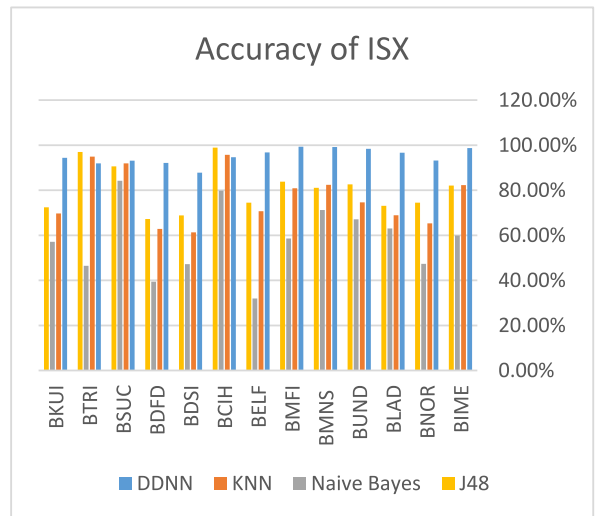Fig. 6. Accuracy of Table 3.

Fig. 7. Accuracy of Table 4.

models. Similarly, from Tables 5 and 6, it can be illustrated that the average Root Mean Squared Error of 0.15 is lower in the proposed model. This indicates that the proposed model had better efficiency. Moreover, the outcomes of accuracy are visualized in Fig. 6 and Fig. 7.

6. Discussion

Although ISX was relatively affected by external conditions, especially after 2014. This was because of the ISIS events in Iraq, the economic crisis, and the impact of the Corona pandemic [39], as shown previously in Fig. 5. However, the proposed model presents good results. This indicates that the model succeeded in performing the forecasting function during this period under such conditions.

By looking at the results, it is evident that the proposed model shows better results after applying all evaluation measures.

Firstly, in terms of accuracy, the proposed model achieves the best accuracy of 99.30% for the BASH-BMFI banks and the worst accuracy of 87.80% for the BDSI bank. In contrast, the best accuracy is 98.94% for the J48 method and the worst accuracy was 31.93% for the BELF bank for the Naive Bayes method.

Secondly, as for the RMSE measure, the best result of the proposed model was 0.08 for the BCOI bank and the worst result was 0.25 for the BDSI bank. On the other hand, the best result was 0.08 for the BCIH bank for the J48 method and the worst result was 0.66 for the BEFI bank for the Naive Bayes method.

Thirdly, the results of the proposed model were much better than the other three methods, except for three banks namely, BCIH, BINT, and BTRI in which their results were close. The possible reason for this is due to fewer trading days, as shown in Table 2, where the values are 94, 69, and 99 respectively.

Finally, the results of the proposed model were compared with standard prediction models on the same dataset. However, the researchers could not compare the research findings with previous literature because there are no earlier studies that used the same dataset. It should be clear that if there is any research, it may differ in the study period, methodology, and/or evaluation measures. In comparison with previous research, the prediction model of this present study was built to work at the same time to predict the closing price of the stock as a regression model, as well as providing a decision to buy, sell, or wait as a classifier model.

7. Conclusions

This study developed the feed-forward NN (MLP) predictor in the historical stocks predicting data to generate decision procedures that provide references to purchase or sell stocks and shares in the stock market. In addition, a benchmark of Iraq was built where the banks' sector was taken as a case study to prove the construction precision. Then, the impact on the efficiency of the prediction model was performed. Investors can use the suggested model as a useful tool for making the right decision about the market. The rationale of this is that it was based on analysing historical stock price data to find any useful predictive information. The results of the proposed model are perfect after comparing them with other prediction models (Naive Bayes, KNN, and DT).

Regardless of the contributions and significant findings of this research, it is not without limitations. First, this study is not delving into external influences and their impact on the stock market. Furthermore, the proposed model has not applied technical indicators as inputs. Because of such limitations, the future work lies in building an integrated system for the Iraqi stock market by organizing an integrated dataset for all the registered companies. It will also build a system that works on choosing the best investment sector. Finally, the proposed model will be further developed by choosing the best companies for that sector and predicting their prices using deep learning.

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