Predicting Nike Company Stock Price in Stock Market Using NARX Artificial Neural Network Method

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Abstract

Purpose: One of the biggest challenges for companies in the stock market is predicting the trend. This research aims to study the price action of the Nike stock trend on the NYSE.
Methods: The price data was gathered from NYSE in a certain period, and other variables such as Volume, Crude Oil Prices in Brent – Europe, Effective Federal Funds Rate, Gold Fixing Price, those who are recognized as influential variables in stock price, are gathered from The World Bank data source. We used one Artificial Neural Network model to analyze the data for predicting time series (NARX). After correcting the objections such as invalid data, the Error Autocorrelation gets 95% desired, and with 0.36 MSE error, we get the approval and the model adequate to predict the trend. With these settings, the input vectors and target vectors will be randomly divided into three sets, and then the model tries to learn from the first part of the data and then test it on the test data, and at the end, the last 24 months data predicted from the model and then compared with the central values.
Results: The data comparison showed a high overlap near 95%, which proved the adequacy of the model in predicting the price trend of Nike company.
Conclusion: Companies and traders can use this method to predict their stock trends in the stock market to take control of the trend.
Keywords: Stock Market, Artificial Neural Network, Nike, Time-series, NARX

Introduction

The stock market is spatial, where people buy and sell stock. The owners of corporations are looking for a convenient way to raise money to hire more employees, expand their companies, and upgrade their equipment. They raise income by issuing shares of stock in their corporation. On the other hand, people buy shares of stock. Thus, the place where the buyers and sellers exchange the stock shares is called the stock market (Beygi & Abdolvand, 2017).

It is difficult for a corporation to be listed on or join a stock exchange because each exchange has many rules and regulations. It can take years for a corporation to meet all the requirements and join the exchange (Beygi & Abdolvand, 2017). The stock exchanges list corporations that fit the goals and philosophy of the particular exchange. For example, the companies listed on the NYSE are some of the well-known and most prominent corporations in the United States—blue-chip corporations like Wal-Mart, Procter & Gamble, Johnson & Johnson, and Coca-Cola. One of these companies is Nike (Bennett & Wei, 2006).

The stock markets are crucial to every country's economy. So, every company wants to be prepared to enter this market and take advantage (Atsalakis & Valavanis, 2009; Fathian & Kia, 2012). Companies that participate in the stock market with other participants try to earn a profit. Therefore, they inevitably should study and analyze the stock market using various methods to buy lower-priced stocks and sell higher-priced ones (Hsieh, Hsiao, & Yeh, 2011). In this era, understanding the market, trends, and price is the best way to predict the future and profit (Na & Sohn, 2011). One of the brand-new methods of stock price prediction is an Artificial Neural Network. ANN has potent processing and data analyzing parts that can make many complex projects very easy to solve (Rodríguez-González, García-Crespo, Colomo-Palacios, Iglesias, & Gómez-Berbís, 2011)

Many companies worldwide from different industries, such as transportation, petrochemical, banks, commodities, and sport, are engaging in stock markets (Bennett & Wei, 2006). Nike is one of the biggest sports companies in the world, active in one of the biggest stock markets NYSE (New York Stock Exchange). The company is an American factory manufacturing and designing (Fathian & Kia, 2012). Nike was founded on January 25, 1964, by Bill Bowerman and Phil Knight, his coach, who named it "Blue Ribbon Sports." Eight years later, they paid a university student to design the logo as it has now. Then, BRS officially became Nike, Inc. On May 30, 1971. Nike officially entered the stock market in 1980 with a 0.18$ stock price per share. Later, the company grew and developed more (Flynn, 2015).

All companies understand that to survive in the stock market, they must concern about various aspects in all circumstances. The market analyzers found so many effective factors that influence the stock price. Some of the important ones are GDP (gross domestic production), amount of salary among different groups of people, exchange rate, inflation rate, crude oil price, effective federal funds rate, gold price, and trade volume as an internal market factor (Chortareas & Noikokyris, 2014). All of these factors are important for companies, but also, they are essential financial and economic factors on a large scale for the countries (Tang, 2017). Each of these factors has its system that affects the country's economy, e.g., the oil price is one the most important or even most important ones in middle east countries like Iran (Ghobadi & Sharifi, 2015). The exchange rate is the world financial relationship bridge, so this factor must be the first place of attention for having a relationship with other countries in the financial area (Fathian & Kia, 2012).

In any country and society, the inflation rate and expected inflation rate are the factors that affect people's lifestyles and purchasing power, so they cannot be disregarded. Other crucial factors in the stock market, such as trading volume, trend, price, supply, and demand, can affect the share price (Rodríguez-González et al., 2011). Dealing with the stock market is one of the not convenient problems faced by all people who are related to the market, so predicting the trend and share price becomes essential. All companies taking part in the market know the importance of prediction, so they try to hire scientists to help them predict the market as much as accurately (Anderson & McNeill, 1992). The most reasonable goal for those investigations is to control and lead the share price on behalf of benefits for whole company management strategies. One of the most critical factors for companies like Nike is controlling share prices to avoid increasing or decreasing too much from what they expected or planned (Flynn, 2015).

Many researchers have studied the stock market details to find a way to predict the share price, So they analyze the factors that may affect share prices, like share volume as well as the prediction methods to meet high accuracy. An artificial Neural Network is one of the newest methods to analyze the stock market and predict the share price (Anderson & McNeill, 1992). The method has been trendy among scholars in many fields in recent years because it provides accurate, functional predictions.

Artificial neural networks are being touted as the future method of computing and analyzing. They are self-learning mechanisms that do not require old and slow programming and computing methods. Most researchers who worked with this machine were excited that this mechanism could do almost anything. Nevertheless, these theories cannot change the fact that some problems did not achieve results by utilizing this mechanism (Hsieh et al., 2011).

Indeed, artificial neural networks are relatively electronic models based on the human brain's neural structure. It is known that the human brain has a learning ability that works with the experience factor, and when a human experience something many times, the brain keeps the experience process, which is called learning. Based on this fact, neural networks are the mechanism that uses the human brain's learning factor to solve problems. The most improved computers are not even close to solving problems, even simple animals' brains (Anderson & McNeill, 1992). Nevertheless, neural networks can also learn and utilize patterns to solve complicated problems.

The exact working processes of the human brain are still a mystery. Nevertheless, some aspects of this fantastic process are known. In particular, the essential element of the human brain is a specific type of cell called neuro-cell (neuron) with many components like synapses. These synapses are the neuron terminals for connecting with other neurons. The human brain likely has 100 billion of these neurons, and also one of these neurons can connect with up to 200000 other neurons, so it takes approximately 10^{16} synapses in our brain; this is the fact that nothing can take the human brain's place in processing and data transition (Villarrubia, De Paz, Chamoso, & De la Prieta, 2018).

These artificial neural networks try to replicate only the most essential elements of the complicated and powerful organism. They do it in a primitive way. However, neural computing was never about replicating human brains for researchers trying to solve problems. It is about machines and a new way to solve problems (Averchenko & Aldyrev, 2018). The basic unit and structure of neural networks are the artificial neurons, which simulate the four essential functions of biological neurons. Figure 1 shows the structure and basic form of artificial neural networks (Lewis, 2017).

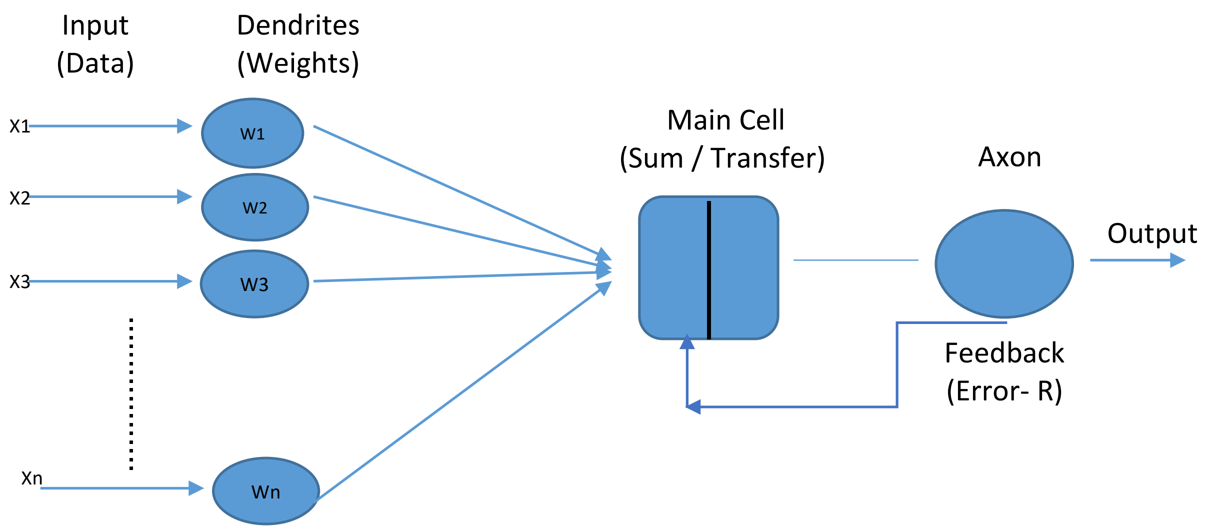

Figure 1. The structure of the neural networks

In Figure 1, various inputs to the network are represented by the mathematical symbol x (n) (Anderson & McNeill, 1992). Each of these inputs is multiplied by a connection weight. These weights are represented by w (n). In the simplest case, these products are summed and fed through a transfer function to generate a result and output. This process lends itself to physical implementation on a large scale in a small package. This electronic implementation is still possible with other network structures that utilize different summing and transfer functions (Averchenko & Aldyrev, 2018).

In recent years, many researchers have tried to understand the stock market, the efficiency factors on the price, prediction, and applying it for analyzing and predicting. For example, Chen, Roll, and Ross (1986) studied the factors that affected the economy and the stock market and listed the factors that significantly impacted the economy and the share price in the stock market. They found that factors like share volume, price range, supply and demand, effective federal funds rate, and inflation rate are critical and practical to stock prices. Kuntomah (2013) studied volatility effects on stock market prices, and the results suggested that the foreign exchange market has a spillover effect (though insignificant) on the economy in general; however, the study aimed to assess the effect of exchange rate volatility on stock prices that shows a significant relationship between them. Moreover, the oil price shocks are adequate for stock index changes in Iran's stock market (Ghobadi & Sharifi, 2015).

Park, Lee, and Lee (2019) demonstrated the classification method's ability to predict stock prices. They investigated data mining and pattern recognition methods in forecasting; in the result, they classified the data gathered with the neural network method and used it to predict the S&P 500 index. They used the time series model to make the prediction errors as low as possible in boosted mode to reach the results quickly. Balvers, Cosimano, and McDonald (1990) studied an intertemporal general equilibrium model that relates financial asset returns to movements in aggregate output. The standard model was a classification growth model with a correction function that made the data classified and predictable, so the stock market and financial indexes were predictable. Hellstrom and Holmstrom (1998) developed a model with overtraining and correction abilities. The model was based on neural networks that tried to correct the errors and make the forecast correct as the loop continued. Weng, Lu, Wang, Megahed, and Martinez (2018) predicted short-term stock prices using ensemble methods and online data sources. At the beginning of testing the model, they designed a case study based on the Citi Group stock with data collected from 01/01/2013 - 12/31/2016; then, they realized the expert system could predict the 1-day stock price with a mean absolute percent error (MAPE) ≤1.50% and the 1–10 day ahead with a MAPE ≤1.89%, which is better than the reported results that they expected. So they resulted that it is better to use the machine learning method and online data sources besides the other models for predicting short-term stock prices to get better results.

Therefore, the current study studied the prediction of price trends using the Artificial Neural Network (NARX) method for Nike's stock price trends from 2012 until 2018. The model of the study was developed through the following phases relatively; training, testing, and re-testing the model according to the results of the last data.

Material and Method

Financial data mining has proven highly efficient and profitable for studying this field. Data mining has developed in recent years by increasing the interest in the data gathering method and the artificial neural network time series model. Many researchers have used the time series model to collect and analyze financial data from the stock market to make them useful for other research. Among the various types of time-series data, we can find many valuable tips for this research. We gathered so much data about the types and started to select the best ones; in the end, we reached these three types on a similar base with this description for each.

In the first type of time series, predicting future values of a time series y (t) from past values of that time series and past values of a second-time series x (t) would be liked. This form of prediction is called nonlinear autoregressive with exogenous (external) input, or NARX (see "NARX Network" (narxnet, close-loop)), and can be written as follows:

$$y(t) = f(y(t-1), \ldots, y(t-d), x(t-1), \ldots, (t-d))$$

This model could predict future stock or bond values based on economic variables such as unemployment rates, GDP, etc. It could also be used for system identification, in which models are developed to represent dynamic systems, such as chemical processes, manufacturing systems, robotics, aerospace vehicles, etc.

In the second type of time series, only one series is involved. The future values of a time series y (t) are predicted only from the past values of that series. This form of prediction is called nonlinear autoregressive, or NAR, and can be written as follows:

$$y(t) = f(y(t-1), \ldots, y(t-d))$$

The model could also predict financial instruments without using a companion series.

The third time series is similar to the first type in that the two series are involved, an input series x (t) and an output/target series y (t). Here it is wanted to predict values of y (t) from previous values of x (t) but without knowledge of the previous values of y (t). This input/output model can be written as follows:

$$y(t) = f(x(t-1), \ldots, x(t-d))$$

The NARX model will provide better predictions than the input-output model because it uses the additional information in the previous y (t) values. However, some applications may be where the previous y (t) values would not be available. Those are the only cases where it is wanted to use the input-output model instead of the NARX model.

The standard NARX network is a two-layer feedforward network, with a signed transfer function in the hidden layer and a linear transfer function in the output layer. This network also uses tapped delay lines to store previous x (t) and y (t) sequences. Note that the output of the NARX network, y(t), is fed back to the input of the network (through delays) since y(t) is a function of y(t − 1), y(t − 2), ..., y(t − d). However, for efficient training, this feedback loop can be opened.

We selected the NARX model for this research because of the ability of the model to predict the financial stock market price values by the previous price values of that index.

For gathering the price data of Nike Co. In the NYSE stock market, we had to use some reliable financial websites such as yahoo finance. We gathered the price data from 01/01/2013 till 31/12/2018 in 5 years. The selected period is mid-term because it is not so short that the model cannot reach the maximum efficiency level or not so long that it faces overlearning errors.

After choosing the model type, we consider which impact factors can be helpful in this model and have more efficiency than other factors for predicting price trends. There are more than 24 impact factors that had a very significant impact on price, but we choose the seven most influential factors for the model as names; Volume of the stock per day, Crude Oil Prices: Brent – Europe, U.S. / Euro Foreign Exchange Rate, Effective Federal Funds Rate, Gold Fixing Price, Inflation Rate and Inflation Expectation Rate. After gathering the data about all these factors in a specified period, we consider the artificial neural network model in two matrices, including the price data and the other seven impact factors data for the training part of the model. All gathered data in these matrices are divided into three parts for the model processing unit.

The validation and test data sets are 15% of the original data. With these settings, the input vectors and target vectors were randomly divided into three sets as follows:

- 70% will be used for training.
- 15% will validate that the network was generalizing and stopping trains before overfitting.
- The last 15% was used as a completely independent test network generalization.

The program coding starts, inputs are defined, and the training process begins with data correlation. In this section, we will face errors that need to be solved. The model's ability to solve these errors is another reason for choosing this method.

The errors that occurred during the program are the ones below.

The ean Squared Error (MSE) = $\frac{\sum_{i}^{n}(t_i - x_i)^2}{n}$

RMSE = √MSE

(Regression) $R^2 = 1 - \frac{MSE}{F_0}$

the $F_0 = \sum_{i=1}^{n} \frac{(t_i - t_i)^2}{n}$

N: the amount of training data

t_i: (real) exact output

a_i: program output

t_i : (second t_i in F_0 formula) – multiple averages

If MSE is less than 0.01, RMSE is less than 0.1, and R^2 is more than 0.9, our data is reliable, and the results are acceptable.

Results

The results we are looking for were based on solving the errors during the program. The data must be normalized and acceptable for running the program to solve the errors. The NARX method could relearn the parts that had shown errors during the run and solve them for the next loop. The most common errors that could occur during the program are MSE, RMSE, etc. For solving these errors to get the most efficiency from the program, the error autocorrelation function is used below.

It is used to validate the network performance. Figure 2 displays the error autocorrelation function. It describes how the prediction errors are related to time. For a perfect prediction model, there should only be one nonzero value of the autocorrelation function, which should occur at zero lag (square error). It would mean the prediction errors were utterly uncorrelated (white noise). If there was a significant correlation in the prediction errors, it should be possible to improve the prediction, perhaps by increasing the number of delays in the tapped delay lines. In this case, the correlations, except for the one at zero lag, fall approximately within the 95% confidence limits around zero, so the model seems adequate.

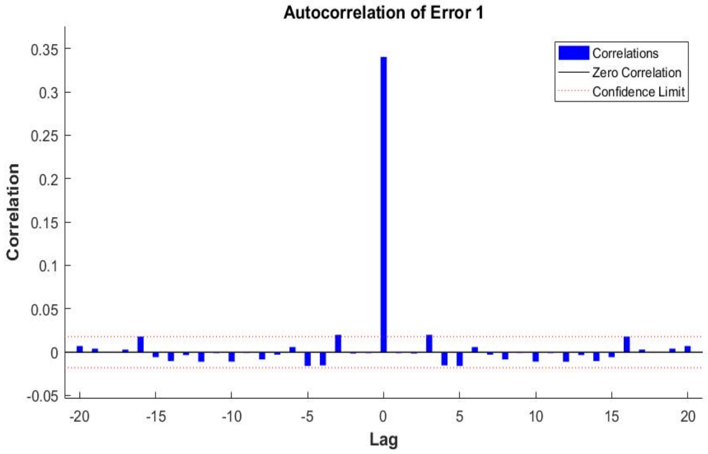

Figure 2. The input-error cross-correlation function to obtain additional verification of network performance

As shown in Figure 2, the input-error cross-correlation function illustrates how the errors correlate with the input sequence x (t). For a perfect prediction model, all of the correlations should be zero. If the input is correlated with the error, improving the prediction by increasing the number of delays in the tapped delay lines should be possible. In this case, all correlations fall within the confidence bounds of around zero.

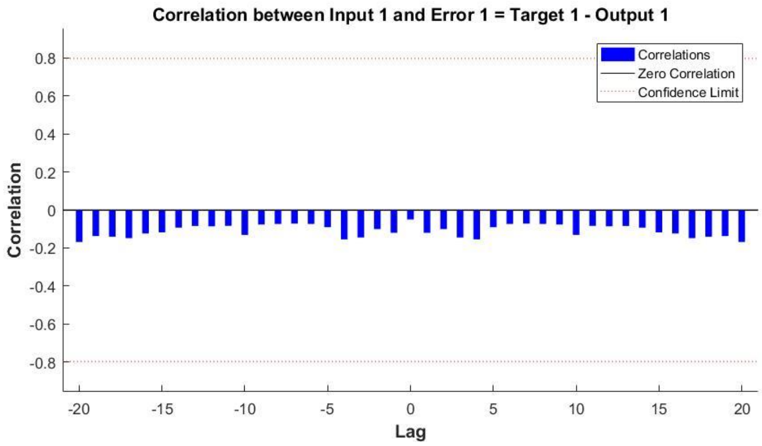

Figure 3. Responses of the output elements for time series and error correlation

Figure 3 displays the inputs, targets, and errors versus time. It also indicates which time points were selected for training, testing, and validation.

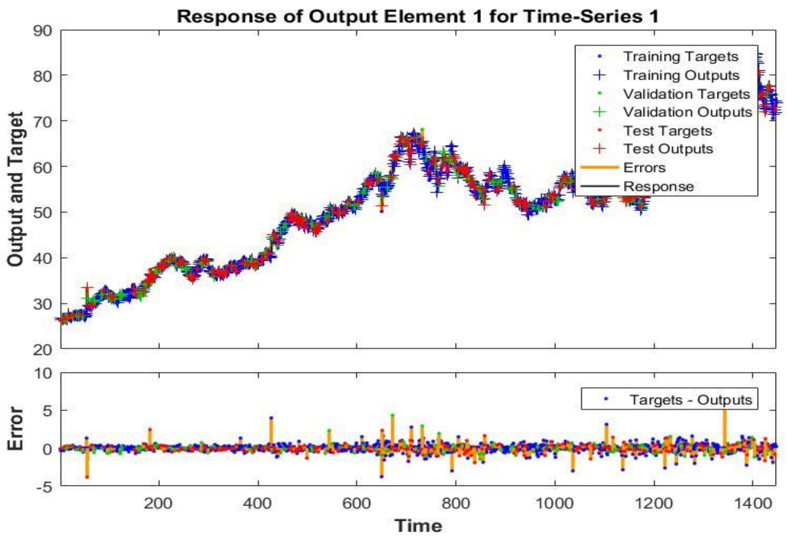

Figure 4. Responses of output elements 1 for time-series 1 in the program

As shown in Figure 4, all the data types and their regression after running the program and their fitting with proper learning time delays are used to validate the program predicting ability by testing the program output and data targets.

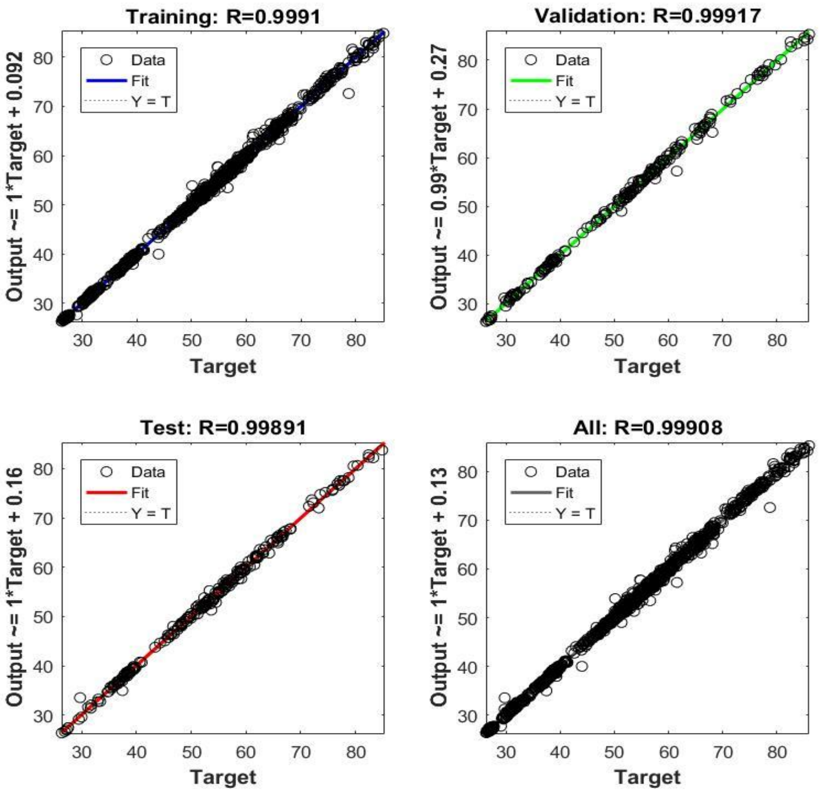

Figure 5. The regressions of the data types

The linear regressions and the correlation between the target values and the program's output are shown in Table 2-1 below.

Table 1. Correlation and regression between the target value and output

Target Values	MSE	R
1015	0.328	0.999
217	0.367	0.999
217	0.369	0.998

- Regression R Values measure the correlation between outputs and targets. An R-value of 1 means a close relationship, and Ziro was a random relationship.
- Mean Squared Error is the average squared difference between outputs and targets. Lower values are preferable, and zero means no error.

As an application of the proposed method, the consumption forecast for data prices of Nike in the stock market is presented in this section. The Price data is precisely 1449 days of the stock market and other variables that had established their effects on the price in three categories: data Training – data validation – data test.

After the training and validation parted, and became apparent that the program was running under invalid circumstances and could predict the price data by a 95% validation rate, so the test data was used as input. The output of the program was as shown in table 2, The testing period (last 12 months) and the target values (price data of Nike in stock) had sufficient overlap (83%), so the prediction is valid to be done by NARX method of artificial neural network for price data in the stock market.

Table 2. Program output and expected output

Month	Output	Target Value
1	73.470001	73.66399473
2	72.690002	72.01190148
3	72	72.68673576
4	73.260002	74.97956152
5	73.07	76.0341787
6	75.5	76.95139766
7	75.230003	76.58007721
8	77.529999	77.64376912
9	76.489998	76.64196226
10	77.339996	77.64139199
11	76.940002	77.60555239
12	77.690002	75.6243633

13	77.709999	75.99523964
14	75.529999	75.68410508
15	76.32	73.70761941
16	74.440002	74.43846317
17	73.760002	72.37087919
18	74.690002	71.50542999
19	70.489998	72.36243976
20	71.989998	72.35519152
21	72.050003	73.0595826
22	72.339996	71.79968542
23	72.279999	74.43374158
24	72.300003	73.96282157

As figured out from the outputs of the validation data by the NARX method and the overlapping percentage of the predicting data (test data), the method can predict the price in any period; however, it is very effective for a long-term period. This predicting ability of the NARX method of an Artificial Neural network can benefit other stocks. Companies can use this method to predict their stock market stock trends to take control of the trend. Traders can also use this method to profit from their trades by predicting annual profits, indicators, and oscillator trends.

In addition, by merging other methods besides the NARX, predictive validity can be used for other types of prediction in any other field.

Also, the most crucial purpose of this article is to make a reliable way for other companies, especially sports companies, to make their way to the stock market and help improve their financial power.

Discussion

Input data (the stock price of the Nike Sports Company on the New York Stock Exchange) from 2013-3-21 to 2019-3-20 was taught by an artificial neural network model (time series) after collecting and preparing the program. Then it was approved and tested. After careful investigations, including reduction of error percentage, validation of existing correlations, and final test of the model, the validity coefficient was obtained higher than 95%. Subsequently, the experimental data prediction showed an upward trend in the stock price of Nike Sports Corporation over the past 24 months, which significantly overlapped with the target output.

According to the initial objectives of this research and the results obtained from using the neural network in prediction, the following results are obtained from this research. Artificial neural networks have efficiency in the prediction model. At the same time, this network's ability to forecast economics, especially the stock market, is another result of this research. The artificial neural network of the time series model, due to the function of the model in this research, can be used in similar studies for prediction and even for analytical purposes for both groups; companies and stockholders. For example, in AhmadKhanBeygi and Abdolvand's (2017) research, the prediction was made using the neural network and chaos algorithm. The results show that the neural network can predict while the chaos algorithm offers reliable results. Hence, providing a complementary model of the artificial neural network, which in this study is the NARX time series model, helps the network optimize the results. In addition, Ramazani and Ameli (2015) used genetic algorithms and claimed that it is necessary to use advanced models to achieve better results.

The main result of this research, which was considered along with the confirmation of the main objectives, was the efficiency of the artificial neural network method in predicting the price trend of the Nike Sport stock index in the stock market. According to the results obtained in Table 2 and the high correlation between program output and target output, this method can be used to predict trends in the other stock markets by companies, especially sports companies. Also, It can be used to enter new companies in the stock market by forecasting the current stock market, forecasting the total stock market index, and examining the company's price trend in the coming years. The prediction helps the company's risk management.

Also, the existence of more sports companies with a definite future promise to prevent the decline by examining the upcoming problems and obstacles to their market share. On the other hand, the efficiency of artificial neural network prediction, such as forecasting interest rates of listed companies, incomes of market shares in different periods, trends of indicators, and oscillators in the short and long term, could be helpful for traders in the stock market.

Conclusion

This study has significant implications for researchers, policymakers, and investors. It helps researchers to develop this model and test it in various fields. Contrary to the poor-form performance theorem that invalidates historical data in future predictions, this study proves the predictability and usefulness of historical data. Policymakers and corporate executives are familiar with the variables affecting their stock prices and try to manage them differently. Importantly, this study helps investors predict stock prices before buying or selling stocks.

Although this study focused on the predictability of performance metrics, it eliminated some internal and external factors affecting stock prices that reach their limits. Therefore, future research can cover sports companies' forecasts to enter the Iranian stock market. This research can also consider factors other than performance to test their predictability and impact on stock prices. This study can cover other important dimensions, such as risk measurement, stock return fluctuations, and optimal portfolio development in the Iranian stock market.

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