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STOCK MARKET PREDICTION USING NEURAL NETWORKS

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Abstract. Trading on the stock exchange is a fundamental part of a country's economic development, resulting in profits directly or indirectly from market transactions. However, the stock exchange is highly dynamic, stocks rise and fall as a result of changes in various parameters. Some techniques have already been used to try to predict these changes in the market, but there is still a need for improvements to ensure greater accuracy in the market's bets, as most of them are high risk. Predicting an asset's closing value is a difficult task because the asset's value is constantly changing and has a variety of parameters that influence its increase and decrease. In this work, an algorithm based on Multilayer Perceptron Neural Network (MLP) was implemented to estimate the price of assets, predicting the closing value of the stock market shares. The proposed network architecture was modeled with two hidden layers, containing six neurons in the first layer and four neurons in the second layer and one neuron in the output. In this case, MLP considerably closed the closing of all the proposed shares (EQTL, PETR4, IBM, ABEV3, BBAS3, CIEL3, COGN3, LAME4, OIBR3 and VALE3) in the period of 10 consecutive years, forecasting an average of 93.60% of the value of the actions in the year following the training of the network.

Keywords: Stock Exchange. Artificial intelligence. Neural networks.

1 Introduction

The stock market undergoes constant fluctuations that make it difficult to know the right time to make a purchase or sale of a stock. This oscillation is due to several factors, such as changes in a company, politics, financial market situation, among other factors. The stock markets are quite dynamic and exhibit wide variation, and their forecasting becomes a challenging task, due to the highly non-linear nature with complex dimensionality. According Nascimento [1], to commonly used techniques, such as fundamental analysis and technical analysis, they seek to predict price changes based on the analysis of data and information from a company and on techniques for reading and analyzing graphs.

Trading in stocks on the stock exchange is a process that requires a lot of knowledge from the investor about economics and politics from around the world. Stock selection is identified as a very important topic. However, it is challenging in the research area of financial market analysis, as it aims to facilitate investment decision-making. In this way, the ability to predict the closing price on the stock exchange allows you to trade shares at a profit.

Second Roque [2], the main motivation for trying to predict the conduct of the shares is, of course, the profit when trading them. Because of this, researchers and investors, exclusively engineers and economists, are studying and looking for better techniques and systems that give them the best returns. With the development of information technology, they suggest new means for forecasting prices, applied to the stock market.

Currently, there is a wide variety of evolutionary based algorithms that have already been applied in stock market prediction, such as classifying systems, resource selection algorithms, genetic algorithm, genetic programming, association, decision tree and Fuzzy systems, artificial neural network, fuzzy inference systems and others. Khan and Sahai [3]. However, it is not just using these algorithms in any way, but finding better indicators to obtain a good prediction of stock market indexes. Kara et al. [4] proposed two models based on two classification techniques, artificial neural network (RNA) and vector machine support (SVM), showing that the average performance of the RNA model was found significantly better than that of the SVM model. Naeini et al. [5] examined the stock exchange estimate using neural systems. Using two types of neural systems, a multi-layer feed-forward perceptron (MLP) and a recurring Elman network, they were able to predict the value of the stock depending on its history of stock values. In addition, the authors were able to show that the use of the MLP neural system was more significant in predicting changes in stock values, rather than Elman's recurrent network and the linear regression method.

In this work, an MLP network was used, with the objective of ascertaining the best solution in the prediction of the stock exchange. The neural network was implemented to estimate the price of the assets, trying to predict the closing value of the shares of the stock market, using as a selection criterion the closing price of the shares that suffered the least variation between the previous quotes.

2 Methodology

2.1 Data Set

The data set used for the planned actions consisted of data from EQTL, PETR4, IBM, ABEV3, BBAS3, CIEL3, COGN3, LAME4, OIBR3 and VALE3, for the period from October 2009 to October 2019. All data were extracted from the Investing.com website and the attributes provided were date, closing value, maximum value, opening value, minimum value, variation and volume.

2.2 Neural network architecture

For this work, the MLP network architecture was modeled with two hidden layers, being 6 input neurons, 4 neurons in the middle layer and one neuron in the output, represented in Figure 15. It is known that this type of feedforward network is similar to the simple perceptron, however, it has more than one layer of neurons in direct feed. Learning was performed using the error back propagation algorithm. The MLP network script was developed in MATLAB and the data was in a text file (.txt).

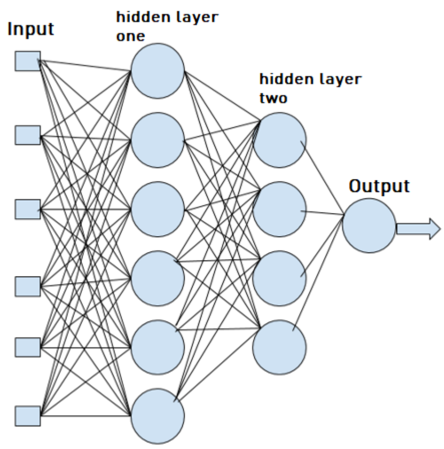

Figure 1. Proposed MLP Network

As parameters for network input, the data of the opening value, the closing value, the maximum value, the minimum value, the variation and the volume starting from the oldest date to the most current date were used. However, before being inserted in the network, the data were normalized using Min-Max in order to reduce the distance between the values of the widely spaced variables, consequently reducing the influence caused by values that are too high in relation to the others. For this to happen, the Equation 1:

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

The closing value variable was chosen as the output of the neural network. According to the defined proportion of the set of input values, the forecast period runs from September 2018 to October 2019.

As the activation function for neurons in the hidden layer, the Sigmoid function was chosen, which is a smooth and continuously differentiable function, represented in Equation 2. The function varies from 0 to 1 and has an S shape. The best feature that this function has is that it presents a balance between linear and non-linear behavior.

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The performance function used was the mean quadratic error (MSE) function, which aims to measure the performance of the network by calculating its mean error, according to the following equation 3:

$$MSE = \frac{1}{n} \times \sum_{i=1}^{n} (y_i - \widehat{y_i})^2 \tag{3}$$

Another important parameter is the number of epochs, which consists of the maximum number of iterations that the network must do. No method was adopted to define this, that is, according to the results presented, it was being configured, thus being decided in 9000 times. After normalizing the data, they were separated in the following proportion: 80% for training (from October 2009 to approximately August 2018) and 20% for testing (from September 2018 to October 2019).

3 Results and Discussion

The results of stock price differences predicted in the neural network are shown in table 1. The difference between stock prices shows satisfactory results in almost all databases evaluated, showing that the proposed method was sufficient in the forecast and that it can be used in different scenarios. It is possible to observe that the error found in the predictions of the shares of Petrobras and IBM were relatively small, while in Equatorial's shares the average error was zero, it is concluded that the prediction of stock values using Artificial Neural Networks is possible. So it can be used in conjunction with other techniques to assist investors in making decisions, increasing their profit and decreasing risk.

Table 1. Difference in stock values (maximum and minimum).

Actions	Records	Maximum Difference	Minimum Difference	Mean Square Error
EQTL3	1978	0.45936	0.00012138	0.000000
PETR4	1995	0.53345	0.000035109	0.000009
IBM	2031	3.268400	0.0005441	0.000006
ABEV3	1995	0.44974	0.000074326	0.000016
BBAS3	1995	0.55191	0.000026018	0.000001
CIEL3	1995	0.34507	0.0015073	0.000007
COGN3	1995	0.07758	0.00000729	0.000000
LAME4	1995	0.17751	0.00012775	0.000002
OIBR3	1974	29.55970	0.00015762	0.000065
VALE3	1995	1.74	0.0011	0.000005

Taking into account the first three best known companies, the figures of the implementation of the implemented neural network are presented. Figure 2 shows the results of the EQTL3 action forecast, where 1978 records correspond to 80 % of the network training. By denormalizing the output data from the network, the difference between the desired values and the predicted values of the network was calculated. The biggest difference for EQTL3 action was 0.45936 cents, and the smallest difference was 0.00012138 cents. The number of predicted values corresponding to the 20 % of the dataset was 495 and 495 were within the established limit of half a dollar, that is, about 100%.

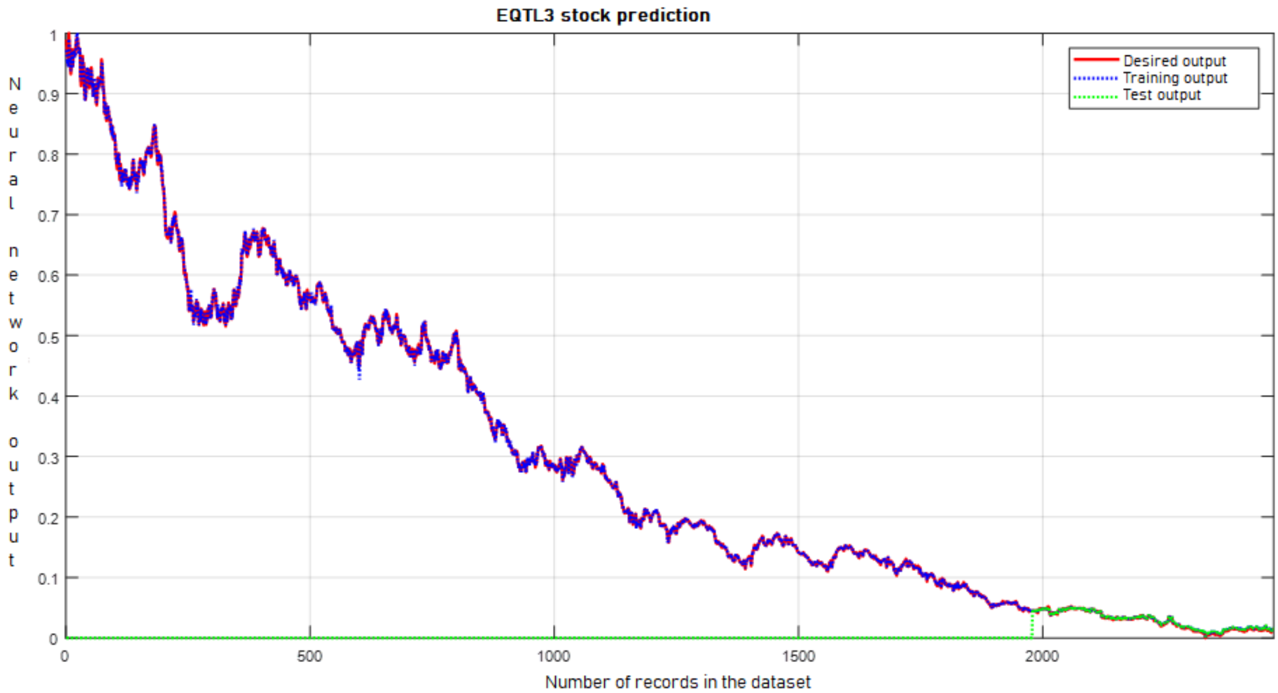

Figure 2. Results of the EQTL3 action.

Figure 3 shows the results of the PETR4 action forecast, where 1995 records correspond to 80 % of the network's training. When denormalizing the network output data, the difference between the desired values and the predicted values of the network was calculated. The biggest difference for PETR4 stock was 0.53345 cents, and the smallest difference was 3.510910^{-5} cents. The number of predicted values corresponding to 20 % of the dataset was 499, with 496 being within the established half dollar limit, that is, about 99.4%. The mean square error during the training of the PETR4 action was 0.000009.

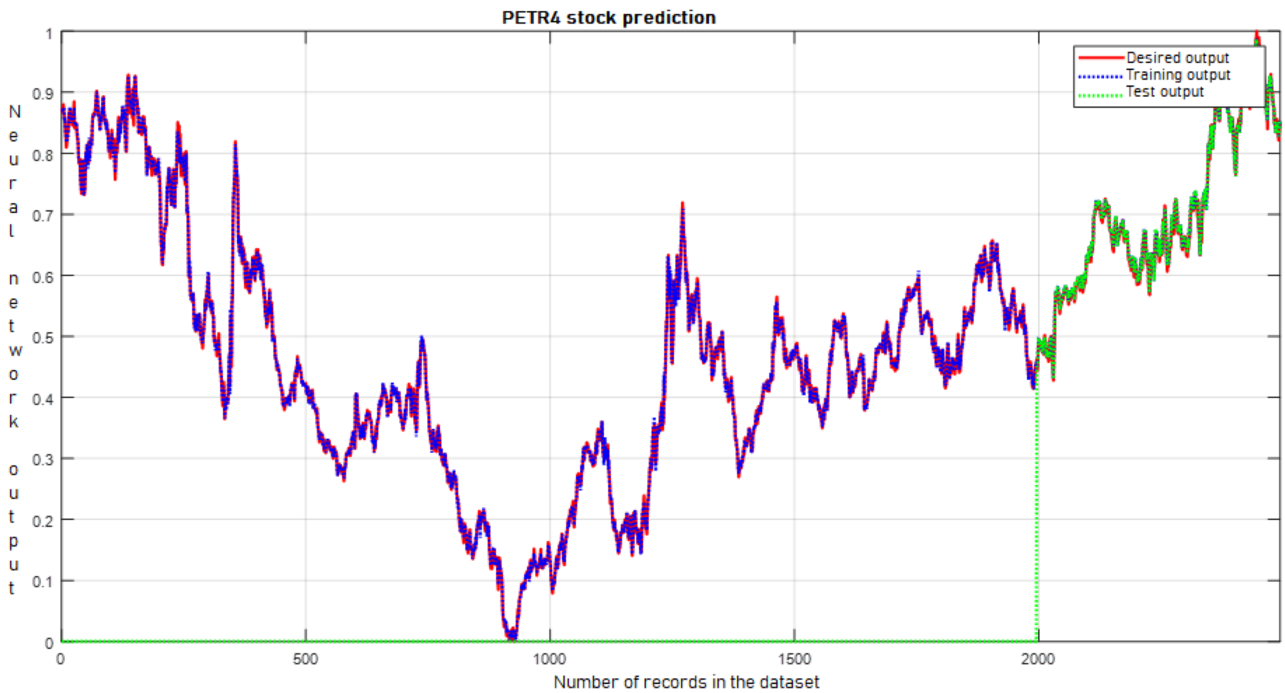

Figure 3. Results of the PETR4 action.

Figure 4 shows the results of the IBM action forecast, where 2031 records correspond to 80 % of the network training. When denormalizing the network output data, the difference between the desired values and the predicted values of the network was calculated. The biggest difference for IBM stock was $ 3.2684, and the smallest difference was 0.0005441 cents. The number of predicted values corresponding to 20 % of the dataset was 508, with 337 being within the established limit of half a dollar, that is, about 66.39 %. The average square error during the training of the IBM stock was 0.000006.

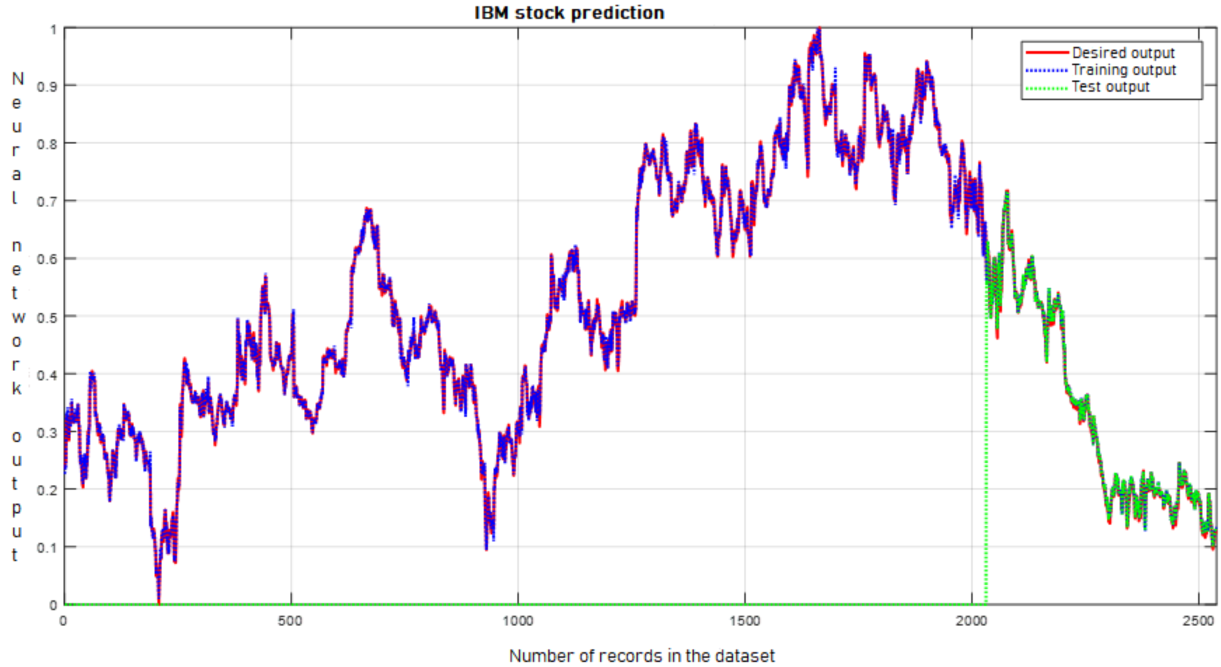

Figure 4. Results of the IBM action.

Thus, these three actions EQTL, PETR4 and IBM obtained an average of 88.6 % of prediction within the half dollar limit and forecasting about 16 months, it was decided to provide the other actions to ascertain the proposed RNA. Data from the following actions were extracted: ABEV3, BBAS3, CIEL3, COGN3, LAME4, OIBR3 and VALE3. The results are following.

The results of the ABEV3 action forecast where 1995 records correspond to 80% of the network training. When denormalizing the network output data, the difference between the desired values and the predicted values of the network was calculated. The biggest difference for ABEV3 stock was 0.44974 cents, and the smallest difference was 7.432610^{-5} cents. The number of predicted values corresponding to 20 % of the dataset was 499, with 499 falling within the established limit of half a dollar. The mean square error during the training of the ABEV3 action was 0.000016. For action BBAS3 where 1995 records correspond to 80% of the network's training. The biggest difference for BBAS3 stock was 0.55191 cents, and the smallest difference was 2.601810^{-6}cents. The amount of predicted values corresponding to 20% of the dataset was 499, with 498 falling within the established half dollar limit, that is, about 99.8%. The mean quadratic error during the training of the BBAS3 action was 0.000001.

However, for CIEL3 action where 1995 records correspond to 80 % of network training. The biggest difference for CIEL3 stock was 0.34507 cents, and the smallest difference was 0.0015073 cents. The number of predicted values corresponding to 20% of the dataset was 499, with 499 falling within the established limit of half a dollar. The average quadratic error during the CIEL3 action training was 0.000007. As for the COGN3 action, where 1995 records correspond to 80% of the network's training. The biggest difference for COGN3 stock was 0.07758 cents, and the smallest difference was 7.290610^{-6} cents. The amount of predicted values corresponding to the 20% of the dataset was 499 and 499 were within the established limit of half a dollar, that is, about 100%. The mean quadratic error during COGN3 action training was 0.000000.

The results of the prediction of the LAME4 action where 1995 records correspond to 80% of the network training. The biggest difference for LAME4 stock was 0.17751 cents, and the smallest difference was 0.00012775 cents. The amount of predicted values corresponding to the 20% of the dataset was 499 and 499 were within the established limit of half a dollar, that is, about 100%. The mean square error during the training of the LAME4 action was 0.000002. The forecast results of the OIBR3 action where 1974 records correspond to 80% of the network training. The biggest difference for OIBR3 stock was $29,5597, and the smallest difference was 0.00015762 cents. The amount of predicted values corresponding to the 20% of the dataset was 493 and 382 were within the established limit of half a dollar, that is, about 77.49%. The mean square error during the training of the OIBR3 action was 0.000065.

Finally, the results of the VALE3 action forecast, with 1995 records corresponding to 80% of the network's training. The biggest difference for VALE3 stock was \$1.74, and the smallest difference was 0.0011 cents. The number of predicted values corresponding to 20% of the dataset was 499, with 464 being within the established half dollar limit, that is, about 92.99%. The average square error during the training of the VALE3 action was 0.000005.

4 Conclusions

In this work, it was proposed to use an MLP to predict variations in different actions such as EQTL, PETR4, IBM, ABEV3, BBAS3, CIEL3, COGN3, LAME4, OIBR3 and VALE3.Considering the analyzes presented, it is possible to observe that the ANN generated acceptable results for the problem in question. Thus, the three stocks such as EQTL, PETR4 and IBM achieved an average of 88.6% prediction within the half dollar limit and forecasting about 16 months.

With the results obtained, it can be said that RNA managed to predict 66% (for IBM) tending to 100% (for CIEL3, COGN3 and LAME4) of the values of the 10 shares chosen for a period of almost 16 months following, based only on the basic parameters available on virtual platforms. In this way, it was possible to analyze 10 years of stock exchange data, making the neural network learn from about 9 years of financial movement. Thus, obtaining an excellent prediction for future values, adjusting the value within the limit of 0.5 dollar of the recurring stock in a wide field of view.

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