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Forecasting the Tehran Stock Market by Machine Learning Methods Using a New Loss Function

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ABSTRACT

Stock market forecasting has attracted so many researchers and investors that many studies have been done in this field. These studies have led to the development of many predictive methods, the most widely used of which are machine learning-based methods. In machine learning-based methods, loss function has a key role in determining the model weights. In this study a new loss function is introduced, that has some special features, making the investing in the stock market more accurate and profitable than other popular techniques. To assess its accuracy, a two-stage experiment has been designed using data of Tehran Stock market. In the first part of the experiment, we select the most accurate algorithm among some of the well-known machine learning algorithms based on artificial neural network, ANN, support vector machine, SVM. In the second stage of the experiment, the various popular loss functions are compared with the proposed one. As a result, we introduce a new neural network using a new loss function, which is trained based on genetic algorithm. This network has been shown to be more accurate than other well-known and common networks such as long short-term memory (LSTM) for both train and test data.

1 Introduction

Forecasting the price of financial markets such as the stock market has always been an interesting issue to investors and researchers. The complexities of the financial markets like volatility, irregularities, noise and chaining trends result in a variety of methods for predicting it. In general, financial market forecasting has a long history. One of the earliest methods of forecasting was technical and fundamental analysis [1], which is still used by many investors to buy and sell. With the development of statistical methods [2], these methods such as AutoRgressive Moving-Average (ARMA), Autoregressive Conditional Heteroskedasticity (ARCH), Generalized AutoRegressive Conditional Heteroskedasticity (GARCH), became very popular among researchers. Even today, some of them, or a combination of them with machine learning methods, are very popular. With the advancement of computer science and artificial intelligence, the variety and complexity of prediction methods has become much greater. Today, machine learning methods are among the most widely used prediction methods. Some of its popular types can be mentioned such as Artificial Neural Network (ANN), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Decision Support System

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(DSS), Naive Bayes (NB), long short-term memory (LSTM), Support Vector Machine (SVM), using various algorithms like Back Propagation (BP) algorithm, and Genetic Algorithm (GA), are used for predicting the stock market returns. Of these techniques, the ANN (first time presented by [3]) and SVM (one of the most robust prediction methods introduced by [4]) are extensively used in forecasting financial market [5], [6], [7] and [8]. There are countless studies and researches in which predictions are based on machine learning techniques such as [9,15, 41, 43, 46]. The table below explains some of studies related to the commonly used methods of machine learning techniques.

Table 1: Some researches related to machine learning methods

Authors	Reference Number	Description of their work
Roh	[16]	Combination of time series model and ANN for forecasting the volatility of stock price index
Rashid and Ahmad	[17]	[Predicting stock returns volatility: An evaluation of linear vs. nonlinear methods
Manish and Thenmozhi	[18]	Predicting of the S&P CNX NIFTY Index return based on traditional discriminant and logit models, SVM, ANN and random forest regression models
Xu et al.	[19]	Credit scoring algorithm based on link analysis ranking with support vector machine
Kara et al.	[20]	Predicting direction of stock price index movement using artificial machines: the sample of the IStanbul STock Exchange
Kara et al.	[21]	Forecasting of market index direction of the Istanbul Stock Exchange index based on SVM and ANN
Patel et al.	[22,23]	Predicting stock and stock price index and index movement using trend deterministic data preparation and machine learning techniques
Stepanek et al.	[24]	Aplying GA to multi agent simulation in stock market by combination of ARIMA, ANN, SVM and Random regressions
Montri et al.	[25]	Combining ANN and GA for predicting Thailand's SET50 index. By a lot of inputs, they resulted for an accurate model
Hsu et al.	[26]	Bridging the divide in financial market forecasting: machine learners vs. Financial economists
Inthachot et al.	[27]	Artificial Neural Network and Genetic Algorithm Hybrid Intelligence for Predicting Thai Stock Price Index Trend
Ramadan et al.	[28]	Integrating the genetic network and MLP to predict daily stock returns of Tehran
Matyjaszek	[29]	Investigating the performance of coke coal prices by traditional time series models, multilayer feeding networks and general regression neural networks
Matheus et al	[30]	Using artificial intelligence for Bitcoin market

Table 1: Continue

Authors	Reference Number	Description of their work
Albert et al.	[31]	Using Multi linear Weighted Regression (MWE) with Neural Networks for trend prediction
Dattatray et al.	[8]	Reviewing 50 studies related to the most commonly used stock market prediction
Botchkarev et al.	[32]	Applying various types of performance functions with the aim of expanding and extending their methodology
Shah et al.	[33]	Stock market analysis: A review and taxonomy of prediction techniques
Zhong and Enke	[34]	Predicting the daily return direction of the stock market using hybrid machine learning algorithms
Wen et al.	[35]	Stock Market Trend Prediction Using High-Order Information of Time Series
Cervelló and Guijarro	[36]	Forecasting stock market trend: A comparison of machine learning algorithms
Papageorgiou et al.	[37]	Exploring an Ensemble of Methods that Combines Fuzzy Cognitive Maps and Neural Networks in Solving the Time Series Prediction
Nabipour et al.	[11]	Deep Learning for Stock Market Prediction
Etebar et al.	[38]	Evaluation of Intelligent and Statistical Prediction Models for Overconfidence of Managers in the Iranian Capital Market Companies
Ghasemzadeha et al.	[39]	Machine learning algorithms for time series in financial markets
Davoodi et al.	[40]	Stock price prediction using the Chaid rule-based algorithm and particle swarm optimization (pso)

One of the reasons for the variety of methods for predicting machine learning is the different architectures used to estimate parameters or weights. In all architectures, a loss function, or performance function, is used to evaluate the performance of the model in each step. The most common loss function is Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE). In other word, in most forecasting methods, whether for the purpose of buying or selling, the criterion for determining the accuracy of determined weights is MSE or MAPE [8]. Although studies such as [8] and [32] have been performed in which their loss function has been compared with other ones, their number is small. The rest of the paper is organized as follows: In Section 2, the loss function is discussed in more detail, and a loss function is introduced which is more useful for investing in the stock market. Section 3 describes the data and the design of experiment which is performed in two steps for prediction of Tehran stock market. In section 3.1 the first step of the experiment which is performed in order to choose an appropriate algorithm for the second step of the experiment, is illustrated. Section 3.2 includes the second step, comparison and prediction. The Conclusion of this research is provided in Section 4.

2 The Proposed Loss Function

Obviously, loss function is one of the necessary tools in machine learning problems. Machine learning algorithms are based on the loss, or performance function, so that the parameters are adjusted based on minimizing the loss function, or maximizing the performance function. Of course, the application of the loss function is not limited to neural networks. Rather, for statistical problems such as regression and time series, it is the minimization of the loss function that leads to the determination of model parameters. The most frequently used loss functions are Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) [8]. Although some research has been done to compare different loss functions with each other, there is no specific result by which the strength of one was shown over the other. Rather, various loss functions may work better for various issues. The fundamental question is whether a loss function can be introduced and created that is significantly better than other well-known loss functions. In other words, the purpose of this section is to create a loss function which can be much more accurate than other competitors for investing in the stock market, such as buying a share. Suppose our problem is to buy shares of the Tehran Stock Exchange in order to profit from price fluctuations. So, of course, the investor buys the stock when he predicts that the price changes in the next few days will be large and the price of the share will rise. For example, an investor with a goal of 5 days wants to buy a share which is predicted that the price change is greater than a certain date, such as e. Therefore, having price information until the nth day, they should predict price changes until the 5th day. The proposed loss function to predict the future price volatility is as follows:

$$\mathrm{T}_{\mathrm{e,n}} = \frac{\partial_1 . n_3 + n_2 + (\sum_{i=1}^{n} \hat{y}_i)/n}{n_1 + \partial_2}, \tag{1}$$

In which, $y = (y_1, y_2, \dots y_n)$ and, $\hat{y} = (\hat{y}_1, \hat{y}_2, \dots \hat{y}_n)$, are the targets and the outputs of the price change. $n_1 = \#(\mathrm{y} > e \ and \ \hat{y} > e)$, represents the number of times when both predicted growth and actual growth are greater than e. $n_2 = \#(\hat{y} < e)$ represents the number of times when predicted growth is less than e. $n_3 = \#(\mathrm{y} < e \ and \ \hat{y} > e)$, represents the number of times, when predicted growth is higher than e, while actual growth is less than e. Also, $\partial_1 \in (1, \infty)$ denotes any positive value, and $0 < \partial_2 < 1$ denotes a very small amount to prevent the denominator of the fraction being zero. Admittedly, in Formula 1, the error is low when the values of $\hat{y}_i$ is as small as possible. Because we prefer $\hat{y}_i$ to be large only when $\hat{y}_i$ is large, and this happens when n_1 is large and n_3 is small. Also, as a buyer, we want the weights of the model to be set so that the number of $[\mathrm{y} > e \ and \ \hat{y} > e]$ is maximum, so we want n_2 to be small, but not as much as n_3. Thus, the reason for putting ∂_1 is that if n_3 is too large, we will lose a lot, however, if n_2 is large, we just do not profit. Moreover, the values ∂_1 and ∂_2 can be adjusted so that the optimization process leads to convergence.

Forecasting based on the above loss function is expected to be highly accurate (in comparison with the other loss function) for several reasons:

First, this function focuses on important outputs (outputs larger than e). Therefore, a small amount of production does not affect weight. As a result, the weight of the network is estimated in line with the investor's expected profit. Second, $T_{e,n}$ is a function of e. That is, the investor first defines the value of e (expected profit from price fluctuations) and then looks for the shares whose expected profit is greater than e. This allows the network weights to be adjusted in a way that depends on the level of risk of the investor. Of course, the lower the expected profit, the greater the number of shares found by the algorithm, which reduces the risk of buying. In general, the choice of e depends on the investor's risk-taking.

3 Experiment Design

In this study, the survey is performed on all the shares of Tehran Stock Exchange, from 2012 to 2019, except those whose data are insufficient. The number of these shares is 320. The last three months of

data are intended for testing. The inputs consist of three groups:
a) Technical indicators including: Distribution oscillator, Chaikin oscillator, Moving Average Convergence/Divergence(MACD), Stochastic oscillator, Acceleration between times, Momentum between times, Chaikin volatility, Fast stochastics, Slow stochastics, Williams %R, Negative volume index, Positive volume index, RSI, Highest high, Lowest low, Median price, On-Balance Volume (OBV), Price rate of change, Price and Volume Trend (PVT), Typical price, Volume rate of change.
b) Price growth percentage of five past days including: High price, Low price, Open price, Close price and Volume.
c) Dollar/Rial price: As an economic and political variable (Because every economic and political phenomenon in Iran has a direct impact on the price of the dollar).
The target is the highest price growth in the future five days.

3.1 The First Part of the Experiment

The experiment is carried out in two stages: In the first stage of the experiment, we first fit the train data using the below well-known models (table 2) and then select the most accurate one for the second stage of the experiment. In fact, after selecting the most accurate model in the first step, in the second step, different loss functions (table 4) are applied for comparison as well as prediction in the representative model. It should be noted that the reason for using these four methods in the table 2 is their high efficiency [28], [42]. Genetic algorithm, which is a technique for generating high-quality solutions to optimization, (GA) has become very popular and well-known since it was used to train the network weights [44], [45], and Levenberg–Marquard algorithm (LM) is also one of the most common ones.
For the first step, the following popular models are used:

Table 2: Applied models in first stage of the experiment

Applied models in first stage
1) Feedforward ANN training by GA.
2) Feedforward ANN training by LM Algorithm.
3) SVM using Gaussian Kernel function.
4) SVM using polynomial Kernel function.

After applying the models in Table 2 to the train data, their accuracy is compared with each other .Although there are many criteria for measuring goodness of a model, we use a criterion that is applicable in practice:

$$A_e = \frac{TP}{TP+FP}, \tag{2}$$

in which, TP is True Positives, ‹the number of times that ($\hat{y} > e$ and $y > e$). FP is False Positives, the number of times that ($\hat{y} > e$ and $y < e$). This criterion indicates correct percentage of the predicted days with positive and significant fluctuation. The Table 3 indicates the average of the accuracy of the whole shares for each method.

Table 3: The Accuracy of models with train data (e=0.02)

Model	1) ANN-GA	2) ANN-LM	3)SVM-Gaussian	4)SVM- polynomial
Accuracy	0.680	0.640	0.622	0.637

As we can see in Table 3, the most accurate model relates to Feedforward ANN training by GA with 0.68 percent. In other words, the correct percentage of the predicted days with positive and significant fluctuation (in which the price growth in the next five days is more than e=0.02), is 68 in 100 days. So, we consider ANN-GA network as the most appropriate method for the second step experiment.

3.2 The Second Part of The Experiment

At the second stage, we use the following regression loss functions (table 4) in order to compare their accuracy in both of the train and the test data.

Table 4: The various Loss functions of $(y_i, \hat{y}_i)$

Symbol	Name	Formula		
MSE	Mean Square Error	$\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n}$	(3)	
MAE	Mean Absolute Error	$\frac{\sum_{i=1}^{n}\lvert y_i-\hat{y}_i\rvert}{n}$	(4)	
MAPE	Mean Absolute Percentage Error	$\frac{\sum_{i=1}^{n}\lvert (y_i-\hat{y}_i)/y_i\rvert}{n}$	(5)	
H_δ	Huber Loss	$\begin{cases}\frac{1}{2}(y_i-\hat{y}_i)^2 & \text{for } \lvert y_i-\hat{y}_i\rvert \le \delta \\ \delta\lvert y_i-\hat{y}_i\rvert - \frac{1}{2} & \text{otherwise}\end{cases}$	(6)	$\delta\epsilon(0,1)$
L	Log-Cosh Loss	$\sum_{i=0}^{n}\log(\cosh(y_i-\hat{y}_i))$	(7)	
$T_{e,n}$	The Propoded Loss	$\frac{\partial_2.n_3+n_2+(\sum_{i=1}^{n}\hat{y}_i)/n}{n_1+\partial_1}$	(8)	$n_1 = \#(y > e \ and\ \hat{y} > e)$ $n_2 = \#(\hat{y} < e)$ $n_3 = \#(y < e \ and\ \hat{y} > e)$ $\partial 2 = 100, \quad \partial 2 = 0.0001$

Table 4 provides various common-used loss functions. MSE is the most popular loss function theoretically and practically. MAE, H and L are well-known regression loss functions as well [32]. Also, $T_{e,p}$ is the proposed loss function discussed in previous section. At this point, using these five loss functions, five neural networks are created based on the genetic algorithm. Each of these networks has been applied to each of the 320 stock shares. Table 5 shows the performance of these networks on the test and train data, separately. Table 5 indicates the accuracy of the models examined for all shares of Tehran stock market, and also the average values for all 320 stocks. Five shares are presented in the table as a sample. Regarding the average of the accuracies, it can be seen that the highest average relates to model T for both test and training data, which are 0.850 and 0.730 respectively.

Table 5: The accuracy of the prediction for train and test data

share / Used Loss function	data	Pars.Int.Mfg.	Novin.Bime	Daroupakhsh	Insurance.Inv.	Petro.Inv.		Average
MSE	Train	0.722	0.721	0.669	0.747	0.747	…	0.686
	Test	0.760	0.596	0.720	0.708	0.600	…	0.632
MAE	Train	0.730	0.742	0.658	0.753	0.712	…	0.685
	Test	0.769	0.483	0.720	0.674	0.640	…	0.644
$H_{\delta=0.02}$	Train	0.717	0.710	0.667	0.758	0.744	…	0.679
	Test	0.867	0.875	0.710	0.714	0.000	…	0.632
MAPE	Train	0.720	0.729	0.652	0.770	0.734	…	0.682
	Test	0.743	0.889	0.771	0.70	0.667	…	0.650
L	Train	0.723	0.721	0.650	0.792	0.723	…	0.681
	Test	0.760	0.333	0.710	0.686	0.600	…	0.629
$T_{e,n}$	Train	0.910	0.804	0.917	0.837	0.856	…	0.850
	Test	1.000	1.000	0.810	0.909	0.833	…	0.730

In other words, for prediction of the days with positive and significant fluctuation (in which the price growth in the next five days is more than e=0.02), this model has performed correctly in 73 percent of the days. It means that if the investor invests 100 units in one year according to the proposed model, the amount of his profit is approximately 73 unit in one year, as:

Profit =number of weeks in a year $*$ profit per week $*$ correct amount of forecast

$$= 50 * 0.02 * 0.73 = 73.$$

As for the accuracy of the other networks in table 5, it can be seen that they are very close to one another, especially for training data.

Remark. It is noteworthy that in order to show the accuracy of the proposed model, we also compared it with the powerful model LSTM. According to Nabipour et.al [11] LSTM is the most accurate one with the highest model fitting ability for prediction of Tehran stock market among various methods of machine learning such as decision tree, bagging, random forest, adaptive boosting (Adaboost), gradient boosting, and eXtreme gradient boosting (XGBoost), and artificial neural networks (ANN), recurrent neural network (RNN). The average accuracy of LSTM according to Formula 2 is 0.695 and 0.646 for the test and the train data, respectively. As it is clear, our proposed model performs better.

4 Conclusion

The issue of financial market forecasting has always been of interest to investors and researchers. Due to this interest, several methods have been introduced for prediction, the most widely used of which is the machine learning method. In machine learning issues, the loss function plays an important role in problem solving. A few studies have compared the loss functions in different issues. In this paper, a loss function is introduced, which is significantly more accurate than the other well-known loss functions used in various research. Indeed, if a person intends to buy a share of the stock market in order to

receive a profit from its growth in the next n day, and his expected profit is more than e in n days, the proposed loss function will meet his expectations higher than other ones. The values n and e depend on the investor's risk-taking and investment duration. For example for $n = 5$ and $e = 0.02$, the average of accuracy is 73% ,which means of the 100 days that the network predicts positive and high volatility, 73 days are correct and it is significantly more efficient than methods based on the other loss functions.
Regarding the comparison of this research with similar researches, it can be expressed that the variation in the accuracy criterion limits the comparison. For example, in a similar study [47], the accuracy of the network with method ANN-LM is 99%. The measure of accuracy in that research is R^2(coefficient of determination). However, in this research, we have applied the same method to the data, and according to Table 3, the accuracy criterion with formula 2 is only 64% on the training data. The point to consider is that in most articles, the accuracy criterion is MSE or R^2, and this is why these studies do not provide good predictions in practice. Therefore, we have presented a measure of accuracy that is used in practice to buy the shares with the purpose of profitability. Thus, this research has introduced a loss function that is more applicable in practice to buying or selling the shares of the stock market. The combination of this loss function, in other machine learning algorithms, can be considered as a suggestion for future research.

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