Stock Price Prediction using a Combination of Deep Learning Models: A case study on Iran stock market

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ABSTRACT

Nowadays, investing in the stock market is one of the interesting and also challenging areas for investment. Predicting stock prices using behavioral patterns of the stock price generation process is possible. Over the years, numerous algorithms and software with various complexities and structures have been proposed for this purpose. Due to the complexities of the stock market and the high volume of processed information, often using a simple system does not yield satisfactory results. Therefore, in recent years, researchers have attempted to provide hybrid models to reduce complexity and improve efficiency and accuracy. In the proposed method, features of the dataset are extracted using a deep autoencoder, and these extracted features are then fed into a perceptron neural network for stock price prediction. To evaluate the efficiency of the proposed model, it is applied as a case study on data from 6 active companies in the Tehran Stock Exchange, and its performance is compared with the mean squared error of other methods including perceptron neural network, support vector machine, decision tree, random forest, and principal component analysis. The results of the proposed method show an improvement in average mean squared error compared to other methods.

KEYWORDS: Stock price, deep learning, autoencoder network, multilayer perceptron neural network.

1 INTRODUCTION

Today, the majority of funds are transferred through the stock and securities markets worldwide. The stock market (stock exchange or securities exchange) is a place where shares of various companies in investment, industrial, agricultural, manufacturing, and service sectors are bought and sold. The stock market, by gathering idle funds, increases the volume of investment in society. The stock market establishes communication between sellers and buyers of shares and manages and controls capital market transactions [1].

Stock price prediction can be carried out using linear, nonlinear, or random models. Researchers and investors are always seeking to optimize prediction models and study the behavior of stock prices. Maximizing profits is the main reason individuals invest in the stock market, requiring sufficient knowledge of the stock market, stock price fluctuations, and predicting their future trends. Therefore, shareholders need reliable and robust tools to make stock price predictions [2].

Despite the presentation of various stock price prediction models, none of them are completely accurate and precise yet. Using a simple model for stock price prediction is not suitable due to the characteristics of the stock market and the vast amount of processed information. As a result, researchers have recently proposed composite models to have high efficiency, accuracy, and low complexity. With the advancement of artificial intelligence and machine learning, novel methods have been introduced that offer greater accuracy and efficiency compared to traditional models. The most common of these methods are artificial neural networks. The problem addressed in this research is stock price prediction in the securities exchange.

In this paper, in order to predict stock prices using intelligent methods, a combination of the perceptron neural network and deep autoencoders has been utilized. The remainder of this paper is organized as follows. Section 2 provides a review of the literature related to the stock price prediction problem and previous related studies. Then, in Section 3, the details of the proposed method in the paper are presented. Section 4 is dedicated to describing the conducted experiments and presenting the obtained results. Finally, in Section 5, a summary of the paper's content will be provided.

2 LITERATURE REVIEW

Deep learning involves the use of artificial neural networks for performing learning tasks using multi-layered networks. This technique has greater learning power compared to shallow neural networks [3]. Deep learning was initially proposed by Hinton in 2006 [4]. Until 2006, the use of deep learning was limited to fully connected neural networks that outperformed shallow learning methods and utilized feature engineering [4].

The multi-layer perceptron network is one of the simplest and most widely used artificial neural networks, consisting of an input layer, zero or more hidden layers, and an output layer. The number of neurons in each layer is not dependent on the number of neurons in other layers. Information processing flows from the input layer to the output layer, and there is no direct connection between neurons in subsequent layers [5].

Autoencoders are unsupervised machine learning algorithms used for learning features, representations, compression, or encoding data and discovering hidden factors. This neural network consists of two parts: an encoder and a decoder. Data samples are input into the autoencoder, and the neural network encodes the data into hidden factors in the encoding layer. Then, in the decoding part, the network generates the output using these factors. This algorithm reduces the difference between input and output.

In this section, it is essential to review the research related to the topic of this paper. Mostly, in recent years, traditional methods have been used for stock price prediction. However, with the continuous progress and advancement of artificial intelligence approaches such as evolutionary algorithms, artificial neural networks, fuzzy systems, and machine and deep learning, they have found extensive applications in stock price prediction in the stock market. In this regard, there are three types of methods: classical, AI-based, and hybrid. In this section, we focus only on reviewing studies conducted with deep learning approaches in the field of stock price prediction.

Deep learning for stock prediction was introduced in [6], and its performance was evaluated on Google's stock price multimedia data from the nearby exchange. The aim of this paper demonstrates that deep learning can enhance stock market prediction accuracy. For this purpose, PCA (Principal Component Analysis) was combined with deep neural networks and compared with the PCA combined with RBFNN (Radial Basis Function Neural Network) method. It was found that the proposed method in the paper has better performance than the existing RBFNN method, improving accuracy by 4.8%. Additionally, the results of the presented model were compared with a Recurrent Neural Network (RNN), showing an improvement of 15.6% in accuracy.

Researchers in [7] propose a hybrid method for predicting stock price movements using machine learning, deep learning, and natural language processing. They create various predictive models using machine learning and utilize these models to predict stock prices with a one-week prediction horizon. For predicting price movement patterns, they employ several classification techniques, while for predicting actual final stock prices, various regression models are employed. Additionally, they create a long short-term memory (LSTM) based deep learning network for predicting final stock prices and compare the prediction accuracy of machine learning models with the LSTM model.

In [8], researchers focus on stock price prediction using a concentrated deep learning model. This is a challenging task due to the presence of noisy and uncertain information in stock price data. Therefore, in this paper, they employ a one-dimensional sparse autoencoder combined with residual convolutional networks as a deep learning model to eliminate data noise. Subsequently, a Long Short-Term Memory (LSTM) network is utilized for stock price prediction. Historical prices, indicators, and macroeconomic variables serve as features for predicting the next day's stock price. Furthermore, they compare their model's performance using two different objectives for predicting stock prices: absolute stock price and price change rate. The results show that predicting stock prices through the price change rate yields better results compared to direct absolute price prediction. Table 1 summarize some articles that utilize deep learning techniques in the field of stock price prediction.

Table 1 Recent Studies on Deep Learning Methods in Stock Price Prediction

Research	Deep Learning Technique	Dataset
Roberts et al. [9]	CNN+LSTM	benchmark LOB
Sethia and Raut [10]	LSTM	Yahoo Finance
Song et al. [11]	MLP	KOSPI / KOSDAQ
Sezer and Ozbayoglu [12]	CNN	30 Dow Jones stocks
Chen et al. [13]	RBM+AE	China Stock Exchange
Pang [14]	AE+LSTM	Shanghai Stock Exchange
Swathi et al. [15]	TBLO+LSTM	Twitter data
Md et al. [16]	Multi-layered sequential LSTM	Samsung’s stock prices
Rezaei et al. [17]	Deep learning and frequency decomposition	S&P500, Dow Jones, DAX, and Nikkei225

Deep learning has managed to address many challenges in the field of stock price prediction. This approach has excelled in overcoming feature extraction problems and has provided satisfactory accuracy and speed for predicting stock prices. Unlike conventional neural networks, deep learning networks have the capability to work with labeled and unlabeled data, and since they can automatically extract features, they possess a significant advantage. On the other hand, current approaches to stock price prediction require dimensionality reduction and feature selection techniques, whereas in deep learning multi-layer networks, feature selection is automatically performed.

3 THE PROPOSED METHOD

The input data for the proposed model consists of stock price variables over the time period from 2010 to 2015, captured on a daily basis. These data are sourced from the Stock Exchange Organization and other reputable entities (such as the Central Bank's official websites, global gold prices, and the US Department of Energy). In this paper, data from six companies, including Iran Khodro, Isfahan Oil Refining Company, Persian Gulf Petrochemical Industries, Lotus Gold Backed Securities Fund, Bank Tejarat, and National Iranian Copper Industries, have recently been collected.

After extensive investigations to identify the variables, the influential factors on stock prices have been categorized into two main groups, due to existing constraints:

1. Technical Variables: This group includes the minimum stock price, maximum stock price, initial stock price, trading volume, transaction value, primary market index, and total market index.
2. Economic Variables: This group encompasses exchange rates for the US dollar, global price per ounce of gold, and global oil price (Brent North Sea).

In the proposed method, considering the 10 selected variables, the initial feature count is set at 10. The neural network in the proposed approach also has one output, which represents the predicted stock price. The goal of stock price prediction is to utilize these 10 features as input.

In the proposed method, a deep autoencoder is employed to reduce the initial stock features. For this purpose, each row of the database matrix (with 10 features) serves as input to the autoencoder. As a result, a lower-dimensional representation of the features, denoted as k-dimensional, is obtained from it. These reduced representations of all features (reduced features) are stored in matrix D with a size of (k×m), where m represents the number of rows in the stock dataset under examination.

In the proposed model, a stacked autoencoder version is utilized, and a deep model is trained. Linearly scalable exponential units [18] are used in this process. The architecture of the decoder in the proposed model mirrors that of the encoder, leading to a halving of the parameter count. The objective of employing a deep autoencoder in the proposed method is to reduce the dimensions of the features and map them to a new space. In essence, to derive new features from the database in the proposed method, rows of the stock database matrix are utilized as input samples and fed into the autoencoder network.

In the proposed autoencoder model, both the encoding and decoding components consist of feedforward neural networks with n fully connected classical layers, which compute l=f(W*x+b), where f represents a nonlinear activation function. The choice of the activation function f in the hidden layers is critically important, particularly requiring non-zero negative components. For this reason, SELU units are employed. This activation function exhibits two distinguishing properties: 1) non-zero negative part, and 2) unbounded positive part. Consequently, we deduce that these attributes are highly significant for successful training in this domain. Therefore, the *SELU* activation function is utilized. The formula for this activation function is provided below:

$$selu(x) = \lambda \begin{cases} x & if\ x > 0 \\ \alpha e^{x} - \alpha & if\ x \leq 0 \end{cases} \tag{1}$$

If the architecture of the decoder is tied to the encoder, then the weights of the decoder W_k^l can be constrained to the transpose of the weights of the encoder W_e^l in the corresponding layer *l*. Such autoencoders are referred to as "tied" or "restricted" autoencoders and often have approximately half the parameters compared to unconstrained autoencoders. Figure 1 illustrates the architecture of a deep neural network autoencoder for feature reduction in stocks. In this figure, *x* represents the input features from the stock dataset (10 variables influencing stock prices), *z* denotes the newly derived features obtained by the proposed model with lower dimensions, and *y* corresponds to the reconstructed stock features. During the forward pass and inference, the proposed model takes the initial features $x \in R^n$ as input and aims to obtain their representation as reduced-dimensional feature vectors. Additionally, the output of the decoder is used to obtain this representation $f(x) \in R^n$ and includes the reconstruction of the initial features.

As observed in Figure 1, the number of neurons in the encoder layer e_l is equal to that in the decoder layer $d_{|l-(n+1)|}$, and the number of neurons in subsequent layers of the encoder is fewer than the current encoder layer, and consequently, the number of neurons in subsequent layers of the decoder is greater than the current decoder layer. The number of layers and neurons per layer are hyperparameters determined based on the input size and experimentation. In autoencoder, for each input x with n features, the resulting representation (z) has a lower dimensionality of k, where k<n.

The root mean squared error (RMSE) is used as the loss function for the neural network autoencoder:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (x_t - y_t)^2} \tag{2}$$

where x_t is denoted as the vector of initial stock features on day *t*. Also,the reconstruction or prediction of the vector of initial stock features on day *t* is denoted as y_t and n represents the number of days (rows) in the stock dataset under examination.

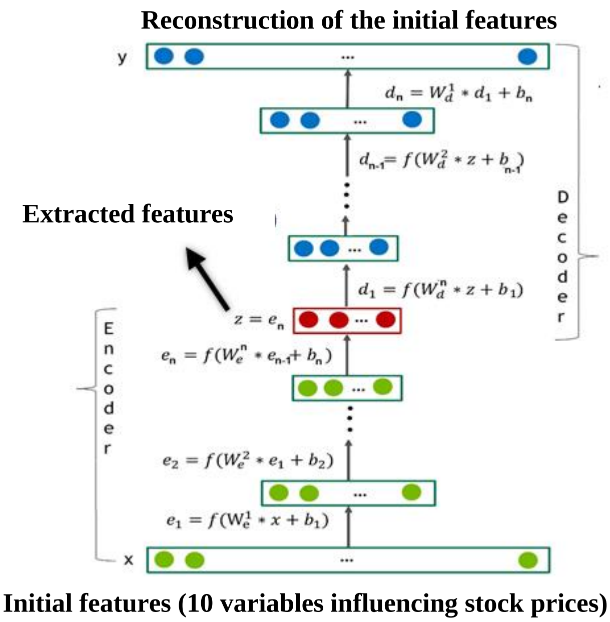

Figure 1: Architecture of a Deep Neural Network Autoencoder for Feature Reduction in Stock Dataset

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In the proposed method, a Multi-Layer Perceptron (MLP) neural network is created to predict stock prices based on the new feature matrix D obtained by the deep autoencoder in the previous step.

Since the hidden features of stocks are extracted using the deep autoencoder, the number of inputs for the neural network is equal to the number of dimensions in the obtained representations for the new feature vectors, denoted as k. The neural network in the proposed method also has an output, which represents the predicted stock price for day i. The number of hidden layers, denoted as *h*>2, to make a deep MLP. The Rectified Linear Unit (ReLU) is used as activation function.

4 ANALYSIS AND EVALUATION

The main aim of this study is to develop an effective method by combining deep autoencoder neural networks and Multi-Layer Perceptron (MLP) for predicting stock prices in the stock exchange. To assess the effectiveness of the proposed model, a case study is conducted using data from six active companies in the Tehran Stock Exchange. The dataset includes 10 influential variables on stock prices within a specific period. The proposed model is implemented and executed using Matlab R2017a on a computer with 8 GB of RAM and a 2.4 GHz quad-core processor.

The quality of the proposed stock price prediction algorithm (MLP+AE) is evaluated using the Mean Squared Error (MSE) metric. The performance of the proposed method is compared with other techniques, including the neural network (MLP) trained with backpropagation, Support Vector Machine (SVM), Decision Tree (CART), Random Forest (RF), and Principal Component Analysis (PCA) for dimensionality reduction.

To achieve reliable predictions, it's essential to utilize techniques and strategies that yield trustworthy estimates. In our proposed method, we employ cross-validation as a technique to ensure reliable predictions. In this approach, the value of k is set to 10. To evaluate the proposed method, the Mean Squared Error (MSE) obtained from the proposed approach for data from six companies in the Tehran Stock Exchange is compared with the MSE obtained from other methods for the same dataset. Table 2 provides the parameters of the alternative methods against which the proposed approach is compared.

Table 2 Parameters of Various Methods

Method	**Method Description**	**Parameters**
MLP	Multi-Layer Perceptron Neural Network	Number of hidden layers = 3, Number of neurons in each hidden layer = 4, 3, 2
SVM	SVM Support Vector Machine	Kernel function = Gaussian
DT	CART Decision Tree	Minimum branches = 10, Minimum leaf nodes = 1
RF	Random Forest	Number of trees = 10
PCA	Principal Component Analysis	Number of components = 5

Figures 2 to 7 present comparison graphs depicting the average MSE across 10 runs of various stock price prediction methods for each of the company's datasets.

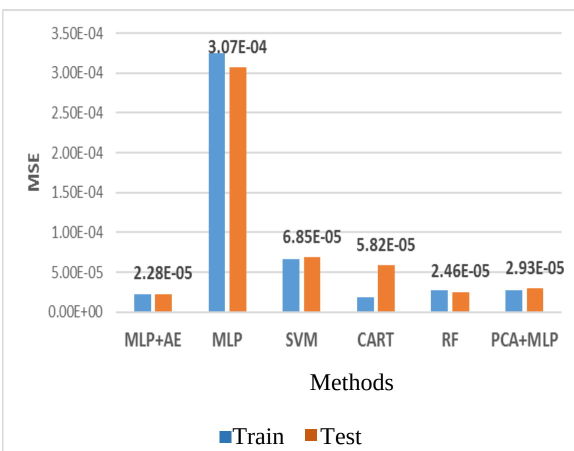

Figure 2: Comparison of Average Error for Isfahan Oil Refinery Company

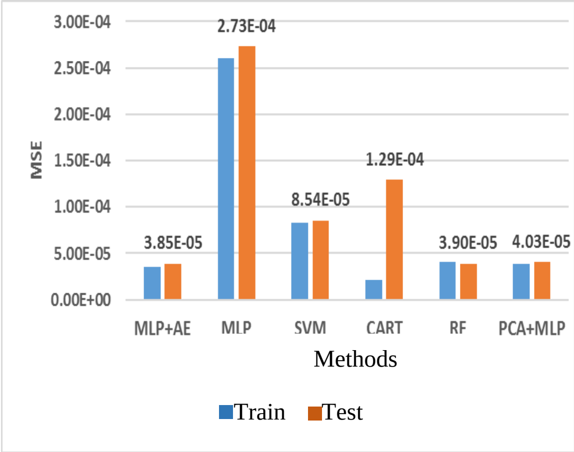

Figure 3: Comparison of Average Error for Iran Khodro Company

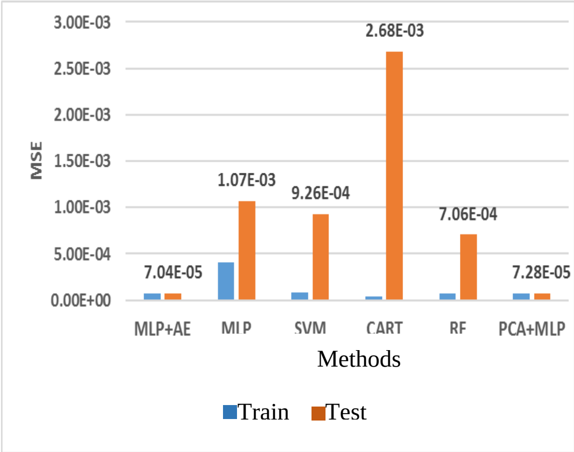

Figure 4: Comparison of Average Error for Khalij Fars Petrochemical Company

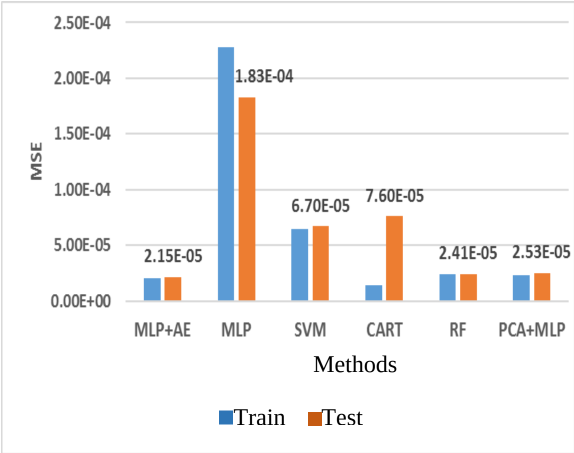

Figure 5: Comparison of Average Error for Lotus Gold Bankroll Fund Company

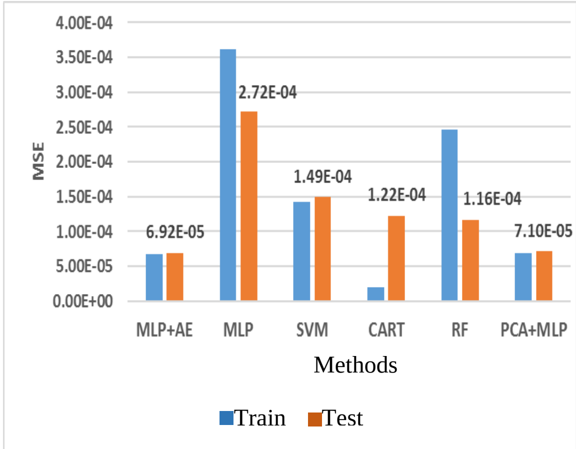

Figure 6: Comparison of Average Error for Tejarat Bank

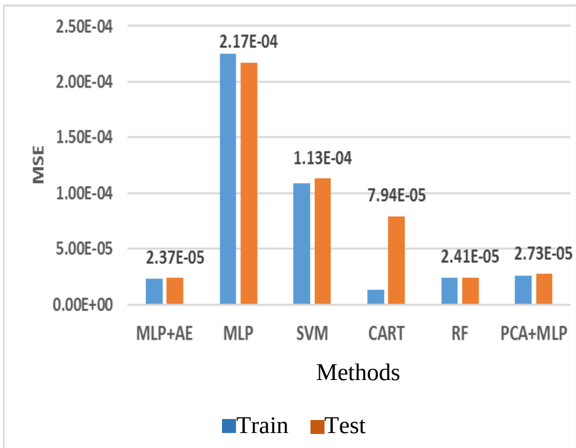

Figure 7: Comparison of Average Error for National Iranian Copper Industries Company

As observed in the figures, the proposed method MLP+AE demonstrates better performance in terms of both training and testing errors compared to MLP and SVM methods. Furthermore, in comparison to other conventional prediction methods such as CART and RF, although the proposed method has a higher training error, it exhibits a lower testing error. This implies that CART and RF methods are prone to overfitting, whereas the proposed method has a higher generalization capability, effectively preventing overfitting.

5 CONCLUSION

The main goal of this research was to explore the application of deep learning in stock price prediction. In this study, we presented a hybrid model for predicting stock prices in the Tehran Stock Exchange market by utilizing an autoencoder and a perceptron neural network. Essentially, the stock price prediction is achieved using the perceptron neural network model, with its input being extracted from the dataset through an autoencoder.

In the proposed method, the autoencoder network has 10 inputs, including various stock price influencing variables such as the lowest stock price, highest stock price, initial stock price, trading volume, transaction value, market index of the first trading hall, overall market index, USD exchange rate, global price of gold per ounce (GoldP), and global price of Brent North Sea crude oil (OilP). To evaluate the proposed method, it was implemented along with conventional prediction methods on data from 6 active companies in the Tehran Stock Exchange during the period from 2010 to 2015. The results obtained from the simulations of these models indicate that the proposed hybrid model exhibits lower error and improves the prediction process.

The successful and efficient execution of the proposed model in predicting stock prices using the data from the six selected companies demonstrates that hybrid models can effectively deal with the turbulent nature of the stock market. Consequently, with the use of these proposed models, it is possible to accurately predict the trend of stock prices in the Tehran Stock Exchange. This implies that despite the inherent volatility of the stock market, the prediction of stock prices is feasible, and artificial intelligence and machine learning models, based on novel methods and approaches in this field, can be utilized for predictions, especially in stock price forecasting.

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