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Research paper

Improving financial investment by deep learning method: predicting stock returns of Tehran stock exchange companies

Maryam Moradi[1], Najme Neshat[2], Amir Mohammad Ahmadzade Semeskande[3]

[1] Department of Industrial Engineering, Engineering Faculty, Meybod University, Yazd, Iran
mary.mdi1996@gmail.com

[2] Department of Industrial Engineering, Engineering Faculty, Meybod University, Yazd, Iran
neshat@meybod.ac.ir

[3] Department of Industrial Engineering, Engineering Faculty, Meybod University, Yazd, Iran
amirahmadzadeu73@gmail.com

Abstract:
Safe investment can be experienced by incorporating human experience and modern predicting science.Artificial Intelligence (AI) plays a vital role in reducing errors in this winning layout. This study aims at performance analysis of Deep Learning (DL) and Machine Learning (ML) methods in modelling and predicting the stock returns time series based on the return rate of previous periods and a set of exogenous variables. The data used includes the weekly data of the stock return index of 200 companies included in the Tehran Stock Exchange market from 2016 to 2021. Two Long Short-Term Memory (LSTM) and Deep Q-Network (DQN) models as DL processes and two Random Forest (RF) and Support Vector Machine (SVM) models as ML algorithms were selected. The results showed the superiority of DL algorithms over ML, which can indicate the existence of strong dependence patterns in these time series, as well as relatively complex nonlinear relationships with uncertainty between the determinant variables. Meanwhile, LSTM with R-squared equals to 87 percent and the analysis of the results of five other evaluation models have shown the highest accuracy and the least error of prediction. On the other hand, the RF model results in the least prediction accuracy by including the highest amount of error.

Keywords: Financial Investment, Changes In Stock Returns, Time Series Modelling, Deep Learning, Machine Learning.
Classification: MSC2010 or JEL Classifications: At most 3 items.

[2]Corresponding author
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1 Introduction

The stock market has the main task of providing long-term financial resources and risk management. In this market, the activity follows the analysis of the yield trend, and the recognition of the influencing factors on the behavior and fluctuations as one of the most important parameters has always been the focus of the activists in this field. Because parameters such as efficiency are non-linear, dynamic, and non-parametric, using linear methods to predict financial time series will not bring desirable results due to their linear nature. Therefore, it is necessary to use methods based on scientific and reliable principles with minimal error and high prediction accuracy, such as ML models and Artificial Neural Networks (ANN) by learning the relationships between variables to provide predicting of trends and analysis of relationships can be very beneficial in financial markets [34]. While ML and DL are often used interchangeably, they are distinct branches of Artificial Intelligence (AN).

ML is a subset of AN and has provided the ability to simulate dependencies in the sequence of stock returns with its exploratory properties and non-linear and resistant structure [20]. According to the research of Shahverdiani and Khajezade (2018), stock return predicting is more capable than the linear communication algorithm using the communication vector machine algorithm [33].

Deep Learning algorithms are a subset of MLs and have been widely implemented in the financial sector over the past few years. DL is a process that involves continuous improvement, but the most important feature of this method is that it is very powerful when dealing with unstructured data. Being resistant to fluctuations, shocks, and outliers fills the void in existing procedures [32]. The results of its application are very accurate and perform outperforms other mathematical and Machine learning (ML) models.

According to the issues raised, answering the basic research question "Comparison of the performance of DL and ML approaches in predicting stock returns "Comparison of the performance of DL approaches in predicting stock returns" will be discussed in five sections. The second section of the research is dedicated to providing theoretical foundations and a review of previous studies. The methodological step of the research will describe the conceptual model and statistical population, introduce variables, models, performance evaluation criteria, and the used software. The description of the research findings is done in the fourth section, and the conclusion of the results and suggestions will be presented at the end.

2 Literature Review and research background

This chapter will provide an overview of the background of past research, which focuses on the field of DL and improving stock return forecasting. The reason for the formation of the research question will be determined as well.

2.1 Fundamental Concepts

In this section, the different types of ANN used in this research as well as their technical structure are introduced.

Deep Neural Network

DL is a type of ML and AI that mimics the way the human mind learns a particular subject. Deep Convolution Neural Network is one of the most widely used and famous DL methods [31]. A definition of DL can be expressed as follows: It is a group of ML techniques that uses many layers of non-linear information processing to extract and transform supervised or unsupervised features. The capability of DL is that it converts raw data into vectors and feeds them into the network without the need to manually extract features on the data [39]. This modelis shown in Figure 1. [12]

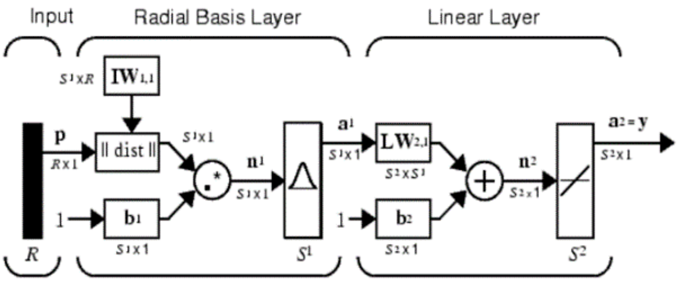


Figure 1: The general model of an RBF network with input data R

The first step to using DNNs is to set the parameters that lead to the discovery of the behavioral pattern of the network inputs. This network uses the learning rule to produce the desired output using network inputs. The role of input nodes is to transfer information to hidden layers. The layers of this network are made up of nodes. In each node, the input data is multiplied by a weight. In the next step, the hidden layers process the information after performing the calculations and transfer the information to the next layer. The input data to the output layer is the data mapped in the hidden layer. Finally, this sum passes through an activation function to reach the output. The complexity of the model depends on the number of layers and nerves in the hidden layers. When NNs contain more than three input and output layers they are called DNN. Deepness means multi-layered NN, therefore, in forecasting time series LSTM and DQN models have been used to forecast returns.
LSTM model: LSTM neural network has a special feature of Recurrent Neural Network (RNN). LSTM networks use a series of more complex units called memory blocks instead of neurons. The most basic concept about each block is its status, which is a non-linear result of the input of the block, the status of the block in

the previous stages, the output of the adjacent blocks, and also the status of the previous block [21]. figure 2. shows the structure of the memory block in LSTM:

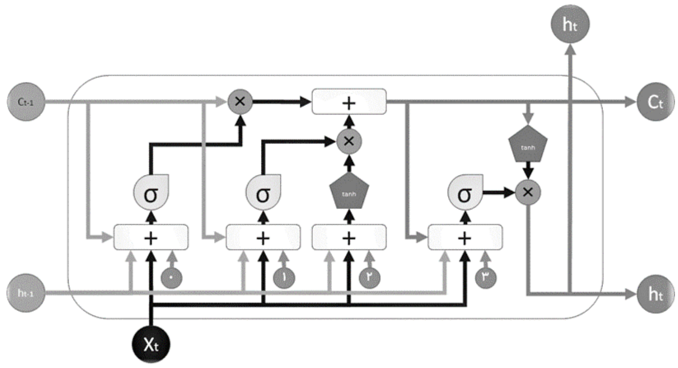


Figure 2: LSTM network

DQN model: Deep reinforcement learning is actually a subset of ML that combines DL and Reinforcement Learning (RL). This algorithm transforms a set of inputs into outputs by means of an ANN. A deep neural network is placed in the role of function estimator in DQN algorithm and at the end it outputs the action value of the given state. In other words, the learning process interacts with the environment and receives observations and rewards by performing the action, and continues until reaching the optimal value. Q (s, a; w) is called the value-action function. DQN saves the (st', at', rt', st+1) agent experiences at each time step, which reward received, action selected, and mode selected are st, at, rt , and mode st+1 is the next step respectively [13]. Similarly, target values of DQN are shown according to the following equation:

$$y_i = r + \lambda \, max_{a'} Q(s', a', \bar{w}_{i-1}) \tag{1}$$

S: Set of states that $s, s' \in \mathcal{S}$, A: Set of actions that $a, a' \in \mathcal{A}$, w: Target network parameter, r: Reward function, a: Learning rate, y: Optimal value, λ : Backup control parameter, $\lambda \in [0, 1]$. The general trend of this process is shown in Figure 3:

2.2 Research background

Financial markets consist of a dynamic system that has a corrective process. Stock market operators have always tried to use methods to increase their profits. It is necessary to obtain this profit by receiving information, analyzing them, and forecasting the future trend of stocks. Long-term investment plans can be managed if the influencing factors are known and the parameters of this market are fully mastered [36].

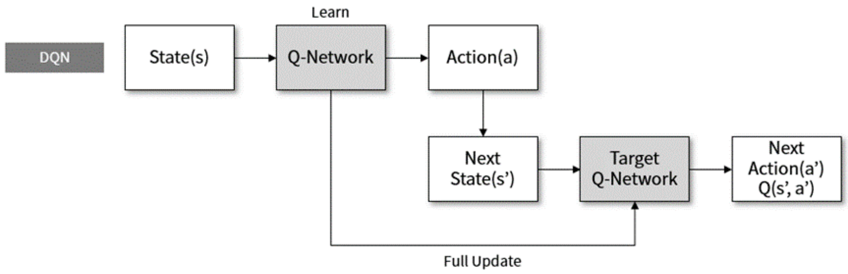


Figure 3: DQN network

Stock returns have a complex nature due to the involvement of many influencing factors [1]. Uncertainty, non-linear nature, dynamics, and fluctuations of price returns make forecasting with classical models difficult [15]. Various models have been developed in order to model the trend of time series data, which can be divided into two categories: parametric and non-parametric. Classic models such as Ordinary least squares (OLS) , Generalized autoregressive conditional heteroscedasticity (GARCH) , Autoregressive conditional heteroskedasticity (ARCH) , Autoregressive Moving Average (ARMA) , and Autoregressive integrated moving average (ARIMA) are included in the parametric models. These models have many limitations compared to the non-parametric models, limitations such as problems of correlation of independent variables, loss of a degree of freedom, and limiting statistical assumptions [9].

Recently, solving forecasting problems using DL models has received special attention. Compared to Artificial Neural Networks (ANNs), DNNs have more layers, different activation functions, and more efficient training techniques; among the most common ones are convolutional DNNs, all-connected and recurrent [24]. According to a recently published paper, DL performs better than basic methods for forecasting the trend of stock prices [35].

The big advantage that DL has over traditional ML models is that it has the ability to process a large amount of data. On the other hand, other models do not improve after their saturation limit [39]. It makes problem-solving easier because it completely automates what used to be the most important step in the ML workflow. The difference between DL and Neural Network (NN) is that DL has a wider scope than NN and includes Reinforcement Learning algorithms.

ANNs can lead to an increase in the accuracy of foresight regarding policies [8]. The result of using NNs in forecasting EFT data on the American stock market led to a higher return than the market return [43]. In the following, Wang et al. also used the same method in England and the result of their research was to increase the quality of stock portfolio optimization by using the ANN method [40]. According to the research of Bao et al. [4] in the comparison between DL models and ML, DL models perform better than other ML methods. However, the superiority of DNNs over Support Vector Machine (SVM) and Linear Regression methods in forecasting the American stock market index has been proven by Ta et al. [37].

LSTM networks are one of the most up-to-date sequential learning methods [3]. The architecture of LSTM networks has a structure similar to the normal perceptron model, input, output, and a memory cell. Sharif far et al. [34] evaluated the ability of the LSTM model to forecast stock prices and used three groups of technical indicators, shareholder transactions, and price data to implement the model. Also, he evaluated the ability of the LSTM model to forecast stock prices and used three groups of technical indicators, shareholder transactions, and price data to implement the model. In RNN, there is the limitation of being unable to store high, but the problem of reducing gradient descent. Therefore, data scientists and analysts use LSTM to forecast the movement of stock prices [5]. Aminimehr et al. [2] have presented a combined model of NN of short-term and long-term permanent memory and combined probability. This model has obtained higher accuracy and efficiency than the model without diet. Zolfaghari et al. [44] reached the conclusion that the forecasting accuracy of the presented model is higher than each of the models individually. However, EGARCH-LSTM-RNN has shown the least forecasting error compared to other methods [23]. Neshat et al. [24] and also Panggabean and Dewi [27] investigated a combined model of LSTM and GRU Deep Recurrent networks (DRNs) and Deep Fully Connected networks (DFCNs) and it was concluded that Deep LSTM Recurrent Neural Network (RNN) combined with Fully Connected Networks (FCNs) is the superior topology of nonlinear relationships between problems.

ML methods try to discover patterns in historical data and identify the underlying function and identify linear and non-linear models in the data [10]. Forecasting of stock returns using the Communication Vector Machine algorithm shows that the non-linear communication algorithm works better than the linear communication algorithm [33]. Ehsan Safari [30] showed that ML models perform better than s steps and ARIMA statistical models and DL methods show higher accuracy than SVR methods.

One of the most important advantages of Random Forest (RF) is its versatility. The time-consuming nature of this process is also one of its disadvantages. The need for large resources to store data and the problem of overfitting are other disadvantages of this model. This model is used in various issues; for example, RF can be used in finance and investment to identify the behavior of the stock market and forecast its price and return in the future. Experimental results on nine stocks from the Shanghai stock exchange in China show that both SVM and RF are effective for trend forecasting and SVM performs better than RF [42]. In the research of Bathla [5], LSTM with SVR were analyzed using different stock index data such as S&P 500, NYSE, NSE, BSE, NASDAQ and the analysis of this research showed that LSTM provides better accuracy compared to SVR. The combination of two ML models, RF and SVR, and the combination of three DL models, LSTM, DMLP, and ANN were used, and the results proved the effectiveness and increased accuracy of the combined models [16].

Due to the the evolution of studies on financial time series forecasting models according to Table 1, in this research, different models of deep neural networks are examined in order to introduce a more accurate model for predicting stock returns. These models are:

(i) Able to model existing complex conditional and non-linear relationships;

(ii) Unlike Conventional Artificial Neural models, they are able to include long-term delayed patterns in the model, and also;

(iii) In order to increase the robustness of the proposed models, exogenous variables of the model, and dummy variables have also been included in their development.

3 Research methodology

The current research is practical in terms of its purpose because its results can be used in decision-making, planning, and financial policies. It can also be called descriptive-analytical because the purpose of modelling is to use patterns among variables and determine the best method. In this regard, the library method, domestic and foreign articles, books, and theses have been used. This chapter deals with presenting the conceptual model of the research and explaining the used models, operational definition of performance evaluation variables and criteria, society and statistical sample.

According to figure 2b, the following conceptual model has been drawn for a better understanding of the executive part of the research in which deep learning and machine learning models i.e, LSTM, DQN, RF, SVR are used as implementation tools. In this model, the percentage of changes in return of the previous period of the company compared to the market, the period of influence of political, economic, and social shocks, liquidity, profitability, size, and type of the company are considered as the input, and the percentage of changes in the current period's efficiency of the companies is considered as the output of the network. It predicts future behavior and fluctuations of returns by modelling the relationships between inputs and outputs. The validity of the model is done by validating the training process and the reliability of the models is done by testing the trained networks. Finally, the superior method is introduced as the superior method of the highest prediction accuracy and the least amount of error.

The statistical population of this research includes the top 200 confirmed companies of the Tehran stock exchange, for which statistical information has been

Deep multi-layer perceptron

Table 1: Overview of research background purposes

		Target				Technique	Ability to support issues							
		Forecasting	Modelling/ estimation	Diagnosis/ evaluation	Exploratory		Non-linear and complex	Uncertain parameters	Independent of initial assumptions	Ability to generalize	Long-term memory	Ability to learning	White box modelling	
Proposed model	2023	✓		✓		LSTM, DQN, RF, SVR	✓	✓	✓	✓	✓	✓		
Ferreira de Mendonca and Faria	2013			✓	✓	Least squares							✓	[7]
Xu et al.	2013	✓				SVM, RF	✓						✓	[42]
Bildirici and Ersin	2018		✓	✓		GARCH, MLP, NN, ARMA, Markov switching	✓	✓	✓			✓		[6]
Mehregan and Ahmadi Ghomi	2016	✓				Panel vector, Auto regression	✓						✓	[18]
Nayeb et al.	2016				✓	ARCH							✓	[22]
Najarzadeh et al.	2020	✓	✓	✓		FIGARCH, FIEGARCH, ANN	✓	✓	✓			✓		[23]
Shahverdiani and Khajezade	2018	✓	✓	✓		Communication vector machine	✓						✓	[33]
Zolfaghari et al.	2020	✓	✓	✓		RNN, LSTM, GARCH, EGARCH	✓	✓	✓		✓	✓		[44]
Badiei	2018	✓				LSTM, RF, DNN, LOG	✓	✓	✓		✓	✓		[3]
Neshat et al.	2020		✓	✓		LSTM, GRU, Fully connected deep neural network	✓	✓	✓		✓	✓		[24]
Safari	2019	✓	✓	✓		ARIMA, SVR, Random walk	✓						✓	[30]
Zhong and Enke	2019	✓	✓			DNN	✓	✓	✓		✓	✓		[43]
Rahman et al.	2021				✓	Least squares							✓	[28]
Sharif far et al.	2022	✓	✓	✓		LSTM, RNN	✓	✓	✓		✓	✓		[34]
Aminimehr et al.	2021	✓	✓	✓		LSTM, Combined probability neural network	✓	✓	✓		✓	✓		[2]
Shi et al.	2021	✓		✓		DQN	✓	✓	✓		✓	✓		[35]
GhaziAskari et al.	2022	✓	✓	✓		MLP	✓	✓	✓	✓		✓		[8]
Rostami and Makiyan	2022	✓	✓	✓		Bayesian, Exponential smoothing, Bucks Jenkins	✓						✓	[29]
Maulana et al.	2023	✓		✓		Panel vector, Auto regression	✓						✓	[17]

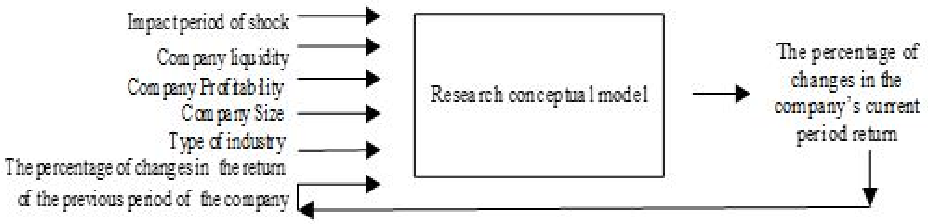


Figure 4: The conceptual model of the research

used from April 2015 to March 2019. It should be noted that more than half of the companies in the Tehran stock return market whose prices and cash returns are registered at the mentioned time intervals are not subject to suspension. The returns are five days, and the most important events in this 5-year period have been selected after refinement. Part of the data has been collected directly from the official website of the Tehran stock exchange.

Transaction delays are among the problems which this research face in the implementation of event research. There is no price for the desired share and therefore it is difficult to calculate the real return. Using the close price for the break days is a solution that has been used for solving the issue. The method is that the stock price is considered fixed and unchanged on the break days. This means that on the days when there is no trading for stocks, the return is considered zero. The modelling of the upcoming research includes twelve industries among the forty industries. All the industries that have less than 5 companies under the group have been removed, and a total of 200 companies from the real estate and real estate mass production industries, banks, and credit institutions, automobiles and parts, pharmaceuticals, investments, cement, lime, gypsum, chemical, food industries, basic metals, financial and monetary intermediation, machinery and equipment, and petroleum products have been selected and examined for modelling. Another filtering is based on the nature of industries. Those industries whose production processes are more affected by political, economic, social, and biological events have been prioritized. A total of 200 companies have been selected and analyzed for modelling. The information related to the input and output variables of the problem can be seen in Table No. 2.

In the current research, the average abnormal return has been calculated for five days from Saturday to Wednesday. The calculation process includes the following steps:

1- Calling the daily price of companies' shares

2- Calculation of daily returns

$$AR_{it} = R_{it} - E(R_{it}) \tag{2}$$

Table 2: Introduction of problem variables

	Model output	**Model inputs**					
Variables	The percentage of changes in the company's current period return	Type of industry	Company size	Profitability of the company	Liquidity	Shock impact period	The percentage of changes in the return of the previous period of the company
Initial values	–	12 selected industries	[5.5120,9.4888]	[-2469,9940]	[0.1269, 4.0410]	According to table 3	–
Prepaid amounts	–	Coded from 1 to 12	Three categories small, medium and large	Three categories of low-profit, medium-profit and high-profit companies	Coded in the range of 1 to 5	Binary vector zero and one	–

AR_{it}: The abnormal return of stock i at time t

$R_{it:}$ The real return on stock i at time t

$E(R_{it})$: The expected return of share i at time t

$$R_{it} = Ln(\frac{\mathrm{P_t}}{\mathrm{P_{t-1}}}) \tag{3}$$

P_t: The price of share i at time t

P_{t-1}: The price of share i at time $t-1$

3- Insertion of all trading symbols along with relevant information in the period of 2015-2019

4- The last days of the previous year along with the 5 days of the first holiday of the year until the arrival of the first Saturday are recognized as the first week of the year and the price of those days is considered exactly equivalent to the first Saturday of the year.

5- Calculation of five-day returns

A number of events were selected as representatives and their impact was determined according to Table 3. Incidents that have been selected in this research can be used in similar cases in the future.

Adjusting the Models Parameters: Excel spreadsheet software was used for the input data preparation process and Python programming language was used to implement the model in IDIE. Also, Anaconda program was installed and used to run the codes and use the existing libraries.

Development of LSTM model: To implement the LSTM model in the Python environment a function called getModel was designed. To build this function, a sequential model is defined in an empty form with 50 LSTM cells. The activation functions were selected in the sigmoid and linear middle layers, and Adam's mechanism was used for optimization and the mean squared error function was used to modify the weight function and the cost function. In fully connected LSTM layers, which the values of two hundred, seventy, and one have also been used has been

Table 3: Selected events and time frame of influence on stock returns

Event	Date of occurrence	Effective time frame
The election of Trump as the president of the United States	Nov 9, 2016	2 weeks
Extension of sanctions for 10 years	Dec 1, 2016	4 weeks
Presidential election	May 19, 2017	2 weeks before to 4 weeks after
Nationwide demonstrations	Dec 28, 2017	3 intense days – 3 normal weeks
CFT approval	Oct 17, 2018	1 week
Dollar exchange rate increase	Oct 21, 2018	1 week
November protests following the increase in gasoline prices	Nov 16, 2019	2 weeks
Spreading the news of the spread of the corona virus	Feb 9, 2020	4 weeks
Equity release	Apr 28, 2020	2 weeks
Underwriting "1st refining investment fund"	Aug 31, 2020	1 week

obtained by trial and error to get the optimal value. The steps of doing the work are explained according to figure No. 3a:

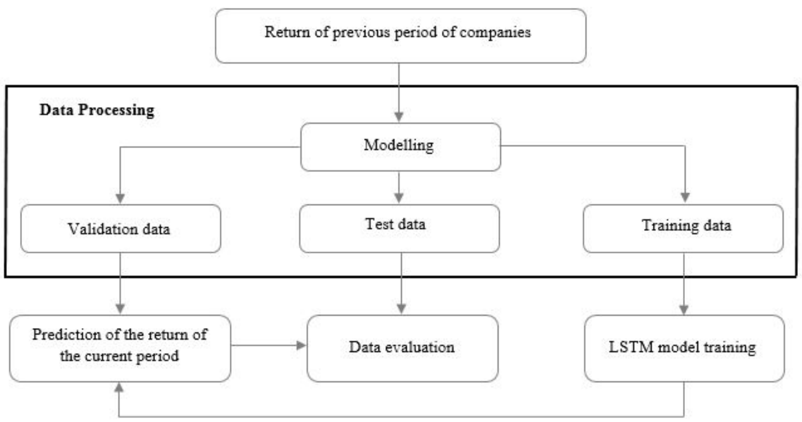


Figure 5: Steps of research

Development of DQN model: In order to run the DQN model, should first convert two-dimensional data into three-dimensional and then run the model by changing the type of input and output matrix to float 32. A function named "getSimpleRNNModel" has been designed to implement DQN. The structure of this function is exactly the same as the structure of the "getModel" function, with the only difference that instead of LSTM, simple recurrent neural networks (SimpleRNN) is used in the design of its layers.

Development of RF model: To implement the Random Forest model in Python, "RandomForestRegressor" is called from the "syckit-learn" library, and then the optimal number of layers is chosen by trial and error. The best number for optimal layers in this research was seven numbers. Then, by using the matrix of training inputs and outputs, the model is trained and the prediction operation is done using the isolated test values.

Development of SVR model: To predict return using SVR in the Python, this model is called from the "syckit-learn" library and an empty model is created. The function used in this kernel model is "RBF". The SVR model, which is one of the SVM algorithms, uses mathematical functions called "kernels". The kernel takes the input data and converts it to the required output. There are different types of kernel functions. including several linear, non-linear, sigmoid, and "RBF" functions, the most widely used of which is RBF. To implement the kernel in Python, use the "numpy" library. RBF is suitable for general purposes and can be used when there is no prior knowledge about the data. Using the matrix of input and output data, the model is trained so that the model performs the prediction operation using the test data. Table 4 shows the settings of the SVR model.

Table 4: Settings related to the SVR model

Epsilon	C	Gamma	Kernel
0.000001	100	0.1	rbf

The final step of the research is to evaluate the performance of the results obtained from each of the above models. The analysis obtained from this stage is of great importance. The performance evaluation criteria used in this research are introduced below.

R^2: The coefficient of determination R^2 or R-squared correlation measures the changes between the dependent variable and the independent variable, which varies in the interval [0,1] and the best possible case is when $R^2 = 1$.

MSE: One of the most widely used criteria is Mean Squared Error. This behavioral criterion shows a contribution and bigger errors are given more weight.

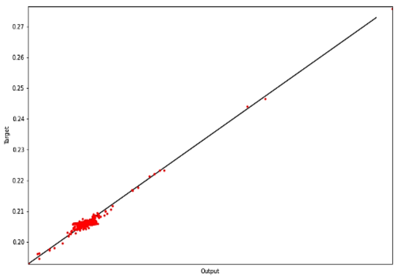
RMSE: Root Mean Squared Error is widely used in results reports due to the same scale and dimension as the target characteristic.

MAE: Mean Absolute Error is used in comparing models and reporting results. When you want the model to be more stable to outlier data the average absolute value of the error is a suitable option.

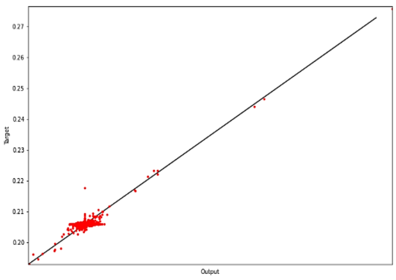
MAPE: Mean Absolute Percentage Error works similarly to the mean absolute percentage error with the difference that the relative error is used instead of the error and the output will be a number in the range [0,1], which by multiplying it by 100, it will be in percentage format.

4 Research Results and Findings

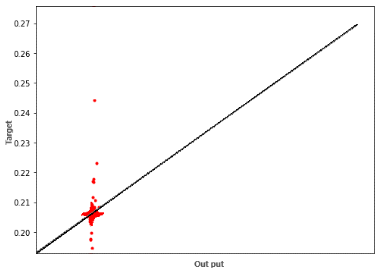
The purpose of this research is to compare the performance of deep learning and machine learning models in predicting the percentage of stock return changes. To achieve this goal, four LSTM, DQN, RF, and SVR models have been used. For this purpose, the weekly returns have been collected and the financial and organizational information of the companies have been entered in the dataset as the output of the model. After that, empty and non-numeric containing value cells were removed and the behavior of the model was improved. A total of 49,795 rows of data were entered as input to the network. 60 percent of the data are allocated for training, 20 percent for testing and 20 percent for validation. The values of training, prediction, and estimation are randomly selected from the data. According to figure 6 the results of comparing the predicted values by each of the models with their actual values can be seen in figure 3b.



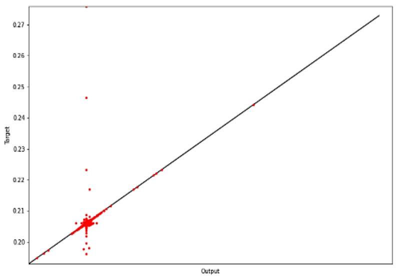
(a) LSTM model



(b) DQN model



(c) SVR model



(d) RF model

Figure 6: Chart of test data and real data based on model execution model

Figures 6a to 6d shows the comparison of real and predicted data of Tehran stock exchange returns. The horizontal axis represents the actual values and the vertical axis represents the predicted values. The 45-degree angle of the R graphs is the criterion of optimality. According to the results of the implementation of the models the highest convergence in the optimal line is related to the LSTM model. Therefore, this model has the least error and the highest predictive power compared to the other presented ones. The convergence of cloud points in DQN model also has a high percentage after LSTM. The outlier data from RF and SVM implementations are also observed almost close to each other, which is a sign of lower prediction accuracy and higher measurement error compared to deep models. So, it is concluded that the recurrent networks, especially the LSTM, are more powerful than the other methods for predicting stock returns. This superiority indicates the presence of strong dependency patterns between the predicted and real data in the studied time series. Therefore, the matching percentage of the predicted yield compared to the actual yield follows the following relationship: LSTM > DQN > SVM > RF In the next step, ML and DL models are compared and after that, the two best models of each method are evaluated. In the graphs 4 to 9 the horizontal axis represents the return and the vertical axis shows the number of the week:

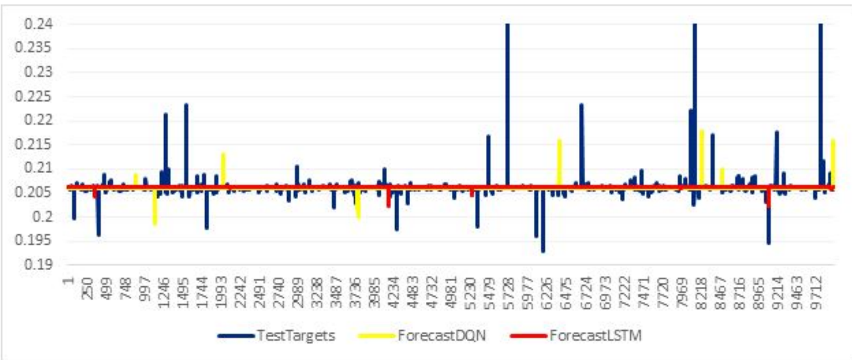


Figure 7: LSTM and DQN models evaluation results

In the figure 4, the data predicted by both methods are very similar, but the LSTM method has higher stability and its fluctuations have been reported in the direction of real data changes; so that seemingly, there is a difference of about 0.2 between the predicted and the estimated actual yield. The reason for this is that short-term memory is one of the RNN algorithms, which is able to deal with the problems of gradient disappearance and pattern preservation by changing the activation functions. However, the amount of violation resulting from the DQN method is more than that of the LSTM method. Therefore, LSTM reports better results than DQN with a slight difference. DL algorithms have a good potential in handling unstructured data such as stock return volatility, which indicates the existence of strong dependency patterns between the predicted and the actual data in the time series. However, the problem of overfitting and high computational time have been reported as disadvantages of Deep Neural Networks (DNN).

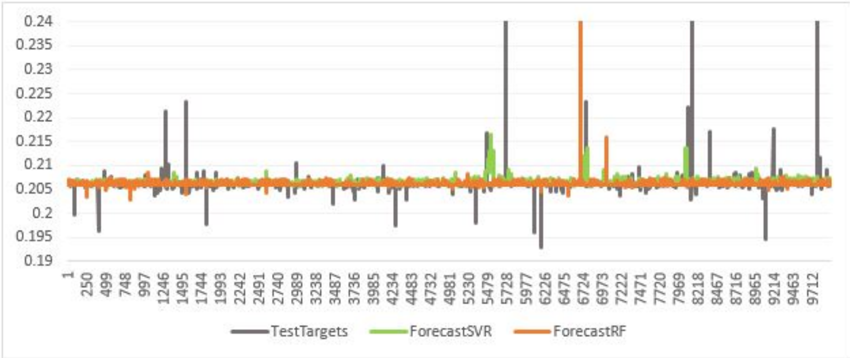


Figure 8: Evaluation results of RF and SVR models

In figure 8, the graph of the real data is shown in gray, the graph of the data predicted by the RF method is shown in orange and the data predicted by the SVR method is shown in green. In general, the amount of violation resulting from the SVM method is lower than RF. In the same way, SVM reports better results than RF. The data predicted by the SVM is more consistent with the real ones, and its fluctuations have been reported in the direction of the changes of them; Because SVM avoids the problem of overfitting and obtains the boundary based on support vectors, it works well in high dimensions. The graph obtained by the RF also has a lot of fluctuations and reasonably, the decision forest cannot improve the accuracy of the base model by increasing the number of trees more than its optimum.

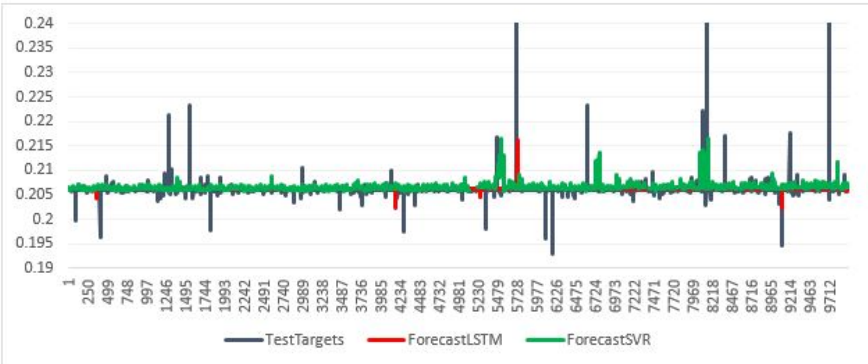


Figure 9: LSTM and SVR models evaluation results

Figure 9 compares the best models, LSTM and SVR. It clearly shows the superiority of the LSTM model from the DL group over the SVR model from the ML group. As can be seen from the above figure, the high compatibility of LSTM with real data shows higher predictive power and lower error The high matching of LSTM with the real data indicates higher predictive power and lower error. Deep learning algorithms have great potential in modeling unstructured data such as volatility of stock returns. The LSTM model provides more accurate results than the SVR model due to the presence of more and fully connected layers, different activation functions and more efficient training methods.

In the following, in order to validate the results obtained from the analysis of the graphs, the amount of error obtained from each method has been evaluated with a set of evaluation criteria.

Table 5: The results of evaluating models using evaluation models

Evaluation Criteria	RF	DQN	RF	SVR
R^2	0.720314254	0.765429543	0.864328300	0.854975360
MAE	0.000188287	0.000123133	0.000121678	0.000180966
MSE	2.64771E-05	1.07514E-06	1.05153E-06	1.09422E-06
MAPE	0.000897477	0.000581143	0.000671040	0.000861899
Max Error	0.500463081	0.069927533	0.069558177	0.069436877
RMSE	0.005145588	0.001036887	0.001033094	0.001407868

Considering the R^2, MAE, MAPE, RMSE, and MSE parameters in the training and testing phase, as seen in Table 5, the LSTM RN generally has high accuracy and is more successful than other methods in predicting the stock return index than other methods. According to the studies of [38], the RMSE and MAPE are used as the strongest and most common two indicators in the evaluation of the quality of fit, whose values are reported as 0.001033094 and 0.000471040 for the LSTM model respectively. Also, the output of this model has the R^2 equals to 0.864328300, which is very close to one and shows the high accuracy of the model. These results indicate that the LSTM model, when faced with the new data, can provide results close to reality with acceptable accuracy. Since stock returns are a time series dependent on time lags, and LSTM works better than other methods for modelling time lags, therefore LSTM is an effective method in predicting financial time series such as returns. After that, we see the close relationship between the evaluation results of SVR and DQN models according to the three criteria MAE, MSE, MAPE, RMSE, and finally, RF with the inclusion of acceptable results placed at the last place of this comparison; and finally, RF with the highest value of RMSE equals to 0.005145588 and MAPE, 0.000897477 has provided acceptable results, but it is in the last place of this comparison. Therefore, according to that the training of deep recurrent networks is generally time-consuming, but it has a very high accuracy and provides a lower violation rate than other methods.

5 Conclusion and Recommendations

Since the most important feature of financial time series such as stock returns, is their non-linearity, using linear methods to predict financial time series will not bring favorable results; therefore, most of the algorithms based on the irregularity approach and due to the presence of complex and non-linear relationships in the time series model and the existence of strong patterns resulting from dependence on previous values in the data have attracted the attention of investors. The purpose of the current research is to compare the performance of DL and ML models in predicting percentage changes in stock returns of companies in the Tehran Stock Exchange market. Considering the fact that DL and ML models are among Artificial Intelligence (AI) models and each has different topologies and functions. In this research, four selected models of DL and ML models, namely DQN, LSTM, RF, and SVM have been investigated and the weekly stock return data of Tehran Stock Exchange companies have been used as input to the models. The investigations indicated that the effective parameters in building the optimal architecture of the mentioned models include items such as the size of the batch, the number of filters, and the activation function; therefore, in the first stage, using different combinations of the mentioned parameters, optimal values were obtained for each architecture, and in the final stage, the superiority of each model was measured using five criteria, R^2, MSE, RMSE, MAE, and MAPE. The results of evaluating the models in accordance with the research of Nikou et al. (2019) [26] and Abe and Nakayama (2018) [1] reveal the fact that DL models provide more accurate predictions compared to MLs (discussed), which This superiority proves: 1) the presence of strong dependence patterns between the predicted data and previous data in the mentioned time series, 2) the existence of relatively complex non-linear relationships with uncertainty between the input variables of the model and the response variable, and 3) the difference of time delays in the time series input to the model. Meanwhile, the LSTM RN has represents the best performance as the strongest indicators in the quality evaluation by changing the activation functions in dealing with the problems of gradient disappearance, maintaining the pattern, and having the long-term memory capability for financial time series, with RMSE and MAPE of 0.001033094 and 0.000471040 respectively. Since stock returns are a time series dependent on time lags and LSTM works better than other methods for modeling time lags; therefore, LSTM is an effective method in predicting financial time series such as returns; after that, DQN ranks second. A group of researchers such as Wu et al. (2022) [41] and Shi et al. (2021) [35] have pointed out the improvement of the results obtained by combining the two mentioned methods and the superiority of each one over the others.

In the same way, the data predicted by the SVM is more consistent with the real ones than the RF, and its fluctuations have been reported in the direction of real data changes. SVM works well in high dimensions because of avoiding the problem of overfitting and obtaining the boundary based on support vectors; but RF is ranked last in this comparison with the highest RMSE and MAPE which equals 0.000897477 and 0.005145588 respectively; the disability of decision forest to improve the accuracy of the base model by increasing the number of trees beyond its optimal limit is the reason for that. According to the present results, Kumar and Thenmozhi (2006) [14] and Khaidem et al. (2016) [11] also acknowledge the superiority of the SVM method over other MLs, including RF. Finally, the results of Bathla (2020) [5] and Mehtab and Sen (2020) [19] confirm the validity of the final result of the current research that the prediction accuracy of the LSTM method is superior to the SVM.

According to the results of the current research, which presents the superiority of the LSTM model over other methods, researchers are suggested to conduct additional studies to examine this model in more detail and to compare other LSTM models such as Bidirectional LSTMs, Generative LSTMs, Stacked LSTMs, CNN LSTMs, Encoder-Decoder LSTMs. It should be noted that the data examined in this research is a time series of weekly stock price returns, and it is suggested that the accuracy of the model be checked with other inputs as well. Combining DL models with various meta-heuristic algorithms such as the meta-heuristic algorithm of shrimp groups can also help to optimize the goal and predict problems more accurately.

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