Adv. Math. Fin. App., 2024, 9(4), P.1233-1248

Advances in Mathematical Finance & Applications

www.amfa.iau-arak.ac.ir

Print ISSN: 2538-5569

Online ISSN: 2645-4610

Doi: 10.22034/amfa.2023.1973199.1826

Original Research

Predicting Stock Price Crash Risk with a Deep Learning Approach from Artificial Intelligence and Comparing its Efficiency with Classical Predicting Methods

Meysam Rahmati*, Ehsan Taieby Sani

Department of Financial Sciences, Kharazmi University, Tehran, Iran

ARTICLE INFO

Article history:

Received 2022-11-20

Accepted 2023-05-27

Keywords:

Stock Price Crash Risk

Deep Learning Approach

Artificial Intelligence

Comparing its Efficiency

Classical Predicting Methods

ABSTRACT

Purpose of this research is Predicting Stock Price Crash Risk with a Deep Learning Approach from Artificial Intelligence and Comparing its Efficiency with Classical Predicting Methods. This research is post-event correlation type and practical in terms of purpose. The research data were extracted from the website of the Stock Exchange Organization and Codal website. The risk variable of crashing stock prices was introduced as a predictor. 3200 observations were obtained from 10-year data of 320 companies between 2012 and 2021. In the following, 29 variables were identified as variables that can affect the risk of crashing stock prices. Statistical methods such as unit root test, composite data, Hausman test and variance heterogeneity test were used. Next, the top 10 algorithms in the field of deep learning were selected and used to model the mentioned variables with the CNN method. Python, Eviews and Excel software were used in this research. Examining the performance of different deep learning algorithms shows that the convolutional neural network method performs better compared to other algorithms and can improve the prediction accuracy. Therefore, it is suggested to use this algorithm in reviewing econometric data and especially predicting the risk of crashing stock prices.

1 Introduction

Theoretical and empirical studies have shown that there is a positive relationship between financial markets and economic growth [4, 18, 24, 25, 28]. Considering the importance of financial markets, predicting financial returns has an important place in investment decisions. However, financial markets are characterized by volatility, dynamism and complexity [6, 14, 34]. Movements in stock markets are affected by several factors such as macroeconomic factors, international events and human behaviour. Therefore, predicting changes in the stock price index can be a difficult task. The profitability of investing in the stock markets largely depends on the ability to predict share movements. If a

* Corresponding author. Tel.: +989127662560
E-mail address: *rahmatimeysam700@gmail.com*

forecasting model or method can accurately predict the direction of the market, investment risk and estimated error can be minimized. This issue attracts more investment to the stock markets and is also useful for law enforcement and market regulators in making appropriate decisions and corrective actions [20].Decision making is a complex process that includes analysing several factors and following different steps. It is believed that decision making is basically based on two things: personal resources or barriers and technical factors. Likewise, investors trust these two factors while making decisions in the stock market. Decision making by individual investors is usually based on their personal factors such as age, education, income and investment portfolio, etc. At the same time, their investment decisions are also made from complex financial models. These models include models based on risk and expected returns related to investment and asset pricing models based on risk such as the capital asset pricing model. But decisions should never be made by relying only on personal resources and complex models that do not consider situational factors. Situational factors are extended not only to the problem that the decision maker is facing, but also to the environment. Therefore, in order to make a proper decision, the variables of the problem should be analysed through the use of cognitive psychology. Decision making can be defined as the process of choosing a specific alternative among a number of options [13].Financial markets are one of the most attractive innovations of our time. They have a significant impact on many fields such as trade, education, jobs, technology and subsequently on the economy [12]. Over the years, investors and researchers have been interested in developing and testing stock price behaviour models [11]. Nevertheless, analysis of stock market changes and its price change method is a very difficult challenge due to market dynamics and its non-linear, fluctuating, non-parametric, chaotic and chaotic nature[1].According to Zhong and Enke [35], stock markets are influenced by multiple and interdependent factors, among which economic, political, psychological factors, and variables specific to each company can be mentioned. Technical and fundamental analysis are two basic approaches for analysing financial markets [21, 23]. Investors use these two approaches to make decisions in financial markets in order to invest in stocks and achieve high profits with low risk [3].The methods of fundamental analysis and technical analysis were challenged in the 1960s by the random walk known as the efficient market theory [9]. , which proposed that future changes in stock prices cannot be predicted based on stock price changes in to take place in the past Some empirical studies showed the presence of a random walk in stock prices [8, 16],(for example: Tong et al [32] However, most empirical findings have proven that stock prices are predictable [2].Forecasting the stock market price is a difficult and laborious task. Several theories about stock markets have been conceptualized during these years. They have tried to explain the nature of the stock markets or they have tried to explain whether the markets can be broken or not.Hence, decision makers should keep themselves updated by acquiring information. Knowledge from various fields in order to be able to perform the tasks they have to perform. Effective decision-making in the stock market requires a better insight and understanding of human nature in a global perspective, apart from strong financial skills and the ability to obtain the best results through investments. Positive perspective, foresight, perseverance and motivation are essential for the success of an investor in his investment decisions [15].The characteristics of investors are different due to demographic factors such as socio-economic background, education level, age, gender and similar things. Therefore, it is difficult for an investor to make the right investment decision based on the decisions made by another person. This means that the optimal investment decision for one investor may not be suitable for another investor [17]. Every investor has his own investment goals; the level of risk tolerance, money input and output, and other restrictions are different for each person, and based on this, he designs his investment portfolio by considering all these factors [22].Institutional investors should also estimate the optimization of production variance. But when it comes to investment decisions by individual investors, they cannot follow the standard procedure for designing the optimal investment strategy. In this way, it is said that they suffer from behavioural biases [29].Psychological biases may affect their investment decision making process. The influence of behavioural factors on decisions is often ignored by individual investors and this disrupts their investment performance in the stock market [30].There are different methods for forecasting the stock market with the help of historical data. In one classification, these methods are classified into two groups, linear and non-linear, and in another type, they are classified into machine learning and statistical methods; but the proper classification is to group them in smart and classic ways. In classical forecasting methods, it is assumed that the future values of the price follow the linear trend of the past values, and regression, Garch and Arima models are included in this category. Neural networks, fuzzy logic, support vector machines and collective learning models are included in the category of intelligent methods [5]. The results of the comparisons have shown that intelligent methods overcome the limitations of linear models in comparison with classical methods, and have better ability to extract models from data and more accuracy for prediction. In recent years, most of the studies done to predict the stock market are focused on intelligent methods, and among them, the neural network has been used the most and has a better efficiency than other models. Neural network is also used for forecasting in cases such as bankruptcy of companies in the stock market. Despite the complexity of forecasting in the stock market, the results of researches have shown that the neural network can be sufficient for modelling a complex system with the desired accuracy [10]. According to the above-mentioned materials, in this research, a new approach is used in predicting the risk of crashing stock prices, and since the previous research shows that the performance of intelligent methods is far They are better than classical methods, for this purpose deep learning method of artificial intelligence is used. Deep learning is a subfield of machine learning that uses multiple layers of linear transformations to process sensory signals such as audio and video. In this method, the machine divides each complex concept into simpler concepts, and by continuing this process, it reaches the basic concepts for which it is able to make decisions, and thus there is no need for full human supervision to determine the necessary information of the machine at any moment. Therefore, deep learning is a class of machine learning algorithms that use multiple layers to extract high-level features from the raw input. In other words, a category of machine learning techniques that uses several layers of information processing, especially non-linear information, to transform or extract supervised or unsupervised features, generally with the aim of analysing or recognizing patterns, classification, clustering [7]. According to the explanations given above, the main problem of the research is: Predicting the risk of crashing stock prices with a deep learning approach from artificial intelligence. Also, in order to evaluate the effectiveness of the proposed method of this research, the results obtained from forecasting based on this approach are compared with classical forecasting methods, and based on RMSE and MAE criteria, the efficiency of the model the research is evaluated.

2 Literature Review

Stock price crash risk is a phenomenon in which stock prices are subject to severe negative and sudden adjustments. So far, different approaches have been proposed to model and predict the stock price crash risk, which in most cases have been the main emphasis on the factors affecting it, and often traditional methods have been used for prediction [36]. Financial markets play an important role on the economic and social organization of modern society. In these kinds of markets, information is an invaluable asset. However, with the modernization of the financial transactions and the information systems, the large amount of information available for a trader can make prohibitive the analysis of a financial asset. In the last decades, many researchers have attempted to develop computational intelligent methods and algorithms to support the decision-making in different financial market segments [5]. Stock market is characterized as dynamic, unpredictable and non-linear in nature. Predicting stock prices is a challenging task as it depends on various factors including but not limited to political conditions, global economy, company's financial reports and performance etc. Thus, to maximize the profit and minimize the losses, techniques to predict values of the stock in advance by analysing the trend over the last few years, could prove to be highly useful for making stock market movements . Traditionally, two main approaches have been proposed for predicting the stock price of an organization. Technical analysis method uses historical price of stocks like closing and opening price, volume traded, adjacent close values etc. of the stock for predicting the future price of the stock. The second type of analysis is qualitative, which is performed on the basis of external factors like company profile, market situation, political and economic factors, and textual information in the form of financial new articles, social media and even blogs by economic analyst. Now a days, advanced intelligent techniques based on either technical or fundamental analysis are used for predicting stock prices. Particularly, for stock market analysis, the data size is huge and also non-linear. To deal with this variety of data efficient model is needed that can identify the hidden patterns and complex relations in this large data set [33]. The importance and unique position of the capital market in the economy of countries is not hidden from anyone; this financial institution has a decisive role in the optimal allocation of resources and the provision of financial resources of economic enterprises, which ultimately contributes greatly to the growth and prosperity of a country's economy. The quantitative and qualitative expansion and development of Iran's capital market in recent years, along with the use of modern financial tools, has led to liquidity from parallel markets to this area, which has led to an increase in the volume of transactions and increased attention of society members to the capital market. Knowing and investigating stock price behaviour has always been of interest to investors and researchers in this field; the actors of this market are trying to find and apply methods so that they can increase the profit of their capital by predicting the future stock price. Therefore, it is necessary that appropriate, correct and scientific methods are used to determine the future price of shares for investors. Some phenomena such as stock prices have a complex nature that makes it difficult to find a mathematical model to model the nonlinear relationship between input and output elements; Price changes in the stock market are influenced by several factors such as macroeconomic variables - bank interest rates, currency exchange rates, inflation - as well as political events, industry conditions, corporate policies, investors' expectations and movements of other parallel markets. Historical data shows that the complex characteristics of stock prices, such as non-linearity, uncertainty, volatility and dynamics, make it difficult to predict and the prediction results face great uncertainty. Considering that most researchers are of the opinion that financial markets follow a non-linear process. The use of non-linear models and advanced techniques has become increasingly popular among financial market experts for price prediction; the use of artificial intelligence methods are among such activities. In recent years, prediction models based on deep learning have emerged, which mostly perform better than traditional methods. Deep learning is one of the topics of machine learning and artificial intelligence and is a set of algorithms that try to model high-level abstract concepts using learning at different levels. In other words, the algorithms of this method use several information processing methods, especially non-linear information, to extract the best suitable features from the raw input [27].On the other hand, financial time series prediction can be considered one of the main challenges in the time series and machine learning literature. In the last decades, several approaches have been proposed to predict financial time series and to provide decision-making support systems .Two major classes of work which attempt to forecast financial time series are the statistical models and machine learning approaches. Traditional statistical methods generally assume that the time series under study are generated from a linear process, and try to model the underlying time series generation process in order to make predictions about the future values of the series. However, financial time series are essentially complex, highly noisy, dynamic, nonlinear, nonparametric, and chaotic in nature. Machine learning techniques have been applied with relative success in modelling and predicting financial time series. Many machine learning techniques are able to capture nonlinear relationship between relevant factors with no prior knowledge about the input data. Among these techniques, artificial neural networks (ANN) have been widely used in forecasting time series, since they are data-driven, self-adaptive methods able to capture nonlinear behaviors of time series without any statistical assumptions about the data. Due to these advantages, several types of ANNs and hybrid mechanisms have been used in forecasting financial time series [27]. Artificial Intelligence (AI) provides us an ideal opportunity to precisely capture investor sentiment, as AI can directly estimate investor sentiment without a pre - set emotional dictionary or selecting principle component, and thus help reduce forecasting bias caused by subjective interference or common approximation errors. In addition, with its independent deep learning ability, AI can precisely tell the assignment of a word "s sentiment value in a specific scenario, given that one word may reflect different degree of sentiment with respect to different scenarios [26]. All kinds of artificial intelligence models have established their place in financial market calculations and forecasts; In the meantime, architectures based on deep learning, which are based on machine learning algorithms, have been taken into consideration by solving the weaknesses of traditional neural network models regarding the prediction of dynamic structures. The most important advantage of deep learning algorithms compared to traditional neural network models is the automatic extraction of appropriate features from raw inputs, which it uses for the learning process of the model; In other words, the algorithms of this method use several layers of information processing and especially non-linear information to extract the best suitable features from the raw input [27].Most of the previous work in this area use classical algorithms like linear regression, Random Walk Theory (RWT), Moving Average Convergence . Divergence (MACD) and also using some linear models like Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), for predicting stock prices. Recent work shows that stock market prediction can be enhanced using machine learning. Techniques such as Support Vector Machine (SVM), Random Forest (RF). Some techniques based on neural networks such as Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and deep neural networks like Long Short Term Memory (LSTM) also have shown promising results. ANN is capable for finding hidden features through a self-learning process. These are good approximators and are able to find the input and output relationship of a very large complex dataset. Thus, ANN proves to be a good choice for predicting stock price for an organization. Selvin et al predicted stock price of NSE listed companies by a comparative analysis of different Deep learning techniques [33]. Also, in this field, different researchers analysed in this regard. for example Ruan et al. [26] investigated a research titled A New Investor Index Based on Artificial Intelligence: A Predictor of Return Power in China. This paper proposes an investor sentiment index that is compatible with the purpose of predicting stock market returns using the deep learning method that has been widely used in artificial intelligence. The results show that the investor-sentiment index has a positive relationship with the future return of the stock market in a monthly period, but it has a negative relationship with the future return in a longer horizon. In addition, the investor sentiment index performs better than other known predictors in the sample and out of the sample and can predict cross-sectional stock returns sorted by industry. It also shows a positive relationship between the monthly investor sentiment index and the dividend growth rate. Investors' expectations about future cash liabilities can help predict the returns of the investor sentiment index. Vijh et al [33] investigated a research entitled predicting the closing price of stocks using machine learning techniques. The results showed that accurately predicting stock market returns is a very challenging task due to the unstable and non-linear nature of financial stock markets. With the introduction of artificial intelligence and increasing computing capabilities, it has been proven that programmed methods are more effective for predicting stock prices. In this work, artificial neural network and random forest have been used to predict the closing price of the next day for five companies belonging to different operational departments. Financial data such as open, high, low, and close stock prices are used to create new variables that are used as input to the model. Standard strategic indicators of evaluation show that the models are efficient in predicting the final stock price. Lin et al [19] suggested to use the ELM method due to the problems that exist in the classical methods, and the results of their research showed that this method is very efficient. In their research, they showed that, in general, the predictive assembly of a set of neural networks will lead to improving the predictive accuracy and stability of the results. These results are more accurate than the models that make them up. Takach and Werner [31] used intelligent methods to predict the stock market and showed that the neural network is more useful and has better efficiency than other models. He has investigated neural network programs in various business fields with 412 applications, which were published in influential and prestigious journals between 1994 and 2015. Although the reviewed authors have successfully used neural networks for various tasks, our results show that the most investigated cases in our study were economic distress and bankruptcy, stock price forecasting, and credit scoring. Sharif-far et al [27] conducted a research under the title of evaluation and validation of the optimal deep learning architecture in stock price prediction (short-term persistent memory algorithm approach). In this research, the ability of short-term persistent memory algorithm architectures to predict stock prices has been investigated; In addition, while classifying the factors affecting the stock price, the components indicating the transactions of real and legal shareholders have been introduced and examined as a factor affecting the stock price. To implement the model, three groups of price data, technical indicators and transactions of real and legal shareholders have been used. The results of the research show the better performance of the short-term persistent memory algorithm architecture compared to its simple model as well as the RNN model. Faghihi-Nejad and Minaei [10] conducted a research titled "Prediction of stock market behaviour based on artificial neural networks with intelligent collective learning approach". Forecasting financial time series is one of the challenging and important issues in forecasting, and researchers try to extract hidden patterns to predict the future of the stock market. The aim is to provide an intelligent model for predicting stock market behaviour. In this article, to increase accuracy, a model based on collective learning algorithms with basic models of neural networks is used. To consider the direction of the price change in the forecast, a two-stage structure has been used. In the first step, the next direction of stock price movement (increase or decrease) is predicted and it is used to predict the price in the second step. The accuracy of the results and increasing the forecasting efficiency are the most important challenges of the proposed models in the stock market. The important point for the profitability of transactions is to pay attention to the direction of the stock price change in its price prediction, which has been given less attention in forecasting models. The proposed model using methods based on artificial intelligence shows that it is possible to predict the behaviour of the stock market despite its fluctuating and unstable nature. The results of evaluation criteria on real stock price data show that the proposed model can more accurately overcome market fluctuations and be used as a reliable and practical method in stock markets compared to other methods. Arévalo et al [3] studied a dynamic trading rule based on filtered flag pattern recognition for stock market price forecasting. In this paper they proposed and validated a trading rule based on flag pattern recognition, incorporating important innovations with respect to the previous research. Firstly, they proposed a dynamic window scheme that allows the stop loss and take profit to be updated on a quarterly basis. In addition, since the flag pattern is a trend-following pattern, we have added the EMA indicator to filter trades. This technical analysis indicator is calculated both for 15-min and 1-day timeframes, which enables short and medium terms to be considered simultaneously. We also filter the flags according to the price range on which they are developed and have limited the maximum loss of each trade to 100 points. The proposed methodology was applied to 91,309 intraday observations of the DJIA index, considerably improving the results obtained in the previous proposals and those obtained by the buy & hold strategy, both for profitability and risk, and also after taking into account the transaction costs. These results seem to challenge market efficiency in line with other similar studies, in the specific analysis carried out on the DJIA index and is also limited to the setup considered. Klashanov et al. [15] studied Artificial intelligence and organizing decision in construction. . The proposed method is effective implementation of organizational and technological solutions with the use of its information models and systems of making management decisions on the results of monitoring the construction process. The basic information based on models of knowledge representation (semantic, frames, production rules and regulations, precedents), and concepts on the application of artificial neural networks in construction and information about the methods of extraction of knowledge and formation of knowledge bases. Examines the structure and functions of expert systems and decision support systems solutions .Cavalcante et al [5] studied Computational Intelligence and Financial Markets: A Survey and Future Directions. This paper gives an overview of the most important primary studies published from 2009 to 2015, which cover techniques for pre-processing and clustering of financial data, for forecasting future market movements, for mining financial text information, among others. The main contributions of this paper are: (i) a comprehensive review of the literature of this field, (ii) the definition of a systematic procedure for guiding the task of building an intelligent trading system and (iii) a discussion about the main challenges and open problems in this scientific field.

3 Research Objectives

3.1 The main objective

Forecasting the risk of crashing stock prices with a deep learning approach from artificial intelligence and comparing its efficiency with classical forecasting methods

3.2 Sub-goals

Comparing the performance of different deep learning algorithms from artificial intelligence

Comparing the effectiveness of the best deep learning approach from artificial intelligence with classical forecasting methods (exponential smoothing and ARIMA)

4 Methodology

This research is post-event correlation type and practical in terms of purpose. The research data were extracted from the website of the Stock Exchange Organization and Codal website. The risk variable of crashing stock prices was introduced as a predictor. 3200 observations were obtained from 10-year data of 320 companies between 2012 and 2021. In the following, 29 variables were identified as variables that can affect the risk of crashing stock prices. These variables are: "TTM Net Profit Margin", "MRQ Net Profit Margin", and “Return on Assets, Return on Equity “,” Earnings". "Fixed assets turnover", "Inventory turnover", "Inventory turnover period", "Accounts receivable turnover", "Debt collection period", "Total liabilities to total assets", "Debt to equity ratio" ", "debt ratio", "debt-to-equity ratio", "long-term debt ratio", "accumulated profit-to-asset ratio", "interest expense coverage ratio", "current ratio", "current ratio", "liquidity ratio" "Ratio of free cash" of the company to net profit, "Ratio of shareholders' cash flow to net profit", "Ratio of capital expenditure to net profit", "Ratio of operating cash to total liabilities", "Ratio of investment cash flow to Income", "enterprise value logarithm", "book value logarithm" and "operating cash flow logarithm". Statistical methods such as unit root test, composite data, Hausman test and variance heterogeneity test were used. Next, the top 10 algorithms in the field of deep learning were selected and used to model the mentioned variables with the CNN method. Python, EViews and Excel software were used in this research.

$$\mathrm{NCSKEW}_{it} = -[n(n-1)^{\frac{3}{2}} \sum W_{i,\theta}^{3}].[(n-1)(n-2)(\sum W_{i,\theta}^{2})^{\frac{3}{2}} \quad (1)$$

In formula (1) relationship $W_{i,\theta}$ Company specific monthly return :$i$per month θ And$n$the number of : her the negative skewness In this model, the hig .monthly returns observed during the financial year coefficient, the more the company will be subject to acrashin the stock price. The specific monthly return of the company, which is$W_{i,\theta}$is equal to the natural logarithm of the number 1 ,indicated by g number, which is calculated from the following equationplus the remainin

$$W_{i,\theta} = \ln(1+\varepsilon_{i,t}) \quad (2)$$

In formula relationship(2) $\varepsilon_{i,\theta}$ the residual yield of the company's stock$i$in the month $\theta$is calculated values obtained from the estimation of model through the residual(3).

$$r_{i,t} = \alpha + \beta_{1i} r_{m,\theta-2} + \beta_{2i} r_{m,\theta-1} + \beta_{3i} r_{m,\theta} + \beta_{4i} r_{m,\theta+1} + \beta_{5i} r_{m,\theta+2} + \varepsilon_{i,\theta} \quad (3)$$

In this regard:

In formula relationship(3) $r_{i,\theta}$ Return of the company's stock :$i$in the month θ

$r_{m,\theta}$Market return per month :θ

Is. To calculate the monthly return of the market, the index at the beginning of the month is subtracted from the index at the end of the month and the result is divided by the index at the beginning of the month.

5 Findings

5.1 Pre-Test Statistical Techniques

Before analyzing and testing the hypotheses, the reliability of the research variables has been investigated. The results show that the significance level of all research variables was less than 5%, so all these variables are at a stable level in the period under review.

Table 1: The Results of Levin, Lin and Chu Test to Check the Significance of Research Variables

Variable	symbol	Statistics Levin, Lin and Chu	p-value	Test result
Net profit margin TTM	X1	73.4793	0.0001	H_0 is rejected (the desired variable is mean)
Net profit margin MRQ	X2	196.453	0.0001	H_0 is rejected (the desired variable is mean)
on assets	X3	-0574.18	0.0001	H_0 is rejected (the desired variable is mean)
Return on equity	X4	260.419	0.0001	H_0 is rejected (the desired variable is mean)
The ratio of earnings before interest and	X5	27.3757	0.0001	H_0 is rejected (the desired variable is mean)
of assets	X6	-0531.28	0.0001	H_0 is rejected (the desired variable is mean)
Circulation of fixed assets	X7	8.96298	0.0001	H_0 is rejected (the desired variable is mean)
Inventory turnover	X8	307.702	0.0001	H_0 is rejected (the desired variable is mean)
Inventory turnover period	X9	53.1181	0.0001	H_0 is rejected (the desired variable is mean)
receivable circulation	X10	379.857	0.0001	H_0 is rejected (the desired variable is mean)
Periodicals Collec-tion	X11	-8488.31	0.0001	H_0 is rejected (the desired variable is mean)
Total liabilities to - total assets	X12	-9506.44	0.0001	H_0 is rejected (the desired variable is mean)
Total liabilities to equity	X13	259.634	0.0001	H_0 is rejected (the desired variable is mean)
debt ratio	X14	-87.1081	0.0001	H_0 is rejected (the desired variable is mean)
debt to equity ratio	X15	171.355	0.0001	H_0 is rejected (the desired variable is mean)
Long term debt ratio	X16	-35.8747	0.0001	H_0 is rejected (the desired variable is mean)
The ratio of retained earnings to assets	X17	-8819.59	0.0001	H_0 is rejected (the desired variable is mean)
Interest expense coverage ratio	X18	1.50327	0.0001	H_0 is rejected (the desired variable is mean)
current ratio	X19	-6245.27	0.0001	H_0 is rejected (the desired variable is mean)
instantaneous ratio	X20	8000.72	0.0001	H_0 is rejected (the desired variable is mean)
cash ratio	X21	-8445.62	0.0001	H_0 is rejected (the desired variable is mean)
The ratio of the company's free cash	X22	1.17138	0.0001	H_0 is rejected (the desired variable is mean)
The ratio of share-holders' cash flow to	X23	-9832.64	0.0001	H_0 is rejected (the desired variable is mean)
Ratio of capital expenditure to net	X24	124.873	0.0001	H_0 is rejected (the desired variable is mean)
The ratio of operat-ing cash to total lia-	X25	-7908.53	0.0001	H_0 is rejected (the desired variable is mean)
The ratio of invest-ment cash flow to in-	X26	-12.2708	0.0001	H_0 is rejected (the desired variable is mean)
The logarithm of the firm's value	X27	839.147	0.0001	H_0 is rejected (the desired variable is mean)
Logarithm of book value	X28	-699.710	0.0001	H_0 is rejected (the desired variable is mean)
Logarithm of operat-ing cash	X29	-74.4251	0.0001	H_0 is rejected (the desired variable is mean)
The risk of crashing stock prices	Y	-0939.42	0.0001	H_0 is rejected (the desired variable is mean)

The table shows the results of Chow's test (F statistic) related to the mentioned hypotheses about the research model:

Table 2: The Results of the F Test (Limer) for Choosing the Pooling or Panel Method

Model	null hypothesis (H0)	statistics	Degrees of freedom	p -value	Test result
Research	Company-specific effects -are not significant	58.409	319	0.0005	panel method is suitable

As can be seen in Table 2, the null hypothesis of the test has been rejected at the 95% confidence level in the research model, so the panel data method should be used. As a result, there is a discussion of choosing between fixed and random effects models, for which Hausman's test is used.Hausman test is used to choose between random effects or fixed effects model. The results of the Hausman test for the research model are as described in Table 3:

Table 3: Results of the Hausman Test for Choosing Between Fixed Effects and Random Effects Models

Model	null hypothesis (H0)	Statistics	Degrees of freedom	p -value	Test result
Research	The random effects method is appropriate	560.45	29	0.0259	fixed effects method is appropriate

the research The results of the above table indicate that the fixed effects method should be used in model. In this research, the Brusch Pagan-Cook and Weisberg test was used to check the existence of the problem of heterogeneity of variance.

Table 4: The Results of Pagan-Cook and Weisberg Brush Test to Detect Heterogeneity of Variance

Model	null hypothesis (H0)	Brush χ^2 pagan - Cook and Weisberg statistic	p -value	Test result
Research	variances are the same	717.2	0.2571	variances are the same

The results of the table show that there is no variance heterogeneity problem in the model, because the calculated probability or p-value is greater than 0.05.

5.2 Predicting the Risk of Crashing Stock Prices

In this research, 4 classical methods and 10 deep learning methods were used in predicting the risk of crashing stock prices. In the table below, the accuracy of different algorithms in predicting this index has been investigated.

Based on the results obtained in the initial modelling of different deep learning algorithms, it can be seen that three algorithms have better performance and can be considered as the superior algorithms compared to the classical prediction algorithms. be used Based on the obtained results, the convolutional neural network algorithm has performed best in predicting the risk of crashing stock prices, followed by short-term memory network algorithms and multi-layer perceptrons. The next ones are placed. Below are the graphs related to the loss function of these algorithms in predicting the risk of crashing stock prices.

Table 5: Performance Comparison of Different Deep Learning Algorithms from Artificial Intelligence

Algorithm	**symbol**	**MAE index**	**RMSE index**	**Select for the next step**
Convolutional neural network	CNN	0.5944	0.78416	Yes
Short -term memory -networks	LSTM	0.59567	0.78433	Yes
Recurrent Neural Networks-	RNN	0.60227	0.77697	no
Hostile productive networks-	GAN	0.6149	0.81553	no
Radial basis function networks-	RBFN	0.61215	0.81853	no
Multilayer perceptrons-	M.P	0.59808	0.78897	Yes
Self-organizing maps-	SOM	0.61927	0.81367	no
Deep belief networks-	DBN	0.61149	0.80232	no
Restricted Boltzmann machines-	RBM	0.6121	0.80361	no
Auto encoders	AC	0.61281	0.8169	no

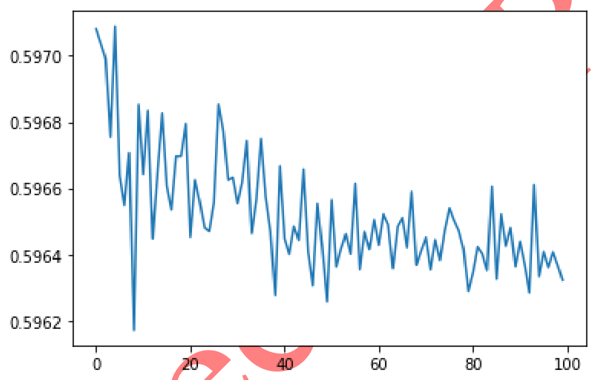

Fig. 1: The Loss Function Obtained From Modelling the Risk of Crashing Stock Prices Using the Convolutional Neural Network Algorithm

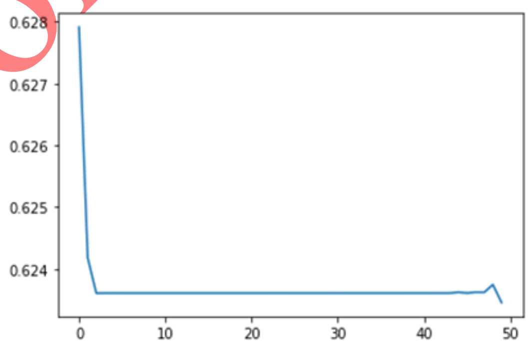

Fig. 2: The loss function resulting from modelling the risk of crashing stock prices using the algorithm of short-term memory networks

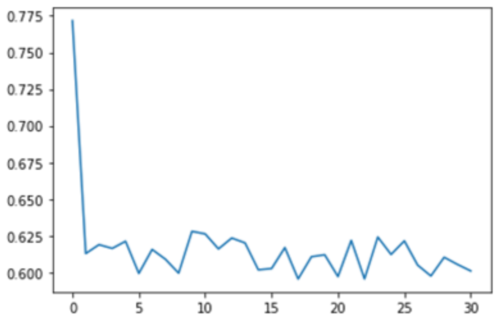

Fig. 3: The loss function resulting from modelling the risk of crashing stock prices using multilayer perceptrons algorithm

5.2.1 Classical Algorithms

In this research, 4 classic algorithms are used to predict the risk of crashing stock prices. In the table below, the accuracy of different algorithms in predicting this index has been investigated.

Table 6: Comparing the Performance of Different Classical Algorithms

Algorithm	symbol	MAE index	RMSE index
pattern of cumulative moving average	ARIMA	0.60307	0.7897
Simple exponential smoothing	ESS	0.60606	0.79298
Double Exponential Smoothing	ESD	0.60606	0.79298
Triple Exponential Smoothing	EST	0.60606	0.79298

As can be seen, the performance of ARIMA method is better than different ES models, and as a result, this model can be compared with superior deep learning algorithms.

5.2.2 Comparing the effectiveness of the best deep learning approach with classical prediction methods

Table 7: Comparing the Effectiveness of the Best Deep Learning Approach With Classical Prediction Methods

Algorithm	symbol	MAE index	RMSE index
Convolutional neural network	CNN	0.5944	0.78416
pattern of cumulative moving average	ARIMA	0.60307	0.7897
Simple exponential smoothing	ESS	0.60606	0.79298
Double Exponential Smoothing	ESD	0.60606	0.79298
Triple Exponential Smoothing	EST	0.60606	0.79298

6 Discussion and Conclusions

According to the indices considered to compare the performance between different algorithms (RMSE and MAE), the best algorithm in predicting the risk of crashing stock prices was the convolutional neural network algorithm. The results show that the prediction error of this algorithm is 0.78416, which is better compared to other algorithms .In order to compare the efficiency between modern algorithms and classical algorithms in forecasting econometric data, ARIMA and exponential smoothing algorithms were used as representatives of classical algorithms. According to the obtained results, the accuracy of these algorithms is lower compared to the algorithm selected in deep learning, and as a result, it can be said that deep learning algorithms (especially the convolutional neural network algorithm), They have better efficiency and can predict the risk of crashing stock prices with higher accuracy. According to the obtained results, it is suggested to use deep learning algorithms in reviewing the econometric data and forecasting the state of the stock exchange and in general the companies admitted to the stock exchange; Because they have a higher accuracy in predicting the main variables (especially the variable of the risk of crashing stock prices) and compared to classical forecasting methods, they can predict these variables with less error. Also, the investigation of the performance of different deep learning algorithms shows that among the investigated methods, the convolutional neural network method has a better performance compared to other algorithms and can improve the prediction accuracy. Therefore, it is suggested to use this algorithm in checking econometric data and especially predicting the risk of crashing stock prices .The results show that, apart from the convolutional neural network algorithm, the algorithms of short-term memory networks and multilayer perceptrons also have good performance and can be used in predicting the risk of crashing stock prices. Become In general, it is suggested not to use only one algorithm in the review of econometric data and the review of data related to companies admitted to the stock exchange, and the results of the best algorithms should be evaluated side by side. To be placed this action helps in different predictions, the errors that some algorithms may have in data evaluation (for various reasons such as the incompleteness of some data, the presence of outlier data and...), to be fixed to some extent and in general, to have a better performance in data prediction .In this research, in order to check the efficiency of different methods, the data from the years 2013 to 2014 were used. In another research, by extending the years, different results can be obtained and after examining the data, the obtained results can be compared with the results calculated in this research. The results of this research are consistent with the research of Ruan, Qingsong, et al [26].The results show that the investor-sentiment index has a positive relationship with the future return of the stock market in a monthly period, but it has a negative relationship with the future return in a longer horizon. In addition, the investor sentiment index performs better than other known predictors in the sample and out of the sample and can predict cross-sectional stock returns sorted by industry. It also shows a positive relationship between the monthly investor sentiment index and the dividend growth rate. Investors' expectations about future cash liabilities can help predict the returns of the investor sentiment index. Also Park, Cheol-Ho] and Scott H. Irwin [23] investigated a research titled predicting the closing price of stocks using machine learning techniques. The results showed that accurately predicting stock market returns is a very challenging task due to the unstable and non-linear nature of financial stock markets. With the introduction of artificial intelligence and increasing computing capabilities, it has been proven that programmed methods are more effective for predicting stock prices. In this work, artificial neural network and random forest have been used to predict the closing price of the next day for five companies belonging to different operational departments. Financial data such as open, high, low, and close stock prices are used to create new variables that are used as input to the model. Standard strategic indicators of evaluation show that the models are efficient in predicting the final stock price. Lin, Lin, et al [19] suggested to use the ELM method due to the problems that exist in the classical methods, and the results of their research showed that this method is very efficient. In their research, they showed that, in general, the predictive assembly of a set of neural networks will lead to improving the predictive accuracy and stability of the results. These results are more accurate than the models that make them up. Tkáč, Michal, and Robert Verner [31] used intelligent methods to predict the stock market and showed that the neural network is more useful and has better efficiency than other models. He has investigated neural network programs in various business fields with 412 applications, which were published in influential and prestigious journals between 1994 and 2015. Although the reviewed authors have successfully used neural networks for various tasks, our results show that the most investigated cases in our study were economic distress and bankruptcy, stock price forecasting, and credit scoring .In this research, in order to cover the set goals, the risk variable of stock price fall was used as a dependent variable and in fact, different modelling were used to predict this variable. In another research, other variables can be examined and different data can be examined by choosing those variables as criterion variables. It is expected that the performance of different algorithms in checking the variables of the new criterion will be the same; if the performance results of the algorithms were different, the reasons for this difference can be investigated. By examining deep learning algorithms among different predictor variables, a number of variables were selected as superior variables. In another research, the data can be re-examined by changing the predictor variables and the results obtained from changing the variables can be compared with the results obtained in this research. In this research, 10 deep learning algorithms were selected and used to model the risk of falling stock prices. In another research, other algorithms can be used and the accuracy results of the investigated algorithms can be compared with the accuracy of classical algorithms. In this research, two classic models were investigated, which are: ARIMA and exponential smoothing. In another research, the performance of different algorithms can be compared by using other algorithms (such as GARCH, etc.).

References

[1] Abu-Mostafa, Yaser S., and Amir F. Atiya, Introduction to financial forecasting, *applied intelligence*, 1996; 6(3):205-213. Doi: 10.1007.BF00126626

[2] Almudhaf, F., Predictability, Price bubbles, and efficiency in the Indonesian stock-market, *Bulletin of Indonesian Economic Studies*, 2018; 54(1):113-124. Doi:10.1080.00074918.2017.1311007

[3] Arévalo, Rubén, et al., A dynamic trading rule based on filtered flag pattern recognition for stock market price forecasting, *Expert Systems with Applications*, 2017; 81 :177-192.

[4] Beck, Thorsten, and Ross Levine,Stock markets, banks, and growth: Panel evidence, *Journal of Banking and Finance*,2004; 28(3): 423-442.

[5] Cavalcante, Rodolfo C., et al.,Computational intelligence and financial markets: A survey and future directions, *Expert Systems with Applications* ,2016; 55:194-211.

[6] Cristelli, Matthieu, Complexity in financial markets: modeling psychological behavior in agent-based models and order book models, *Springer Science and Business Media*, 2013.

[7] Deng, Li, and Dong Yu.,Foundations and Trends in Signal Processing: DEEP LEARNING–Methods and Applications,2014.

[8] Erdem, Ekrem, and Recep Ulucak, Efficiency of stock exchange markets in G7 countries: bootstrap causality approach, *Economics World*, 2016; 4(1): 17-24.

[9] Eugene, F. Fama, Efficient capital markets: A review of theory and empirical work, *The Journal of Finance*, 1970; 25(2): 383.

[10] Faghihi Nezhad, M. T., Minaei, B., Prediction of Stock Market Behavior Based on Artificial Neural Networks through Intelligent Ensemble Learning Approach, *Industrial Management Journal*, 2018; 10(2): 315-334, (in Persian).

[11] Fama, Eugene F.,Random walks in stock market prices, *Financial analysts journal* , 1995; 51(1): 75-80.

[12] Hiransha, Ma, et al.,NSE stock market prediction using deep-learning models , *Procedia computer science* 132 2018: 1351-1362.

[13] Jarrahi, M. H., Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making, *Business horizons*, 2018*; 61*(4): 577-586.

[14] Johnson, Neil F., Paul Jefferies, and Pak Ming Hui., Financial market complexity, *OUP Catalogue* 2003

[15] Klashanov, Fedor,Artificial intelligence and organizing decision in construction ,*Procedia Engineering* ,2016; 165: 1016-1020.

[16] Konak, Fatih, and Yasin Şeker,The efficiency of developed markets: Empirical evidence from FTSE 100,*Journal of Advanced Management Science,* 2014; 2(1)

[17] Laurent, Alexandre,La guerre des intelligences, *Intelligence artificielle versus intelligence humaine, Paris: JC Lattès* ,2017; 131-133.

[18] Levine, Ross, Financial development and economic growth: views and agenda, *Journal of economic literature*, 1997; 35(2): 688-726.

[19] Lin, Lin, et al.,Random forests-based extreme learning machine ensemble for multi-regime time series prediction, *Expert Systems with Applications* ,2017; 83: 164-176.

[20] Mallikarjuna, Mejari, and R. Prabhakara Rao,Evaluation of forecasting methods from selected stock market returns,*Financial Innovation* ,2019; 5(1): 1-16.

[21] Nguyen, Thien Hai, Kiyoaki Shirai, and Julien Velcin., Sentiment analysis on social media for stock movement prediction, *Expert Systems with Applications*,2015 ; 42(24): 9603-9611.

[22] Pan, Yunhe,Heading toward artificial intelligence 2.0, *Engineering* 2016; 2(4): 409-413.

[23] Park, Cheol-Ho, and Scott H. Irwin,What do we know about the profitability of technical analysis?, *Journal of Economic surveys* ,2007 ;21(4): 786-826.

[24] Rajan, Raghuram, and Luigi Zingales,Financial dependence and growth, 1996

[25] Rousseau, Peter L., and Paul Wachtel,Equity markets and growth: Cross-country evidence on timing and outcomes, 1980–1995, *Journal of Banking and Finance* ,2000; 24(12): 1933-1957.

[26] Ruan, Qingsong, et al.,A new investor sentiment indicator (ISI) based on artificial intelligence: A powerful return predictor in China, *Economic Modelling* ,2020; 88: 47-58.

[27] Sharif far, A., Khalili Araghi, M., Raeesi Vanani, I., Fallah, M. ,The Assessment of the optimal Deep Learning Algorithm on Stock Price Prediction (Long Short-Term Memory Approach). *Financial Engineering and Portfolio Management*, 2021; 12(48): 348-370, (in Persian).

[28] Siva Kiran Guptha, K., and R. Prabhakar Rao.,The causal relationship between financial development and economic growth: an experience with BRICS economies, *Journal of Social and Economic Development*, 2018; 20(2): 308-326.

[29] Snow, Charles C., Øystein Devik Fjeldstad, and Arthur M. Langer, Designing the digital organization, *Journal of organization Design*, 2017; 6(1): 1-13.

[30] Syam, Niladri, and Arun Sharma,Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice, *Industrial marketing management* , 2018; 69: 135-146.

[31] Tkáč, Michal, and Robert Verner,Artificial neural networks in business: Two decades of research, *Applied Soft Computing* , 2016; 38: 788-804.

[32] Tong, Tong, Bin Li, and Omar Benkato,Revisiting the weak form efficiency of the Australian stock market, *Corp Ownersh Control*, 2014; 11(2): 21-28.

[33] Vijh, Mehar, et al.,Stock closing price prediction using machine learning techniques, *Procedia computer science* , 2020; 167: 599-606.

[34] Wieland, Oxana L.,Modern financial markets and the complexity of financial innovation, *Universal Journal of Accounting and Finance* ,2015; 3(3): 117-125.

[35] Zhong, Xiao, and David Enke, Forecasting daily stock market return using dimensionality reduction ,*Expert Systems with Applications* , 2017; 67: 126-139.

[36] Farzad, Malekian, Fakhari and Ghasemi, Predict the Stock price crash risk by using firefly algorithm and comparison with regression, *Advances in mathematical finance and applications*, 2018; 5: 43-58.