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Research Article

Applying the Deep Learning Algorithm in Order to Provide a Model for Predicting the Financial Risk Management of Companies with a Quantitative Approach

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ABSTRACT

Companies face various risks during their business and financial cycle. These risks can be divided into different categories so that they can be identified and evaluated more easily. Therefore, it is important to monitor and accept changes caused by structural failures in the risk management process. The purpose of this research is to use deep learning algorithm in order to provide a model for predicting the financial risk of companies. Therefore, it is practical in terms of purpose. In terms of information gathering method, the research was library based and based on literature and theoretical background. It was also a quantitative research approach. Therefore, there is a need to provide a community and local model of risk forecasting that fits the financial and economic structure of companies active in Iran's capital market. In a small part of the statistical community, there were companies active in the capital market of Iran.The statistical sample was based on the method of systematic targeting of 199 active companies in the stock market between 2013 and 2014. The results of this research can lead to the expansion of the theoretical foundations of past researches related to predicting the financial risk of companies admitted to the stock exchange in Iran. In addition, the evidence of the research will show that this issue as a scientific achievement can provide useful information to the compilers of financial standards as well as the supervisory institutions of the country. Also, the results of the research can suggest new ideas for conducting new researches in the field of financial engineering, financial management and economics. The results showed that the error values of the training models in the deep learning approach in all cases of Lasso regression, ridge regression, artificial neural network training. And the random forest regression was less than 0.05.And the best method for machine learning is to use the combined method of ridge regression and artificial neural network.

Keywords: deep learning, financial risk, hypercombination, artificial neural network.

1. Introduction

Financial and economic decisions are always faced with risk due to future uncertainty (Hamidian et al., 2015). Risk is anything that threatens the present or future of an individual's, institution's, or organization's assets or earning power. Risk is an integral part of all business activities, and risk prediction not only helps the company in preventing financial problems, but also improves the decision-making process (Razmanesh Venabizadeh, 1400). Today, risk prediction has become one of the main fields of increasing probability and statistical modeling. When corporate risk is mentioned, one thinks of portfolio management, option pricing, and other financial instruments. Risk forecasting is something that predicts the possibility of a financial crisis with statistics, etc. for companies by analyzing the company's financial report and related materials (Alboutchi et al., 2018).Enterprise risks are often seen as a latent and invisible factor, even after they are identified. Finding a suitable way to quantify or estimate them is in itself a major problem, leading to greater costs and uncertainty. (Caulkant et al., 2016). In addition to quantification and creation of estimation methods, it is necessary to identify the recurrence of these risks and the primary areas of risk creation. There are many methods that try to model, understand and predict risks. Unlike traditional models,

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intelligent methods have recently gained traction and are often non-linear, including methods such as machine learning and deep learning, evolutionary algorithms, and fuzzy logic (Ji et al., 2022).Various studies have been conducted to use different approaches to predict the risk of companies, but very few of these studies have tried to provide a method based on deep learning for training machines. Most of the researches conducted either do not mention the machine learning method (algorithm used in machine learning) or simply state that they use a standard gradient descent algorithm (Kim et al., 2020).

Companies are faced with intense competition and a rapidly changing market environment. Early warning of a company's risk can be done based on the company's financial information. First, it is necessary to determine and observe the trend of some sensitive financial indicators and at the same time monitor and predict the risks that the company will take (Wenping et al., 2015).The purpose of systematic and continuous identification and classification of various risks is the potential and objective existence and the analysis of the cause that has not happened yet. Due to the changes in the economic environment and the complexity of relations and supply of production factors, the need to study and predict the risk of companies has become more necessary. Therefore, it is necessary to establish an effective early warning system about risk through reasonable financial forecasting methods, and predict and discover changes in business operations and financial conditions over time (Yanyan and Na, 2015). As the capital market improves, the competition between companies is more consistent with the market rules, and more people participate in investing in financial assets such as stocks (Ying, 2015).One of the most important topics in the capital market is the awareness of the company's risk level, which plays an effective role in decision-making. Because it is believed that the return of companies' shares is a function of systematic risk and systematic risk shows the changes in the rate of return of a share compared to the changes in the rate of return of the entire stock market (Dehghan Khavari and Mirjalili, 2018). Returns and risks go hand in hand in most cases, and open markets make early warning about a company's financial risks all the more important. There is risk in all stages of company development, and when risk accumulates at a certain stage, there is a possibility of a financial crisis (Fraung, 2019).

The performance of companies is inseparable from the huge economic environment, and the uncertainty of the external environment will clearly affect the normal performance of companies, and this will increase the risk of companies.In order to reduce risks and improve the operational efficiency of the company, it is an undeniable necessity to identify the risks that the company is facing and to gain knowledge regarding the type and impact of the risks on the company (Khiaving, 2015). The traditional method of identifying company risks is associated with weakness in evaluation and forecasting, and also does not identify external factors that lead to risk (Wei, 2017).

The survival of the company is in the constructive interaction with the internal and external environment. Every company must not only create the environment through internal management, but also adapt to changes in the external environment. If the company does not take active control and prevention, when the situation leads to the accumulation of crisis, the company cannot deal with it. Therefore, the company needs to create a risk monitoring index system and then needs to consider and analyze the risks in real time (Denglin, 2016).The modern model of corporate risk management inevitably requires dynamic risk management systems. A system that can examine the risks of the company in all its aspects. In order to fully fulfill the role of early risk analysis, this system must be able to identify warning signs of risk before risk occurs in companies. In order to evaluate this problem, it is necessary to provide a system that has the ability to evaluate risks based on data combination technology. Kao et al.'s study (2022) showed that one of the best systems for quick risk warning is the use of deep learning algorithms.

Financial risk and deep learning have been combined in recent years, and this combination has become one of the advanced tools for financial risk analysis and management. Deep learning, as a branch of artificial intelligence, uses multilayer neural network models to identify patterns, predict events, and optimize decision-making processes. These capabilities can help reduce uncertainty and better predict financial risks. Deep learning models can analyze customers' credit behavior and predict the probability of debt default. These models are highly accurate in forecasting using big data such as financial records, social data, and transaction information.Using convolutional neural networks in deep learning can model market volatility, asset price changes, and macroeconomic factors and identify associated risks. By analyzing historical data and company workflows, deep learning models can identify potential failures or weaknesses in financial operations (Ekso et al., 2024).

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Deep learning models can analyze financial and non-financial variables of companies (such as capital structure, cash flow, or management changes) and estimate the probability of bankruptcy. Deep learning can detect complex and non-linear patterns that cannot be detected by traditional methods.Deep learning helps investors find the best combination of assets, taking into account a certain level of risk and return, the ability to process big data, and models are updated by continuous data processing and can adapt to changing market conditions (Chen and Long, 2023).

If financial risk is not a positive phenomenon, understanding it leads to better and more informed decisions in the field of business or investment and helps to evaluate the value (ratio of risk and reward). Evaluating and predicting financial risk helps to determine the value of that investment, and if financial risk is not controlled, it will have irreparable consequences that will be difficult to overcome and the possibility of their expansion and impact on the entire sector. There will be markets (Boiko, 2019). Financial risk arises in the field of financial relations of the company and is known as the risk caused by the way the company is financed.Financial risk indicates the risk of not being able to estimate the previous claims of the partnership, which includes a major part of debt obligations. In recent years, financial risk from various dimensions, such as the risk caused by the structure of the statement of financial position, the risk caused by the structure of income and profitability, capital adequacy risk, rate of return risk, market risk, liquidity risk, and currency risk. has been checked. Deregulation, financial innovations, increasing alternative capital sources, convergence of financial services and changing the role of non-bank institutions and intermediaries have different consequences on financial risk, which includes the relevant sector as well as the entire financial market (Rezaei Menesh et al. , 2015; Caroline, 2015).

There are two aspects to the concept of liquidity: funding liquidity and market liquidity.Crockett (2008) defines market liquidity as the speed at which an asset can be converted into cash easily and without loss in the asset's price. Low and Sadka (2011) define liquidity risk as the risk that arises from the security's response to changes in market conditions. Bakir (2017) defines financing liquidity as the ability of an organization or institution to meet or cover its obligations. Kapadia et al. (2012) define it as the ability to pay debts to required parties. Liquidity is the main element that is used to pay expected debts and liquid assets are ready for use (Hossein, 2016).

Legal risk is the risk associated with the uncertainty of legal actions or the application or interpretation of contracts, laws or regulations. Legal risks vary greatly from country to country.In some cases, legal risk arises from unclear laws that can lead to ambiguous legal interpretation. Laws passed in the European Union or the United States often reach across borders and may limit a bank's international banking activities. and customer data protection legislation around the world, legal risk has evolved as a prominent risk (Zetzch et al., 2018).

Systems risk is related to the use of computer technology and computer systems. All banks rely heavily on computers to support their daily activities. In fact, banks today cannot function without computerized systems. Risks of technology-related systems can be caused by the following: Data corruption: An electrical wave changes data during processing.Inadequate project control: Lack of proper planning can affect the quality of the risk report produced by the computer system.

Programming errors: Computer models can be unintentionally programmed to produce incorrect results (Acharya et al., 2017).

Over reliance on "black box" technology:. This problem is when users believe that the internal mathematical models of computer systems are correct without considering the problem and its solution from a conceptual or qualitative perspective and without sufficiently stress testing the system. Service Interruption(s): Electrical failure results in staff not having access to reports. System security problems: computer viruses and computer hacking are increasingly problematic. System Inadequacy: The system hardware may not be sufficient to handle high traffic volumes and failures, or may provide incorrect results.People risk, the risk associated with a bank employee, is one of the sources of operational risk. People's risk can occur in any part of the bank, even the bank's risk management function. People risk is most likely to occur due to: high staff turnover: frequent changes in staff means that new people do not have the necessary background, experience or training; They may not fully understand processes and are prone to making frequent mistakes. Poor management practices: An unclear control structure where employees report different risk events to multiple separate risk functions and each separate risk function follows inconsistent procedures, practices, and policies (Inodin et al., 2014).

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2. Research background

Cao et al. (2022) conducted a research entitled the study of early warning of financial risk of e-commerce company based on deep learning algorithm. Based on the deep learning algorithm, this research is studied from the perspective of establishing a financial risk early warning model based on deep learning and building an early warning mechanism of financial risk of e-commerce companies and analyzes and predicts the financial risks of listed companies. Through the construction of the financial security early warning system, crisis signals can be recognized as soon as possible, and using deep learning algorithms, crisis signals can be presented to the user in a timely and effective manner. Peng and Yan (2022) presented a survey research on deep learning for financial risk prediction.The main purpose of this research was to investigate the ability of deep learning to predict financial risk considering three prominent features of financial data, including data heterogeneity, data from different sources, and imbalance among the collected data. In this research, some classic deep learning models were briefly presented as the basis of the financial risk prediction model. Then the characteristics of the financial data were discussed and analyzed. Then, the differences of common deep learning models were studied according to the characteristics of different data. The results showed that the use of deep learning algorithm effectively predicts risk. Liu et al. (2022) conducted a research titled Analysis of Internet Financial Risks Based on Deep Learning and Backpropagation Neural Network.These researchers first introduced the theory of Internet financial risks and then created a theoretical framework for analyzing and predicting financial risks. Then, the model based on backpropagation and deep learning neural network was presented to improve the early warning of financial risk, the analysis of GDP data, currency, non-current loan records and Shanghai was implemented. The time frame of the data was from 2006 to 2020, and the risks were predicted in 2021. Through the model based on deep learning and back-propagation neural network, we can see what the trend of China's GDP growth rate will be. The results showed that the model based on post-propagation neural network and deep learning greatly improves the timeliness of risk predictions and has a positive effect on the stability of China's financial environment.

3- Research hypotheses

The main hypotheses

-In order to create the ability to train the artificial neural network modeling machine, it is used to process information layers related to financial risk.

-In order to identify and estimate financial risk, machine learning modeling can be used based on deep structure learning approach.

-In order to predict financial risk, the simultaneous combination of deep learning approach and artificial neural network can be used.

Sub-hypotheses

1. Applying deep learning algorithm can predict the liquidity risk of companies.

2. Applying deep learning algorithm can predict the profit risk of companies.

3. Application of deep learning algorithm can predict the credit risk of companies.

4. Application of deep learning algorithm can predict the market risk of companies.

5. Application of deep learning algorithm can predict the business risk of companies.

6. Applying deep learning algorithm can predict the investment risk of companies.

4. Research methodology

The overall goal of the research is to design a risk prediction model based on a deep learning algorithm with a quantitative approach. Based on the objectives of the research, the current research is of an applied type and the method of doing it is quantitative and the method of data collection is library-field. In terms of information gathering method, the research was library based and based on literature and theoretical background.

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5. Research findings

The main goal of this chapter is to collect and analyze systematically to design a risk prediction model based on deep learning algorithm in companies. Data analysis is of particular importance to check the correctness of the hypothesis in any type of research, and today, in most researches that rely on the information collected from the research subject, data analysis is one of the main and most important parts. It is considered research. Raw data are analyzed using statistical software and after processing, they are available to users in the form of information.

Descriptive statistics includes a set of methods used to collect, summarize, classify and describe numerical facts.In fact, this type of analysis describes the research data and information and provides a general design or pattern of data for quick and better use of them. Descriptive statistics show information about central parameters and dispersion of research data. In a summary, with the appropriate use of descriptive statistics, the characteristics of a group of information can be expressed, and in addition to better understanding the results of a test, it also facilitates the comparison of the results of that test with other tests and observations.

Table (1). descriptive statistics of variables related to credit risk

kurtosis	skewness	standard deviation	median,	Mean,	Variable	Type of financial risk
98/214	**5/900**	**0/051**	**0/045**	**0/056**	Cost of financing	Credit risk
9/796	**2/691**	**0/076**	**0/035**	**0/062**	Financial leverage	
0/856	**0/641**	**1/720**	**14/880**	**15/110**	Company size	
1/146	**0/154**	**2/035**	**11/662**	**11/672**	ownership structure	
-0/541	**0/987**	**0/319**	**0/028**	**0/249**	The capital structure of the company	
7/796	**2/521**	**0/082**	**0/017**	**0/054**	Ability to provide capital	

The mean of financial leverage variable is equal to 0.062 and its median is 0.035. This indicates that the data distribution is skewed toward higher values because the mean is greater than the median. The standard deviation is equal to 0.076, which indicates high volatility in financial leverage data. The average company size is 15,110 and the median is 14,880. A small difference between the mean and the median indicates a relatively symmetrical distribution. The standard deviation of 1.720 refers to the average fluctuation in the size of the companies. The average ownership structure is 11.672 and the median is 11.662. This small difference indicates a close to normal distribution. The standard deviation of 2.035 indicates relatively high volatility in the ownership structure data. The average capital structure of the company is 0.249 and its median is 0.028. This large difference indicates an asymmetric distribution towards higher values. The standard deviation of 0.319 indicates high volatility in the capital structure. The average ability to provide capital is 0.054 and its median is 0.017.A large difference between the two indicates an asymmetric distribution towards higher values. The standard deviation of 0.082 indicates the high volatility of the data on the ability to provide capital.

Table (2). Descriptive statistics of variables related to profit risk, investment risk, business risk, liquidity risk

kurtosis	skewness	standard deviation	median	Mean	Variable	Type of financial risk
-0/787	0/309	1/303	3/175	3/231	Return volatility	Profit risk
-0/378	0/702	0/268	0/277	0/371	Profit fluctuations	
7/796	2/521	0/082	0/017	0/054	Dividends	
6/252	2/873	0/286	0/000	0/090	loss of the company	
0/411	0/198	0/343	-0/019	-0/036	Profit forecast error	
kurtosis	skewness	standard deviatio	median	Mean	Variable	Type of financial risk

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3/028	1/944	0/161	0/023	0/103	Financing method	Investment risk
0/417	-0/004	0/271	0/147	0/185	capital growth ratio	
26/339	-2/801	0/265	0/182	0/158	Circulation of financial capital	
36/097	3/518	0/191	0/206	0/247	Capital adequacy	
kurtosis	skewness	standard deviatio	median	Mean	Variable	Type of financial risk
457/148	-16/530	0/810	0/325	0/355	Sales changes	Business risk
1/390	0/433	0/180	0/146	0/172	profitability	
0/181	-0/308	0/317	0/055	0/031	Company cost changes	
-0/033	1/402	0/410	0/000	0/213	Financial portability	
-0/841	0/307	5/592	11/000	12/034	Type of industry	
7/336	2/648	0/198	0/044	0/121	Variety of products	
7/564	1/973	0/596	0/268	0/408	Inventory changes	
-0/111	-0/266	0/414	0/144	0/123	Changes in operating leverage	
kurtosis	skewness	standard deviatio	median	Mean	Variable	Type of financial risk
1/146	0/154	2/035	11/662	11/672	Cash held	Liquidity risk
10/748	2/335	0/526	0/245	0/364	Changes in short-term debt	
-1/890	0/332	0/493	0/000	0/418	Financial constraints	
212/391	12/183	0/486	0/036	0/145	Liquidity changes	
4/885	-1/751	3/117	11/574	11/268	Suspicious claims	
1/056	0/831	1/648	14/429	14/651	amount of debt	
-0/908	0/320	0/002	0/003	0/003	Stock turnover rate	
1/066	1/561	0/256	0/169	0/294	current ratio	

Descriptive statistics show the research variables. The most important central index is the mean, which represents the balance point and center of gravity of the distribution, and is a suitable index to show the centrality of the data. Another descriptive parameter is the standard deviation, which indicates the dispersion of the data. Also, the minimum and maximum parameters in the above table show the range of data changes. The midpoint shows the middle point of the data, which half of the data is smaller than and the other half is larger than it. Skewness indicates the asymmetry of the abundance curve. If the coefficient of skewness is zero, the society is completely symmetrical, and if the coefficient is positive, it is skewed to the right, and if it is negative, it is skewed to the left. In general, if the skewness and kurtosis are not in the range (8, -8), the data is far from the normal distribution. (Of course, some statisticians may consider this interval to be smaller or larger).In linear regression models, one of the estimation methods of the model parameters is the least squares method. One of the issues and problems that can challenge this method is the existence of a phenomenon called collinearity. One of the ways to detect the presence of collinearity, which is widely used, is to use the variance inflation factor. This factor shows how much the variance of the estimated coefficients is inflated compared to the case where the estimated variables are not linearly correlated.

Comparison of training methods in deep learning algorithm

In order to choose the best model training method, four methods were tested and the data was divided into two groups, training and test. The training data trained the machine model in a deep way. After learning the model, it was predicted and it was determined which method to use.

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Table (3). Comparison of training methods in deep learning algorithm

The number of variable deletions	The value of R^2	Mean Square Error (MSE)	Type of training
5 variables	0.9933	0.0201	Lasso regression
1 variable	0.9944	0.0168	Ridge regression
1 variable	0.9943	0.0170	Artificial neural network
1 variable	0.9488	0.1544	Random forest regression

In regression, the mean squared error is a measure of model accuracy. In general, the lower the mean squared error value, the better the model, because the model's prediction errors are smaller. Considering that the ridge training method has the highest R^2 value and also the lowest number of variable deletions, it is more powerful than other methods. Also, the value of the mean square error in the ridge regression method is the lowest compared to other methods. Considering that these two values in ridge regression and artificial neural network have almost the same values, the combination of both methods has been used to implement the company's financial risk prediction model.

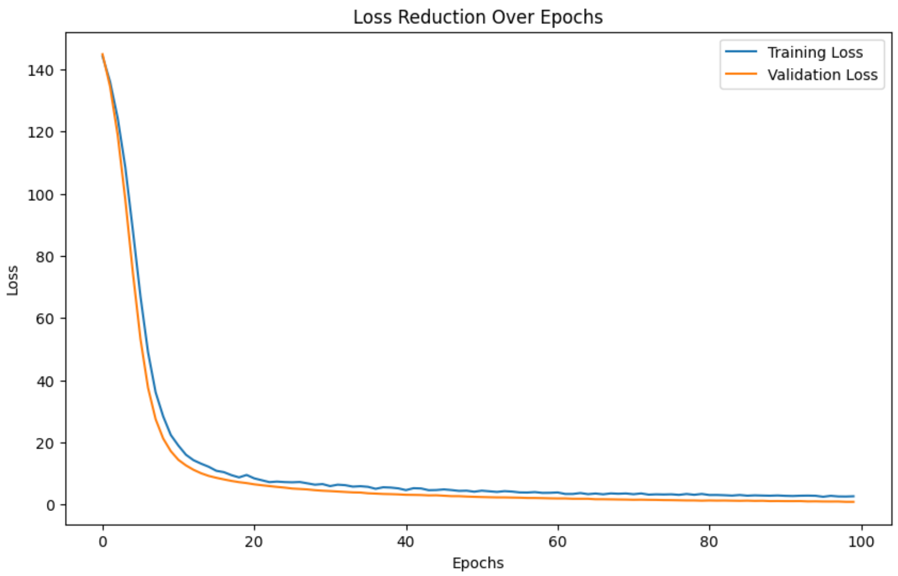
Table (4). Comparison of error values of training methods in deep learning algorithm

NRMSE type error	MAPE type error	Type of training
0.017	0.022	Lasso regression
0.010	0.019	Ridge regression
0.011	0.014	Artificial neural network
0.025	0.031	Random forest regression

As can be seen, the error values of the training models in the deep learning approach are less than 0.05 in all cases. As a result, the studied models for training have the ability to be used in the deep learning model.

Financial risk model based on deep learning

To show the error reduction process in deep learning method using the combined method of ridge regression and artificial neural network, an artificial neural network with dense layers can be used and then ridge regression is used as the output layer



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In this case, the sum of squares of the Lasso regression error is written as:

∑i=1N(yi−β0−∑j=1pxijβj)2+λ∑j∣βj∣i=1∑N(yi−β0−j=1∑pxijβj)2+λj∑∣βj∣

Diagram 1: The process of error reduction in deep learning method using the combined method of ridge regression and artificial neural network

Error values of the provided template

Considering that these two values in ridge regression and artificial neural network have almost the same values, the combination of both methods has been used to implement the company's financial risk prediction model.

Table (5). Comparison of error values of training methods in deep learning algorithm

NRMSE type error	MAPE type error	Financial risk
0.079	0.043	Credit risk
0.181	0.107	Profit risk
0.185	0.110	Investment risk
0.162	0.097	Business risk
0.088	0.050	Liquidity risk

As can be seen, the error values of the training models in the deep learning approach are less than 0.05 in all cases. As a result, the studied models for training have the ability to be used in the deep learning model.

Table (6): Comparison of error values of training methods in deep learning algorithm

Error values (P-Value)	Correlation coefficient	The value of R^2	Mean Square Error (MSE)	Financial risk
0.0001	0.926	0.822	0.539	Credit risk
0.0004	0.291	0.055	2.852	Profit risk
0.0076	0.175	0.021	2.958	Investment risk
0.0001	0.499	0.246	2.278	Business risk
0.0001	0.914	0.776	0.677	Liquidity risk

As it can be seen, the correlation coefficient of the credit risk variable is equal to 0.926 and the R2 value is equal to 0.822, which at the confidence level of 0.95, the model error is smaller than 0.05. As a result, the credit risk variable can be considered as one of the dimensions of financial risk. Acceptance.

As can be seen, the correlation coefficient of profit risk variable is equal to 0.291 and R2 value is equal to 0.055, which is smaller than 0.05 at the confidence level of 0.95. As a result, profit risk variable can be considered as one of the dimensions of financial risk. Acceptance.

As can be seen, the correlation coefficient of the investment risk variable is equal to 0.175 and the R2 value is equal to 0.021, which is smaller than 0.05 at the confidence level of 0.95. As a result, the investment risk variable is one of the dimensions of risk. Finance is acceptable.

As can be seen, the correlation coefficient of the business risk variable is equal to 0.499 and the R2 value is equal to 0.246, which is smaller than 0.05 at the confidence level of 0.95.As a result, the commercial risk variable is acceptable as one of the dimensions of financial risk.

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As can be seen, the correlation coefficient of the liquidity risk variable is equal to 0.914 and the R2 value is equal to 0.776, which at the confidence level of 0.95, the model error is smaller than 0.05. As a result, the liquidity risk variable can be considered as one of the dimensions of financial risk. Acceptance.

Pre-Pine oscillation test

In order to evaluate the ability of the model in predicting financial risk, the prediction volatility chart was used based on the deep learning approach. The diagram below shows the reaction of the model to predict financial risk using deep learning algorithm

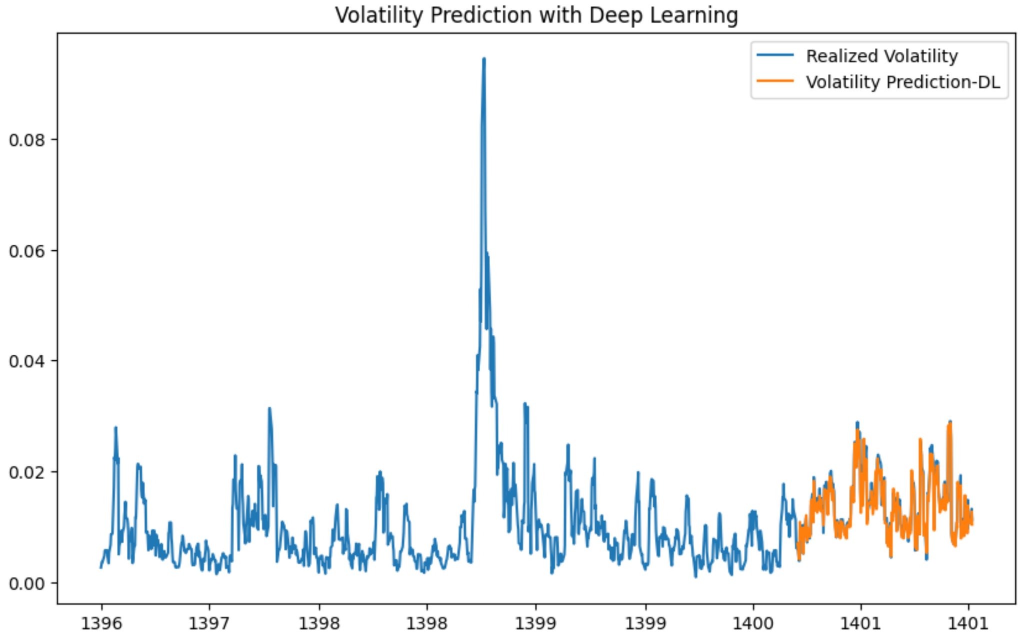

Chart 2: Financial risk prediction volatility test based on deep learning algorithm

The results showed that the model after training has sufficient ability to predict financial risk.

The ridge regression model is defined as:

$$\hat{\beta} = argmin_{\beta}\left\{(y_i - x_i^T\beta)^2 + \lambda\sum_{j=1}^{p}\beta_j^2\right\}$$

6- Conclusions and suggestions

The results of the findings of the quantitative section are consistent with previous studies. Based on this, it can be claimed that the results are consistent with the studies of Mirzaei et al. (2012), Afshari and Pir Vali (2011), Darabi et al. and Amirbeigi Langroudi (1400), Dashtban and Mirzaei (1402), Miraiz and Waqfi (1401), Kardan and Colleagues (2015), Kadhamyari and Islami Mofidabadi (2016), Mozafari and Nikumram (2018), Professor and Teaching Pajoh (2018), Shekarkhah et al. (2009), Arza and Saifi (2019), Keshavarz and Rezaei (2009) and Izadi Nia and Alinkian (1389).Considering that these two values in ridge regression and artificial neural network have almost the same values, the combination of both methods has been used to implement the company's financial risk prediction model. In order to choose the best model training method, four methods were tested and the data was divided into two groups, training and test. The training data trained the machine model in a deep way. After learning the model, it was predicted and it was found that the method of artificial neural network and ridge regression is better for training the machine in the deep learning algorithm. To show the error reduction process in deep learning method using the combined method of ridge regression and artificial neural network, an artificial neural network with dense layers can be used and then ridge regression is used as the output layer. The limitations of the research are data quality: financial data are often noisy, incomplete or inconsistent.Preprocessing and cleaning this data requires time and resources.

Poor quality data can lead to reduced forecast accuracy. Need for powerful processing resources: Running deep learning algorithms requires powerful hardware, such as GPUs and processing units. Providing these resources is costly and technically challenging. Time-consuming training process: Training deep learning models, especially with large financial data, can be very time-consuming.

Future suggestions for researchers to use classical econometric models for deep machine learning: classical methods such as GARCH and VAR models that usually use statistics and regression analysis. These models have limitations, including the inability to analyze large and complex data. However, these models can be used for basic machine training.

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