Designing a Risk Prediction Model based on a Deep Learning Algorithm with a Hybrid Approach

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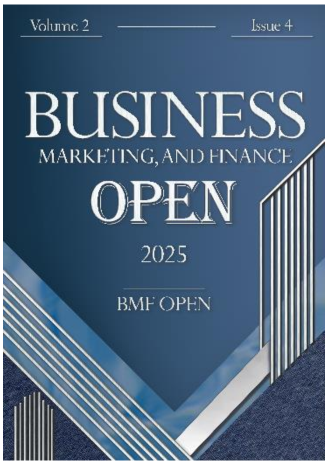

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Abstract: Risk management and forecasting is a constantly changing process. Constant evolution is inevitable, because the long-term performance of risk management cannot keep pace with recent developments or accurately predict emerging crises. Therefore, it is important to monitor and accept changes caused by structural failures in the risk management process. Adopting these changes requires redefining risk management components and tools. Traditionally, empirical research in finance has focused heavily on statistical inference. 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 developmental-applicative in terms of purpose. Considering that it has examined the problem of risk prediction at a general level and in a non-linear way, it is a holistic research in terms of paradigm.In terms of information gathering method, it is library research based on literature and theoretical background. Also, in terms of the research approach, it is exploratory (quantitative-qualitative). The desired method in qualitative analysis is metacomposite. The statistical community of the qualitative section includes scientific research articles and the statistical sample was determined to be 16 documents. In the quantitative part of the statistical society, there are companies active in the capital market of Iran. The statistical sample based on the systematic target method includes 199 active companies in the stock market between 2013 and 2014. The standard framework used to use the deep learning method is the TensorFlow program, which is a free and open-source library for "data flow programming" for machine learning and deep learning. MAXQDA software was used to code and analyze the content of the articles.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 and random forest regression are less than 0.05 and the best method for machine learning is to use the mixed method of ridge regression and It is an artificial neural network.

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

1. Introduction

In the contemporary landscape of financial risk management, the emergence of deep learning algorithms has provided a transformative paradigm for predicting and mitigating complex risk structures. Traditional risk assessment frameworks, which rely heavily on econometric models, often fail to adapt to the nonlinear, multidimensional, and dynamic nature of modern financial environments. These conventional models emphasize parameter estimation and hypothesis testing, which, while effective for controlled analyses, struggle to capture intricate patterns inherent in big financial data and rapidly evolving market conditions [1]. In contrast, deep learning models, with their capacity for abstraction, pattern recognition, and adaptive learning, offer a promising alternative. These models do not presuppose a specific data-generating process, allowing them to excel in environments where uncertainty and volatility dominate [2].

Financial risk is a multidimensional concept encompassing a spectrum of uncertainties, including credit risk, liquidity risk, market risk, investment risk, and operational risk. Companies, particularly those operating in competitive capital markets, face significant exposure to these risks, necessitating robust mechanisms for early detection and forecasting. As global financial markets have grown more integrated and data-intensive, the need for accurate predictive systems has become more pressing [3]. Evolving from basic statistical regression to sophisticated artificial intelligence (AI) methods, financial risk modeling has progressively embraced machine learning techniques to identify hidden patterns and correlations within high-dimensional datasets [4]. Among these, deep learning has emerged as a leading approach, not only for its predictive accuracy but also for its capacity to model nonlinear interdependencies and perform real-time learning updates [5].

The integration of deep learning into financial risk modeling addresses one of the primary limitations of traditional approaches: their rigidity in handling nonlinearity and data heterogeneity. In particular, ensemble models combining artificial neural networks with regression-based algorithms—such as ridge or lasso regression—demonstrate remarkable accuracy in financial prediction contexts [1]. These hybrid models reduce training error and enhance generalizability, which is critical in domains where financial anomalies are rare but consequential. The predictive power of deep learning has already been demonstrated in several domains, including customer credit evaluation, stock price forecasting, liquidity analysis, and fraud detection [2]. The application of convolutional neural networks and recurrent neural networks enables the modeling of time series data, such as historical asset prices and market volatility, which are vital for understanding risk trends [4].

At the microeconomic level, the operational and financial stability of firms is highly susceptible to both internal inefficiencies and external shocks. The ability to accurately model risk factors such as leverage, liquidity ratios, and profitability metrics allows stakeholders to make better-informed investment and governance decisions. Traditional financial indicators—such as cost of capital, debt-to-equity ratio, and return volatility—remain fundamental in evaluating financial risk, but their predictive value is greatly enhanced when processed through deep learning frameworks [6]. Deep learning models improve early warning capabilities by automatically adjusting to new data, capturing abrupt changes in risk patterns, and providing real-time feedback for decision-making systems [7].

The early detection of financial distress is especially vital in environments characterized by macroeconomic volatility, weak regulatory oversight, or political instability. For example, political shocks can significantly alter investor sentiment and asset valuations, thereby increasing systemic risk across markets [8]. Studies show that periods of political uncertainty have tangible effects on market liquidity, risk premiums, and investment flows, underscoring the necessity for dynamic risk prediction tools [8]. Financial crises often emerge when these risks are underestimated or overlooked due to the limitations of static models [9]. Hence, the adoption of dynamic, learning-based systems is not merely a technological shift but a strategic imperative for market resilience and investor protection.

Furthermore, the implementation of financial risk models must consider legal and technological risks. The emergence of blockchain technology and decentralized financial systems introduces new dimensions of liability and regulation. Legal frameworks struggle to keep pace with the distributed nature of blockchain, creating compliance gaps and exposing firms to unforeseen liabilities [10]. In such a context, predictive systems must incorporate not only financial variables but also legal and operational indicators. A holistic model of risk prediction must therefore bridge financial analytics with regulatory intelligence [11].

From a systems perspective, organizational and infrastructural risks must also be considered. Many firms suffer from insufficient data infrastructure, reliance on outdated software, or untrained personnel incapable of implementing advanced AI tools. Deep learning models, despite their advantages, require substantial computational power and specialized programming knowledge, which may limit their adoption in small or medium enterprises [12]. Nonetheless, cloud-based platforms and open-source libraries such as TensorFlow have lowered the entry barrier, enabling broader implementation of deep learning solutions in financial forecasting [13]. To this end, operational risks—including system errors, data corruption, and cyber-attacks—must be addressed in tandem with financial metrics to ensure comprehensive risk coverage [9].

Market risks, including inflation, currency fluctuations, and economic stagnation, further complicate risk prediction. These macroeconomic factors introduce nonlinearity and external variance that traditional linear models cannot capture effectively. Deep learning models, trained on diverse datasets including macroeconomic indicators, commodity prices, and geopolitical news, are better equipped to manage this complexity [14]. By analyzing multi-source data streams, including structured financial records and unstructured market sentiment data, these models improve the accuracy and timeliness of risk forecasts [1]. This integrative capability supports regulatory compliance, investor confidence, and financial system stability.

Moreover, behavioral aspects of financial decision-making, such as managerial overconfidence, insider trading, or unethical reporting, contribute to the unpredictability of financial risk. Predictive models must incorporate these soft variables by analyzing historical patterns, transaction behaviors, and executive performance metrics [15]. This broad scope allows for the identification of latent risk factors, often missed by conventional financial audits. As shown in recent empirical studies, incorporating behavioral data improves model performance in identifying companies at risk of credit default or profit loss [16].

In this regard, one of the most promising applications of deep learning is in the field of corporate credit risk prediction. Using indicators such as capital adequacy, ownership concentration, and dividend volatility, deep neural networks can classify firms based on their probability of financial distress [17]. Additionally, liquidity risk—defined as the firm's ability to meet short-term obligations—can be predicted using indicators such as current ratio, cash holdings, and debt maturity profile [11]. This predictive capacity is critical for banks, regulatory bodies, and investment firms that require timely and accurate insights into corporate solvency and liquidity.

In summary, the integration of deep learning into financial risk modeling represents a fundamental advancement in the field. By leveraging complex data environments and adapting to real-time inputs, these models offer a flexible, robust, and scalable solution to the challenge of financial uncertainty. While traditional models continue to provide valuable insights, their limitations in handling nonlinearity, high-dimensionality, and structural change make them inadequate in isolation. The deep learning approach, therefore, provides a critical enhancement to financial risk management, capable of supporting firms, investors, and policymakers in navigating an increasingly volatile financial landscape. Therefore, it is important to monitor and accept changes caused by structural failures in the risk management process. Adopting these changes requires redefining risk management components and tools. Traditionally, empirical research in finance has focused heavily on statistical inference. The purpose of this research is to use deep learning algorithm in order to provide a model for predicting the financial risk of companies.

2. Methodology

The general purpose of the research is to use deep learning algorithm in order to provide a model for predicting the financial risk of companies. Based on the objectives of the research, the current research is of developmental-applied type and the method of doing it is quantitative and qualitative (combined) and the data collection method is library-field.Considering that it has examined the problem of risk prediction at a general level and in a non-linear way, it is a holistic research in terms of paradigm. In terms of information gathering method, library research is based on literature and theoretical background, and in terms of research approach, it is exploratory (quantitative-qualitative). The desired method in qualitative analysis is metacomposite. In this research, in order to identify the variables affecting the company's financial risk, metacomposition method (coding and recognition of the underlying categories of content or text) was used. MAXQDA software was used to code and analyze the content of the articles. Considering the nature of the method and the complexity of decision-making and risk detection, the deep learning algorithm can be a suitable approach for predicting the risk of companies. The reason for using the neural network as one of the most effective machine learning methods is due to the rapid improvement of learning and also the lack of strong processing resources.This helps shorten the long cycle time required to use programmable digital integrated circuits in deep neural networks. The standard framework used is TensorFlow, a free and open-source library for Dataflow Programming and Discriminatory Programming. (Differentiable Programming), to perform a wide range of tasks. TensorFlow is a library for "Symbolic Math" and has various applications in "Machine Learning", including the implementation of neural networks. This library was developed by the "Google Brain" team for Google's internal use; But it was released on November 9, 2015 with the "Apache 2.0 Open Source" certificate. Currently, the TensorFlow library is used at Google for both research and operational projects.

3. Findings and Results

The main goal of this part is to collect and analyze systematically to design a risk prediction model based on deep learning algorithm in companies. The first part is dedicated to the metacombination method to identify indicators. The second part is dedicated to the use of identified indicators and the use of deep learning algorithm to determine the appropriate model for predicting risk in companies. Also, in the third part, the designed model has been compared and validated. In the qualitative method, all the indicators obtained from the open coding stage were determined in this stage and 256 sub-categories or open codes and 41 main or central categories were obtained.

Table 1. Share of credit risk variable codes in the reviewed documents

Number of documents with code	Overall frequency percentage	Relative abundance percentage	Axial code	Selective code
9	56.25	69.23	Cost of financing	Credit risk
7	43.75	53.85	Financial leverage	
6	37.50	46.15	Company size	
4	25.00	30.77	Ownership structure	
2	12.50	15.38	The capital structure of the company	
1	6.25	7.69	Ability to provide capital	
13	81.25	100.00	Coded documents	Evaluation of documents
3	18.75	-	Documents without this code	
16	100.00	-	Documents reviewed	

Based on the above table, it has been determined that 81.25 percent of the documents had core codes related to the credit risk variable. Also, 18.75 percent of the documents do not have any code related to the credit risk variable were.

Table 2. share of variable profit risk codes in the reviewed documents

Number of documents with code	Overall frequency percentage	Relative abundance percentage	Select code	Selective code
10	62.50	76.92	Return volatility	Profit risk
7	43.75	53.85	Profit fluctuations	
3	18.75	23.08	Dividends	
3	18.75	23.08	Loss of the company	
1	6.25	7.69	Profit forecast error	
13	81.25	100.00	Coded documents	Evaluation of documents
3	18.75	-	Documents without this code	
16	100.00	-	Documents reviewed	

Based on the above table, it has been determined that 81.25 percent of the documents had key codes related to profit risk variable. Also, 18.75 percent of the documents did not have any code related to profit risk variable.

Table 3. share of investment risk variable codes in the examined documents

Number of documents with code	Overall frequency percentage	Relative abundance percentage	Select code	Selective code
2	12.50	40.00	Financing method	Investment risk
2	12.50	40.00	Capital growth ratio	
1	6.25	20.00	Circulation of financial capital	
1	6.25	20.00	Capital adequacy	
5	31.25	100.00	Coded documents	Evaluation of documents
11	68.75	-	Documents without this code	
16	100.00	-	Documents reviewed	

Based on the above table, it has been determined that 31.25 percent of the documents had key codes related to the investment risk variable. Also, 68.75 percent of the documents did not have any code related to the investment risk variable.

Table 4. The share of commercial risk variable codes in the examined documents

Number of documents with code	Overall frequency percentage	Relative abundance percentage	Select code	Selective code
5	31.25	41.67	Sales changes	Business risk
5	31.25	41.67	profitability	
4	25.00	33.33	Company cost changes	
2	12.50	16.67	Financial portability	
2	12.50	16.67	Type of industry	
1	6.25	8.33	Variety of products	
1	6.25	8.33	Inventory changes	
1	6.25	8.33	Changes in operating leverage	
12	75.00	100.00	Coded documents	Evaluation of documents
4	25.00	-	Documents without this code	
16	100.00	-	Documents reviewed	

Based on the above table, it has been determined that 0.75 percent of the documents had key codes related to the commercial risk variable. Also, 0.25 percent of the documents did not have any code related to the commercial risk variable.

Table 5. The share of liquidity risk variable codes in the examined documents

Number of documents with code	Overall frequency percentage	Relative abundance percentage	Select code	Selective code
9	56.25	64.29	Cash held	Liquidity risk
4	25.00	28.57	Changes in short-term debt	
4	25.00	28.57	Financial constraints	
4	25.00	28.57	Liquidity changes	
4	25.00	28.57	Suspicious claims	
3	18.75	21.43	amount of debt	
2	12.50	14.29	Stock turnover rate	
2	12.50	14.29	current ratio	
14	87.50	100.00	Coded documents	Evaluation of documents
2	12.50	-	Documents without this code	
16	100.00	-	Documents reviewed	

Based on the above table, it is determined that 87.50 percent of the documents had key codes related to the liquidity risk variable. Also, 12.50 percent of the documents did not have any codes related to the liquidity risk variable.

Cohen's kappa reliability coefficient is one of the criteria for evaluating the validity of qualitative analysis. This coefficient is used to check the agreement between two evaluators in qualitative analysis.

Table 6. Kappa index for reliability evaluation

variable (risk)	kappa statistic	Standard asymptotic error	T approximation	significant level
Liquidity risk	0.876	0.069	8.124	0.001
Profit risk	0.911	0.061	7.883	0.001
Credit risk	0.854	0.080	7.080	0.001
Market risk	0.906	0.063	7.827	0.001
Business risk	0.838	0.076	7.336	0.001
Investment risk	0.872	0.070	7.483	0.001

The numerical efficiency of Cohen's kappa reliability coefficient is between -1 and 1. In general, the appropriate value of Cohen's kappa reliability coefficient is above 0.6. For the interpretation of the Kappa coefficient, if it is above 0.7, it is considered as good and acceptable reliability, and values higher than 0.8 are considered as excellent reliability. Cohen's kappa reliability coefficient of liquidity risk is equal to 0.876 and the estimated error value is equal to 0.001, which is smaller than the maximum acceptable error of 0.05. As a result, it can be claimed that the coding of texts has sufficient validity. Cohen's kappa reliability coefficient of profit risk is equal to 0.911 and the estimated error value is equal to 0.001, which is smaller than the maximum acceptable error of 0.05. As a result, it can be claimed that the coding of texts has sufficient validity.

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

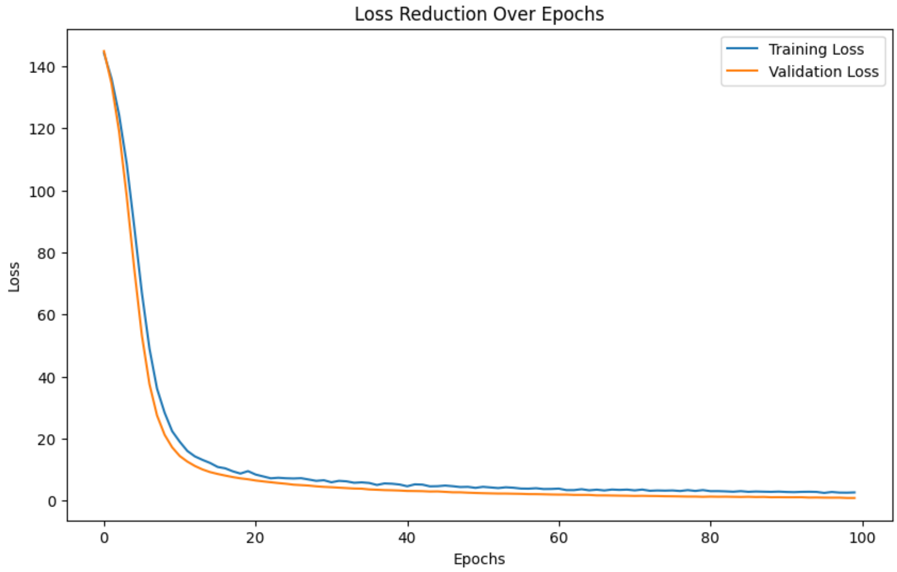

Figure 1. The process of error reduction in deep learning method using the combined method of ridge regression and artificial neural network

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∣

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 7. Comparison of error values of training methods in deep learning algorithm

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

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 8. Comparison of error values of training methods in deep learning algorithm

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

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.

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

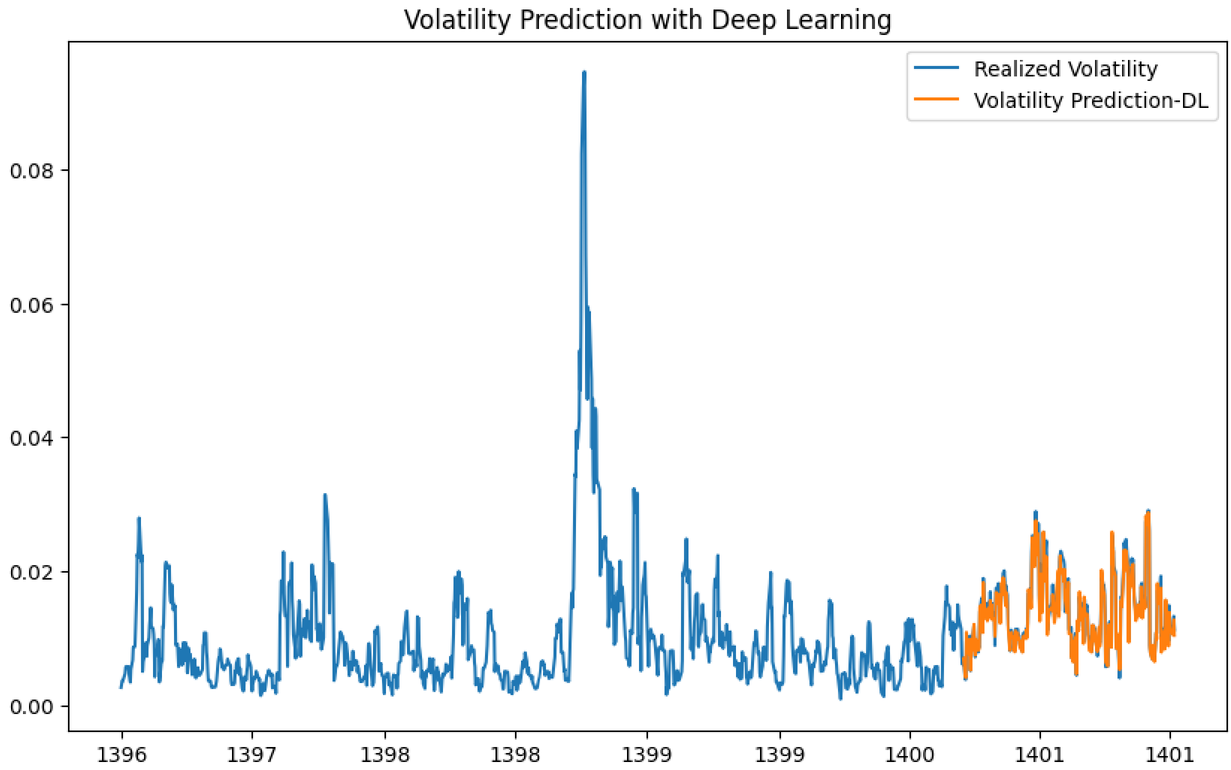

Figure 2. Financial risk prediction volatility test based on deep learning algorithm

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

The ridge regression model is defined as:

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

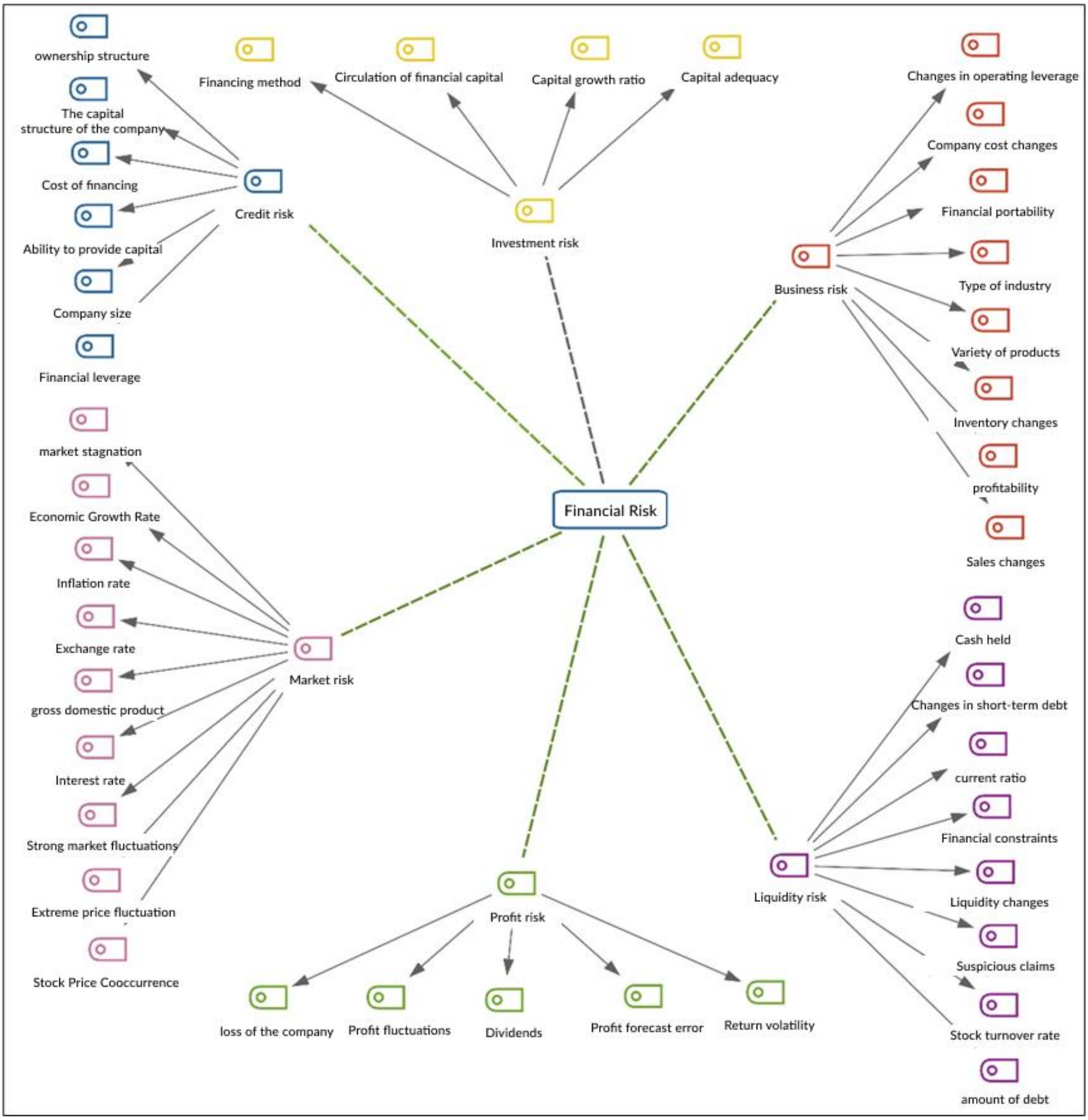

Figure 3. Qualitative model of financial risk variable extraction codes in the examined documents

Table 9. The extracted codes of the financial risk variable in the examined documents

symbol	Measurement method	Axial code	Selective code
COD	The financing cost is calculated by dividing the interest costs by the total debt.	Cost of financing	Credit risk
LEV	It is determined by dividing the long-term liabilities of company i at the end of year t by the total assets of company i at the beginning of year t.	Financial leverage	
SIZE	It is measured by the natural logarithm of the stock market value of company i at the end of year t.	Company size	
LA4	With the logarithm of shares in the hands of four of the largest shareholders of the company, i is measured at the end of year t	ownership structure	
CCP	It is measured based on the debt to equity ratio of company i at the end of year t	The capital structure of the company	
apca	The change in the total net fixed assets, long-term investment and intangible assets is the average of the company's total assets in the year in the year 2017.	Ability to provide capital	
rvol	-	Return volatility	Profit risk
prof	It is equal to the annual average of stock volatility on day d compared to day d-1.	Profit fluctuations	
divi	Changes in company i's profit in year t are compared to year t-1.	Dividends	
LOSS	It is the logarithm of the company's dividend.	loss of the company	
MFE	Virtual variable is (0 and 1).1 if the company has a loss and 0 otherwise.	Profit forecast error	
NSFR	The actual profit in year t minus the first predicted profit of the company's management for the year t is 1 times (the first predicted profit of the company's management)	Financing method	Investment risk
CGR	The ratio is measured through the ratio of stable net financing of firm i in year t.	Capital growth ratio	
fcap	This ratio is calculated through the sustainable division of resources over the sustainable allocation of resources.	Circulation of financial capital	
CAR	It is equal to the change in the equity value of company i in year t compared to year t-1	Capital adequacy	
dsal	It is calculated by subtracting the current liabilities from the current assets of company i in year t.	Sales changes	Business risk
cpro	It is the result of dividing the base capital by the total weighted assets of company i in year t.	profitability	
cosc	It is equal to the change in the sales amount of company i in year t compared to year t-1.	Company cost changes	
spi	It is the profit before tax deduction and the guaranteed profit of bank loans divided by the total assets of company i in year t. According to the research of Hijazi et al. (2013) and Fortin and Pittman (2004), it is calculated through the changes in the cost of company i in year t compared to year t-1.	Financial portability	
indu	It is calculated using the Erima model and considering market shocks.	Type of industry	
varp	It is defined by the company using the virtual variable.	Variety of products	
invc	By using entropy, the diversity of company i's products in period t compared to industry j is measured.	Inventory changes	
ople	It is the percentage change in the inventory of company i in year t.	Changes in operating leverage	
epfl	It is the percentage of changes in operating profit compared to the percentage of changes in company i's sales in year t.	Extreme price fluctuation	Market risk
INF	The logarithm is the number of days that the price of company i in period f fluctuates from -5 to -5 in one year.	Inflation rate	
REX	The inflation rate is equal to the change in the consumer price index.	Exchange rate	
INR	According to the discussion of the mandate of the official exchange rate and to avoid its effects, the real exchange rate index will be used.The real exchange rate variable is denoted by REX, which is obtained from the following relationship:	Interest rate	

GDP		gross domestic product	
mstg		market stagnation	
smfl	where EX is the exchange rate (US dollar) in the informal foreign exchange market, CPIU is the consumer price index of goods and services with the base year of 2005 in the urban areas of America, and CPII is the consumer price index of the goods and services with the base year of 2013 in the urban areas of Iran.	Strong market fluctuations	
grat		Economic growth rate	
SYN	It is calculated based on the official interest rate by the central bank.	Stock price synchronization	
cash	It is the total monetary or market value of all final goods and services produced within the borders of a country during a specific period of time. This index is known as a measure that includes the entire domestic production and indicates the score of a country in terms of economic health.	Cash held	Liquidity risk
shdeb	1 if the economy is in recession and 0 otherwise.	Changes in short-term debt	
fcon	If more than 50% of the market has a volatility of 5 or -5, it is considered 1 and otherwise 0.It is the annual geometric rate of GDP growth between the first and last years in a period of time. This growth rate represents the trend of the average level of GDP over the period and ignores any fluctuations in GDP around this trend.	Financial constraints	
liqc	Stock price synchronicity is the domain in which the market and industry returns show the difference in stock returns at the company level, or in other words, the stock price has combined a large proportion of market information and vice versa. Using the model of Morek et al. (2000), Chan and Hamid (2006), Xing and Anderson (2011) and Nguyen and Trang (2013), the regression model is used.	Liquidity changes	
susc	is the cash held by company i in year t.	Suspicious claims	
deb	It is calculated through changes in short-term debt of company i in year t compared to year t-1.	amount of debt	
str	It is a time when companies are faced with a gap between internal use and external use of allocated funds.To measure the financial constraint, the model of Kaplan and Zinklas is used, which Tehrani and Hesarzadeh (2008) have localized.	Stock turnover rate	
curr	The criteria of stock turnover ratio, Amihud illiquidity ratio, percentage of free floating shares and liquidity rate presented in Rahavard Navin software have been chosen to measure stock liquidity.	current ratio	

In the quantitative section, to test the normality of the distribution of the model data, the subject of the normality of the distribution of the model data was tested through the Shapiro-Wilks test. In linear regression models, one of the methods of estimating 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

Table 10. The absolute coefficients of the variables in the training mode with the ridge regression method

Type of financial risk	Variable	Coefficient
Credit risk	Cost of financing	1.313
	Financial leverage	1.373
	Company size	0.257
	ownership structure	0.212
	The capital structure of the company	0.228
	Ability to provide capital	0.240

Profit risk	Return volatility	-0.250
	Profit fluctuations	0.172
	Dividends	0.240
	loss of the company	0.244
	Profit forecast error	0.148
Investment risk	Financing method	0.320
	Capital growth ratio	0.196
	Circulation of financial capital	0.161
	Capital adequacy	0.414
Business risk	Sales changes	0.111
	profitability	0.337
	Company cost changes	0.228
	Financial portability	0.125
	Type of industry	0.104
	Variety of products	0.279
	Inventory changes	0.200
	Changes in operating leverage	0.172
Liquidity risk	Cash held	0.212
	Changes in short-term debt	0.170
	Financial constraints	0.061
	Liquidity changes	0.137
	Suspicious claims	0.141
	amount of debt	0.015
	Stock turnover rate	0.162
	current ratio	0.184

Based on the above table, the ridge regression method suggests to remove the variable with a coefficient of 0 from the model in the use of deep learning algorithm to predict the financial risk. The graph below also shows the absolute coefficients for predicting financial risk using the ridge regression method in deep learning (as the initial stage of the deep learning method).

4. Discussion and Conclusion

The findings of the current study, which aimed to design a financial risk prediction model using a hybrid deep learning approach integrating ridge regression and artificial neural networks, revealed significant predictive accuracy across multiple dimensions of financial risk. Based on the meta-combination and regression analyses, five primary categories of risk—credit, profit, investment, business, and liquidity—were identified, modeled, and validated through both qualitative coding and quantitative testing. The results demonstrated that the hybrid model provided consistently low error rates (MAPE < 0.05) across all risk categories, confirming its robustness in real-world prediction tasks. Among the different risk dimensions, credit risk and liquidity risk exhibited the strongest predictive associations, with R^2 values of 0.822 and 0.776, respectively, and high correlation coefficients of 0.926 and 0.914, highlighting the model's efficiency in identifying these risk categories.

The accuracy of credit risk prediction underscores the effectiveness of using financial indicators such as financing cost, leverage, firm size, and ownership structure in deep learning frameworks. This finding aligns with previous studies, such as those by [17], who emphasized the predictive relevance of capital structure and financial leverage in understanding systemic financial instability. Moreover, the study by [15] supports the present results by indicating that variables such as real earnings management and financing structure are critical in affecting the cost of capital and company risk. The current study expands upon these insights by employing a deep learning mechanism, which not only processes these variables more efficiently but also models their nonlinear interactions, which are typically difficult to capture in classical econometric models.

In the context of liquidity risk, the study confirmed the importance of features such as cash held, short-term debt changes, and financial constraints. The model demonstrated a high degree of predictive accuracy for liquidity risk, in line with the framework proposed by [11], who argued for a fuzzy evaluation method to capture the uncertainties surrounding liquidity management in SMEs. Furthermore, the integration of deep learning has allowed the model to learn from both structured data (e.g., financial statements) and latent patterns within these indicators, enhancing its predictive performance. This approach resonates with the findings of [4], who demonstrated the efficacy of neural network architectures—particularly FA-PSO-LSTM hybrids—in e-commerce firms for financial risk forecasting, reinforcing the current study's methodological orientation.

Despite the lower R^2 values observed in the prediction of investment and profit risk, the model still achieved statistically significant p-values, indicating that these dimensions remain essential in a comprehensive financial risk profile. The relatively lower predictive power in these categories can be attributed to the complexity of investment decisions and profit volatility, which are often influenced by external macroeconomic shocks and internal strategic shifts. This observation aligns with [8], who pointed out the sensitivity of asset prices to political uncertainty and unanticipated economic events. Additionally, [3] emphasized the challenge of modeling heterogeneous and imbalanced financial data, particularly in investment risk prediction, and advocated for the application of deep learning models that adaptively learn from such complexities—precisely the approach taken in the present study.

The identification and modeling of business risk using variables such as sales changes, profitability, and cost structure reaffirmed the dynamic relationship between operational performance and financial stability. Although the R^2 value for business risk was moderate (0.246), the model's correlation coefficient of 0.499 demonstrates a reasonable capacity to capture relevant variations in business conditions. This supports the arguments of [7], who emphasized the role of internal control and financial reporting systems in early financial risk detection. Likewise, the findings echo those of [12], who proposed a real-time risk monitoring index system for firms as a necessary evolution from traditional static methods, and this study's use of deep learning answers that call for dynamic system development.

One notable strength of this research is the application of ridge regression in tandem with deep neural networks. The results showed that both methods independently generated comparable error values, yet their combination yielded superior accuracy and interpretability. This result reinforces the findings by [1], who asserted that deep learning models achieve better generalization when complemented with regularization techniques like ridge regression. The effective fusion of these methods enabled the model to minimize overfitting while preserving explanatory power—especially crucial for financial datasets characterized by multicollinearity and heteroscedasticity. Furthermore, the application of TensorFlow as a development framework ensured computational efficiency and reproducibility of the predictive models, in line with recommendations from [5], who used similar deep learning tools in risk behavior forecasting.

The study's methodology also allowed the inclusion of legal and systemic risk dimensions into the overall modeling framework. Legal risks—arising from ambiguous regulations or contractual uncertainties—pose non-negligible threats to financial stability, especially in fintech and cross-border operations. [10] highlighted these legal challenges, particularly in blockchain and distributed ledger technologies, suggesting that any forward-looking risk model must integrate legal indicators. Similarly, [9] pointed out the systemic implications of relying on opaque "black box" technologies without conceptual safeguards, a limitation partially mitigated in this study through model transparency and structured variable selection.

Incorporating macroeconomic variables—such as GDP, inflation, and exchange rate fluctuations—into the deep learning architecture proved to be a significant step in aligning with market-based risk dynamics. These variables were crucial in market and investment risk predictions and support the position of [14], who developed an early warning model for construction enterprises by incorporating such macroeconomic metrics. The study's use of extensive variable coding, inspired by meta-composite qualitative analysis, further validates the modeling framework by ensuring a granular understanding of each risk dimension's internal composition.

The cross-validation of variables through the Kappa coefficient established excellent inter-coder reliability (all above 0.8), confirming the robustness of the qualitative content analysis. This also adds methodological rigor to the meta-composite phase and aligns with the validation standards discussed by [16], who emphasized the importance of perceptual agreement in risk-related qualitative research.

While the study contributes meaningfully to financial risk modeling, several limitations should be noted. First, the deep learning algorithms used, though accurate, require substantial computational resources and may not be easily deployable in organizations with limited technological infrastructure. Second, although the hybrid model performed well overall, its lower predictive power in profit and investment risk categories suggests that certain latent variables may remain unobserved or insufficiently modeled. Furthermore, the data used was primarily historical and sourced from companies active in Iran's capital market during 2013–2014. This narrow geographic and temporal scope may limit the generalizability of the findings to other markets or time periods. Lastly, although efforts were made to ensure model transparency, deep learning inherently suffers from a degree of interpretability loss, which could be problematic for regulatory compliance and internal auditing purposes.

Future research should consider expanding the dataset across multiple countries and financial markets to enhance the generalizability of the model. Incorporating real-time financial news and sentiment analysis through natural language processing (NLP) could further improve predictive accuracy, particularly in profit and investment risk forecasting. Additionally, researchers should explore the integration of other AI paradigms, such as reinforcement learning or evolutionary algorithms, to capture the adaptive behavior of firms under varying economic scenarios. It would also be beneficial to assess the performance of the proposed model under stress-testing environments and simulate its behavior during financial crises to evaluate its resilience.

Practitioners and financial managers can utilize the proposed deep learning-based risk prediction model as an early warning system to detect vulnerabilities in credit and liquidity dimensions. By deploying this model in real-time, financial institutions can proactively adjust their capital buffers, liquidity reserves, and investment strategies. Moreover, the modular nature of the model allows for tailored risk profiling based on industry type, firm size, or market volatility. Policymakers can also leverage these findings to craft more adaptive regulatory frameworks that encourage transparency and data sharing without stifling innovation. Ultimately, the practical application of this model lies in its ability to inform evidence-based decision-making and reduce the systemic impacts of financial crises.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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