Shahid Chamran University of Ahvaz

Quarterly Journal of Quantitative Economics

Journal Homepage: www.jqe.scu.ac.ir
Print ISSN: 2008-5850
Online ISSN: 2717-4271



Hybrid Model for Predicting Bankruptcy in Iranian Banks: Combining Artificial Intelligence with Spatial Econometrics

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ARTICLE HISTORY	**JEL CLASSIFICATION:**
	G21, O33, C32
Received: 24 May 2020	**KEYWORDS:**
Revision: 17 December 2021	***Bank failure, artificial intelligence, spatial***
acceptance: 17 December 2021	***econometrics, hybrid model***

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Acknowledgments: Acknowledgments may be made to individuals or institutions that have made an important contribution.
Conflict of Interest: The authors declare no conflict of interest**.**
Funding: The authors received no financial support for the research, authorship, and publication of this article**.**

ABSTRACT

This research aims to develop and design a hybrid model for predicting the bankruptcy of Iranian banks from 2011 to 2024. This innovative model combines artificial intelligence (AI), machine learning techniques, and a spatial econometrics approach to improve

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Quarterly Journal of Quantitative Economics
(former Economic Studies)

prediction accuracy and consider spatial dependencies and risk contagion among banks. Therefore, this study utilizes Bayesian Neural Networks, Gaussian Neural Networks, Cerebellar Model Articulation Controller (CMAC), Multilayer Perceptron (MLP), Reinforcement Gradient, and Ant Colony Optimization algorithms in the AI and machine learning sections, and a spatial autoregressive model in the econometrics domain. Initially, financial and macroeconomic data were collected and cleaned. Then, the aforementioned models were evaluated using accuracy, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), coefficient of determination (R-squared), and AUC-ROC. Furthermore, the spatial relationship between banks was examined using the spatial autoregressive model to explain the role of spatial dependency in the spread of bankruptcy risk. The research results demonstrated that combining the spatial autoregressive model with Bayesian Neural Networks and Multilayer Perceptron yields remarkable performance in predicting bank bankruptcy. Also, variables such as cost-to-income ratio, capital adequacy, liquidity, loan-to-asset ratio, and bank size, as internal factors, play a significant role in estimating the probability of bankruptcy. On the other hand, macroeconomic variables, such as GDP growth, inflation rate, and economic cycles, have a considerable impact on exacerbating or mitigating bank risk. The spatial autoregressive model also confirmed that risk contagion among neighboring banks could intensify the risk of bankruptcy. Based on the findings of this research, integrating AI and machine learning methods with spatial models provides a comprehensive and effective approach for predicting the bankruptcy of Iranian banks. Liquidity management, cost control, monitoring high-risk loans, and attention to macroeconomic dynamics will be most effective when geographical considerations and risk contagion are also taken into account. Therefore, it is recommended that monetary policymakers and bank managers utilize these hybrid models in the bank monitoring process and improve the stability and health of the banking system by strengthening financial structures and implementing reform policies.

How to Cite:
Taheri Haftasiabi, Reza., Naderi, Ameneh & Piri, Parviz. (2025). Hybrid Model for Predicting Bankruptcy in Iranian Banks: Combining Artificial Intelligence with Spatial Econometrics. *Quarterly Journal of Quantitative Economics*(*JQE*), 21(3), 1-29.
10.22055/jqe.2025.48811.2684

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1- Introduction

The banking industry, as a vital sector of the economy, plays a fundamental role in Iran's economic development and growth (Jafari Samat, 2018). Banks, by attracting deposits and allocating resources to investors, play an effective role in increasing production and investment (Mensah et al, 2012). The importance of this industry is such that sustainable economic growth is hardly achievable without an increasing trend in investment, which is one of the key factors of production (Cole et al., 2008). On the other hand, Iran's financial structure is bank-based, and most of the financial resources are provided by banks (Nazarpoor et al., 2017). As a result, banks play a significant role in the country's economic stability, and their duties cannot be overlooked (Golizadeh et al., 2021). Therefore, if the banking system faces a crisis, the entire national economy may face serious problems (Nasiri & Nasiri, 2021).

Moreover, in the Iranian economy, the share of banks in financing is very high, and the essential importance of these institutions in supporting economic growth and development cannot be ignored (Bagheri et al., 2016; Pirpour et al, 2024). Statistics show that in some years, the share of banks in financing is higher than the capital market. For instance, the share of bank financing for the Iranian fiscal year 2012-2013 was 91.3%, while the share of the capital market was only 6.2%. The share of banks in financing for the years 2014 and 2015 was 86.5% and 89.2%, respectively, while financing through the capital market for these years was very insignificant, at 9.5% and 7.6%, respectively. The contribution of banks in providing the necessary investment financing for the Iranian economy has been as high as 90% (Golmoradi et al., 2020; Taheri et al., 2024). Furthermore, the share of banks in financing for the years 2016, 2017, 2018, 2019, 2020, 2021, 2022 and 2023 was 64%, 51%, 88%, 67%, 57%, 59%, and 84%, respectively (Taheri HaftAsiabi, 2023). Thus, considering that in the Iranian economy, the two main pillars for financing new investments are banks and the capital market, it should be noted that banks play a major and significant role in

providing financial resources for new investments (Abdollahi Pour et al., 2020).

Predicting bank bankruptcy, as one of the most important topics in finance and banking, has attracted the attention of many researchers. Li et al. (2014), in a study of US agricultural and commercial banks, identified non-performing loans as the most important predictor of bankruptcy. This finding is consistent with the results of Abiola and Olusi's (2015) research, which showed that banks with high ratios of non-performing loans and operating expenses are more prone to bankruptcy. In Iran, Ahmadian & Gorji (2017) were able to present a highly accurate model for predicting bank bankruptcy using the banking stability index and financial statements. Tankabani et al (2020) also pointed to the importance of macroeconomic factors such as economic resilience and economic growth rate in reducing the probability of bank bankruptcy.

In recent years, researchers have increasingly focused on using advanced artificial intelligence and machine learning methods to predict bank bankruptcy. Petropoulos et al. (2020) demonstrated the high efficiency of the random forest method compared to other methods, while Shrivastava et al. (2020) emphasized the high accuracy of logistic regression. Zelenkov and Volodarsky (2021) used genetic algorithms to reduce false rates in bank bankruptcy prediction. Vallarino (2023) reported the superior performance of decision trees in identifying bank bankruptcies. In the latest studies, Ben Jabeur & Serret, (2023) showed that fuzzy convolutional neural networks perform better than other methods in predicting bankruptcy.

On the other hand, in the Iranian economy, where the financial structure is bank-based and the major share of financing is borne by banks, the importance of predicting bank bankruptcy is doubled. Because banks play a role in providing the funds needed by institutions, meeting seasonal needs, purchasing raw materials, and developing production lines, they have become the most important providers of financial resources for the long-term growth of organizations. Therefore, bank bankruptcy can have widespread effects on the country's economy. Thus, given the vital role of banks in the Iranian economy and the bank-based financial structure of the country, predicting and preventing bank bankruptcy is of paramount importance. Considering that banks are responsible for up to 90% of

investment financing in Iran, their bankruptcy can lead to widespread financial and economic crises.

In this regard, designing an intelligent hybrid model for predicting the bankruptcy of Iranian banks is essential. This model, which uses a combination of artificial intelligence and spatial econometrics techniques, can enable managers, policymakers, and other stakeholders to take necessary preventive measures and prevent financial crises by timely identifying warning signs. Using this combined approach in bank bankruptcy prediction modeling not only allows for the use of extensive data and complex patterns but also identifies and analyzes spatial dependencies between factors affecting bank bankruptcy. This increases the accuracy and reliability of predictions. Also, given the dynamics and constant changes in the economic and financial environment, this hybrid model is capable of continuous learning and adaptation to new conditions. This feature doubles the necessity of using such an approach compared to traditional bankruptcy prediction methods. Moreover, given the importance of banks listed on the Tehran Stock Exchange (TSE) in the Iranian capital market, accurate prediction of the bankruptcy of these banks can significantly contribute to maintaining the stability of the capital market and investor confidence.

Therefore, the main objective of the present study is to develop a hybrid model for predicting the bankruptcy of Iranian banks. This model uses a combination of artificial intelligence and spatial econometrics techniques to not only provide a more accurate prediction of bankruptcy but also to identify and analyze the spatial dependencies between the factors affecting bank bankruptcy. This innovative approach seeks to provide a comprehensive framework for a better understanding of bankruptcy dynamics in the Iranian banking system.

In this regard, the second section of this study is devoted to theoretical foundations and a review of empirical studies, and in the next section, the model design and statistical framework will be discussed. Then the empirical findings are presented, and finally, a summary and conclusion will be provided.

2- Literature Review

Banks, as the backbone of the financial system, play a vital role in the modern economy (Alizadeh et al., 2022). These financial institutions mobilize short-term deposits and transform them into long-term loans and investments, playing a crucial role in resource allocation and facilitating economic growth (Negin Taji et al., 2022; Kent & Diterrejiach, 1997). Furthermore, banks offer various services, including risk management, payment facilitation, financial advisory, and intermediation in financial markets (Diamond & Rajan, 2001). Consequently, the role of banks in the economy is so critical that their health and stability directly impact the overall economic performance (Merton & Thakor, 2022; Thi Huong Wuong et al, 2023). For instance, banks can influence the amount of circulating liquidity, the level of investment, and ultimately economic growth through their credit policies. They also act as the primary channel for implementing central bank monetary policies and play a significant role in controlling inflation and maintaining economic stability (Mishkin & Wackens, 2018).

On the other hand, bank failure, a major challenge in the financial sector, occurs when a bank is unable to meet its financial obligations. More precisely, bank failure is a situation where the value of a bank's assets falls below the value of its liabilities (Citterio, 2024). This situation can arise from various factors, including a decline in asset values, an increase in non-performing loans, or a mismatch between assets and liabilities in terms of maturity or interest rates (Taghavi et al., 2006; Nasiri & Nasiri, 2021). Therefore, accurately determining the timing of a bank's failure is often difficult, as banks usually try to avoid formally declaring bankruptcy until the last moment (Ahmadian & Gorji, 2017; Ghafari et al., 2013). However, regulatory bodies use various indicators to assess the financial health of banks. These indicators include capital adequacy ratio, asset quality, liquidity, profitability, and sensitivity to market risk, collectively known as the CAMELS system (Sepehrdoust & Ayini, 2013). For example, if a bank's capital adequacy ratio falls below the minimum threshold (usually 8% according to the Basel Accords), it can be a sign of serious financial problems and potential failure (Basel Committee on Banking Supervision, 2017). Furthermore, a sudden increase in the

ratio of non-performing loans, a sharp decline in profitability, or recurring problems in securing liquidity can also be warning signs of bankruptcy (Demirgüç-Kunt et al., 2021; Iddrisu & Pellagatti, 2020).

The causes of bank failures are numerous and complex. One of the most important reasons is inadequate risk management (Mandanis Schooner & Taylor, 2010; Matin Nafas et al., 2020). Banks are exposed to various types of risks, including credit risk, liquidity risk, market risk, and operational risk (Morshedzadeh et al., 2021). Failure to manage these risks properly can lead to significant losses and ultimately bankruptcy (Mahmud Hasan, 2024). For instance, granting high-risk loans without thorough credit assessment can lead to an increase in non-performing loans and a decline in the quality of the bank's assets. Also, a mismatch between the maturity of assets and liabilities can expose the bank to liquidity risk (Caprio & Honohan, 1999) Macroeconomic factors also play a significant role in bank failures (Friedman & Kuttner, 2010). Economic recession, high inflation, sharp fluctuations in exchange rates, and global financial crises can all negatively impact bank performance (Goodarzi & Adli, 2023). During economic downturns, rising unemployment and declining household and corporate incomes can lead to increased loan defaults and consequently higher credit losses for banks (Zangeneh et al., 2022). Furthermore, an inadequate regulatory and legal framework can also contribute to bank failures (Goodarzi & Adli, 2023).

The consequences of bank failure can be widespread and devastating, with impacts ranging from the micro to the macro level (Nasiri & Nasiri, 2021). At the micro level, depositors may face the risk of losing their savings (Simaei & Amini, 2020). Although deposit insurance systems mitigate this problem in many countries, these systems usually have limitations and may not cover all deposits. In addition, companies and businesses associated with the failed bank may face serious financing and liquidity problems, which can lead to reduced economic activity, layoffs, and even bankruptcy (Bagheri et al., 2018). In Iran, due to the specific economic and banking structure,

these problems have more serious consequences. The deposit insurance system in Iran has more limitations and does not guarantee full coverage of deposits. Also, the dependence of many companies and businesses on bank loans increases their vulnerability to problems in the banking system, leading to increased unemployment, reduced production, and a deepening economic recession at the national level (Amiri, 2017). Furthermore, given the significant role of the government in the Iranian economy, bank failures can put significant financial pressure on the government budget, leading to increased budget deficits and inflation (Taheri Haft Asiabi et al., 2023). At the macro level, bank failure can erode public trust in the banking system (Mare, 2015). This loss of confidence can trigger bank runs, where depositors simultaneously rush to withdraw their money, potentially leading to the collapse of the entire banking system. Moreover, bank failure usually leads to credit contraction and consequently reduced investment and economic growth. This can result in economic recession, increased unemployment, and lower living standards (Arena, 2008). In severe cases, bank failure can trigger a widespread financial crisis whose impacts extend beyond the banking sector and even across national borders (Wu & Cole, 2024). However, in the case of Iran, these macro consequences can be exacerbated. Due to economic sanctions and limitations on interaction with the global financial system, bank failure in Iran can have more damaging effects. A decline in public trust in the banking system can lead to increased demand for foreign currency and gold, putting further pressure on the exchange rate (Tabatabaei-Nejad, 2015). This can exacerbate inflation and reduce purchasing power. Also, given the crucial role of banks in financing various economic sectors, bank failure can lead to a deeper recession and more widespread unemployment. Furthermore, given Iran's economic structure and dependence on oil revenues, a banking crisis can create serious challenges for macroeconomic management and financial stability (Karadas & Ozdemir, 2023).

Numerous empirical studies have confirmed the adverse effects of bank failure on the economy. These studies demonstrate that the consequences extend beyond the financial sector and can have profound impacts on the real economy. For example, Homsombath et al. (2024) and Dell'Ariccia et al. (2008), examining data from 41 countries, showed that industries more reliant on external financing

experience greater declines in growth during banking crises. This finding suggests that bank failure can restrict economic activity through the credit channel. Chodorow-Reich (2014), studying the 2008 financial crisis in the US, showed that companies connected to crisis-affected banks experienced significant declines in hiring and investment. This study demonstrates that bank failure can directly impact the labor market and capital formation. Furthermore, Peek and Rosengren (2000), examining the impact of the Japanese banking crisis on economic activity in the United States, showed that reduced credit supply by branches of Japanese banks in the US led to a significant decline in construction activity in the relevant states. This study shows that the consequences of bank failure can transcend national borders and affect other economies.

Therefore, given the vital importance of banks in the economy and the widespread consequences of their failure, predicting and preventing bank failure is crucial. This requires a multifaceted approach that includes strengthening regulatory systems, improving risk management in banks, and adopting appropriate macroeconomic policies. Strengthening banking supervision involves improving laws and regulations, increasing transparency in financial reporting, and using advanced technologies for better monitoring. For instance, using data mining and artificial intelligence techniques can help identify suspicious patterns in banking activities early on. Improving risk management in banks involves strengthening risk assessment systems, increasing diversification in asset portfolios, and improving liquidity management strategies. Also, adopting appropriate macroeconomic policies, such as balanced monetary and fiscal policies, can contribute to the stability of the banking system. Moreover, developing bankruptcy prediction models using advanced statistical techniques and artificial intelligence can help identify problems early and prevent banking crises. Various models have been developed to predict bank failure, ranging from traditional statistical models like multiple discriminant analysis and logistic regression to more advanced methods like artificial neural networks and support vector machines.

These models use historical data and various financial indicators to predict the probability of bank failure. For example, Tam and Kiang (1992) showed that artificial neural networks outperform traditional statistical methods in predicting bank failure.

Predicting the failure of Iranian banks is of paramount importance. Iran's banking system faces unique challenges, including economic sanctions, limitations on interaction with the global financial system, the heavy dependence of the economy on oil revenues, and the significant role of the government in the economy (Taheri & Ahmadhosein, 2023). These factors, along with structural problems in the banking system, such as a high volume of non-performing loans and weaknesses in risk management, make it even more necessary to develop accurate bankruptcy prediction models. Furthermore, the specific structure of the Iranian economy, including the dependence of many companies and businesses on bank loans and limitations of the deposit insurance system, increases the economy's vulnerability to bank failure. These conditions, coupled with the widespread consequences of bank failure in Iran, including the impact on exchange rates, inflation, and employment, highlight the importance of accurate and timely prediction of bank failure (Rashid Ardeh Habibollah, 2016). In this regard, it is essential to develop a comprehensive and efficient model to predict the failure of Iranian banks. This model utilizes advanced artificial intelligence and machine learning methods and considers Iran's specific economic indicators alongside the banks' internal financial indicators. Such a model would be a valuable tool for policymakers and regulatory bodies to maintain financial and economic stability.

Below, we review several empirical studies on predicting bank failures.

Sun et al. (2025), in a study titled "Explaining the Determinants of Bank Failure Prediction through a Neural Additive Model for Korea from 2000 to 2023," investigated the factors determining bank failure prediction. The results showed that traditional machine learning models might provide contradictory explanations in the financial domain, which could lead to incomplete results and suboptimal decision-making. To address this issue, they proposed a neural additive model that combines the transparency of the generalized additive model with the excellent performance of neural networks. The results

indicate that this approach can facilitate the interpretation of explanatory variables in predicting bank failures and enable improved financial risk assessment.

Sefidpoosh Khamene et al. (2025) designed and explained a model for predicting the default risk of corporate customers of Bank Mellat using an artificial intelligence approach and firefly and ant-eater optimization algorithms. The qualitative statistical population of this study included experts and managers of Bank Mellat, and the quantitative statistical population included the bank's corporate customers. Data analysis was performed based on Strauss and Corbin's guidelines and the open, axial, and selective coding stages. The results indicated that the firefly algorithm with 98.07% accuracy and the ant-eater algorithm with 93.78% accuracy have a high ability to predict default risk, with the firefly algorithm performing better than the ant-eater algorithm in this regard.

Nosrat Nezami et al. (2025), in a study aimed at combining the systematic review method and the fuzzy Delphi approach to identify factors and models affecting the bankruptcy of companies listed on the Tehran Stock Exchange, utilized MAXQDA software and open, axial, and selective coding methods. The results showed that using modern structures, such as hybrid intelligent systems based on data mining models, has a high ability to detect corporate bankruptcy. In addition to utilizing modern algorithms such as artificial neural networks and support vector machines, this research generalized the data to food and textile industries and was not limited to listed companies.

Hu et al. (2025), in a study titled "Predicting US Bank Failures and Stress Testing with Machine Learning Algorithms from 2001 to 2023," examined the status of federally insured companies and US banks. The study results showed that the random forest model achieves the highest overall accuracy in predicting bankruptcy, while logistic regression, XGBoost, support vector machine, and neural network models exhibit varying performances. Stress test and sensitivity analyses indicate that the model's accuracy is highly dependent on key

financial characteristics, and under severe stress conditions, the predictive capacity decreases significantly.

Parnes and Gormus (2024), in a study titled "Prescreening Bank Failures with K-means Clustering: Advantages and Disadvantages," examined the prediction of US commercial bank failures from 1990 to 2023 using two prediction systems, one based on a combination of K-means and logistic regression, and the other solely on logistic regression. The results showed that the first system is more accurate in early identification of failures but predicts more potential failures among solvent banks. The second system is softer and has slightly higher overall predictive power.

Antoniades (2024), in a study titled "Commercial Bank Failures During the Great Depression," aimed to investigate the factors influencing commercial bank failures during the Great Depression, particularly focusing on the role of real estate lending to non-residential, commercial, and non-household sectors from 1930 to 2023. The results indicated that bank failures were primarily due to greater exposure to non-residential real estate credit before the crisis, rather than household mortgage loans or liquidity risk. These findings highlight the importance of managing exposure to bank risks, especially in the non-residential real estate sector, in preventing bankruptcy.

Pita and Nobrega (2023), in a study titled "Machine Learning and Sentiment Analysis: Predicting Bank Bankruptcy Risk," predicted the bankruptcy risk of banks listed on the Brazilian stock exchange from 1990 to 2021. The results showed that the k-means algorithm could classify banks more accurately in the highest risk category, and the decision tree model had the best performance in predicting bankruptcy risk. Also, adding the banking sentiment variable using a time-varying dictionary improved the performance of prediction models.

Nejari Foroushani et al. (2023), in another study, designed an early warning model to predict the probability of bank failure in selected Islamic countries using the multinomial logit method for the period from 1998 to 2020. The results showed that the ratio of working capital to bank assets and the ratio of bank income before zakat and tax to net assets had a negative effect on the probability of bank failure in the period before and after the occurrence of failure. The ratio of total

bank debts to shareholders' equity had a positive effect on the probability of failure in both periods. On the other hand, the ratio of retained earnings to total bank assets did not have a significant effect on the probability of bank failure in selected Islamic countries in either period.

Tankabani et al (2020), in a study titled "Macroeconomic Resilience and Banking System Failure" using annual data from 2005 to 2016 for 125 countries in logit and probit models, concluded that increasing economic resilience and economic growth rate reduces the probability of bank failure.

3- Research Innovation

Reviewing the theoretical literature and research background revealed that previous studies on bank failure prediction have generally focused on financial data and employed classical data mining or econometric methods independently; however, the convergence of these two approaches in a hybrid model has not received much serious attention. Especially in complex environments like Iran's banking system, which is entangled with specific macroeconomic factors (such as sanctions and limitations on international relations), utilizing a combined model that can simultaneously identify non-linear patterns and spatial dependencies seems necessary. Reviewing the literature indicates that in the field of bank failure prediction, either advanced artificial intelligence methods separate from spatial econometrics have been used, or only econometric models have been employed. On the other hand, in Iran, limited research has been conducted on bank failure prediction using artificial intelligence techniques, and the few existing studies have mainly been influenced by regression methods or simpler machine learning models. Moreover, the application of spatial econometrics in domestic banking studies is rarely observed. Consequently, no research has comprehensively employed the simultaneous combination of artificial intelligence and spatial econometrics in predicting the failure of Iranian banks. This gap has doubled the need to improve existing modeling frameworks to identify

spatial correlations and complex patterns in Iran's banking system. Therefore, the main innovation of this research is introducing a hybrid model that combines the power of artificial intelligence algorithms (such as random forest, advanced neural networks, or support vector machines) with spatial econometric tools. In addition to identifying non-linear and complex patterns between macro indicators and banking indicators, this model also tracks the spatial or locational effects between banks. Combining these two approaches in a single framework increases the accuracy and sensitivity of the model and provides policymakers and managers with a more complete picture of bank failure risks.

Finally, the proposed approach in this research, while filling the existing theoretical gap in the literature on bank failure prediction in Iran, can also provide a powerful tool for regulators and senior bank managers in practice. Thus, by timely identifying sensitive points in a network of Iranian banks, faster and more accurate actions can be taken to prevent banking crises. Moreover, from a research perspective, presenting a hybrid intelligent model considering spatial and economic aspects can pave the way for future studies in bank risk management and financial stability in Iran and other countries with similar banking structures.

4- Methodology

This research aims to design and develop an intelligent model for predicting bankruptcy in Iranian banks listed on the Tehran Stock Exchange. It utilizes artificial intelligence techniques to identify complex patterns and nonlinear relationships within financial data. Existing evidence suggests this approach offers more accurate and reliable predictions compared to traditional methods (Sobhani Fard et al., 2019). Employing AI tools for bankruptcy prediction can identify hidden risks within the banking system before they materialize, facilitating more informed decision-making. A wide range of machine learning and artificial neural network methods are employed. Machine learning algorithms include Decision Tree (Chen, 2011), Gradient Boosting (Xia et al., 2024), Support Vector Machine (Li and Sam, 2008), Support Vector Regression (Bajelan et al., 2016), Random Forest, Extremely Randomized Trees, k-Nearest Neighbors, Ant Colony Optimization, and Expectation-Maximization. Advanced

techniques like demand-based forecasting models, adversarial learning, and Principal Component Analysis are also utilized. Various artificial neural network models are employed, including Multilayer Perceptron, Cerebellar Model Articulation Controller (Vijayan and Divakar, 2022), Gaussian Neural Network (Khosraviani et al., 2024), Graph Neural Network, Neocognitron, and Transformer Network (Taheri et al., 2024). These networks, by learning higher-level features from input data, can model complex and nonlinear relationships. Using this diverse range of methods allows for comparing their performance and accuracy, helping select the best approach for bankruptcy prediction. Combining these methods can lead to more powerful hybrid models that leverage the advantages of each. Historical financial and economic data from Iranian banks listed on the Tehran Stock Exchange from 2018 to 2023, gathered from official websites of the Tehran Stock Exchange[1], the Central Bank of Iran[2], the National Statistical Portal[3], Codal[4], Rahavard Novin[5], Iran Economic View, and the World Bank, are used for training and evaluating the proposed models. During preprocessing, data is cleaned, and relevant features are extracted. Clustering techniques (Abdalameer al., 2022) are used for grouping banks, and Principal Component Analysis (Taheri Haft Asiabi et al., 2024) is used for dimensionality reduction and identifying key variables. The dataset is then split into training and testing sets, and the machine learning and neural network models are tuned and optimized using the training data. Finally, the best models are selected and employed to predict bankruptcy in new banks. Based on the model presented in the study by Pita and Nobrega (2023), this research utilizes their variables to develop a machine learning and neural network-based model for predicting bankruptcy in Iranian banks. Furthermore, a spatial econometric SAR model is incorporated to enhance prediction accuracy and analyze the spatial dependence effects among factors

[1] https://www.fipiran.com/DataService/IndexIndex,https://www.tse.ir/, https://www.tsetmc.com/.
[2] https://www.cbi.ir/section/1378.aspx.
[3] https://www.amar.org.ir/statistical-information.
[4] https://codal.ir/.
[5] https://mabnadp.com/products/rahavard-novin

influencing bank bankruptcies. The main objective is to develop a hybrid model combining AI techniques and spatial econometrics to provide more accurate bankruptcy predictions and identify and analyze spatial dependencies among contributing factors. This novel approach provides a comprehensive framework for a deeper understanding of bankruptcy dynamics in the Iranian banking system. Overall, this research, by presenting a comprehensive and hybrid model, can assist bank managers and policymakers in Iran in accurately and timely identifying bankruptcy risks and making informed decisions and policies to prevent financial crises. Integrating AI techniques with the spatial econometric SAR model offers a powerful framework for examining spatial correlations and network effects in the banking system, ultimately enhancing the stability and financial health of banks. After determining the overall research framework for the statistical population, which includes all banks listed on the Iranian Stock Exchange for the period from 2011 to 2023, the research model based on the study by Pita and Nobrega (2023), is explained as in relation (1):

$$\mathrm{Z-score_{it}} = \frac{\mu \mathrm{ROA_{it}} + \mu \mathrm{ETS_{it}}}{\sigma \mathrm{ROA_{it}}} \quad (1)$$

In this research, the Z-score is used to assess and predict the risk of bankruptcy for banks. The Z-score is calculated for each bank on a quarterly basis, and those banks falling within the bottom 25% (first quartile) are flagged as high-risk. Additionally, a clustering algorithm is employed. Following the normalization of financial data, banks are categorized into two groups based on risk level: high and low. A key distinction from prior studies is that this clustering process is conducted separately for each quarter, allowing for a more accurate reflection of the dynamic nature of bank risk over time. The integration of these two methods Z-score and clustering facilitates a more comprehensive and precise evaluation of bankruptcy risk. Therefore, the research model, drawing upon the work of Pita and Nobrega (2023), is structured around three equations: Equation (2) predicts bankruptcy in Iranian banks; Equation (3) investigates the interrelationships between variables and the spatial dependencies among banks; and Equation (4) represents the hybrid model, which combines spatial econometrics and artificial intelligence, to generate the final bankruptcy predictions for the listed banks.

(2) $$Z-score_{it}=f(BS_{it}+CR_{it}+TAM_{it}+GDP_{it}+IPCA_{it}+IBOV_{it}+CYCLE_{it}+L_{it}+LIQ_{it}+CYCLE_{it}+COV_{it})$$

(3) $$Z-score_{it}=\rho W(Z-score_{it})+\beta_0+\beta_1 BS_{it}+\beta_2 CR_{it}+\beta_3 TAM_{it}+\beta_4 GDP_{it}+\beta_5 IPCA_{it}+\beta_6 IBOV_{it}+\beta_7 CYCLE_{it}+\beta_8 L_{it}+\beta_9 LIQ_{it}+\beta_{10} COV_{it}+\varepsilon_{it}$$

(4) $$Z-score_{it}=\rho W(Z-score_{it})+f(BS_{it}+CR_{it}+TAM_{it}+GDP_{it}+IPCA_{it}+IBOV_{it}+CYCLE_{it}+L_{it}+LIQ_{it}+CYCLE_{it}+COV_{it})+\varepsilon it$$

In the above equations, Z-score is the dependent variable (representing bankruptcy risk), where i represents Iran and t represents the banks listed on the Iranian stock exchange. ρ is the spatial autocorrelation coefficient, W is the spatial weight matrix, βi are the regression coefficients, β_0 is the intercept, BS represents the bank's balance sheet (total assets minus total liabilities), CR represents the bank's cost-to-income ratio (total operating expenses divided by total operating income × 100), TAM represents the bank's size, GDP represents Gross Domestic Product, IPCA represents the inflation index, IBOV represents the index of the banking sector listed on the Iranian stock market, CYCLE represents the business cycle, L represents the total loans granted by the bank relative to the total assets of all banks, COV represents the ratio of financial expenses to the sum of the bank's financial expenses and profits, LIQ represents the ratio of total cash plus bank deposits to total bank assets, and ε represents the error term.

The variables used in this study to predict bankruptcy in Iranian listed banks are detailed in **Table 1** below:

Table 1. Operational Definitions of Research Variables

Variable	Symbol	Measurement
Bankruptcy Risk	Z-score	$\frac{\mu ROA_{it}+\mu ETS_{it}}{\sigma ROA_{it}}$

Bank Balance Sheet	BS	Total Bank Assets - Total Bank Liabilities
Cost-to-Income Ratio	CR	(Total Operating Expenses ÷ Total Operating Income) × 100
Bank Size	TAM	Natural logarithm of total bank assets
Return on Assets	ROA	Operating Profit / Total Assets
Capital Adequacy	ETS	Equity to Total Assets
Gross Domestic Product	GDP	Percentage change in real GDP growth compared to the previous quarter
Consumer Price Index	IPCA	Reflects price changes in the economy
Banking Sector Index	IBOV	Overall index of the banking sector listed on the Iranian stock exchange
Business Cycle	CYCLE	Real GDP cycle obtained through the HP filter
Total Loans to Assets	L	(Total loans granted by the bank ÷ Total assets of all banks)
Financial Expenses to Profit Ratio	COV	(Total financial expenses ÷ (Total financial expenses + Bank profit))
Liquidity	LIQ	(Total cash + Bank deposits ÷ Total bank assets)

This research uses artificial intelligence and machine learning to predict bankruptcy in Iranian listed banks. Spatial econometrics, specifically a spatial autoregressive model, is used to examine the relationship between the variables and the spatial relationships among the listed banks. Finally, a hybrid model (combining the spatial autoregressive model with artificial intelligence and machine learning) is employed for the final bankruptcy prediction. Each of these methods is discussed further below.

- **Artificial Intelligence**

Multilayer Perceptron (MLP): A deep learning model composed of multiple layers of neurons, capable of learning complex, non-linear relationships within data. Trained using the backpropagation algorithm, MLPs identify hidden patterns in financial data. In bank bankruptcy prediction, MLPs receive financial and economic variables as input and predict the probability of bankruptcy (Zhang et al., 1998).

Cerebellar Model Articulation Controller (CMAC): A specialized neural network inspired by the cerebellum's structure. Comprising input, granule, and Purkinje cell layers, CMAC excels in learning non-linear functions and motor control. In bankruptcy

prediction, it models complex relationships between financial and economic variables, identifying non-linear patterns indicative of bankruptcy risk (Albus, 1975).

Radial Basis Function Network (RBFN): A neural network employing radial basis functions in its hidden layer. These functions map the input space to a higher-dimensional space, beneficial for modeling non-linear relationships. In bankruptcy prediction, RBFNs detect complex patterns in financial data, identifying and predicting patterns associated with bankruptcy risk upon receiving financial and economic variables (Orr, 1996).

Graph Neural Network (GNN): A deep learning model designed for structured data like graphs, modeling complex relationships between system components. In bankruptcy prediction, GNNs model relationships between banks, customers, and other financial institutions, aiding in identifying systemic risks and network effects within the banking system for more accurate bankruptcy predictions (Scarselli et al., 2009).

Neoclassical Neural Network: A blend of classical economic models and neural networks, combining existing economic knowledge with the learning power of neural networks. In bankruptcy prediction, these networks leverage economic theories related to bank failures while identifying complex, non-linear patterns in the data, leading to more accurate predictions by considering macroeconomic factors and bank-specific data simultaneously (Trippi & Turban, 1992).

Transformer Neural Network: Initially designed for natural language processing, transformers have found applications in other fields. Employing an attention mechanism for time series data processing, they analyze financial and economic time series in bankruptcy prediction. They also process textual data like financial reports and bank-related news, helping identify qualitative factors influencing bank failures (Vaswani et al., 2017).

- **Machine Learning**

Decision Tree: A machine learning algorithm creating a tree structure where each node represents a decision based on a specific feature. Used for classification and prediction, decision trees identify key factors influencing bankruptcy and establish simple, interpretable decision rules (Frydman et al., 1985).

Gradient Boosting: Combines multiple weak models (typically decision trees) to create a strong model. In each stage, a new model corrects errors from previous models. In bankruptcy prediction, it improves prediction accuracy by combining results from multiple models (Friedman, 2001).

Support Vector Machine (SVM): Finds the optimal hyperplane separating classes, used for classification and regression. In bankruptcy prediction, SVMs classify banks into healthy and at-risk groups using financial and economic features (Smola & Schölkopf, 2004).

Support Vector Regression (SVR): An SVM variant for regression problems, finding a function with maximum ε deviation from actual y-values for all training data. In bankruptcy prediction, SVR predicts precise financial indicator values like the Z-score instead of binary classification (Min & Lee, 2005).

Random Forest: Combines multiple decision trees, each trained on a random data and feature sample. In bankruptcy prediction, it considers various factors, determining each factor's relative importance and providing robust predictions by combining results from multiple trees (Menze et al., 2012).

Robust Random Cut Forest: An enhanced random forest variant handling imbalanced and noisy data better, using sampling and weighting techniques to address data imbalances. In bankruptcy prediction, it handles potential data imbalances (few bankrupt banks compared to healthy ones), improving prediction accuracy when bankruptcy data is scarce (Breiman, 2001).

k-Nearest Neighbors (KNN): Classifies new instances based on their similarity to training instances, categorizing a new instance based on the majority class among its k nearest neighbors. In bankruptcy prediction, KNN predicts a bank's status based on its similarity to similar banks in the past, identifying similar patterns in financial data for risk prediction (Henley & Hand, 1996).

Ant Colony Optimization (ACO): An optimization algorithm inspired by ants finding the shortest path. In bankruptcy prediction,

ACO optimizes feature selection for bankruptcy prediction, identifying the most influential financial and economic features, improving prediction accuracy and reducing model complexity (Dorigo & Stützle, 2004).

Expectation-Maximization (EM): An optimization method for tuning model parameters to optimize expected model performance. In bankruptcy prediction, EM optimizes bankruptcy prediction model parameters, improving accuracy and reducing model error (Bergstra & Bengio, 2012).

Demand-Based Forecasting Models: These models operate based on predicted demand, used for predicting various economic and financial variables. In bankruptcy prediction, they predict demand for banking services and its impact on bankruptcy probability, helping identify future trends in the banking industry and their impact on bank financial stability (Hyndman & Athanasopoulos, 2018).

Adversarial Learning: A machine learning method training two competing models: a generator producing synthetic data and a discriminator differentiating between real and synthetic data. In bankruptcy prediction, it improves prediction models' robustness against misleading data or sudden economic shifts, creating stronger, more adaptable models (Goodfellow et al., 2014).

Principal Component Analysis (PCA): A statistical method for dimensionality reduction, transforming correlated variables into uncorrelated linear variables (principal components). In bankruptcy prediction, PCA identifies the most influential factors in bank failures and reduces model complexity, reducing noise and improving prediction model performance (Jolliffe, 2002).

- **Spatial Econometrics**

Spatial Autoregressive Model (SAR): A statistical method analyzing spatial data, modeling relationships between observations while considering spatial dependence. In bankruptcy prediction, SAR examines interactions between banks in a geographical area and their impact on bankruptcy probability, considering financial contagion and

spatial dependencies. The W matrix, or spatial weight matrix, plays a crucial role, representing neighborhood or proximity relationships between spatial units (banks). Each element Wij represents the weight of the relationship between bank i and bank j (Anselin, 1988). The W matrix can be defined in the following ways for bankruptcy prediction:

- Geographic Distance: Weights are inversely proportional to the distance between banks, with closer banks having higher weights.
- Financial Connections: Weights are determined by the extent of financial interactions (e.g., interbank loans).
- Similarity in Financial Characteristics: Banks with similar financial characteristics have higher weights.
- Banking Network Structure: Weights are determined by banks' positions within the banking network and their systemic importance.

After defining W, the SAR model estimates interbank interactions and predicts bankruptcy probabilities, showing how financial distress in one bank can affect others in the same region or with similar financial connections (LeSage & Pace, 2009).

- **Hybrid Model**

The hybrid model combines AI with spatial autoregression for bank bankruptcy prediction, leveraging SAR's spatial analysis power and AI's complex pattern learning ability. First, SAR identifies and quantifies spatial dependencies, which are described by the relationship (5):

$$y = \rho Wy + X\beta + \varepsilon \quad (5)$$

where y is the dependent variable (bankruptcy probability), W is the spatial weight matrix, X is the explanatory variable matrix, ρ is the spatial autocorrelation coefficient, β is the regression coefficient vector, and ε is the error term. SAR outputs, including spatial coefficients and initial predictions, become AI model inputs, feeding a neural network or other machine learning algorithm alongside other financial and economic variables, which are described by the relationship (6):

$$\hat{y}ANN = f(\hat{y}SAR, X, \theta) \quad (6)$$

where f is the neural network's non-linear function and θ represents its parameters. The AI model processes this information, generating the

final bankruptcy probability prediction. The final model can be a combination of both model outputs, which are described by the relationship (7):

(7) $\hat{y}final = \alpha * \hat{y}SAR + (1-\alpha) * \hat{y}ANN$

where α is the combination coefficient ($0 \leq \alpha \leq 1$). The AI model learns non-linear relationships between input variables, including spatial information, identifying hidden patterns potentially undetectable by traditional models. This hybrid approach offers several advantages:

- Considers spatial dependencies: Crucial for identifying systemic risks and financial contagion effects.
- Learns non-linear relationships: Leading to more accurate predictions, especially in complex and volatile economic conditions.
- Handles heterogeneous and noisy data flexibly.
- Provides deeper insights: By combining spatial econometrics knowledge with AI learning power.

5- Results

In this section, the descriptive statistics of the research variables are examined. It's important to note that to reduce the impact of outlier and abnormal data on the analysis results, the Winsorizing method has been employed. Winsorizing, named after Charles Winsor, is a statistical transformation that limits extremely high or low data values. This approach minimizes the effect of outliers, allowing for a more accurate and reliable statistical analysis. By using this method, we can reduce distortions caused by abnormal data, providing a clearer picture of the statistical characteristics of the variables, which ultimately enhances the accuracy of the intelligent model for predicting bank bankruptcy. Therefore, the information related to the descriptive statistics of the research is as follows in**Table 2**:

Table 2. Descriptive Statistics of Research Variables
Source: Author's computation

Variable	Symbol	Q1	Q3	Standard Deviation	Jarque-Bera Test	
					Statistic	Prob

Bankruptcy Risk	Z-score	79/47	178/9	0/0012015	1/002515	0/068
Bank's Balance Sheet	BS	41671	10600	0/9632145	2/532145	0/007
Cost-to-Income Ratio	CR	0/219	0/775	0/165581	1/089630	0/029
Bank Size	TAM	8749/4	9179	0/0063214	0/156632	0/081
Return on Assets	ROA	7/200	18/40	0/1393713	5/322201	0/000
Equity to Total Assets	ETS	039/0	0/414	0/5105821	3/000017	0/000
Real GDP Growth Rate	GDP	081/0	0/251	0/3080106	5/922241	0/000
Consumer Price Index	IPCA	12/852	16/043	0/7831474	8/556314	0/202
Banking Sector Index	IBOV	12174	11416	20322141	4/333215	0/000
Economic Cycle	CYCLE	0/210	0/530	0/5392135	4/112001	0/083
Loans to Assets Ratio	L	88343	85217	0/2976083	2/322012	0/000
Financial Expenses to Profit Ratio	COV	0/261	0/748	0/208255	4/121431	0/051
Liquidity	LIQ	0/003	0/012	0/0050674 8	6/333214	0/043

Based on**Table 2**, the descriptive statistics of the research variables indicate significant variation in the data. For instance, the Z-score, as an indicator of bankruptcy risk, ranges between the first quartile of 79.47 and the third quartile of 178.9, reflecting a wide range of risk levels among the studied banks. The low standard deviation of the Z-score indicates data clustering around the mean. Other variables, such as bank balance sheet size, return on assets, and loan-to-asset ratio, also demonstrate data dispersion. These variations in financial ratios and economic indicators are crucial for constructing an intelligent bankruptcy prediction model, as they reflect differences among banks that may lead to varying bankruptcy risks. Furthermore, the results of the Jarque-Bera normality test reveal that several variables do not

follow a normal distribution. For example, variables such as return on assets, capital adequacy, GDP, banking sector index, loan-to-asset ratio, financial expenses to profit ratio, and bank liquidity have probability values less than 0.05, indicating deviations from normality.

Table 3. Bankruptcy Prediction of Listed Banks Using Artificial Intelligence and Machine Learning
Source: Author's computation

Model/Metric	MAE	RMSE	MSE	MAPE	SMAPE	Accuracy	R^2	AUC-ROC	Log-Loss
AI									
Cerebellar NN	0.0515	0.0673	0.0045	5.757	0.6244	81%	0.822	0.9743	0.0177
Bayesian NN	0.0384	0.0488	0.0023	3.736	0.3863	89%	0.709	0.9894	0.0495
Graph NN	0.1358	0.2252	0.0510	9.982	1.0215	65.5%	0.817	0.9621	0.0292
Gaussian NN	0.0386	0.0488	0.0023	3.741	0.3863	89.5%	0.821	0.9683	0.0497
MLP	0.0383	0.0486	0.0024	3.721	0.3851	89%	0.798	0.9583	0.0145
Neoclassical NN	0.0482	0.0263	0.0069	2.521	1.3195	86%	0.860	0.9623	0.0165
Transformer NN	0.0896	0.0391	0.0027	2.157	1.689	79%	0.830	0.9584	0.0105
ML									
Random Forest	0.2417	0.3466	0.1201	18.409	1.9104	39%	0.784	0.9647	0.0478
SVM	0.0980	0.1514	0.0229	10.145	1.1747	71.5%	0.720	0.9710	0.0133
KNN	0.3454	0.4504	0.2028	28.906	2.8689	29.5%	0.818	0.9520	0.0412
Ant Colony	0.0385	0.0487	0.0023	3.736	0.3858	89.5%	0.821	0.9889	0.0221
Decision Tree	0.5100	0.6506	0.4233	38.316	4.0345	18.5%	0.779	0.9731	0.0307
Gradient Boosting	0.1726	0.2405	0.0578	15.003	1.4110	52%	0.819	0.9567	0.0268
Support Vector Regression	0.1383	0.2375	0.0564	13.624	1.5307	67.5%	0.752	0.9800	0.0473
Demand-Based Forecasting	0.0207	0.0252	0.00063	1.4613	1.0268	78%	0.682	0.9534	0.0143
Generative Adversarial Networks	0.0254	0.0527	0.00278	2.8075	1.7401	66%	0.561	0.9617	0.0264

Principal Component Analysis	0.0201	0.0226	0.000511	2.8064	1.1118	59%	0.581	0.9719	0.0372
Optimization Algorithm	0.0160	0.0217	0.000473	1.7393	1.5860	76%	0.767	0.9851	0.0205
Extremely Randomized Trees	0.0389	0.0223	0.000501	2.4013	2.9269	82%	0.861	0.9862	0.0458

Examination of the results in Table 3. Bankruptcy Prediction of Listed **Banks Using** Artificial Intelligence and Machine Learning

reveals that neural network-based models exhibit superior performance in predicting the bankruptcy of Iranian banks. The Bayesian Neural Network and Gaussian Neural Network, with MAE values around 0.038 and RMSE close to 0.048, demonstrate the lowest prediction errors among the AI models. These models also exhibit high accuracy (89.5%) and, with AUC-ROC values above 0.96, demonstrate good ability to discriminate between bankrupt and non-bankrupt banks. The Multilayer Perceptron also performs remarkably well, with 89% accuracy and an MAE of 0.0383. The Cerebellar Neural Network, with an AUC-ROC of 0.9743 and R^2 of 0.822, shows high discriminatory and explanatory power. These results highlight the outstanding capabilities of neural network-based models in processing complex relationships among banks' financial and operational variables. On the other hand, considerable differences are observed among machine learning models. The Ant Colony algorithm, with 89.5% accuracy and an MAE of 0.0385, performs on par with the best neural networks and achieves the highest AUC-ROC (0.9899) among all models. The Extremely Randomized Trees, with 82% accuracy and an R^2 of 0.861, also demonstrates good predictive ability. In contrast, models such as Decision Tree (with 18.5% accuracy), K-Nearest Neighbors (with 29.5% accuracy), and Random Forest (with 39% accuracy) perform poorly. Comparison of error metrics shows that the Optimization Algorithm, with an MAE of 0.0160, and Principal Component Analysis, with an MAE of 0.0201, have the lowest mean absolute errors, but their prediction accuracy (76% and 59%, respectively) is lower than the top-performing neural networks. Overall, this study suggests that a combination of hybrid AI and machine learning models can be a powerful tool for predicting the bankruptcy of Iranian banks.

Bayesian, Gaussian, and Multilayer Perceptron neural networks, along with the Ant Colony algorithm, deliver the best results, indicating the effectiveness of these models in extracting hidden patterns from bank financial data. High AUC-ROC values (over 0.95 in most models) suggest high reliability in assessing bankruptcy risk.

Table 4. Spatial Econometric Diagnostic Tests
Source: Author's computation

Statistic	**P-value**	**Test**
4.5854	0.5981	Hausman Test
32.269	0.0000	LM Test for Spatial Dependence
36.032	0.00000	Moran's I Test for all Residuals

The statistical test results presented in the **Table 4** indicate that the examined model possesses specific characteristics. The Hausman test, with a statistic of 4.5854 and a significance level of 0.5981 (greater than 0.05), suggests that the null hypothesis is not rejected, therefore the use of a random effects model is more appropriate than a fixed effects model in this study. On the other hand, the LM test for spatial dependence, with a statistic of 32.269 and a P-value close to zero (0.0000), and Moran's I test, with a statistic of 36.032 and a P-value close to zero (0.00000), both strongly indicate the presence of spatial dependence or spatial autocorrelation in the studied data. These results confirm the importance of considering spatial and geographical factors in analyzing bank bankruptcy and reveal the necessity of using spatial econometric models or models that can account for these spatial dependencies in their predictions. Therefore, a spatial autoregressive model was used to examine the spatial relationship between banks and variables for bankruptcy prediction.

Table 5. Relationship between Research Variables and Spatial Dependence among Iranian Banks
Source: Author's computation

Variable	Symbol	Estimate	Standard Error	Z-statistic	P-value
Intercept	C	2.490	0.5820	-0.4279	0.6687
Bank Balance Sheet	BS	3.000	0.2633	1139.7391	0.0000
Cost-to-Income Ratio	CR	-2.0036	0.0143	-140.3011	0.0000
Bank Size	TAM	3.085	0.0778	43.5244	0.0000
Return on Assets	ROA	-4.6524	0.0214	-17.19632	0.0000
Capital Adequacy	ETS	-26.5321	0.0154	-1725.253	0.0000

GDP Growth	GDP	4.2764	0.5138	2.8259	0.0047
Consumer Price Index	IPCA	1.9856	0.2143	163.6466	0.0000
Banking Sector Index	IBOV	3.000	0.6370	2577.5766	0.0000
Economic Cycle	CYCLE	1.7049	0.7805	2.3562	0.0000
Total Loans to Assets	L	3.1747	0.5775	20.1478	0.0000
Financial Expenses to Profit	COV	-2.5498	0.3751	-6.7985	0.0000
Liquidity	LIQ	-4.3810	0.2633	-16.6370	0.0000

Normality Test of Residuals:		
Test	Statistic	P-value
Shapiro-Wilk	0.6897	0.5523
Dorbin Shapiro-Wilk	0.5987	0.3652

Model Fit and Accuracy Tests (Spatial Econometric Model):	
	Value
Rho	0.24076
R-squared	0.912531
Log likelihood	217.7114
AIC	-419.42
AIC for lm	-337.35

Effects/Criteria	Statistic	P-value
LR	84.075	0.0000
Z-Value	9.8323	0.0000
Wald Statistic	96.674	0.0000
LM	143.38	0.0000

According to **Table 5**, The results of the spatial econometric model in predicting the bankruptcy of Iranian banks indicate a significant impact of various internal and external variables. The model, with an R-squared of 0.912531, possesses very high explanatory power, explaining over 91% of the variation in the bankruptcy status of banks. Also, the Rho parameter, with a value of 0.24076, indicates the presence of positive spatial dependence in the data, meaning that the bankruptcy status of a bank is significantly related to neighboring banks. Among the model variables, Bank Balance Sheet (BS), with a positive coefficient of 3.000 and a very high Z-statistic of 1139.7391, has a substantial impact on the probability of bankruptcy. Bank Size (TAM) with a coefficient of 3.085 and Banking Sector Index (IBOV) with a coefficient of 3.000 also have a positive and significant impact on the probability of bankruptcy. These findings suggest that larger banks with stronger balance sheets are not necessarily immune to bankruptcy and may even bear higher risk due to their more complex structure and greater obligations. On the other hand, Cost-to-Income Ratio (CR) with a negative coefficient of -2.0036, Return on Assets (ROA) with a negative coefficient of -4.6524, Capital Adequacy (ETS) with a negative coefficient of -26.5321, and Liquidity (LIQ) with a negative coefficient of -4.3810 all have an inverse relationship with the

probability of bank bankruptcy. This is because banks with higher efficiency (lower cost-to-income), greater profitability, sufficient capital, and adequate liquidity are less vulnerable to bankruptcy. Furthermore, macroeconomic variables also play a significant role in predicting bank bankruptcy. GDP Growth (GDP) with a positive coefficient of 4.2764 and Consumer Price Index (IPCA) with a positive coefficient of 1.9856 both have a significant impact on the probability of bankruptcy. These findings reflect the specific conditions of the Iranian economy, where economic growth has not always been accompanied by bank financial stability, and inflation has a detrimental effect on banks' financial health. The Economic Cycle (CYCLE), with a positive coefficient of 1.7049, also indicates that periods of economic boom and bust can influence the bankruptcy status of banks. The Total Loans to Assets ratio (L), with a positive coefficient of 3.1747, suggests that an increase in lending (possibly due to increased credit risk) may increase the probability of bankruptcy. Diagnostic tests of the model indicate that the residuals follow a normal distribution (Shapiro-Wilk test with a probability of 0.5523). Also, model fit tests, including LR (84.075), Z-Value (9.8323), Wald statistic (96.674), and LM (143.38), are all significant at the 0.0000 level, indicating the appropriateness of the spatial econometric model. Comparing the Akaike Information Criterion (AIC) for the spatial model (-419.42) with the ordinary linear model (-337.35) also confirms that the spatial model has a better fit. Overall, these results emphasize the importance of considering spatial dependencies in the analysis and prediction of bankruptcy of Iranian banks and identify key variables affecting banks' financial health. Finally, after determining the results related to artificial intelligence, machine learning, and the spatial autoregressive model, the final prediction of the model is based on a hybrid model, which is a combination of artificial intelligence and machine learning with spatial autoregression. The results are as follows in **Table 6**.

Table 6. Bankruptcy Prediction of Listed Banks Using a Hybrid Model
Source: Author's computation

Model/Metric	MAE	RMSE	MSE	MAPE	SMAPE	Accuracy	R^2	AUC-ROC	Log-Loss

AI									
Cerebellar NN	0.001522	0.00189	0.00036	0.0080	0.0065	92.30%	0.9983	0.9743	0.0177
Bayesian NN	0.001918	0.00243	0.00059	0.0084	0.0079	93.62%	0.9991	0.9894	0.0495
Graph NN	0.001528	0.00192	0.00037	0.0077	0.0066	91.29%	0.9810	0.9621	0.0292
Gaussian NN	0.001322	0.00201	0.00017	0.0067	0.0067	89.49%	0.9921	0.9810	0.0497
MLP	0.001529	0.00190	0.00032	0.0081	0.0075	94.10%	0.9919	0.9614	0.0279
Neoclassical NN	0.0377	0.0394	0.00155	0.0278	0.0280	81.08%	0.9529	0.9683	0.0145
Transformer NN	0.0251	0.0594	0.00353	0.00511	0.0044	79.10%	0.9815	0.9584	0.0165
ML									
Random Forest	0.001653	0.00209	0.00043	0.0096	0.0069	89.15%	0.9554	0.9647	0.0478
SVM	0.001938	0.00238	0.00056	0.0102	0.0080	90.46%	0.9915	0.9710	0.0133
KNN	0.001530	0.00195	0.00036	0.0079	0.0066	91.70%	0.9248	0.9520	0.0412
Ant Colony	0.001532	0.00191	0.00036	0.0082	0.0066	92.01%	0.9989	0.9889	0.0221
Decision Tree	0.001677	0.00211	0.00044	0.0092	0.0071	89.70%	0.8430	0.9731	0.0307
Gradient Boosting	0.001539	0.00199	0.00036	0.0081	0.0067	92.68%	0.9785	0.9567	0.0268
Support Vector Regression	0.00174	0.00224	0.00050	0.0087	0.0067	91.79%	0.9790	0.9800	0.0473
Demand-Based Forecasting	0.0368	0.0204	0.00042	0.0096	0.0018	82.39%	0.9808	0.9534	0.0143
Generative Adversarial Networks	0.0431	0.0325	0.00105	0.0221	0.0089	80.53%	0.9532	0.9617	0.0264
Principal Component Analysis	0.02983	0.0509	0.00259	0.0051	0.0568	82.30%	0.9614	0.9719	0.0372
Optimization Algorithm	0.0231	0.0396	0.00156	0.0063	0.0014	81.80%	0.9554	0.9851	0.0205
Extremely Randomized Trees	0.0172	0.0546	0.00298	0.0004	0.0631	84.41%	0.9570	0.9862	0.0458

Table 6 presents the results of the hybrid model, which combines artificial intelligence, machine learning, and spatial econometrics techniques to predict the bankruptcy of Iranian banks. This unique combined approach not only inherits the power of processing complex data and extracting hidden patterns from AI and machine learning but also, by utilizing spatial econometrics, incorporates the interrelationships and spatial dependencies between banks into the modeling. The results indicate that this optimal combination leads to a significant improvement in prediction accuracy and error reduction. Among AI models, the Multilayer Perceptron (MLP) demonstrates outstanding performance in this hybrid approach with an extraordinary

accuracy of 94.10% and an R^2 of 0.9919. This model, with a very low MAE (0.001529) and a small RMSE (0.00190), minimized prediction error. The Bayesian Neural Network is ranked second, with an accuracy of 93.62% and an R^2 of 0.9991 (almost perfect). The superiority of these models suggests that probabilistic and layered approaches, combined with spatial analysis, effectively model the complexities of bank financial behavior and their interrelationships with each other and the economic environment. The Cerebellar Neural Network and Graph Neural Network also performed well, with accuracies above 90%, indicating the ability of these architectures to process the complex relationships between financial and spatial variables. In the machine learning section, combining the Gradient Boosting algorithm with spatial analysis resulted in a stunning accuracy of 92.68%. This combined model, with an MAE of 0.001539 and R^2 of 0.9785, effectively predicted trends in bank financial changes, considering their spatial dependencies. The Ant Colony algorithm, in combination with spatial econometrics, also performed exceptionally well, with 92.01% accuracy and the highest R^2 among machine learning models (0.9989). This algorithm also achieved the highest AUC-ROC (0.9889), demonstrating its excellent ability to distinguish healthy banks from those at risk of bankruptcy. By considering spatial dependencies, Support Vector Regression and K-Nearest Neighbors also achieved accuracies above 91%, which is remarkable. Therefore, comparing the error indices in this innovative hybrid model with the results of individual models (previous tables 5 of the study) indicates a significant improvement in all metrics. For instance, MAE values in most models have decreased to less than 0.002, indicating a several-fold reduction in Mean Absolute Error compared to non-hybrid models. Also, MAPE and SMAPE values in the top models have reached less than 1%, indicating very high relative accuracy of these models. This significant improvement can be attributed to the intelligent combination of the deep learning capabilities of AI with the pattern extraction ability of machine learning and the spatial dependency modeling of spatial econometrics.

The presence of the Rho parameter in the spatial econometric model (mentioned in previous tables 5) enables modeling the mutual influence of banks on each other and leads to significant improvements in prediction accuracy. Thus, in the final summary, this study demonstrates that the hybrid approach based on the combination of artificial intelligence, machine learning, and spatial econometrics is a highly efficient and accurate method for predicting the bankruptcy of Iranian banks. This innovative model considers not only internal and external financial variables but also models the interrelationships of banks and their spatial-geographical effects on each other. The superiority of models such as Multilayer Perceptron, Bayesian Neural Network, and Gradient Boosting, with accuracies above 92% and R^2 close to 1, indicates the high potential of this combined approach. These findings can be extremely valuable for monetary policymakers, bank managers, and regulatory bodies like the Central Bank, as they enable very accurate and early identification of at-risk banks. It can also be used as an advanced tool to assess the health of the country's banking system and design appropriate preventive or corrective measures.

6- Conclusions

This research aimed to develop a hybrid model for predicting bankruptcy in Iranian banks from 1390 to 1402 (2011-2023) using a combination of artificial intelligence, machine learning, and spatial econometric models. The AI/machine learning component employed models like Bayesian neural networks, Gaussian neural networks, cerebellar model articulation controller (CMAC) networks, multilayer perceptrons (MLPs), reinforcement gradient boosting, and ant colony optimization. Each model was evaluated using metrics such as accuracy, root mean squared error (RMSE), mean absolute error (MAE), coefficient of determination (R^2), and area under the ROC curve (AUC-ROC). The econometric analysis utilized a spatial autoregressive model, revealing that bankruptcy risk is exacerbated among neighboring banks due to risk contagion and spatial dependencies.

The results highlighted the superior performance of MLPs and Bayesian neural networks combined with the spatial autoregressive model. The MLP achieved 94.10% accuracy and an R^2 of approximately 0.992, while the Bayesian neural network reached

93.62% accuracy and an R^2 close to 0.9991. The research also emphasized the influence of factors such as cost-to-income ratio, capital adequacy, liquidity, the ratio of total loans to assets, and bank size in predicting bankruptcy. From a macroeconomic perspective, GDP growth, inflation rate, and economic cycles significantly impacted the banks' default risk.

The spatial autoregressive model demonstrated a significant positive correlation between spatial dependence and bank status. Proximity to high-risk banks increased the likelihood of bankruptcy in neighboring banks, underscoring the importance of branch distribution and geographical risk management. Furthermore, combining neural networks with AI in identifying spatial autocorrelation showed that deep learning models can effectively interpret complex financial relationships. Incorporating spatial structures significantly reduced prediction errors, consistent with the findings of Sun et al. (2025) and Abiola and Olusi's (2015), who emphasized the power of neural networks in predicting financial events. Similarly, studies by Tankabani et al (2020), Ahmadian & Gorji (2017), and Li et al. (2014) highlighted the importance of combining macro and micro indicators for assessing bankruptcy risk, aligning with the present study's results.

Practically, the findings suggest that banks and regulatory bodies should prioritize liquidity management, operational cost control, continuous monitoring of non-household and commercial lending, and macroeconomic developments. Echoing the studies of Antoniades (2024) a high concentration of high-risk commitments in real estate can lead to liquidity shortages and accelerate bank failures. Therefore, monetary and fiscal policies aimed at reducing inflation volatility and supporting sustainable economic growth are crucial for maintaining a healthy banking system. The combined use of AI, machine learning, and spatial econometrics offers a powerful tool for early identification of banks nearing bankruptcy. Policymakers are advised to prioritize corrective measures such as improving balance sheet structure, strengthening capital base, and diversifying loan portfolios to mitigate the costs of bank failures. This approach can

prevent the spread of bankruptcies regionally and enhance financial stability at the macro level, promoting greater stability within the national banking system. Finally, integrating machine learning and neural networks into early warning systems for policymakers and bank managers provides a valuable opportunity for simultaneous analysis of micro and macro variables, leading to more informed decisions.

Overall, the study demonstrates that combining AI, machine learning, and spatial models provides an efficient and comprehensive approach to predicting bankruptcy in Iranian banks. MLPs, Bayesian neural networks, and ant colony optimization, particularly within a hybrid framework, delivered high accuracy and minimal error in assessing bank risk. This confirms the power of deep learning in identifying complex patterns and highlights the importance of considering spatial interactions between banks in modeling. From a policy perspective, the prominence of internal financial variables (e.g., cost-to-income, liquidity, and capital) and external factors (economic growth, inflation, and economic cycle) underscores the critical role of meticulous credit risk management and adherence to capital and liquidity standards in mitigating risks within the banking system. Furthermore, attention to geographical selection can assist monetary authorities and regulatory bodies in prioritizing preventive interventions. Therefore, it is recommended that spatial considerations and the degree of risk concentration be incorporated into the development of supervisory policies and banking strategies. By employing AI tools and diversifying loan portfolios while intelligently monitoring bank balance sheets, the stability and robustness of the banking system can be ensured. Based on these findings, the following policy recommendations are proposed for policymakers and bank managers:

- Banks: Continuously improve financial indicators, including efficiency, profitability, capital adequacy, and liquidity, to reduce bankruptcy risk.
- Policymakers: Design and implement monetary and fiscal policies that promote economic stability and prevent severe fluctuations in macroeconomic variables.
- Regulatory bodies: Consider spatial dependencies and spillover effects between banks in systemic risk assessments.

- Utilize advanced AI and machine learning models: Incorporate these models, combined with spatial analysis, as effective tools for continuous monitoring of the banking system's health and early identification of at-risk banks.

Acknowledgments: Acknowledgments may be made to individuals or institutions that have made an important contribution.
Conflict of Interest: The authors declare no conflict of interest.
Funding: The authors received no financial support for the research, authorship, and publication of this article.

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