KMANPUB | AI and Tech in Behavioral and Social Sciences Vol. 3 No. 1 (2025): 65-73

Article history:
Received 01 August 2024
Revised 15 September 2024
Accepted 25 September 2024
Published online 01 January 2025

Identification and Control of Credit Risk in Banks Utilizing New Supervisory Technologies with Neural Network Algorithm and Random Forest Algorithm

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Article Info

Article type:
Original Research

How to cite this article:
Mashrooti, M., Mohammadi, A., & Mohammadi, M. (2025). Identification and Control of Credit Risk in Banks Utilizing New Supervisory Technologies with Neural Network Algorithm and Random Forest Algorithm. *AI and Tech in Behavioral and Social Sciences, 3*(1), 65-73.
https://doi.org/10.61838/kman.aitech.3.1.7

ABSTRACT

The purpose of this study is to identify and control credit risk in banks utilizing new supervisory technologies with the neural network algorithm and the random forest algorithm. This research, in terms of its nature and objective, is categorized as theoretical and applied research. Given the quantitative nature of the study and the use of data mining for customer credit scoring, this investigation is data-driven. The primary foundation of this research is the discovery of knowledge from banking databases. In this study, real customers who received credit facilities from Tejarat Bank and Saman Bank in Tehran over a one-year period, whether they returned the loans to the bank or not, were defined as the statistical population. Consequently, for sampling, all individual credit customers of the selected branches of these banks during the specified time frame were examined. Out of 500 credit customers, a simple random sampling method was employed to select those who had received loans during this period, resulting in the selection of 230 samples for this study. After collecting the previous bank customer data from the relevant database and cleaning the data, the influential variables in customer ranking were identified by reviewing previous scientific research. In the next phase, using the neural network algorithm and the random forest algorithm, and with the help of relevant software, customers were classified based on their characteristics, and their behavior was predicted. The findings indicated that the random forest algorithm was more efficient in predicting customer credit risk. Statistical test results showed that the support vector machine model had higher accuracy in predicting customer credit risk. The random forest (DT) algorithm used in this research had the highest accuracy among all models, and with feature selection, the model's accuracy increased compared to the base model, achieving the highest accuracy (81.49%) among all techniques.

Keywords: *Credit risk, bank, credit facilities, neural network algorithm, random forest algorithm*

1. Introduction

In many countries, regulatory authorities have the power to intervene to prevent bank failures or to address issues such as fraud or ethical problems. However, research on deposit insurance shows that deposit insurance schemes are typically associated with moral hazard issues. The more comprehensive the deposit insurance scheme, the less market discipline is imposed on banks, and banks have fewer incentives to monitor their borrowers and adhere to their obligations to depositors (Kladakis et al., 2020). To mitigate the moral hazard problems of deposit insurance, authorities often implement measures such as insuring only a portion of deposits, charging banks insurance premiums based on risk assessments, or requiring banks to contribute to reserves held in case of the failure of one of the member banks (Altavilla et al., 2020; Cathcart et al., 2024).

According to Beck, Demirguc-Kunt, and Levine (2006), bank supervisors possess the knowledge and motivation to reduce information asymmetry. Since incomplete information can play a significant role in bank performance, robust supervision can be beneficial for liquidity creation (Haque, 2019). One of the inherent issues of liquidity creation is that it makes banks vulnerable to volatile deposits (volatile deposits refer to deposits that lack stability and include demand deposits and savings deposits), as large withdrawals of deposits can force banks to liquidate a large portion of their assets at a loss. From a public interest perspective, strong supervision can help protect funding and stabilize the banking system. Therefore, in countries where regulatory authorities have more power to access bank information and take action to prevent failure or fraud, banks can create more liquidity through higher risk absorption and lower withdrawals of deposits, which stem from customer trust in the banking system (Eyshi Ravandi et al., 2024; Li et al., 2019).

On the other hand, the extent of intervention power or actions that regulatory authorities can take to prevent problems is not always beneficial for banks. Bank supervisors may misuse their power for personal gain rather than the public interest (Ozili, 2022). Thus, the supportive role of supervisory technologies becomes evident.

The integration of regulations with technological rules necessitates regulatory technology (RegTech). RegTech, through cloud computing and analytical tools, transforms massive data into valuable and actionable information for decision-making. Cloud computing is an emerging low-cost technology that offers numerous new capabilities, including the ability to quickly and securely share information with various entities (Ozili, 2022; Seighali & Moradi, 2022). To date, RegTech has focused on digitizing manual reporting and compliance processes, resulting in significant cost savings for the financial services industry and regulators. However, a 2016 scientific study revealed that RegTech's potential is much greater, stating that "regulatory technology has the potential to identify and predict risks in real-time, adapting to conditions and facilitating compliance with legal regulations" (Buckley et al., 2020).

With the emergence of financial technologies, the banking industry requires a comprehensive view of the main trends and developments impacting the business environment. Banks must provide managers with a redefinition of the financial services industry and insights into the future of banking business models, drawing a comprehensive roadmap for success in this changing environment. To maintain their position in the competitive landscape, banks are forced to invest in emerging technologies and redesign their structures with a focus on customer experience (Daneshvarbandari et al., 2021; Gomber et al., 2017; Höck et al., 2020; Mengfei et al., 2022).

Broeders and Prenio (2018) define supervisory technology (SupTech) as the use of innovative technology by regulatory bodies to support supervision (Broeders & Prenio, 2018). Financial supervision is undergoing a paradigm shift, driven by technology, creating opportunities for the development of complex, data-driven approaches to supervision (Mengfei et al., 2022). Evidence from developed and emerging markets demonstrates the transformative capabilities of SupTech. The key elements of success in deploying SupTech include formulating a well-designed strategy, involving both internal and external stakeholders, defining a clear vision and objectives, adopting an approach suited to the country's characteristics, and starting small with the ability to gradually develop tools. The potential long-term cost savings from SupTech make it a valuable investment, though this technology is undoubtedly still in its early stages. Accordingly, the present study aims to identify and control credit risk in banks utilizing new supervisory technologies through the neural network algorithm and the random forest algorithm.

2. Methods and Materials

This research, in terms of nature and objective, is categorized as theoretical and applied research. Given the quantitative nature of the study and the use of data mining for customer credit scoring, this investigation is data-driven. The primary foundation of this research is the discovery of knowledge from banking databases. In this study, real customers who received credit facilities from Tejarat Bank and Saman Bank in Tehran over a one-year period, whether they returned the loans to the bank or not, were defined as the statistical population. Consequently, for sampling, all individual credit customers of the selected branches of these banks during the specified time frame were examined. Out of 500 credit customers, a simple random sampling method was employed to select those who had received loans during this period. Based on this, the sampling formula for an unlimited population without replacement is as follows:

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$$n = \frac{NZ_{\frac{a}{2}}^2 \sigma^2 x}{\varepsilon^2 (N-1) + Z_{\frac{a}{2}}^2 \sigma^2 x}$$

Where:

N = population size

σ^2X = population standard deviation

n = minimum sample size

ε = allowable error percentage

$Z\_(\alpha/2)^2$ = confidence level of 98%

In the end, 230 samples were selected for this study.

To develop the theoretical foundations, the library research method is employed, and the field method is used to collect data on the creditworthiness of borrowers from the cross-sectional data of the period under study at Tejarat Bank. Initially, explanatory variables, including financial and non-financial variables, are examined, and from these, a number of variables influencing credit risk are selected. Data mining methods are used for data analysis.

3. Findings and Results

The results of the descriptive statistics are presented in Table 1.

Table 1

Descriptive Statistics

Variable Name	Symbol	Mean	Median	Min	Max	Standard Deviation
Education	edu	0.002	0.004	0.199	-0.200	0.116
Gender	sex	0.000	0.002	0.200	-0.199	0.104
Age	age	0.255	0.256	0.500	0.001	0.122
Residence	Address	0.253	0.255	0.499	0.000	0.127
Marital Status	marital status	0.250	0.249	0.500	0.002	0.125
Loan Term	loan term	0.36	0.45	0.4	0.6	0.03
Job	Job	0.59	0.72	0.7	0.89	0.12
Facility Amount	Facility amount	0.81	0.39	0.77	0.42	0.08
Collateral Value	Collateral value	0.23	0.52	0.96	0.75	0.10
Exchange Rate	exchange rate	0.32	0.369	0.81	0.52	0.09
Inflation Rate	Inflation	0.34	0.23	0.45	0.41	0.11
Interest Rate	Interest rate	0.61	0.23	0.79	0.48	0.09

In data preparation, the data should be cleaned and prepared for modeling and classification. This step involves imputing missing data and removing duplicates. However, since there are no missing or duplicate data, this step is unnecessary. The evaluation of the feature selection algorithm in the modeling phase was analyzed based on accuracy parameters. The results of the Shannon entropy algorithm are presented in Table 2.

Table 2

Variable Weights in Information Gain Index

Row	Independent Variables (Predictors)	Weight
1	Education	0.12
2	Gender	0.16
3	Age	0.19
4	Residence	0.20
5	Marital Status	0.35
6	Loan Term	0.31
7	Job	0.24
8	Facility Amount	0.25
9	Collateral Value	0.45
10	Exchange Rate	0.39
11	Inflation Rate	0.46
12	Interest Rate	0.48

In this section, using the neural network algorithm, variables related to each of the four clusters with the data of the years within the sample were input into the model, and the efficiency of each model was considered as the

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dependent variable. After modeling with the aforementioned variables, the efficiency values for each model related to the years outside the sample were predicted separately for each of the three efficiency models. Then, the efficiency vector in the four identified clusters and the efficiency status of each observation is classified into one of the eight possible statuses. In reality, this is done using a five-factor approach, and the prediction is tested against the out-of-sample data. The accuracy of the models is compared based on prediction accuracy. The information of this comparison is presented in Table 3.

Table 3

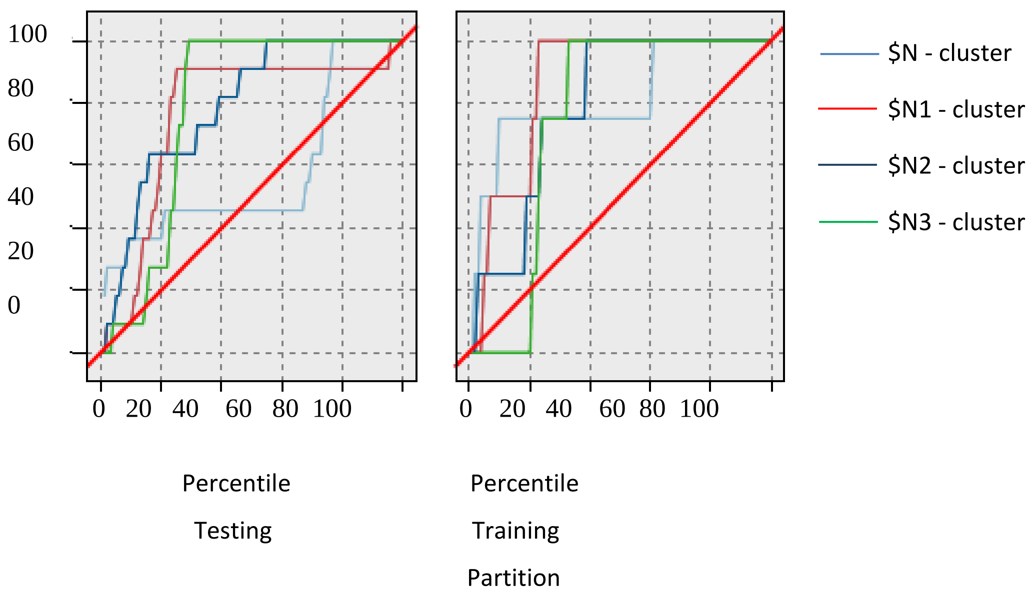
Examination of Neural Network Algorithm Accuracy with Four Research Clusters

Individual Models	Partition	Testing	Training
Comparing $N-category with category	Correct	485	468
	Wrong	150	140
	Total	635	608
Comparing $N1-category with category	Correct	485	464
	Wrong	150	144
	Total	635	608
Comparing $N2-category with category	Correct	500	490
	Wrong	135	118
	Total	635	608
Comparing $N3-category with category	Correct	510	498
	Wrong	125	110
	Total	635	608

As the output of the confusion matrix shows, the classification accuracy in the fourth cluster is higher than in the first, second, and third clusters. Likewise, the classification accuracy in the third cluster is higher than in the second and first clusters, and the accuracy for the second cluster is better than for the first approach.

Figure 1

Adjustment Speed of the Gain Index for the Neural Network Algorithm's Accuracy in Four Research Approaches



As the results in Figure 1 indicate, the Gain index also confirms the results of Table 3. The initial accuracy of the prediction in the fourth cluster is lower than the others, but it increases rapidly, reaching 100%. At this stage, we report the neural network results once without feature selection and once with information gain feature selection on the

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financial statement variables for the years 2022 to 2023 and compare the results.

Figure 2

The Area Under the ROC Curve for the Neural Network Algorithm

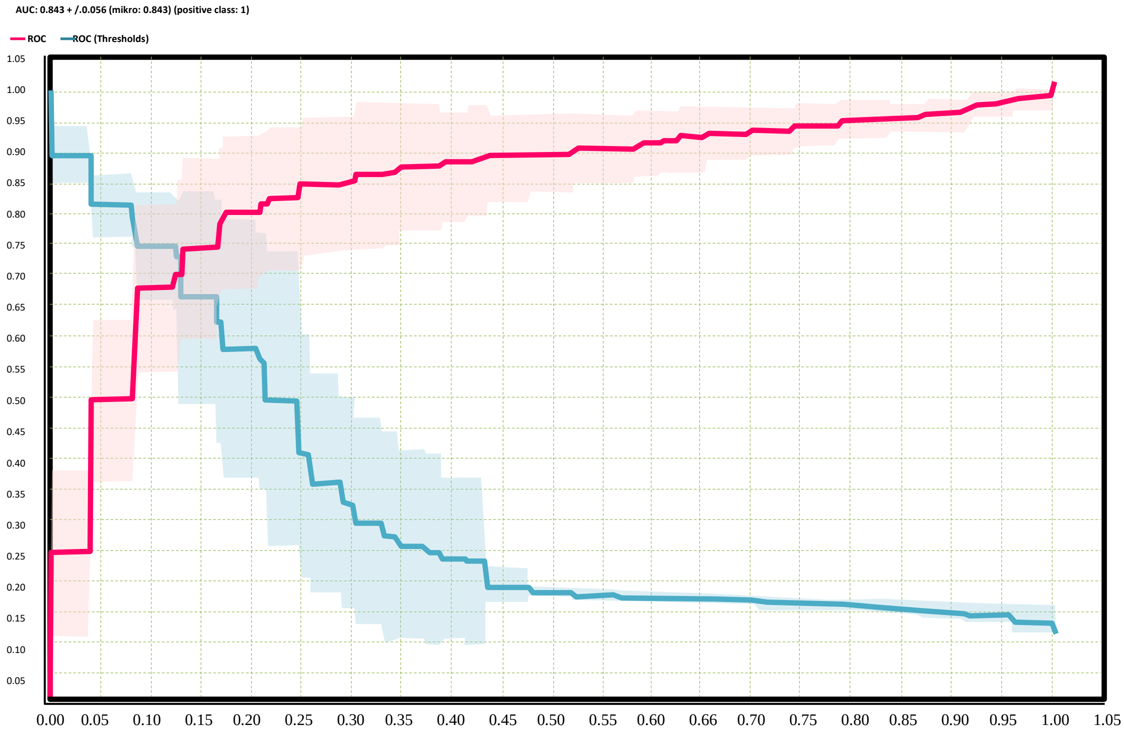


Table 4

Confusion Matrix of the Neural Network with Feature Selection

Sample/Estimate	Positive Class (+)	Negative Class (-)
Negative Class (-)	74	156
Positive Class (+)	182	48

182 samples represent the number of actual positive (risky) cases that were correctly classified as positive by the classifier. 74 samples represent the number of actual negative (non-risky) cases that were incorrectly classified as positive by the classifier. 156 samples represent the number of actual negative cases that were correctly classified as negative by the classifier. 48 samples represent the number of actual positive cases that were incorrectly classified as negative by the classifier.

Table 5

Neural Network Results

AUC	Specificity	Sensitivity	Accuracy (ACC)	Model
0.835	79.95%	80.25%	80.07%	Ann
0.843	79.51%	81.39%	80.47%	Ann + Entropy

The neural network improved accuracy by 0.4 with the selection of influential variables.

In this section, predictions for each of the efficiency models are made separately. Using the random forest algorithm, the variables related to each of the four clusters with the data of the years within the sample were input into the model, and the efficiency of each model was considered as the dependent variable.

Table 6

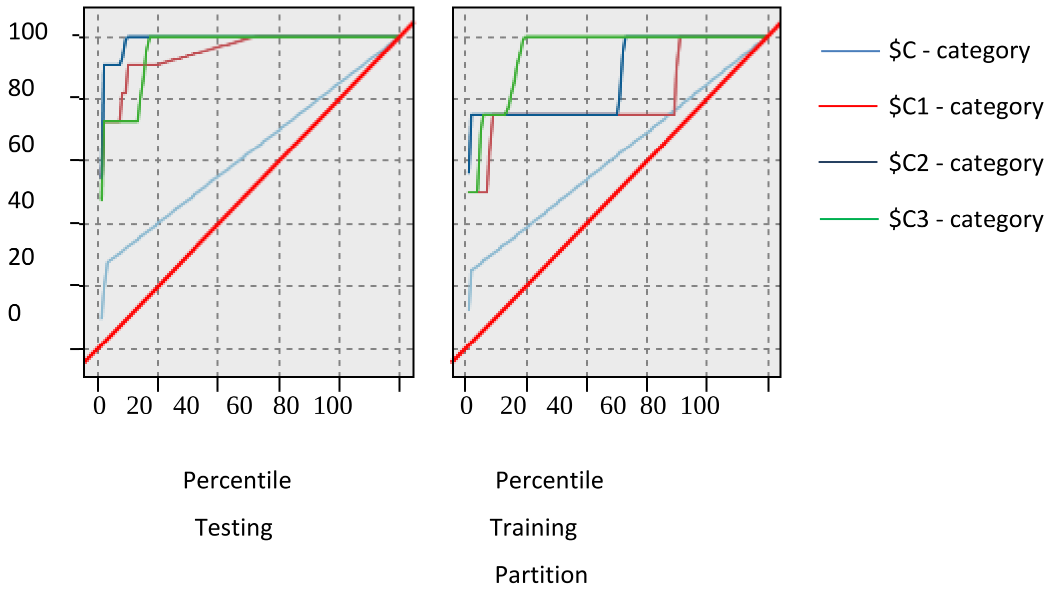
Examination of Random Forest Algorithm Accuracy with Four Research Clusters

Individual Models	Partition	Testing	Testing %	Training	Training %
$C	Correct	501	78 %	450	74 %
	Wrong	34	22 %	158	26 %
	Total	635		608	
$C1	Correct	512	80 %	460	75 %
	Wrong	123	20 %	148	25 %
	Total	635		608	
$C2	Correct	550	86 %	485	79 %
	Wrong	85	14 %	123	21 %
	Total	635		608	
$C3	Correct	600	94 %	500	82 %
	Wrong	35	6 %	108	8 %
	Total	635		608	

As the output of the confusion matrix shows, the classification accuracy in the fourth cluster is higher than in the first, second, and third clusters. Likewise, the classification accuracy in the third cluster is higher than in the second and first clusters, and the accuracy for the second cluster is better than the first.

Figure 3

Adjustment Speed of the Gain Index for the Random Forest Algorithm's Accuracy with Four Research Clusters



The results show that in all three time intervals, the model using data related to the fourth cluster reaches accurate predictions faster than the other clusters. At this stage, we report the random forest algorithm results once without feature selection and once with information gain feature selection on the financial statement variables for the years 2022 to 2023 and compare the results.

Figure 4

The Area Under the ROC Curve for the Random Forest Algorithm

E-ISSN: 3041-9433

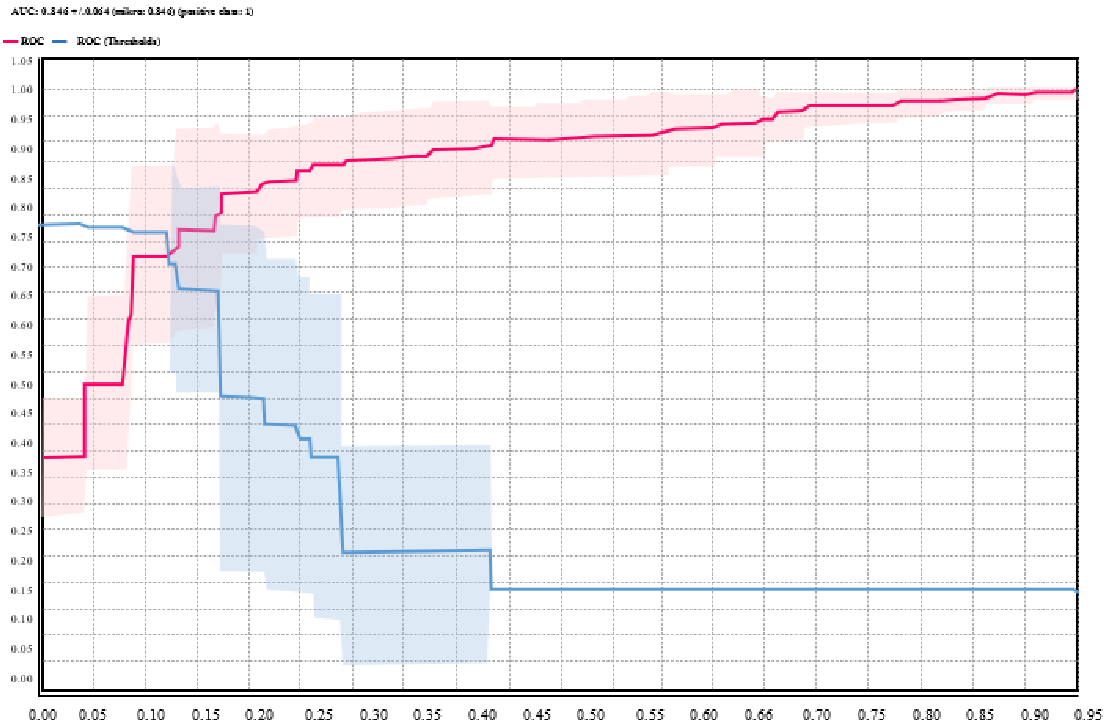


Table 7

Confusion Matrix of the Random Forest Algorithm with Feature Selection

Sample/Estimate	Positive Class (+)	Negative Class (-)
Negative Class (-)	69	161
Positive Class (+)	175	55

175 samples represent the number of actual positive (risky) cases that were correctly classified as positive by the classifier. 69 samples represent the number of actual negative (non-risky) cases that were incorrectly classified as positive by the classifier. 161 samples represent the number of actual negative cases that were correctly classified as negative by the classifier. 55 samples represent the number of actual positive cases that were incorrectly classified as negative by the classifier.

Table 8

Random Forest Results

AUC	Specificity	Sensitivity	Accuracy (ACC)	Model
0.825	80.36%	81.79%	81.18%	DT
0.826	80.12%	82.96%	81.49%	DT + Entropy

The random forest produced better results than the base model. In this method, accuracy increased by 0.31% with the selection of information gain features.

Table 9

Summary of Results and Indicators of Each Technique in Identifying Credit Risk Using Data from 230 Customers

AUC	Specificity	Sensitivity	ACC	Model

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0.835	79.95%	80.25%	80.07%	Ann
0.843	79.51%	81.39%	80.47%	Ann + Entropy
0.825	80.36%	81.79%	81.18%	DT
0.826	80.12%	82.96%	81.49%	DT + Entropy

As indicated by the modeling phase and the ACC column in the above tables, the accuracy of the selected models in this research is excellent. Additionally, as shown in Table 9, feature selection (Entropy) improved the discovery accuracy (ACC) across all techniques.

4. Discussion and Conclusion

The aim of this study was to identify and control credit risk in banks utilizing new supervisory technologies with the neural network algorithm and the random forest algorithm. Banks, in order to meet requirements and provide services, including granting financial and credit facilities to their clients, need to accurately identify them. On the other hand, they may face risks in their operations. One of these risks is credit risk, which must be addressed. Credit scoring can help reduce credit risk by distinguishing between good and bad customers. Various studies have been conducted on credit scoring methods in banks. Initially, credit scoring models were judgmental. Then, parametric methods, and more recently, non-parametric models, have assisted banks in credit scoring. The idea of distinguishing between groups was first introduced by Fisher in 1963, and then David Durand in 1941 classified customers into two groups—good and bad—for loan provision. In 1960, credit cards were introduced in banks, and in 1980, credit scoring was first used in banks. In 1990, credit scoring was used in direct marketing. Decision trees, as one of the data mining techniques, can be employed in credit scoring for bank customers. This technique has a high level of comprehensibility and a fast pattern-learning speed in classification problems such as credit scoring.

The findings of this study indicated that the random forest algorithm was more efficient in predicting customer credit risk. The statistical test results showed that the support vector machine model had higher accuracy in predicting customer credit risk. In the decision tree (DT) model, input data optimization was conducted through the genetic algorithm, leading to better model performance.

The random forest (DT) used in this study had the highest accuracy among all models, and with feature selection, the model's accuracy increased compared to the base model, achieving the highest accuracy (81.49%) among all techniques. Accordingly, the findings of this study are in line with the prior findings (Ghasemi & Talib Moayed, 2020; Koh et al., 2022; Machado & Karray, 2022; Payandeh et al., 2021; Wu, 2022).

This research was conducted on the data from banking databases and related documents, and any errors in data extraction and analysis may limit the findings. Additionally, this study was limited to a specific time period, and time constraints represent the second limitation of the study.

At the micro level, it is recommended that banks consider macroeconomic variable trends when conducting technical and economic assessments of projects for loan provision. This would enable them to grant loans based on relevant forecasts in such a way that the principal and expected profits from the facilities can be recovered. Banks are also advised to adopt credit scoring methods instead of judgmental methods to reduce credit risk. Furthermore, it is suggested that a centralized and integrated customer information system be established, allowing the use of historical customer data to design credit scoring models for predicting the probability of loan repayment defaults.

Authors' Contributions

Authors equally contributed to this study.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

In conducting this research, ethical considerations were strictly observed to ensure the confidentiality and privacy of customer data. All personal and financial information of bank customers was anonymized and securely stored, with access restricted to authorized personnel only. The study adhered to data protection laws and regulations, ensuring that the data used for analysis was obtained with appropriate consent and used solely for research purposes. Additionally, efforts were made to avoid any form of bias in data analysis, ensuring that the findings were objective and scientifically valid.

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