

Modeling the Impact of Banking Competition on Stability (Case Study: Banks of the Islamic Republic of Iran)

Hatam Sanjari Pyraivatloo¹, Arash Hadizadeh^{2*}, Roozbeh Balounejad Nouri³, Beitollah Akbari⁴

¹ *PhD Student, Department of Economics, Qazvin Branch, Islamic Azad University, Qazvin, Iran*

² *Assistant Professor, Department of Economics, Qazvin Branch, Islamic Azad University, Qazvin, Iran*

³ *Assistant Professor, Department of Economics, Qazvin Branch, Islamic Azad University, Qazvin, Iran*

⁴ *Associate Professor, Department of Economics, Qazvin Branch, Islamic Azad University, Qazvin, Iran*

Abstract

The stability of the banking system, as the core of the monetary-financial sector and due to the heavy reliance of other sectors on banking for mobilizing capital resources, requires special attention. Identifying the factors that influence bank stability has become increasingly important. Recent studies have increasingly focused on identifying the elements that affect banking stability, with competition being one of the key factors. The main objective of this dissertation is to model and examine the impact of banking competition on the stability of banks in the Islamic Republic of Iran. This research is descriptive-correlational in terms of its methodology, and applied in terms of its purpose. Since the study investigates the current status of variables by collecting data from historical information, it falls under the category of descriptive-post-event studies. The statistical population consists of banks listed on the Tehran Stock Exchange during the years 2016 to 2021 (1395 to 1400 in the Iranian calendar). Finally, considering AdaBoost tree models—which utilize decision trees during the training phase and are highly accurate—we aim to explain the generated rules and hidden data patterns in terms of marketing concepts and target customers. Most of the reported rules are those with higher probabilities of occurrence and lower errors, thus making them more useful.

Keywords: Banking competition, Banking stability, Iranian banks.

* Corresponding Author

ISSN: 1735-8272, Copyright © 2025 JISE. All rights reserved

1- Introduction

The banking industry is one of the most important sectors of the economy, and banks are considered key institutions within the financial markets of every country. By acting as intermediaries between lenders and borrowers and providing financial resources for other industries, banks facilitate the process of production (Varabadlahaan Kuich et al., 2021). A review of the role of banks in global financial markets shows that over the past 25 years, nearly 69 banking crises have occurred in developing, developed, and emerging economies (particularly in East and Southeast Asia), imposing significant costs on these economies. These experiences are especially important for Iran's economy, where more than 90% of financial intermediation is handled by the banking network. Evidence suggests that Iran's financial system is heavily bank-based. Therefore, having a healthy and efficient banking system is a major prerequisite for economic growth (Goli & Eskandari, 2019).

One of the key concepts in banking is banking stability. This concept is a crucial indicator for financial and credit institutions, such as banks, and has always received significant attention. Stability refers to a condition where systemic financial crises do not threaten macroeconomic stability (Mirbagheri Heir et al., 2016). Assessing the factors influencing instability is among the most important concerns of the banking system for any country's economic growth. Banking stability reflects the durability in the structure of resources and their financing. It acts as the banks' capital buffer, helping absorb financial losses and facilitating the lending process by mitigating shock transmission (Shenasi, 2004; Koohi Leilan et al., 2021).

Bank instability, such as non-performing loans, significantly disrupts the credit-providing capability of commercial banks and hampers the circulation of money in the market. A higher level of non-performing loans damages the money transmission mechanism and severely disrupts the financial intermediation role of institutions, adversely affecting domestic and international trade and investment (Rahman et al., 2021). Consequently, banking system instability and bank failures lead to a sharp reduction in the supply of financial resources, pressure on firms and households to adjust their financial positions, a decline in public trust in banks, reduced savings, and ultimately a fall in output, income, and wealth (Shaigani & Abdollahi Arani, 2011).

Given its central role in the monetary-financial domain, banking system stability requires special attention. A crisis in the banking system, due to its deep linkages with other sectors for capital mobilization, can rapidly spread to the real economy. Therefore, identifying the factors that influence bank stability becomes imperative. Recent economic studies increasingly focus on identifying these influencing factors—one of which is competition (Poustinchi et al., 2016).

Competitiveness is a process through which entities seek to outperform others. At the international level, countries compete due to the scarcity of financial, technical, and human resources needed for wealth creation and public welfare (Golmoradi Adinevand et al., 2020). Competition has gradually become a pervasive aspect of life, leaving no one unaffected. It acts as an invisible hand that significantly shapes market supply and demand, influencing strategic decisions and daily management in every industry. Specifically in the banking sector, competition affects each bank's strategic choices, market position, risk appetite, product development, and daily operations, ultimately determining the bank's sustainability, stability, and outlook (Yuan et al., 2022).

In the banking industry, competition significantly impacts service quality, risk-taking behavior, and the overall risk level of the banking system (Kasman & Kasman, 2015). Therefore, the effect of banking competition on stability has been a longstanding concern and subject of debate among researchers and policymakers. It is generally believed that banking competition affects stability through three main channels: charter value, borrowing costs, and operational behavior. However, the impact of these mechanisms may differ across time periods and environments, leading to different degrees and directions of influence. The primary theoretical perspectives include the “competition-fragility,” “competition-stability,” and nonlinear relationships between competition and stability (Yuan et al., 2022).

The competition-fragility view posits that as competition intensifies, banks lose market power and the ability to earn monopoly rents through interest margins. This reduces their charter value and makes them more vulnerable during crises. Furthermore, in search of higher returns, banks may increase investments in risky portfolios, which undermines the stability of the banking system. The competition-stability view, on the other hand, highlights the moral hazard problem, where "too-big-to-fail" banks, expecting government bailouts during financial distress, engage in riskier behavior due to the safety net they enjoy (Lopez-Penabad et al., 2021; Ijaz et al., 2020; Leroya & Lecoutre, 2017; Keeley, 1990).

In the first part of this study, we employ panel data analysis to examine the relationship between banking stability and its influencing factors. In the second part, we utilize machine learning algorithms to classify bank customers based on their demographic characteristics.

Accordingly, this research aims to provide an optimal model for delivering innovative banking services based on Islamic frameworks, offering a solution to the existing research gap in this area. To achieve this, we first review the literature to identify key influencing factors, and then use interpretive structural modeling (ISM) to present the model. In fact, this research adopts soft operations research methods to design and present an optimal model aligned with Islamic patterns. The study begins by identifying the criteria through a comprehensive literature review and expert consultations, followed by criteria screening, prioritization, and structural modeling to present a suitable model.

2- Literature Review

Banking Competition

Understanding the impact of competition in banking provides policymakers with a better understanding of the effectiveness of monetary policies at various levels of competition (Nazarian et al., 2013). Increased competition and efficiency in the banking market can lead to improved quality and diversity of banking services, as well as lower transaction costs. Without awareness of the structure of the country's banking network, structural changes and spending efforts aimed at advancing the banking system towards greater efficiency and competition may be ineffective and yield unsatisfactory results (Hamidian, 2014).

A wide range of business and household activities are connected to banks through deposit accounts, loans, and other financial services, and are therefore directly influenced by banks’

pricing and other functions. Hence, any flaws, inefficiencies, or non-competitive behavior among banks can impose greater costs on the economy compared to other industries. In particular, interbank competition can lead to increased economic growth and improved social welfare by reducing the cost of banking services (Tari & Shamsian, 2016; Fallah & Nozari, 2021; Irani & Nozari, 2024).

Iran's banking industry has undergone major structural changes in recent decades. In the late 1990s, a law was passed allowing private banks to operate after obtaining the necessary licenses. Initially, several financial institutions and later private banks began their operations. Another significant event in this period was the implementation of the general policies of Article 44 of the Constitution and the Fourth Development Plan Law, which called for the privatization of some state-owned banks. Altogether, these changes gradually transformed the structure of the industry. Bank competition in Iran increased, and with the move toward more competition, the number of banks also rose. The growing number of banks makes external supervision more difficult. As effective oversight declines, banks' risk-taking tends to increase. Larger banks typically have more experienced customers and can mitigate issues of asymmetric information and adverse selection, resulting in less risky loans (Poustinchi, 2013; Golmoradi Adinevand et al., 2020).

In terms of competition in the banking industry and its impact on non-performing loans (NPLs), various views have been proposed. Some believe competition increases NPLs, while others see it as reducing them. Those who believe that competition increases NPLs argue that rising competition and reduced market power decrease the franchise value of banks. This value is the present value of the profits banks can earn as long as they continue operating. A decline in franchise value reduces the opportunity cost of bankruptcy, encouraging banks to take more risks. With increasing competition, the number of banks grows, making supervision more difficult and possibly increasing banks' risk-taking (Golmoradi et al., 2020).

The competitive nature of the banking industry can also influence monetary policy (Nazarian et al., 2013):

If increased competition stems from a rise in the market share of large banks, the transmission of monetary policy through the lending channel may weaken. This is based on the theory that large competitive banks have better access to additional funds. Therefore, an increase in their market share would result in a smaller reduction in money supply and a lesser impact on lending and macroeconomic activities.

If increased competition is accompanied by a reduction in asymmetric information and frictions between banks and borrowers, then borrowers cannot easily shift to other lenders with lower switching costs. Unmet credit demand from small banks cannot be satisfied by large banks that tend to protect their lending portfolios. In such cases, increased competition may weaken the lending channel of monetary policy.

Competition in banking can affect the sensitivity of lending rates to monetary policy shocks. If changes in deposit rates caused by a shock to reserves are directly transmitted to lending rates, then increased banking competition (which makes banks' prices more responsive to marginal costs) can enhance the effectiveness of monetary policy.

Types of Banking Competition

In monetary and banking contexts, several types of competition are discussed (Sobhani & Razm Ahang, 2018):

- Freedom of bank entry and exit
- Competition through offering higher deposit rates
- Competition through offering lower interest rates on loans
- Freedom for foreign banks to operate within the national financial system
- Capital account liberalization And more...

Competition among banks to attract more deposits through higher deposit interest rates can have significant negative consequences for the real economy. The first consequence is the postponement of many real sector investments due to the marginal efficiency of capital being lower than the deposit interest rate. As long as the interest rate exceeds the marginal efficiency of capital, investors prefer to delay their investments. A reduction in interest rates increases the present discounted value of investment projects, encouraging investment, while an increase has the opposite effect (Keynes, 2018).

Another negative consequence of high deposit interest rates is the reduced lending capacity of banks. This is because part of the new money creation each period is used to pay interest on deposits. The more new money is allocated to interest payments, the less ability the banking system has to issue loans. In a country where bank lending is a major source of financing for production, this leads to a decline in production and investment (Doroudian et al., 2017).

Moreover, intense competition among banks to attract deposits leads to higher interest rates. Consequently, in order to meet these high interest payments, banks may be forced to invest in risky projects or extend credit to high-risk, non-creditworthy borrowers. Conversely, if banks can attract cheap deposits, they will be more conservative and prudent in selecting their investment portfolios, and the opposite is also true (Sobhani & Razm Ahang, 2018).

Improving the Competitive Position of Banks

No bank can offer the best services across all areas, nor can a single bank serve the entire potential market or all potential customers. Banks must identify ways to adopt a distinctive strategy to deliver services to customers in a manner that sets them apart from competitors. There are several approaches for creating and developing a distinctive competitive position. One key method is to differentiate services from competitors, which shapes a favorable image of the bank and its services in the minds of customers. Strong competitive positions can be maintained by creating barriers that prevent competitor actions. One way to establish such barriers is by building a positive reputation through the following (Moeini, 2020; Kalogeras et al., 2022):

- Creating customer satisfaction by offering appropriate services to all clients
- Using proprietary technology in delivering technology-based services
- Training staff to interact appropriately and respectfully with customers to build trust and confidence

- Utilizing advanced technologies and superior services as tools to develop deep, lasting relationships with clients and recognizing the importance of consistent customer engagement with the bank

Banking Stability

The stability of the banking system, as the core of the monetary-financial sector, requires special attention. A crisis in the banking system, due to its strong interdependence with other sectors for mobilizing capital resources, can quickly spread to the real sectors of the economy (Masoudian et al., 2011). Financial instability and crises are typically accompanied by sudden changes in most or all banking indicators—such as profitability, rate of return, interest rates, and asset prices (including securities, real estate, and land)—and ultimately lead to the bankruptcy and collapse of financial institutions.

Financial system stability occurs when three key conditions are met: the ability to efficiently allocate economic resources; the capacity to generate other economic processes such as economic growth, public welfare, and asset accumulation; and proper management of risk assessment, pricing, allocation, and financial risk management (Anilo & Sosa, 2012; Kalogeras, 2021).

Among the definitions based on the concept of financial instability are the following: Mishkin defines financial instability as the occurrence of shocks to the financial system that disrupt the flow of information, thereby hindering its main function—investing in high-yield opportunities. Davis considers financial instability to be the intensification of financial crisis risks, in which a financial crisis leads to a system breakdown, resulting in instability in providing payment services and allocating credit to investment opportunities (Hirtel et al., 2016).

According to Alaoud and Al-Sadiq (2008), there are two main approaches to defining financial stability: one that seeks to define financial instability, and another that focuses on defining stability. In their view, a financial system is considered stable when it can facilitate economic functioning and address both endogenous and unforeseen financial imbalances. In contrast, Mishkin argues that financial instability arises when shocks to the financial system interfere with the flow of information, preventing the system from properly performing its fundamental role of fund intermediation (Zolfaghari & Asadi, 2019).

In simple terms, financial stability refers to a condition in which the system does not face crisis conditions (Mirbagheri Heyr et al., 2016). Stability in a financial system exists when the allocation of economic resources (such as saving and investment, lending and borrowing, and economic growth) is carried out efficiently and smoothly (Jahangard & Abdolshah, 2017).

The institutions within a country's financial system are stable when there is a high degree of trust in them—such that they can fulfill their commitments and core responsibilities without difficulty and without external assistance. Financial markets are stable when participants engage in exchanges based on mutual trust and real market prices. Conversely, financial instability arises when the system, in response to a shock, fails to fulfill its primary function of transferring funds from depositors to investors (Rostamzadeh & Yadegar, 2020).

The financial health and stability of a bank is not only a guarantee for depositors, but is equally important for shareholders, employees, and the overall economy (Beck et al., 2006). The stability of the banking system is important for four main reasons. First, a stable banking system creates a conducive environment for attracting deposits. Second, it aids in the transmission of monetary policy. Third, a stable banking system serves as an efficient financial intermediary, allowing for more effective allocation of resources to investments, thereby fostering economic growth and investment. Fourth, a stable banking system enhances the operational efficiency of the banking sector and improves the distribution of resources in the economy (Taghavi et al., 2013).

Theories on Banking Stability

The theories regarding the relationship between competition in the banking industry and bank stability are generally divided into two main categories:

Traditional View: Competition–Fragility or Concentration–Stability

There are contrasting perspectives on the impact of banking competition on system stability. For example, according to the competition–fragility view, increasing competition in banking leads to greater system fragility. In contrast, the competition–stability view emphasizes that greater competition within the banking system leads to increased financial stability (Kasman & Kasman, 2015). All existing theories on the relationship between banking industry competition and bank stability can generally be categorized under these two frameworks (Postinchi et al., 2016).

This traditional view, which was dominant until recently, suggests a trade-off between competition and banking stability. It argues that competition has detrimental effects on bank stability, potentially pushing them to the brink of bankruptcy. On the other hand, concentration and monopoly reduce the likelihood of bankruptcy and, in this way, increase the stability of banks (Postinchi et al., 2016). This view has not only been prevalent in academic literature but has also influenced policymakers. Hence, competition is often seen as a destabilizing force in the banking sector and is something to be curbed to maintain financial stability (Carletti & Hartmann, 2002).

Modern View: Competition–Stability or Concentration–Fragility

The traditional competition–fragility view has recently been challenged by a new branch of literature. In the modern view, it is argued that increased competition can enhance the stability of banks. In other words, financial instability tends to rise when competition decreases. While more recent and less extensively studied, this view presents several channels through which competition can promote bank stability.

The dominant hypothesis in this view is the risk-shifting paradigm, which evaluates how competition in the loan and deposit markets affects moral hazard and adverse selection incentives. Another area of discussion revolves around the impact of market structure on banking regulation and supervision—essentially the opposite argument made by the traditional view. The final discussion touches on the famous concept of "too big to fail," which connects market structure to regulatory policies in the banking system (Postinchi et al., 2016).

3- Research Methodology

This research is descriptive-correlational in terms of execution and applied in terms of purpose. Since this study examines the current status of variables using data collected from past information, it falls under the category of descriptive-post-event (ex post facto) studies.

In the first part, the statistical population consists of banks listed on the Tehran Stock Exchange during the years 2016 to 2021 (1395–1400 in the Persian calendar). The sampling from this population was carried out using the systematic elimination method, and due to potential limitations in the availability of information from the target population, the following criteria were considered in sample selection:

Their financial year ends on March 20th (29 Esfand).

They have been consistently active on the stock exchange during the period from 2016 to 2021.

Complete financial statements and accompanying notes to the financial statements must be available.

The shareholders' equity must not be negative during the review period.

The banks must not have changed their fiscal year during the review period.

In the second part, involving unsupervised machine learning algorithms, the statistical population consists of bank customers. A researcher-made questionnaire based on customers' demographic characteristics is validated and distributed among the customers. Demographic information such as age, gender, education level, history of using electronic banking services, preferred banks, and other variables are included.

For data analysis, the statistical data is first examined, followed by drawing frequency charts. In the data cleaning phase, to balance the data, the improved K-means Cummins method is used to identify outliers in the majority class, and those outliers are removed. Then, intelligent oversampling is applied to the minority class. The balanced data is subsequently compared using classification methods.

To evaluate the best outlier detection model, six classifiers were used, and a total of 12 models were assessed and compared based on three types of accuracy metrics.

4- Research Findings

Evaluation Parameters

Before examining the key classification metrics, it's necessary to first explain the concept of the confusion matrix, which will be used in this section. This matrix illustrates the performance of a classification algorithm based on the input dataset, broken down by the categories (classes) involved in the classification problem.

According to the table, the concepts of True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) are defined as follows:

Table 2: Confusion Matrix

		Estimated Records	
		Negative Class (-)	Positive Class (+)
Actual Records	Negative Class (-)	True Negative (TN)	False Positive (FP)
	Positive Class (+)	False Negative (FN)	True Positive (TP)

- True Positive (TP): It shows the number of samples in the test data where the value is positive (target customer) and the classifier correctly predicted them as an attack.
- False Positive (FP): It shows the number of samples in the test data where the value is normal (non-target) and the classifier incorrectly predicted them as an attack.
- True Negative (TN): It shows the number of samples in the test data where the value is normal (non-target) and the classifier correctly predicted them as non-attack.
- False Negative (FN): It shows the number of samples in the test data where the value is an attack (target customer) and the classifier incorrectly predicted them as non-attack.

Now, let's explain the important evaluation metrics for classification algorithms. The first metric is accuracy or classification rate, which refers to the percentage of test records correctly classified by the classifier. This accuracy can be calculated based on the concepts in the matrix, according to the formula.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

The most important metric in this research is sensitivity, which is calculated using Formula (2). In detecting target customers, it can be stated as the ratio of the number of correct target customer detections (numerator) by the classifier to the total number of customers who were truly target customers (denominator of the relation).

$$\text{Sensitivity} = \text{Recall} = \frac{TP}{FN + TP} \quad (2)$$

Another evaluation metric is the classifier's specificity Formula (3), which, for example, in detecting target customers, refers to the classifier's ability to correctly identify customers who are not target customers (negative class).

$$\text{Specificity} = \text{Recall} = \frac{TN}{TN + FP} \quad (3)$$

In this paper, to predict target customers in the field of direct marketing in a bank and examine the factors influencing an imbalanced, standardized, and validated dataset from Tehran Bank, we used several classification algorithms on a dataset with 4,521 samples and 16 features. First, we described the data. Then, we plotted and analyzed the statistical properties, histograms, and scatter plots of some variables. The main results obtained from this stage are as follows:

Of the 4,521 records, 4,000 records belong to the negative class, and only 521 records belong to the positive class, indicating an imbalanced dataset.

Upon reviewing the dataset, it was found that there are no meaningless values.

The majority of the age range is from 19 to 56, with an average age of 41.17, and only a few records fall between the ages of 57 to 87.

Most deposit applicants are married, employed, have a secondary education, and do not have account credit at the bank.

Target customers typically have at least a secondary education. The results from previous elections show that most of the new customers have not been previously targeted in marketing campaigns.

Analysis of Data Balancing Stages with Clustering

Due to the data imbalance and the low accuracy of the minority class, we applied the clustering method to the data. In the k-means method, the number of clusters was determined automatically based on the informational criterion, and the minimum and maximum clusters were defined. A total of 5 clusters were determined, as shown in Figure 1.

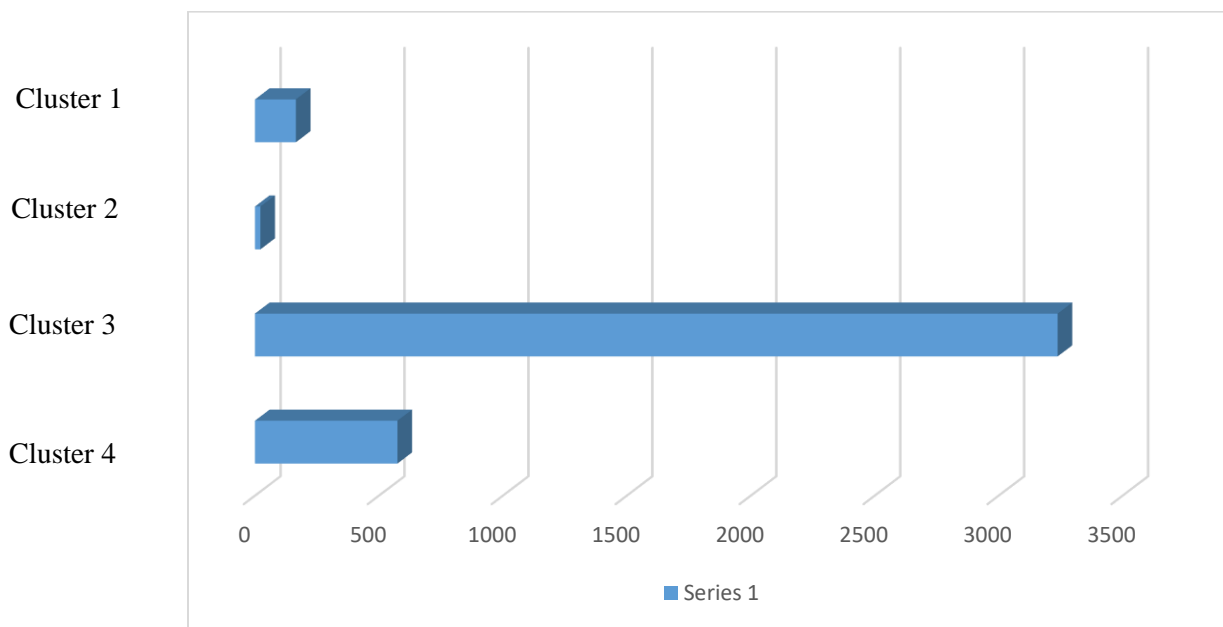


Figure 1 Number of Clusters with x-means

80% of the minority class samples are clustered in Cluster 1, while 20% are scattered in other clusters. The low number of samples in other clusters represents outliers in the majority class. Therefore, from the total of 4,000 samples, the samples in Cluster 2 and Cluster 3 (728 samples) were removed.

Next, the SMOTE oversampling method was applied to balance the minority class. In this step, using the intelligent SMOTE method based on the nearest neighbors, similar samples were created in the neighborhood of each record, and the number of minority class samples was increased to 1,024. Only a 51% increase in samples and intelligent synthetic data production were used, because a high ratio of synthetic data production would lead to a significant amount of noise and artificial data, which would not reflect actual results. For this reason, we only doubled the 521 samples of the minority class (target customers).

We balanced the data with a ratio of 1,024/2,050 samples, aligning the non-target customer/target customer class ratio.

Classification Analysis

In the modeling section, decision tree algorithms, random forests, Bayesian networks, neural networks, gradient boosting, and deep learning were initially applied to the imbalanced data. The results are shown in Table 1.

Then, we applied clustering and k-means + SMOTE methods. The results are presented in Table 2 as well.

Table 2 Comparison of Classifier Accuracies

model	Recall(yes)	Recall(No)	ACC
1-C4.5 with imbalanced data	53.3%	96%	88.98%
2-C4.5(smote)	73%	92%	88.02%
3-C4.5(smote+clustering)	83%	92%	89.14%
Random forest with imbalanced data	26.9%	97.5%	89.33%
Random forest (clustering)	67%	97%	90.66%
Random forest (smote+ clustering)	86%	96%	92.37%
Neural net with imbalanced data	32%	89%	89%
Neural Net (smote)	77%	92%	89%
Neural Net(smote+clustering)	89%	89%	89%
GTB with imbalanced data	42%	95%	89%
GTB (clustering)	87%	93%	91%
GTB (smote+clustering)	88%	94%	92.12%
naiveBeyes with imbalanced data	40.3%	94%	87.81%
naiveBeyes (clusteing)	85%	80%	81.17%
naiveBeyes (smote+ clustering)	76%	87%	84.75%
Svm with imbalanced data	29%	89.47%	83.39%
Svm (clustering)	91%	88.67%	90.77%
Svm(smote+ clustering)	89.67%	92.78%	91.11%

The results clearly show that in all 6 types of classifiers, the accuracy of the minority class, which pertains to target customers, is more important, and with data balancing, it has significantly improved. The overall accuracy and the accuracy of the majority class have also increased.

In all classifiers, the accuracy of the overall class and the minority class improved with the SMOTE method.

The classifier that used the k-means method for removing outliers and then applied oversampling showed an average increase of up to 10% compared to the classifier that only applied SMOTE. In fact, the aim of this research is to improve upon the latest papers that only worked with SMOTE on this data.

In all classifiers, except for Random Forest, the results with the SMOTE+x-means method showed better accuracy in all three parameters.

The highest accuracy was achieved by Gradient Boosting with an overall accuracy of 92.17%, target customer class accuracy of 90%, and non-target customer class accuracy of 94%. The SMOTE+x-means method, combined with Gradient Boosting, is innovative and the proposed method of this thesis, as it had not been applied to the data of this research before.

The results of the combined algorithms, such as AdaBoost and Random Forest, show a significant improvement compared to the basic decision tree classifier.

The Neural Network provided the weakest results, while Deep Learning improved the accuracy of this technique by 17%.

In general, decision tree-based algorithms performed better than other neural network and Bayesian algorithms. These algorithms are part of the "white-box" methods, which provide analytical output and explanatory rules, unlike methods such as Neural Networks and Support Vector Machines, which report results only in terms of accuracy numbers.

5- Conclusion

Considering that AdaBoost models use decision trees in the training phase and perform well on the data, we aim to explain the generated rules and hidden patterns in the data in terms of marketing concepts and target customers. Of course, most of the reported rules are those with a higher likelihood of occurrence and lower error rates, making them more useful.

If the contact duration with the customer is less than 221 seconds (3 minutes), no prior contact has been made with the customer, the individual has taken a loan, has credit in the bank, is single, and has a managerial job, this customer is likely to be a potential long-term deposit customer.

If the contact duration with the customer is less than 221 seconds (3 minutes), but there were prior contacts with the customer that were answered, and the outcome of previous elections is pending, this customer might be a target customer.

If the contact duration with the customer is less than 221 seconds (3 minutes), but there were prior contacts with the customer that were answered, and the outcome of previous elections was successful, this customer is definitely a target customer and should be invested in for acquisition.

If the contact duration with the customer is less than 221 seconds (3 minutes), and the annual credit amount in the bank is more than 1983 euros, even if the customer has not previously taken a loan, this customer is likely to be a target customer.

If the contact duration with the customer is less than 221 seconds (3 minutes), no prior contact was made with the customer, and there is no known fixed contact number for the customer, this customer is most likely not a target customer.

If the contact duration with the customer is less than 221 seconds (3 minutes), no prior contact was made, there is no known fixed contact number for the customer, and the number of unanswered contacts during this period is more than two, with the contact month being August (summer holidays), then this customer is not a target customer.

If the contact duration with the customer is less than 221 seconds (3 minutes), there were prior contacts with the customer that were answered, and the outcome of previous elections was unsuccessful, and the customer is under 46 years old, and their annual credit in the bank is less than 422 euros, this customer is likely not a target customer.

If the contact duration with the customer is greater than 221 seconds (3 minutes), but the individual has little credit in the bank, no prior contact was made, and there is no fixed contact number for the individual in the bank, this customer is not a target customer.

For future research in this area, the following approaches can be considered:

Use of other outlier detection methods such as software techniques like Weka, various proximity-based methods, techniques to improve proximity methods, semi-supervised techniques like Neural Networks, and fuzzy methods for outlier detection.

Additionally, optimization techniques can be used for selecting optimal parameters for classifiers, such as Support Vector Machines and Neural Networks.

References

- Bin Sulaiman, R., Schetinin, V., & Sant, P. (2022). Review of machine learning approach on credit card fraud detection. *Human-Centric Intelligent Systems*, 2(1), 55-68.
- Fallah, M., & Nozari, H. (2021). Quantitative analysis of cyber risks in IoT-based supply chain (FMCG industries). *Journal of Decisions and Operations Research*, 5(4), 510-521.
- Fanai, H., & Abbasimehr, H. (2023). A novel combined approach based on deep Autoencoder and deep classifiers for credit card fraud detection. *Expert Systems with Applications*, 217, 119562.
- Fu, K., Cheng, D., Tu, Y., & Zhang, L. (2016). Credit card fraud detection using convolutional neural networks. In *Neural Information Processing: 23rd International Conference, ICONIP 2016, Kyoto, Japan, October 16–21, 2016, Proceedings, Part III (Vol. 23, pp. 156-163)*. Springer.

- Irani, H. R., & Nozari, H. (Eds.). (2024). *Smart and Sustainable Interactive Marketing*. IGI Global.
- Kalogeras, S. (2021). Transmedia Storytelling Edutainment and the New Testament Lesson. In *Handbook of Research on Contemporary Storytelling Methods Across New Media and Disciplines* (pp. 392-406). IGI Global Scientific Publishing.
- Kalogeras, S., Mejri, S., & Efthimiou, F. (2022). The neuroscience of student engagement: Case studies in narrative pedagogies in mathematics, science, and technology. *International Journal of Online Pedagogy and Course Design (IJOPCD)*, 12(1), 1-19.
- Koomson, S. (2024). Do total quality management and external factors matter? The effect of innovation behaviour on innovation performance in banks. *European Business Review*, ahead-of-print.
- Muntasir Nishat, M., Faisal, F., Jahan Ratul, I., Al-Monsur, A., Ar-Rafi, A. M., Nasrullah, S. M., Reza, M. T., & Khan, M. R. H. (2022). A comprehensive investigation of the performances of different machine learning classifiers with SMOTE-ENN oversampling technique and hyperparameter optimization for imbalanced heart failure dataset. *Scientific Programming*, 2022, 3649406.
- Nizam-Ozogur, H., & Orman, Z. (2024). A heuristic-based hybrid sampling method using a combination of SMOTE and ENN for imbalanced health data. *Expert Systems*, e13596.
- Patel, K. (2023). Credit card analytics: A review of fraud detection and risk assessment techniques. *International Journal of Computer Trends and Technology*, 71(10), 69-79.
- Salekshahrezaee, Z., Leevy, J. L., & Khoshgoftaar, T. M. (2023). The effect of feature extraction and data sampling on credit card fraud detection. *Journal of Big Data*, 10(1), 6.
- Seera, M., Lim, C. P., Kumar, A., Dhamotharan, L., & Tan, K. H. (2024). An intelligent payment card fraud detection system. *Annals of Operations Research*, 334(1), 445-467.
- Statista. (2023). Number of Visa credit cards in the United States and worldwide from 1st quarter of 2008 to 4th quarter of 2023. Retrieved from <https://www.statista.com/statistics/618115/number-of-visa-credit-cards-worldwide-by-region/>
- Statista. (2024). Number of Mastercard credit cards in the United States and worldwide from 4th quarter of 2006 to 1st quarter of 2024. Retrieved from <https://www.statista.com/statistics/618137/number-of-mastercard-credit-cards-worldwide-by-region/>
- Xuan, S., Liu, G., Li, Z., Zheng, L., Wang, S., & Jiang, C. (2018). Random forest for credit card fraud detection. In *2018 IEEE 15th International Conference on Networking, Sensing and Control (ICNSC)* (pp. 332-337). IEEE.