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Evaluating the Efficiency of Explainable Artificial Intelligence Methods in Determining the Importance of Variables in Predictive Models

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Abstract

The prediction of non-performing loan recovery is one of the main challenges in the banking system. Delays in the timely repayment of loans increase credit risk for banks and undermine their financial health. This study aims to design an accurate, interpretable, and AI-based model to assess the importance of variables influencing the prediction of receivables collection over a 30 to 90-day period. The research methodology is analytical-applied in nature. Real credit and banking data from 750,000 individual customers were utilized, and advanced machine learning algorithms (such as Random Forest and XGBoost), along with explainable artificial intelligence (XAI) methods such as SHAP and LIME, were employed. The results indicated that the algorithms were able to predict delinquent contracts with high accuracy, and SHAP successfully identified variables such as the number of negative months and the average overdue debt in the last three months as the most influential features. The use of explainable artificial intelligence not only preserves the accuracy of predictive models but also enables banking analysts to make decisions based on transparent data interpretation—an element directly contributing to the enhancement of risk management strategies.

Keywords: Explainable Artificial Intelligence, SHAP, Machine Learning, Debt Recovery, Default Prediction, Credit Risk Management.

1. Introduction

Given the importance of non-performing loans, this study first addresses the causes and influencing factors of loan default and overdue receivables. The contributing factors to the formation and growth of non-performing loans can be categorized into internal organizational (intra-bank) and external organizational (extra-bank) factors, as well as financial and economic factors. Financial and economic factors, and more broadly the overall economic conditions, are among the most significant contributors to the emergence and escalation of overdue receivables (Mutamimah et al., 2024; Natufe & Evbayiro-Osagie, 2023). Numerous economic studies, such as those by Carey (1998) and Louzis et al. (2012), have identified economic growth and expansion as factors that reduce the volume of non-performing loans, since during periods of economic prosperity both households and businesses are more capable of repaying their debts to banks. According to the life-cycle consumption model by Ando and Modigliani (1963) and Hayek's business cycle theory, economic growth has a significant negative impact on the volume of non-performing loans, as economic expansion enhances the repayment capacity of economic agents (Roshan & Khodarahmi, 2024; Temba et al., 2024).

On the other hand, it can be argued that sustained economic growth and prosperity increase lending across all income levels of society, enabling individuals who lack the repayment capacity to receive loans as well. However, during economic recessions, these borrowers may be unable to repay their debts due to declining asset values and financial incapacity (Klein, 2013). Recession also leads to a decline in the sales of goods and services, which in turn extends the receivables collection period and operating cycle, thereby reducing the ability to repay loans. Thus, economic recession can be considered a significant factor in the increase of non-performing loans (Chen et al., 2021).

According to previous studies, another variable that affects the volume of non-performing loans is the inflation rate. Inflationary conditions in the economy can hinder the ability of economic agents to repay their debts. Rising inflation discourages debt repayment due to increased general price levels, and the expectation that inflation will reduce the real value of debts contributes to the growth of overdue receivables. As inflation rises, the real value of bank loans diminishes, and borrowers, benefiting from this depreciation, become less inclined to repay, which leads to increased delays in repayments and, consequently, an expansion in the volume of non-performing loans. Therefore, the inflation rate can be identified as one of the key factors influencing reduced liquidity flow in commercial banks and increased credit risk (Verbraken, Bravo, et al., 2014; Verbraken, Verbeke, et al., 2014).

Another macroeconomic factor influencing banking behavior and the volume of non-performing loans is the level of government debt. The impact of government debt on non-performing loans can be explained through reduced public expenditures resulting from increased debt, leading to the government's inability to pay adequate salaries and wages to its employees. Inability to pay sufficient salaries triggers financial shocks and budget deficits for households, which, in turn, hampers their ability to repay loans and increases the volume of unpaid bank loans. Additionally, large corporations, due to reduced consumer purchasing power and falling demand, face decreased sales and liquidity shortages, resulting in difficulties repaying their bank loans. The culmination of these developments can lead to an increase in the volume of non-performing loans in the banking system (Zadrozny & Elkan, 2001; Zhang et al., 2021). Other external organizational factors that contribute to the emergence and growth of overdue receivables include politicization of banking operations and mandatory lending policies, lack of integrated and updated information systems, unforeseen events, changes in laws and regulations, absence of adequate cultural frameworks, political-economic transitions, borrower death, and complications in inheritance procedures (Chen et al., 2021). According to studies, internal organizational variables such as emphasis on operational efficiency and risk management, alongside specific characteristics of the banking industry, significantly influence the volume of non-performing loans (Abdesslem et al., 2022; Aduda & Obondy, 2021; Akbarian et al., 2021).

Debt collection processes in banks consist of both internal and external operations. This means that part of the collection process (such as negotiations with customers and internal directives) is developed within the bank, and improvements in these areas are within the bank's control. The use of experienced banking personnel and appropriate collection procedures can improve internal organizational factors and positively influence debt recovery (Chen et al., 2022; Cheng & Qu, 2020). In general, two predictive methods exist for debt collection. The best approach for collecting bank debts involves establishing a conducive framework, which includes granting special authorities to banks to expedite collection processes under current conditions. Furthermore, utilizing debt collection companies under the full supervision of experienced legal and credit experts, and securing adequate guarantees from such companies based on their credibility and capacity, should not be overlooked, as this can save time and cost. As emphasized, debt collection methods depend on customer conditions, the terms of the contract, and the expected duration and process of recovery. Nonetheless, banks generally consider client engagement to be the most effective strategy for debt collection, provided that the client adheres to the bank's contractual terms and conditions. However, if the client refuses to repay for any reason, the bank—as the trustee of depositors and responsible for safeguarding their interests—will pursue legal avenues (Altavilla et al., 2020; Bastan et al., 2019; Bekhet & Eletter, 2014). It must be acknowledged that the current banking structure and its governing regulations often limit effective debt collection actions. If an independent and private institution staffed with experienced personnel in legal, registration, and banking fields were established, the debt collection process would be accelerated, and banks could increase their collection rates while avoiding potential complications (Elahi et al., 2023).

One of the major problems faced by banking systems in various countries, including Iran, is the increasing proportion of past-due and non-performing loans relative to total banking facilities, which reflects a decline in asset quality and potential financial instability in the future. With the global expansion of artificial intelligence applications in banking and the growing need for transparency in financial decision-making—particularly in the area of credit risk—explainable models have gained attention as innovative and reliable tools. The present study aims to utilize machine learning algorithms and explainable artificial intelligence tools such as SHAP to offer a precise, transparent, and effective framework for predicting the probability of non-performing loan recovery and identifying the importance of key predictive variables.

2. Methods and Materials

This study is applied in its objective and analytical-quantitative in its approach. It aims to design a model for predicting the probability of non-performing loan recovery in contracts with overdue debts between 30 and 90 days, using machine learning algorithms and explainable artificial intelligence (XAI) techniques. This research falls under the category of data-driven studies, utilizing real banking and credit data to propose a precise and interpretable framework for credit decision-making. Given the unique characteristics of financial data and the complexity of customer behavior, the research employs a predictive modeling approach to extract and interpret relationships influencing the likelihood of default and repayment through pattern analysis.

Considering the importance of debt recovery in banking processes, proper and systematic engagement with delinquent clients to improve their repayment status requires high-accuracy and timely identification. Therefore, in order to minimize operational and human costs and reduce dissatisfaction among generally reliable customers who may exhibit temporary repayment irregularities, there is a growing need for a highly accurate intelligent model. With the advancement of AI and machine learning algorithms, significant improvements have been observed in various business sectors utilizing data-driven artificial intelligence. Hence, the use of data-centric machine learning algorithms, which offer both precision and speed, can help avoid erroneous decision-making biases. Accordingly, this study adopts machine learning algorithms to identify high-risk clients with a probable deterioration in repayment behavior.

To forecast and detect delinquent clients in line with the objective of loan recovery, the dependent variable must be defined to meet a specific business goal. In this study, the probability of default is taken as the dependent variable. Default is defined as the likelihood that an account will have outstanding overdue debt between 30 and 90 days. Data splitting is commonly used in machine learning to divide datasets into training, testing, and validation sets. The separation of data into training and testing subsets is a standard method for evaluating the performance of machine learning algorithms. Data splitting can be applied in classification or regression tasks and is generally applicable in any supervised learning algorithm.

The statistical population of this research includes all individual customers with a history of banking activity and recorded credit information in the database of the Iran Credit Rating Consulting Company. Established in 2006 under the supervision of the Central Bank of the Islamic Republic of Iran, with support from the Ministry of Economic Affairs and Finance and participation from the country's banks and financial institutions, this company operates as the national credit scoring authority. The data collected by this company are obtained through direct connections with information systems of banks, credit institutions, leasing companies, municipalities, and other financial data providers. Thus, its database encompasses a wide range of financial, credit, demographic, payment behavior, default status, loan history, and other behavioral indicators of individual clients on a national scale. Simple random sampling was used to select the study sample. This method, recognized as one of the most fundamental and scientific statistical sampling techniques, ensures that each member of the population has an equal chance of selection. The rationale for using this method was to avoid any bias in data selection, enhance the validity of results, and ensure model generalizability across the entire target population. For the purpose of achieving generalizable results and accurate modeling, a total of 750,000 records of individual customers were utilized as the research sample. This large sample size was selected purposefully, taking into account the complexity of machine learning algorithms. Advanced models such as Random Forest, Gradient Boosting, or Deep Neural Networks require substantial volumes of training and testing data to achieve high accuracy and avoid overfitting. Therefore, using a wide and diverse dataset not only enhances model performance but also brings the results closer to real-world banking conditions.

In this study, aiming to predict loan recovery risk with maximum accuracy, a combination of advanced deep learning algorithms and explainable artificial intelligence methods was employed. The study's main approach is data-driven, focusing on predictive model design and detailed interpretation of model outputs to ensure both high accuracy and interpretability for end-users such as banks and credit institutions. The research began by introducing the study as applied and developmental in nature, utilizing explainable AI to predict the recovery of non-performing loans. The statistical population included clients with non-performing loans within a defined time frame, and purposive sampling was carried out based on specified criteria. Data were extracted from reliable banking sources and underwent preprocessing including cleaning, normalization, and feature engineering before being input into selected machine learning models such as XGBoost, Random Forest, and Neural Networks. To enhance interpretability and transparency, XAI techniques such as SHAP and LIME were applied. Finally, appropriate evaluation metrics such as accuracy, recall, and AUC were used to assess model performance, aiming to deliver an optimal, accurate, and interpretable model for predicting the probability of non-performing loan recovery.

3. Findings and Results

This section first analyzes the performance of machine learning models in predicting loan recovery. The evaluation of the models was conducted using metrics such as AUC, Precision, Recall, and average accuracy, revealing that the selected models exhibit strong capability in distinguishing between recoverable and defaulted contracts. Additionally, the SHAP method was employed to analyze feature importance and interpret model outputs. A key point in model evaluation is the importance of balancing two common types of error: False Positives (FP), in which reliable customers are mistakenly classified as delinquent, and False Negatives (FN), in which actual defaulters are not identified. This trade-off is directly related to the threshold value used for classification. Threshold tuning is recognized as a critical component in controlling the sensitivity and specificity of the model; lowering the threshold increases the True Positive Rate (TPR) but also raises the False Positive Rate (FPR), and vice versa (Saito & Rehmsmeier, 2015). Therefore, in this study, the threshold was selected to optimize debtor identification accuracy while minimizing prediction errors for reliable customers, as an increase in FP could have negative consequences such as limiting access to credit for qualified applicants (Verbraken, Bravo, et al., 2014; Verbraken, Verbeke, et al., 2014).

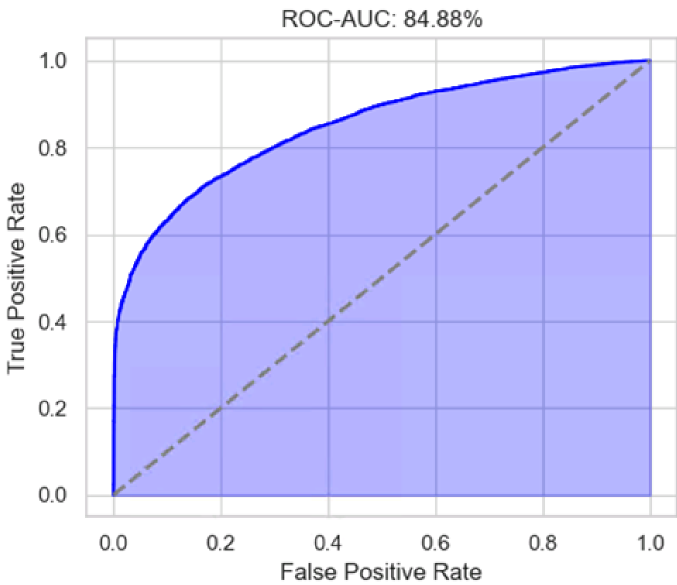

Figure 1. ROC-AUC Curve Analysis

The conclusion of this analysis is that the deep learning model used in this study performed well, achieving a high AUC. Combined with the use of explainable AI techniques, it created a framework that maintained prediction accuracy while preserving the interpretability of credit decisions. Moreover, aligning the threshold with business objectives, such as controlling default rates and reducing classification errors, can significantly aid in more accurate credit policy formulation within financial institutions.

The Precision-Recall curve analysis in this study offers a more detailed picture of the model's performance in predicting non-performing loan recovery under imbalanced data conditions. Unlike the ROC curve, which is more suitable for balanced datasets, the Precision-Recall curve provides a clearer depiction of the model's capability in identifying critical samples (in this case, defaulters) when there is a class imbalance (Saito & Rehmsmeier, 2015). In this study, the Average Precision (AP) was calculated at 89.78%, indicating the model's strong performance in accurately distinguishing between BAD and GOOD classes.

In this curve, the horizontal axis represents Recall, or the correct identification rate of actual defaulters among all defaulters, while the vertical axis represents Precision, or the proportion of correctly identified defaulters among those predicted to be defaulters. The algorithm used in this study produced a curve significantly above the baseline, indicating superior performance compared to random prediction. Specifically, the AP value of 89.78% demonstrates that the algorithm maintained high precision across all threshold values in recognizing true defaulters. This result is competitive and desirable when compared to similar studies in the field of credit risk prediction (Brown & Mues, 2012).

A variance inflation factor (VIF) chart was used to assess multicollinearity among independent variables. The VIF for most variables was below 10, indicating an absence of severe multicollinearity, and justifying their retention in the model. Only a few features, such as the number of delinquent months or the maximum outstanding current debt, exhibited VIF values above 5, suggesting moderate multicollinearity; however, due to their importance in prediction, they were not excluded. Variables with VIF greater than 10 were removed during the initial stages to prevent errors in parameter estimation. As a result, the remaining variables were statistically acceptable and contributed to the development of a stable and accurate model.

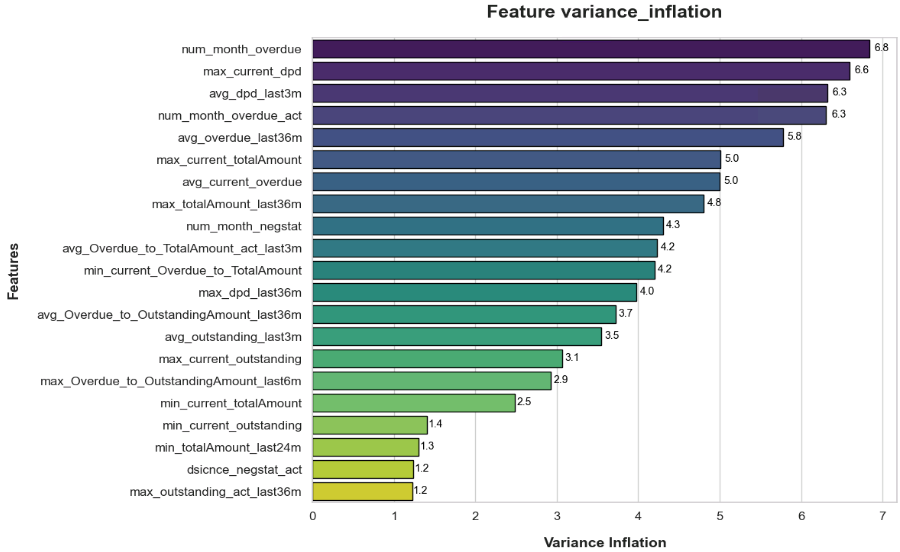

Figure 2. VIF Chart Analysis

To assess linear relationships among input variables, the Pearson correlation matrix was utilized. This matrix shows the degree to which the change in one variable aligns with the change in another. The values in the matrix range from -1 to +1 and indicate the strength and direction of the correlation.

High Positive Correlation: Variables such as the number of delinquent months and the maximum current delinquency amount showed strong positive correlations with each other (coefficients around 0.89 to 0.91). Such high correlations may lead to multicollinearity in the model and impact parameter estimation accuracy.

Significant Negative Correlation: A relatively strong negative correlation was observed between variables like the time since the last negative status and the maximum debt over the past three years (coefficient around -0.78), indicating an inverse relationship.

Low Correlation: Many variables showed weak correlations with each other, which is favorable for modeling, as it suggests that the variables provide distinct and non-redundant information. High correlation among some variables reinforced the likelihood of multicollinearity, as confirmed by the VIF analysis. However, many variables had low correlation and remained in the model as independent and useful features. This balance contributes to model stability and prevents distortion in the results.

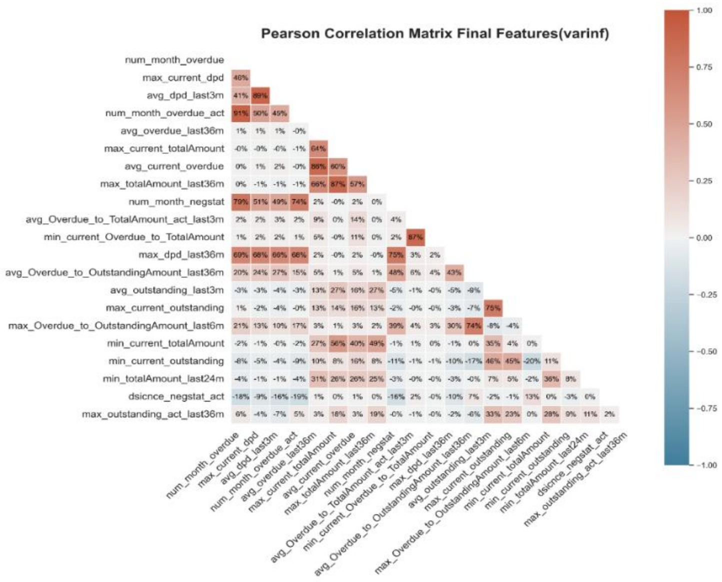

Figure 3. Correlation Matrix Analysis

The SHAP analysis showed that features such as the number of negative months, average overdue debt over the past three months, and time since the last negative status had the most significant impact on predicting contract default. Additionally, the correlation analysis and VIF results indicate that the selected data were statistically valid and improved the model's accuracy. These findings emphasize the model's capacity to detect hidden patterns in credit data.

4. Discussion and Conclusion

The findings of this study demonstrate that the integration of machine learning models with explainable artificial intelligence (XAI) tools, particularly SHAP, not only achieves high predictive performance for defaults but also enables analysts to precisely interpret the reasoning behind the model's predictions. This interpretability is especially critical in the financial domain, where transparency in decision-making is of paramount importance. The present study aimed to leverage machine learning models and explainable AI to predict non-performing loan recovery based on various debt contract features. A special focus was placed on how to interpret and clarify the outcomes of complex models using modern explainability techniques such as SHAP. While machine learning models are known for their strong predictive capabilities in financial tasks like non-performing loan forecasting, one of the primary challenges in their application lies in the complexity of interpreting their outputs. To address this challenge and improve model interpretability, XAI methods were employed. Techniques like SHAP, which can illustrate how different features influence the model's decisions, help resolve this issue and enhance user trust.

The results showed that certain features play a critical role in predicting the status of bad debt and can significantly influence model predictions. For instance, features such as num_month_negstat (number of months with negative status) and avg_Overdue_to_TotalAmount_act_last3m (average overdue amount to total debt over the past three months) had substantial impacts on the model's predictions. The positive SHAP values of these features clearly indicated that higher values increased the likelihood of a loan being categorized as non-performing, aligning with prior findings in the financial literature. These features were identified as key indicators in forecasting financial outcomes of loan contracts and may serve as critical inputs in credit and management decision-making processes. The study's hypothesis is subsequently examined.

By applying XAI-based methods, models can be made interpretable, meaning the relative importance of variables in the model's predictions can be extracted. The core hypothesis of this study is that explainable AI techniques can transform predictive models into transparent and comprehensible systems. In other words, the objective is to determine, through these methods, the importance of various features in the model's predictions. This is especially significant in analyzing complex data, particularly in the context of predicting non-performing loan recovery. In today's world, artificial intelligence and machine learning models often operate as "black boxes," where users lack insight into why the model made a particular decision. This lack of transparency can reduce trust in these models and limit their application in sensitive domains such as finance and risk assessment. Consequently, explainable AI techniques like SHAP, LIME, and other model interpretation tools can enhance trust in these systems and provide a clearer understanding of their functionality.

In this research, SHAP (SHapley Additive exPlanations) was utilized to interpret and clarify the outputs of machine learning models. SHAP is one of the most widely recognized and robust explainability techniques for complex models, capable of showing the precise and transparent effect of each feature on the model's prediction (Lundberg & Lee, 2017). In the analyses conducted, SHAP Dependence Plots were employed to understand the influence of features on model outputs. SHAP is grounded in cooperative game theory and the Shapley value concept, calculating a SHAP value for each feature that represents its impact on the model's prediction. These values may be positive or negative and indicate how increasing or decreasing a feature affects the prediction.

For example, in this study, the features num_month_negstat and avg_Overdue_to_TotalAmount_act_last3m, which had notable predictive influence, were prominently highlighted in SHAP plots with positive values. This means higher values of these features increase the probability of being classified as a non-performing loan. The SHAP Dependence Plot clearly illustrated how SHAP values changed in relation to the features' magnitudes. Specifically, higher values of num_month_negstat were associated with positive SHAP values, directly indicating an increased likelihood of entering default status within the next 90 days. These analyses demonstrate that XAI methods provide a clear understanding of feature impacts and assist analysts in interpreting complex models.

In addition to SHAP, other methods such as LIME (Local Interpretable Model-agnostic Explanations) are also used to generate understandable interpretations of machine learning models. LIME works by approximating complex models with simpler local models to explain individual predictions (Ribeiro et al., 2016). This technique is particularly useful when examining the importance of features at a local level for specific predictions. However, due to SHAP's superior ability to interpret complex models and provide precise impact values for each feature, SHAP was chosen as the primary method in this study.

From a theoretical standpoint, the use of explainable AI techniques in machine learning—especially in applications like non-performing loan prediction—offers several advantages. First, they enhance trust in predictive models by allowing users to understand why the model arrived at a specific prediction. This is crucial in financial contexts, where erroneous decisions can have serious consequences. Second, these methods assist in identifying and analyzing both important and unimportant features in the dataset, thereby facilitating model optimization. For example, features with negligible impact on predictions can be removed, resulting in simpler and more efficient models.

Ultimately, the analyses conducted in this research confirm that using explainable AI methods like SHAP can effectively render complex models transparent and understandable for users. These models can demonstrate the contribution of each feature to the prediction and help analysts identify the most important factors for forecasting non-performing loan recovery. Overall, the results highlight that explainable techniques can significantly enhance the transparency and interpretability of predictive models, thereby strengthening the quality of financial decision-making. In conclusion, explainable AI opens a new avenue in credit risk management for banks. This technology enables credit managers to make more effective and targeted decisions by deeply understanding the rationale behind predictions. It is recommended that banks enhance their data infrastructure and adopt hybrid models like XGBoost integrated with SHAP to shift from intuition-based to data-driven decision-making.

Recommendations for future development to improve XAI-based non-performing loan recovery models include:

- **Combining multiple models to improve predictive accuracy**: Although machine learning models such as decision trees and random forests performed well in this study, ensemble methods like Boosting and Bagging could enhance accuracy by aggregating the strengths of multiple models. This approach can be particularly effective for complex and dynamic financial data.
- **Forecasting with uncertainty estimation**: Machine learning models typically provide precise predictions, but some cases involve inherent uncertainty. Techniques like Bayesian models and probabilistic deep learning can help not only in generating predictions but also in reporting associated uncertainties, leading to more informed decisions.
- **Developing scalable, explainable systems**: A major contribution of this study was the use of SHAP as an explainable method. In the future, such techniques can be deployed more widely across predictive systems, making them accessible

and understandable to various users, including financial analysts, bank managers, and even customers. This broader accessibility can increase trust and promote more effective use of the models.

Ethical Considerations

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

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Conflict of Interest

The authors report no conflict of interest.

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References

Abdesslem, R. B., Chkir, I., & Dabbou, H. (2022). Is managerial ability a moderator? The effect of credit risk and liquidity risk on the likelihood of bank default. *International Review of Financial Analysis*, *80*, 102044. https://doi.org/10.1016/j.irfa.2022.102044

Aduda, J., & Obondy, S. (2021). Credit risk management and efficiency of savings and credit cooperative societies: A review of literature. *Journal of Applied Finance and Banking*, *11*(1), 99-120. https://doi.org/10.47260/jafb/1117

Akbarian, S., Anvari Rostami, R., & Abdi. (2021). The Impact of Social Performance Indicators on Credit Risk in the Banking Industry. *Investment Knowledge*. https://sanad.iau.ir/Journal/jik/Article/843021/FullText

Altavilla, C., Boucinha, M., Peydró, J. L., & Smets, F. (2020). Banking supervision, monetary policy and risk-taking: big data evidence from 15 credit registers. *Monetary Policy and Risk-Taking: Big Data Evidence from 15*. https://doi.org/10.2139/ssrn.3512892

Bastan, M., Akbarpour, S., & Ahmadvand, A. (2019). Profitability Paradox in Iranian Commercial Banks Business Model: A Study Based on System Dynamics Methodology. *Monetary & Financial Economics*, *26*(18), 197-242. https://doi.org/10.22067/pm.v26i17.65314

Bekhet, H., & Eletter, S. (2014). Credit risk assessment model for Jordanian commercial banks: Neural scoring approach. *Review of Development Finance*, *4*, 20-28. https://doi.org/10.1016/j.rdf.2014.03.002

Brown, I., & Mues, C. (2012). An experimental comparison of classification algorithms for imbalanced credit scoring data sets. *Expert Systems with Applications*, *39*(3), 3446-3453. https://doi.org/10.1016/j.eswa.2011.09.033

Chen, J., Li, J., & Ghosh, S. (2021). Explainable AI for Credit Risk Scoring Using Tree-based Models and SHAP Values. *Expert Systems with Applications*, *178*, 115019.

Chen, S., Gulati, R., & Goswami, A. (2022). What drives credit risk in the Indian banking industry? An empirical investigation. *Economic Systems*, *43*(1), 100695. https://doi.org/10.1016/j.ecosys.2018.08.004

Cheng, M., & Qu, Y. (2020). Does bank FinTech reduce credit risk? Evidence from China. *Pacific-Basin Finance Journal*. https://doi.org/10.1016/j.pacfin.2020.101398

Elahi, A. R., Mohammadipour, R., & Mohammadi, E. (2023). Designing a Meta-Heuristic Model for Credit Risk Management in Bank Refah Using an Artificial Intelligence Approach. *Advertising and Sales Management*, *4*(1). https://asm.pgu.ac.ir/article_696645.html

Klein, N. (2013). Non-performing loans in CESEE: Determinants and impact on macroeconomic performance. *IMF Working Papers*, *13*(72). https://doi.org/10.5089/9781484318522.001

Lundberg, S. M., & Lee, S. I. (2017). A Unified Approach to Interpreting Model Predictions. https://arxiv.org/abs/1705.07874

Mutamimah, M., Suryani, A., & Made Dwi, A. (2024). Credit Risk Management Innovation in Bank Based on Blockchain Technology. International Congress on Information and Communication Technology, Singapore. https://doi.org/10.1007/978-981-97-3556-3_3

Natufe, O. K., & Evbayiro-Osagie, E. I. (2023). Credit risk management and the financial performance of deposit money banks: some new evidence. *Journal of Risk and Financial Management*, *16*(7), 302. https://doi.org/10.3390/jrfm16070302

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why Should I Trust You?": Explaining the Predictions of Any Classifier. https://doi.org/10.1145/2939672.2939778

Roshan, M., & Khodarahmi, S. (2024). Measuring Credit Risk and Capital Adequacy Considering the Size and Ownership Structure of Listed Banks in Iran Based on the Generalized Method of Moments (GMM) Panel Model. *Management Accounting and Auditing Knowledge*, *14*(54), 313-329. https://www.jmaak.ir/article_23582.html

Saito, T., & Rehmsmeier, M. (2015). The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. *PLoS One*, *10*(3), e0118432. https://doi.org/10.1371/journal.pone.0118432

Temba, G. I., Kasoga, P. S., & Keregero, C. M. (2024). Impact of the quality of credit risk management practices on financial performance of commercial banks in Tanzania. *SN Business & Economics*, *4*(3), 38. https://doi.org/10.1007/s43546-024-00636-3

Verbraken, T., Bravo, C., Weber, R., & Baesens, B. (2014). Development and application of consumer credit scoring models using profit-based classification measures. *European Journal of Operational Research*, *238*(2), 505-513. https://doi.org/10.1016/j.ejor.2014.04.001

Verbraken, T., Verbeke, W., & Baesens, B. (2014). A novel profit maximizing metric for measuring classification performance of customer churn prediction models. *IEEE Transactions on Knowledge and Data Engineering*, *25*(5), 961-973. https://doi.org/10.1109/TKDE.2012.50

Zadrozny, B., & Elkan, C. (2001). Obtaining calibrated probability estimates from decision trees and naive Bayesian classifiers. https://cseweb.ucsd.edu/~elkan/calibrated.pdf

Zhang, D., Wang, J., & Ji, G. (2021). Explainable artificial intelligence in credit risk management: A review and case study. *Artificial Intelligence Review*, *54*, 3937-3980.