

UDC 336.77:004.8

THE ROLE OF ARTIFICIAL INTELLIGENCE IN IMPROVING LOAN CLASSIFICATION AND CREDIT RISK ASSESSMENT

Kinjayev Kattakul Nurmatovich

samurai6356693@gmail.com

Base Doctoral Student Denov Institute of Entrepreneurship and Pedagogy

Annotatsiya. Ushbu tezis kreditlarni tasniflash va kredit riskini baholash jarayonlarida sun'iy intellekt texnologiyalarining rolini tahlil qiladi. Tadqiqotda mashinaviy o'qitish, ansambl modellari, neyron tarmoqlar va izohlanadigan sun'iy intellekt yondashuvlarining qarz oluvchining to'lovga layoqatini baholash, muammoli kreditlarni erta aniqlash hamda kredit portfelini segmentlashdagi imkoniyatlari ko'rib chiqiladi. Taklif etilgan konseptual model an'anaviy moliyaviy ko'rsatkichlarni tranzaksion va xulq-atvor ma'lumotlari bilan birlashtiradi. Natijalar shuni ko'rsatadiki, sun'iy intellektdan foydalanish risk signallarini aniqlash tezligini oshirishi, tasniflashning aniqligi va izchilligini yaxshilashi hamda kredit qarorlarini qo'llab-quvvatlash tizimlarini kuchaytirishi mumkin. Shu bilan birga, model tavakkali, ma'lumotlar sifati, diskriminatsiya, maxfiylik va izohlanuvchanlik masalalari qat'iy boshqaruvni talab qiladi.

Kalit so'zlar: sun'iy intellekt, kredit riski, kredit tasnifi, mashinaviy o'qitish, kredit skoringi, muammoli kreditlar, model izohlanuvchanligi.

Аннотация. В тезисе рассматривается роль технологий искусственного интеллекта в классификации кредитов и оценке кредитного риска. Анализируются возможности машинного обучения, ансамблевых моделей, нейронных сетей и объяснимого искусственного интеллекта при оценке кредитоспособности заемщика, раннем выявлении проблемных кредитов и сегментации кредитного портфеля. Предлагаемая концептуальная модель объединяет традиционные финансовые показатели с транзакционными и поведенческими данными. Результаты показывают, что применение искусственного интеллекта способно ускорить выявление сигналов риска, повысить точность и последовательность классификации и усилить системы

поддержки кредитных решений. Одновременно риски моделей, качество данных, дискриминация, конфиденциальность и объяснимость требуют строгого управления.

Ключевые слова: искусственный интеллект, кредитный риск, классификация кредитов, машинное обучение, кредитный скоринг, проблемные кредиты, объяснимость модели.

Abstract. This thesis examines the role of artificial intelligence (AI) in improving loan classification and credit risk assessment. It focuses on machine learning, ensemble methods, neural networks, and explainable AI as tools for estimating borrower creditworthiness, detecting early signs of deterioration, and segmenting loan portfolios. The proposed conceptual framework combines conventional financial variables with transactional and behavioral data to support more dynamic risk assessment. The findings indicate that AI can improve the speed, consistency, and discriminatory power of loan classification while strengthening early-warning and credit decision-support systems. However, model risk, data quality, bias, privacy, governance, and explainability remain critical constraints that require robust control frameworks.

Keywords: artificial intelligence, credit risk, loan classification, machine learning, credit scoring, non-performing loans, explainable AI.

INTRODUCTION

Credit risk remains one of the principal sources of financial loss for banks and other lending institutions. Traditional credit assessment relies heavily on financial ratios, credit history, collateral quality, delinquency status, and expert judgment. Although these methods remain indispensable, they may respond slowly to changes in borrower behavior and can be limited when relationships among risk factors are nonlinear or when large volumes of heterogeneous data must be processed.

Artificial intelligence offers a complementary approach to conventional credit analysis. Machine-learning algorithms can identify complex patterns in borrower data, detect interactions among variables, and update risk estimates as new information becomes available. In practice, AI can support several stages of the credit cycle, including application scoring, probability-of-default estimation, loan grading, early-warning detection, collections prioritization, and portfolio monitoring.

The objective of this thesis is to examine how AI can improve loan classification and credit risk assessment, to identify the main analytical components of an AI-enabled framework, and to evaluate the benefits and constraints associated with its implementation. Particular attention is given to the need to combine predictive performance with transparency, regulatory compliance, and human oversight.

MAIN PART

Loan classification is the process of grouping credit exposures according to their level of risk and expected performance. In conventional banking practice, classification is usually based on repayment status, borrower financial condition, collateral coverage, restructuring history, and forward-looking information. AI does not eliminate these criteria; instead, it can process them jointly with additional data and estimate deterioration risk in a more granular and timely manner.

Machine-learning models commonly used in credit risk include logistic regression enhanced with regularization, decision trees, random forests, gradient-boosting algorithms, support vector machines, and neural networks. Their usefulness depends on the structure of the data and the purpose of the model. Tree-based ensemble methods are particularly effective for tabular banking data because they can model nonlinearities and variable interactions. Neural networks can be valuable when datasets are very large or when unstructured information such as text is included.

An AI-supported credit-risk system can use both static and dynamic variables. Static variables include borrower income, leverage, debt-service coverage, sector, collateral, maturity, and credit history. Dynamic variables may include changes in account turnover, payment frequency, arrears patterns, cash-flow volatility, utilization of credit lines, digital transaction behavior, and changes in external credit indicators. The inclusion of dynamic information is especially important for early identification of credit deterioration.

For model development, the target variable must be defined clearly. Depending on the institution, the model can predict default within a fixed horizon, transition to a weaker loan grade, entry into non-performing status, or movement between impairment stages. Model outputs can then be mapped to internal risk grades or classification categories. A robust system should also produce probability of default (PD) estimates and, where relevant, interact with loss given default (LGD) and exposure at default (EAD) components in expected-credit-loss calculations.

Explainability is a central requirement. Highly accurate predictions are not sufficient if credit officers, validators, auditors, regulators, or customers cannot understand the main reasons behind a decision. Techniques such as feature importance, partial dependence, SHAP-based explanations, and reason codes can help identify which variables drive an individual or portfolio-level risk estimate. Explainability also supports model validation and can reveal unintended dependence on inappropriate variables.

Governance is equally important. AI models may reproduce historical bias, deteriorate when economic conditions change, or generate unreliable outputs when data quality falls. Therefore, lenders need data-governance rules, independent model validation, back-testing, performance thresholds, override policies, documentation, and periodic recalibration. Human judgment should remain available for exceptional cases and for decisions involving incomplete or contradictory information.

PROPOSED AI-BASED FRAMEWORK AND RESULTS

The proposed framework consists of five sequential layers: data integration, feature engineering, predictive modeling, explainability and validation, and credit decision support. The first layer consolidates borrower, loan, repayment, transaction, collateral, and macroeconomic data. The second transforms raw information into risk indicators. The third estimates default or migration risk using multiple candidate models. The fourth evaluates model stability, discrimination, calibration, fairness, and interpretability. The fifth converts model outputs into actionable loan classifications and monitoring priorities.

Risk component	AI-supported indicator	Expected management use
Repayment behavior	Days-past-due trend, payment irregularity, missed-payment sequence	Early warning and watch-list assignment
Cash-flow condition	Declining inflows, rising volatility, weakening debt-service capacity	Reassessment of borrower grade
Exposure behavior	Rapid utilization growth, repeated limit exhaustion, concentration increase	Portfolio monitoring and limit review

Borrower profile	Leverage, profitability, liquidity, credit history, sectoral sensitivity	PD estimation and loan classification
Model explanation	Key variable contributions and reason codes	Credit officer review and validation
Model performance	AUC/Gini, precision-recall, calibration, stability metrics	Validation, recalibration, and governance

The analytical results of the proposed framework indicate four major improvements over a purely rule-based approach. First, AI can capture nonlinear relationships among borrower characteristics and repayment behavior, which improves risk differentiation between borrowers with similar conventional ratios. Second, dynamic data allow risk estimates to be updated earlier than classifications based only on overdue status. Third, automated risk scoring increases consistency across branches and credit officers. Fourth, explainability tools make it possible to combine algorithmic predictions with expert review instead of treating the model as a black box.

A practical classification architecture can divide exposures into low-risk, moderate-risk, elevated-risk, and high-risk groups based on calibrated probability-of-default ranges and deterioration signals. Borrowers with stable cash flows, low delinquency risk, and no adverse behavioral indicators remain in the low-risk group. Exposures showing early deterioration are moved to enhanced monitoring. High-risk exposures trigger intensive review, provisioning analysis, collateral reassessment, or restructuring consideration. The exact thresholds should be calibrated to the institution's portfolio and validated against realized defaults rather than copied from another bank.

The main limitation of AI-based assessment is that higher predictive accuracy can create false confidence if the underlying data are incomplete, biased, or unstable. Performance can also decline under structural economic change. For this reason, stress testing, challenger models, periodic recalibration, and independent validation are necessary. AI should therefore be viewed as an advanced decision-support technology, not as a substitute for sound credit policy and professional judgment.

CONCLUSION

Artificial intelligence can materially strengthen loan classification and credit risk assessment by processing large and diverse datasets, detecting nonlinear patterns, identifying early signs of deterioration, and producing more granular risk estimates. Its

greatest value lies in combining traditional financial analysis with dynamic borrower behavior and in supporting continuous portfolio monitoring.

Effective implementation requires more than a high-performing algorithm. Banks must establish clear target definitions, reliable data pipelines, transparent classification rules, explainability mechanisms, validation procedures, fairness controls, and human oversight. When these conditions are satisfied, AI can improve the timeliness and consistency of credit decisions while supporting stronger risk management and more proactive treatment of problem exposures.

REFERENCES

1. Basel Committee on Banking Supervision. (2000). Principles for the management of credit risk. Bank for International Settlements.
2. Basel Committee on Banking Supervision. (2023). Supervisory framework for the use of artificial intelligence and machine learning in financial services: Selected supervisory considerations. Bank for International Settlements.
3. Bazarbash, M. (2019). FinTech in financial inclusion: Machine learning applications in assessing credit risk. IMF Working Paper, 19/109. International Monetary Fund. <https://doi.org/10.5089/9781498314428.001>
4. European Banking Authority. (2020). Report on big data and advanced analytics. European Banking Authority.
5. Financial Stability Board. (2017). Artificial intelligence and machine learning in financial services: Market developments and financial stability implications. Financial Stability Board.
6. Lessmann, S., Baesens, B., Seow, H.-V., & Thomas, L. C. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. European Journal of Operational Research, 247(1), 124–136. <https://doi.org/10.1016/j.ejor.2015.05.030>
7. Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. In Advances in Neural Information Processing Systems (Vol. 30).
8. Siddiqi, N. (2017). Intelligent credit scoring: Building and implementing better credit risk scorecards (2nd ed.). Wiley.
9. Thomas, L. C., Crook, J. N., & Edelman, D. B. (2017). Credit scoring and its applications (2nd ed.). SIAM.
10. World Bank. (2019). Credit scoring approaches guidelines. World Bank Group.