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SPECIFICS OF PREDICTING THE PROFITABILITY OF INDIVIDUAL BANK PRODUCTS BASED ON MACHINE LEARNING

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The article examines the application of machine learning methods for forecasting the profitability of certain banking products. The importance of introducing intelligent algorithms in the banking sector is emphasized, which is due to the need to improve the accuracy of financial forecasts, minimize risks and improve strategic management. The relevance of using machine learning in the context of growing competition in the banking sector, tightening regulatory requirements, and the need to strengthen the financial stability of banking institutions is substantiated. It is shown that traditional econometric models have a limited ability to account for nonlinear dependencies, which limits their effectiveness in a rapidly changing economic environment. The study examines the main determinants of the profitability of banking products, including interest margin, operating expenses, credit risk, macroeconomic factors, and regulatory constraints. It explores the use of machine learning to build adaptive predictive models that can identify hidden patterns in financial data and provide more accurate estimates of the future profitability of banking products. The efficiency of key algorithms, including linear and logistic regression, decision trees, ensemble methods and neural networks, is analyzed. It is shown that neural networks have the highest level of predictive accuracy, but their implementation requires significant computational resources. The study proves that the introduction of machine learning in predicting the profitability of banking products helps to improve the accuracy of financial estimates, reduce risks and improve the strategic planning of banking institutions.

Keywords: profitability forecasting, banking products, machine learning, artificial intelligence, neural networks, gradient boosting, financial risks, adaptive models.

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Introduction and problem statement

Predicting the profitability of individual bank products is one of the key tasks in modern financial management, as it directly affects strategic planning, optimization of the loan portfolio, and the efficient use of capital. In this regard, there is a growing need for innovative approaches that enable highly accurate assessments of future financial outcomes, considering the multifactorial nature of banking operations and the dynamic changes in the economic environment. One of the most promising tools in this context is machine learning methods, which open new opportunities for processing large volumes of data, constructing complex models, and identifying hidden patterns in financial information.

Traditional approaches to forecasting the profitability of banking products widely utilize econometric methods; however, they are often limited in their ability to account for nonlinear dependencies and the variability of external factors. The use of machine learning algorithms helps to overcome these limitations, improving forecast accuracy through adaptive analysis of historical data and rapid trend detection. In particular, deep learning methods, ensemble modeling, and regression analysis with neural networks demonstrate a high level of predictive accuracy, providing banks with significant competitive advantages.

The relevance of this research is driven by increasing competition in the banking sector, the tightening of regulatory requirements, and the need to enhance the financial stability of banking institutions. In the current environment of economic instability and financial market volatility, effective forecasting of the profitability of individual banking products has become a crucial element of risk management and strategic decision-making. The application of machine learning not only improves the quality of forecasts but also minimizes risks associated with the underestimation or overestimation of financial outcomes for specific banking instruments.

The issue of utilizing machine learning for optimizing banking operations is gradually gaining attention among domestic researchers. In particular, the study by Pavliuchenko D.M. [1] explores the implementation of these technologies in the banking sector. The author highlights that the integration of AI and machine learning can facilitate the identification of financial risks, improve financial forecasting, and automate the analysis of accounting and financial data.

The article by Chornovol A.O., Honcharuk Ya.M., Khelemenyka Ye.I., and Kysylytsia S.O. [2] examines the potential of AI in enhancing forecast accuracy, detecting fraudulent schemes, and optimizing the management of credit and insurance risks. Additionally, Yakovlev A.A. and Yatsenko R.M. [3] investigate the application of machine learning models for assessing the financial stability of banks.

Thus, the analysis of scientific sources indicates the growing role of artificial intelligence and machine learning in the banking sector, particularly in the context of financial forecasting, risk management, and financial stability assessment. These studies emphasize the necessity of implementing modern technologies to enhance the efficiency and reliability of banking services.

The purpose of the article

The objective of this study is to justify the feasibility of using machine learning in forecasting the profitability of banking products and to identify optimal approaches for constructing effective predictive models. A key aspect of this research is the analysis of the accuracy of various machine learning methods, comparison of their predictive capabilities, and the development of recommendations for their practical application in banking operations.

The theoretical and practical significance of the study is to improve the methodological framework for financial forecasting, which will contribute to enhancing the efficiency of financial planning and ensuring the stable development of banking institutions.

Presentation of the main material

The profitability of banking products is a key indicator of the financial efficiency of banking operations and determines the stability and competitiveness of a financial institution in a dynamic economic environment. It reflects the bank's ability to generate financial returns from its products and services while considering income levels, costs, risks, and market conditions. The economic nature of banking product profitability is based on a combination of revenue generation, the cost of financial operations, and regulatory influence, which collectively shape a bank's profit strategy.

The primary determinants of banking product profitability include net interest margin, operational costs, credit risk levels, macroeconomic factors, competitive pressure, regulatory changes, and financial market dynamics. The net interest margin represents the difference between income from lending and the cost of acquiring financial resources, serving as the primary source of profit for most banks. Operational costs, which encompass administrative, technological, and marketing expenses, directly impact financial performance and require efficient management to minimize their effect on overall profitability.

The level of credit risk directly influences the formation of provisions for potential losses, which, in turn, reduces the bank's net profit. Additionally, macroeconomic factors, such as inflation rate, central bank policy rates, exchange rate fluctuations, and overall business activity, are significant determinants of banking sector financial performance. Market conditions and regulatory changes in the banking sector also play a critical role in shaping the profitability of banking products, as they define acceptable risk thresholds and establish capitalization and liquidity requirements [4].

Traditional methods for forecasting the profitability of banking products rely on econometric models, statistical techniques, and financial analysis. The primary approaches include trend analysis, regression modeling, time series analysis, and factor analysis. However, classical forecasting methods exhibit several substantial limitations, including the inability to account for complex interactions among financial variables, a lack of adaptability to rapid market fluctuations, and limited capacity for processing large volumes of data.

A fundamental challenge of traditional approaches is their reliance on linear models, which do not always adequately capture real-world financial processes, given the multifactorial and highly volatile nature of banking activities. Furthermore, classical methods often overlook nonlinear effects driven by behavioral market factors, leading to inaccurate predictions, particularly during economic crises or periods of financial instability.

One of the key drawbacks of traditional models is their limited ability to update predictive estimates in real time. Given the constantly evolving macroeconomic and regulatory landscape, the banking sector requires more adaptive approaches to analysis and forecasting. In this regard, machine learning techniques have gained significant relevance, as they enable the identification of intricate patterns and interdependencies among variables, thereby improving the accuracy of profitability predictions for banking products [5].

Machine learning has emerged as a highly effective tool for financial forecasting in the banking sector, leveraging algorithms capable of autonomously detecting trends in large datasets and dynamically refining models in response to market fluctuations.

Financial forecasting through machine learning incorporates various methodologies, including linear and logistic regression, decision trees, neural networks, random forests, and gradient boosting algorithms. While linear and logistic regression serve as fundamental techniques for quantifying the impact of individual factors on financial outcomes, decision trees and ensemble methods facilitate the analysis of complex, multidimensional relationships.

Neural networks stand out as particularly powerful machine learning models, adept at capturing nonlinear dependencies and uncovering hidden trends in financial data. The advancement of deep learning, which utilizes multi-layered neural network architectures, further enhances predictive accuracy by allowing models to adapt to the ever-changing economic environment with greater precision.

The integration of machine learning into the banking sector offers vast opportunities for enhancing the accuracy of financial forecasting, mitigating risks, and improving the management of banking product profitability. As a result, it has become one of the key tools in financial analytics in the 21st century.

Machine learning methods have become an integral part of modern financial analysis and forecasting, providing more precise and flexible models for assessing the profitability of banking products. The selection of a specific algorithm depends on the complexity of the task, the structure of the input data, and the required forecasting accuracy. The primary categories of machine learning methods used in financial forecasting include linear models, tree-based algorithms, ensemble methods, and neural networks.

Linear models, such as multiple linear regression and logistic regression, serve as fundamental tools for evaluating relationships between financial variables and predicting profitability. These methods are particularly effective when there is a linear correlation between predictors and the target variable. However, their accuracy diminishes when modeling complex nonlinear processes, making them less suitable for capturing intricate financial dependencies.

Tree-based algorithms, including Classification and Regression Trees (CART), are capable of capturing complex relationships between variables. These models provide interpretability in decision-making, making them useful for financial applications. However, they are prone to overfitting, which can reduce the model's generalization ability, particularly when dealing with highly variable financial data.

Ensemble methods, such as Random Forest and Gradient Boosting, significantly enhance forecasting accuracy by aggregating the outputs of multiple individual models to produce an optimal prediction. These techniques exhibit high efficiency in financial analysis, particularly when handling a large number of input variables. By combining multiple weak learners, ensemble methods mitigate the risk of overfitting while improving the robustness and precision of financial models [6].

Neural networks, including Multilayer Perceptrons (MLP) and Deep Neural Networks (DNNs), excel in modeling complex nonlinear dependencies. These models are particularly effective when dealing with high-dimensional data with significant noise. However, their application requires substantial computational resources and a sufficiently large volume of training data to achieve reliable predictions [7].

Thus, the selection of the most suitable machine learning method for predicting the profitability of banking products depends on the specific nature of the problem, the availability of historical data, and the required accuracy of predictive estimates.

The quality of forecasting is directly influenced by the correct formation of the data sample and its preprocessing. The process of preparing data for machine learning involves collection, cleaning, normalization, and transformation to enhance model accuracy and ensure the reliability of predictions.

For forecasting the profitability of banking products, both internal and external data sources are utilized:

– internal data includes the bank's financial indicators, customer transaction history, credit ratings, deposit program conditions, and investment portfolio details;

– external data consists of macroeconomic indicators, market trends, regulatory changes, and geopolitical factors that may impact the bank's financial stability.

Before applying machine learning algorithms, data undergoes a cleaning process, which involves removing missing or incorrect values and normalizing variables to ensure the correctness of the modeling process. Another crucial step is feature engineering, which involves creating new predictive variables based on existing data to enhance forecasting accuracy and improve model performance.

An optimal data split involves dividing the dataset into training, validation, and test sets, ensuring that the model generalizes well and mitigating the risk of overfitting. The use of cross-validation is a crucial component of the model training process, as it helps assess the stability of predictions and fine-tune model parameters to enhance performance.

Regression models, particularly multiple linear regression and logistic regression, serve as fundamental methods for financial forecasting. These models help quantify the impact of individual profitability determinants on overall financial outcomes. However, their effectiveness is limited when it comes to capturing complex nonlinear dependencies [8].

Neural networks have demonstrated high efficiency in financial analysis, enabling the construction of adaptive models for banking product profitability forecasting. In particular, Multilayer Perceptrons (MLP), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) represent promising directions in financial prediction [9-10]. These methods allow for the analysis of temporal patterns and dynamic trends in financial data, making them particularly useful for time-series forecasting.

Ensemble methods, such as Random Forest and Gradient Boosting, enhance prediction robustness by combining the outputs of multiple weaker models. Random Forest leverages randomized variable selection to construct independent decision trees, while Gradient Boosting sequentially corrects the errors of previous models, progressively improving forecasting accuracy.

The effectiveness of machine learning models is assessed based on key forecasting metrics, the most commonly used of which include mean squared error (MSE), mean absolute error (MAE), the coefficient of determination (RI), and logarithmic loss (Log Loss). To enhance the accuracy of predictions, it is essential to test models on real financial data from banks and evaluate their adaptability to changes in market conditions. The use of regularization techniques, such as Lasso and Ridge regression, helps prevent overfitting and improves model robustness against variations in the dataset [14].

Thus, the application of machine learning methods in forecasting the profitability of banking products significantly improves prediction accuracy, which is a critical component of strategic management in banking operations.

Within the empirical study, three primary categories of banking products that hold strategic importance for a bank's profitability have been selected:

– credit products;
– deposit programs;
– investment instruments.

Credit products represent one of the key revenue streams for banks, as they generate interest income and directly impact credit risk levels. The profitability analysis of credit products considers various parameters, including:

– average interest rate;
– level of non-performing loans (NPLs);
– dynamics of loan issuance volumes;
– regulatory constraints.

These factors determine the risk-adjusted profitability of credit operations and influence the overall financial stability of the banking institution.

Deposit programs form the funding base of the banking system and determine the cost of attracted capital. Key factors influencing the profitability of deposit products include: trends in deposit interest rates; structure of the deposit portfolio; bank liquidity levels.

These factors play a crucial role in forecasting the profitability of deposit programs, as they directly affect the availability of financial resources and the overall cost of capital for lending and investment activities.

Investment instruments, such as government bonds, corporate securities, and interbank market operations, are essential components of a bank's financial strategy. The profitability of these instruments is analyzed based on: market volatility; yield levels; regulatory requirements for banking investments (Table 1)

The effectiveness of investment decisions is critical for maintaining financial stability, optimizing capital allocation, and ensuring compliance with prudential banking regulations.

To enhance the accuracy of banking product profitability forecasting, we recommend leveraging machine learning techniques that have proven to be highly effective in financial analysis. These include multiple linear regression, random forests, gradient boosting, and neural networks.

Table 1

Characteristics of Banking Products for Forecasting

Banking Product	Source of Income	Key Risks	Key Profitability Factors
Loans	Interest Income	Credit risk, liquidity, macroeconomic changes	Interest rate, default rate, loan volume
Deposits	The difference between the borrowing and placement rate	Liquidity, changes in interest rate policy	Size of the deposit portfolio, structure of borrowed funds
Investments	Income from bonds, shares and other assets	Market volatility, currency risk, regulatory restrictions	Return on assets, risk level, changes in the securities market

Source: generalized by the author according to [7-8, 12-13].

Model training should be based on real financial data from banks, spanning the last five years, and should incorporate macroeconomic indicators, interest rate dynamics, banking transaction volumes, and regulatory requirements (Table 2).

Table 2

Structure of Financial Data for Model Training

Variable	Description	Unit of Measurement
Average Interest Rate	Interest Rate on Loans and Deposits	%
Loan Issuance Volume	Total Volume of Credit Operations	Million UAH (mln UAH)
Default Rate	Share of Non-Performing Loans (NPLs)	%
Bond Yield	Average Yield of Government and Corporate Bonds	%
Overall Liquidity Level	Share of Liquid Assets in Total Balance	%
Gross Domestic Product (GDP)	Overall Level of Economic Development	Billion UAH (bln UAH)

Source: compiled by the author

To assess the effectiveness of profitability forecasting, the following metrics can be used: Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (RI). Based on generalized observations, it is evident that neural networks provide the highest prediction accuracy, as they most effectively capture nonlinear relationships between variables. Random forests and gradient boosting also demonstrate high efficiency, whereas linear regression has limited predictive capability due to the complexity of financial processes [13].

Macroeconomic conditions and government regulation play a crucial role in shaping the profitability of banking products. The analysis incorporates the impact of central bank interest rate fluctuations, inflation levels, changes in tax legislation, and foreign exchange market dynamics (Table 3).

Table 3

Impact Level of Macroeconomic Factors on the Forecasted Profitability of Banking Products

Factor	Impact on Loans	Impact on Deposits	Impact on Investments
Central Bank Interest Rate	High	Medium	High
Inflation	High	Low	Medium
Exchange Rate	Medium	High	High
Regulatory Requirements	High	High	Medium

Source: compiled by the author

The findings of this study confirm that the implementation of machine learning significantly enhances the accuracy of banking product profitability forecasting, contributing to effective financial risk management and strategic planning in banking operations.

Profitability modeling in the banking sector requires adapting machine learning methods to the specific characteristics of financial markets, which are characterized by high volatility, strict regulatory requirements, and complex multifactor dependencies. This necessitates specialized approaches to predictive model development.

One of the key areas for improvement is the selection of optimal predictors. The application of correlation analysis and feature selection techniques, such as LASSO regression or the SHAP algorithm, enables the identification of the most influential variables affecting banking product profitability.

Another critical aspect is adjusting for seasonality and cyclicality in banking processes. For instance, loan demand may fluctuate based on macroeconomic cycles, changes in interest rates, or regulatory constraints. The use of Recurrent Neural Networks (RNNs) and deep learning methods such as Long Short-Term Memory (LSTM) allows for a more effective prediction of these patterns [13].

In addition, the application of data augmentation techniques and adaptive learning (Transfer Learning) enhances the resilience of models to financial market fluctuations, which is particularly crucial during periods of economic instability.

Ensemble machine learning methods have proven to be among the most effective approaches for improving forecasting accuracy in financial analysis. The use of algorithms such as Random Forest, Gradient Boosting (XGBoost, LightGBM, CatBoost), and model stacking (Stacking) allows for the combination of different algorithms' strengths while mitigating their weaknesses. Hybrid models, which integrate multiple machine learning techniques, further improve prediction accuracy. For example, combining neural networks with gradient boosting can create a balance between model flexibility and interpretability.

For the effective implementation of machine learning in the banking sector, several practical considerations must be taken into account to ensure the seamless integration of analytical tools into financial operations. One of the key aspects is the adoption of modern analytical platforms, particularly cloud-based solutions such as AWS, Azure, or Google Cloud, which facilitate automated computations and enable secure storage of large datasets.

Another crucial factor is the regular updating of models, ensuring that they are continuously trained on up-to-date financial data while accounting for macroeconomic shifts and customer behavior patterns. This allows machine learning algorithms to remain highly adaptive in dynamic market conditions, improving their predictive reliability and effectiveness.

Since complex machine learning models require significant computational resources, it is crucial to implement optimization techniques, such as distributed computing and hyperparameter tuning, to reduce computational costs and improve model performance. Another critical aspect is the adoption of Explainable AI (XAI), which ensures the transparency of predictive models, an essential factor for financial regulation and banking supervision. Compliance with explainability requirements is key to ensuring the proper use of algorithms under regulatory oversight.

Beyond technical considerations, special attention should be given to the training of banking analysts, who must be proficient in machine learning fundamentals, financial data processing techniques, and the effective use of analytical tools in daily banking operations [3-4].

Despite the significant advantages of machine learning in the banking sector, its application is associated with several risks that may impact forecast accuracy, operational efficiency, and regulatory compliance.

One of the most critical risks is overfitting, where a model exhibits high accuracy on training data but fails to generalize well to new real-world observations, potentially leading to erroneous financial forecasts. Another major concern is regulatory non-compliance, as the use of so-called «black-box models», where decision-making processes are difficult to interpret, may contradict financial regulators' requirements for model explainability and transparency in forecasting.

Another critical challenge is ensuring cybersecurity and data protection, as the use of confidential financial information in machine learning processes requires strict adherence to security standards and access control measures. Additionally, high computational costs remain a significant concern, as complex algorithms demand substantial computational resources for training, potentially increasing operational expenses for banks.

Moreover, the stability of models in crisis situations must be carefully considered. During periods of financial instability, the accuracy of machine learning algorithms may significantly decline due to changing macroeconomic conditions, necessitating the implementation of adaptive mechanisms for adjusting forecasts [14].

Thus, the integration of machine learning into banking analytics requires a comprehensive approach that includes:

– technical optimization of models;
– regulatory compliance assurance;
– enhancing transparency in predictive algorithms;
– reducing operational costs;
– implementing risk mitigation measures related

to AI adoption in the financial sector.

Table 4 presents an evaluation of the key risks associated with machine learning applications in the banking sector.

Thus, the optimization of machine learning models and the implementation of appropriate risk control mechanisms are essential components for the effective utilization of technology in the banking sector.

Table 4

Risk Analysis of Machine Learning Implementation in Banks

Risk Type	Description	Mitigation Strategies
Overfitting	The model fits the training data too precisely but performs poorly on test data	Use cross-validation, regularization techniques (Lasso, Ridge), and ensemble learning.
Regulatory Constraints	Lack of explainability in predictions may contradict supervisory requirements	Implement Explainable AI (XAI), use interpretable models, and comply with financial regulations
Cybersecurity	Risk of data leaks and attacks on the model	Apply encryption, access control, and secure cloud infrastructure
High Costs	Computational resources can be expensive	Optimize model complexity, use distributed computing, and employ cloud-based solutions

Source: compiled by the author

Conclusions

The findings of this study confirm that machine learning methods are an effective tool for forecasting the profitability of banking products. The theoretical analysis of forecasting methodologies highlighted the limitations of traditional econometric models, which often fail to account for nonlinear dependencies and dynamic market fluctuations. The study substantiates the advantages of modern machine learning algorithms, particularly gradient boosting, random forests, and neural networks, which provide higher predictive accuracy compared to classical methods.

The study further establishes that the effectiveness of profitability forecasting largely depends on data quality, the selection of relevant variables, and model adaptation to macroeconomic conditions. The modeling results confirm that ensemble methods and hybrid models effectively mitigate the weaknesses of individual algorithms, enhancing prediction accuracy. Additionally, incorporating macroeconomic and regulatory factors is crucial for avoiding significant forecasting errors in long-term financial assessments.

The future development of profitability forecasting models in banking lies in the implementation of deep neural networks, adaptive learning techniques, and the integration of predictive analytics into financial information systems. One of the key areas for further research is the development of interpretable artificial intelligence models (Explainable AI, XAI), which will enable the combination of high predictive accuracy with regulatory transparency requirements. Another promising direction is the advancement of online learning techniques, which will allow predictive models to dynamically adjust to real-time market fluctuations.

The practical significance of the obtained results lies in their potential application for optimizing banking financial strategies, improving risk management efficiency, and enhancing decision-making processes related to pricing and structuring banking products. The adoption of machine learning models will contribute to minimizing credit risk, optimizing liquidity management, and strengthening banks’ competitive positions in the financial market.

The results of this research can be utilized by banking institutions, financial analysts, and regulatory authorities to enhance predictive analytics and develop strategic approaches for the sustainable growth of the banking sector in response to rapid economic changes.

REFERENCES

1. Basel Committee on Banking Supervision. (2017). *Implications of fintech developments for banks and bank supervisors*. Bank for International Settlements. Retrieved from https://www.bis.org [in English].

2. Chornovol, A. O., Honcharuk, Y. M., Khelemenyk, Y. I., & Kysylytsia, S. O. (2025). *Vykorystannia shtuchnoho intelektu v upravlinni finansovymy ryzykamy bankiv i strakhovykh kompaniy* [The use of artificial intelligence in managing financial risks of banks and insurance companies]. *Aktualni pytannia ekonomichnykh nauk* [Actual Issues of Economic Sciences]. DOI: https://doi.org/10.5281/zenodo.14887306 [in Ukrainian].

3. Farion, V., & Homotyuk, A. (2024). *Vykorystannia shtuchnoho intelektu dlia prohnozuvannia finansovykh pokaznykiv* [The use of artificial intelligence for financial forecasting]. *Ekonomichnyi analiz* [Economic Analysis], *34*(2), 327. DOI: https://doi.org/10.35774/econa2024.02.327 [in Ukrainian].

4. Krukovets, D. (2020). *Data science opportunities at central banks: Overview. Visnyk of the National Bank of Ukraine, 249*, 13–24. DOI: https://doi.org/10.26531/vnbu2020.249.02 [in English].

5. McKinsey & Company. (2021). *The future of banking: AI-driven strategies for financial institutions*. Retrieved from https://www.mckinsey.com [in English].

6. National Bank of Ukraine. (2023). *Financial stability report*. Retrieved from https://bank.gov.ua/ua/stability/report [in English].

7. National Bank of Ukraine. (2023). *Stratehiia rozvytku finansovoho sektoru Ukrainy* [Strategy for the development of the financial sector of Ukraine]. Retrieved from https://bank.gov.ua/ua/file/download?file=Strategy_finsector_NBU.pdf [in Ukrainian].

8. Oschadbank. (2024). *Shtuchnyi intelekt v ukrainskomu bankivskomu sektori: mozhlyvist chy neobkhidnist?* [Artificial intelligence in the Ukrainian banking sector: Opportunity or necessity?]. Retrieved from https://www.oschadbank.ua/news/stucnij-intelekt-v-ukrainskomu-bankivskomu-sektori-mozlivist-ci-neobhidnist [in Ukrainian].

9. Lukianenko, D., & Strelchenko, I. (2021). *Neuromodeling of features of crisis contagion on financial markets between countries with different levels of economic development.* Neuro-Fuzzy Modeling Techniques in Economics, 10, 136-163. DOI: http://doi.org/10.33111/nfmte.2021.136. Retrieved from https://nfmte.kneu.ua/archive/2021/10.06 [in English].

10. Strelchenko, I., Koczar, J., Pysarkova, V. (2022). Using cluster analysis to assess financial stability as an object of manageriaimpact of regional competitive immunity. *Akademichnyi ohliad – Academy Review, 2(57),* 111-124. DOI: https://doi.org/10.32342/2074-5354-2022-2-57-9. Retrieved from https://ir.duan.edu.ua/handle/123456789/4248 [in English].

11. Pavliuchenko, D. M. (2024). *Vplyv shtuchnoho intelektu ta mashynnoho navchannia na bankivski posluhy* [The impact of artificial intelligence and machine learning on banking services]. *Akademichni vizin* [Academic Visions], *(32).* DOI: https://doi.org/10.5281/zenodo.12936652 [in Ukrainian].

12. World Bank. (2020). *Global financial development report: Bank regulation and supervision a decade after the global financial crisis.* Washington, D.C.: World Bank. Retrieved from https://documents1.worldbank.org/curated/zh/513831574784180010/pdf/Global-Financial- Development-Report-2019-2020-Bank-Regulation-and-Supervision-a-Decade-after-the-Global-Financial-Crisis.pdf [in English].

13. World Economic Forum. (2022). *The future of banking and financial services in the digital age.* Retrieved from https://www.weforum.org [in English].

14. Yakoviev, A. A., & Yatsenko, R. M. (2021). *Zastosuvannia modelei mashynnoho navchannia do otsinky finansovoi stiikosti komertsiinykh bankiv* [Application of machine learning models for assessing the financial stability of commercial banks]. *Suchasni problemy modeliuvannia sotsialno-ekonomichnykh system* [Modern Problems of Modeling Socio-Economic Systems]: *Proceedings of the XIII International Scientific and Practical Conference, April 8-9, 2021.* Bratislava – Kharkiv, VSEM – S. Kuznets National University of Economics. Retrieved from https://mpsesm.hneu.edu.ua/book/2021/thesis04-yaro.html [in Ukrainian].

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ОСОБЛИВОСТІ ПРОГНОЗУВАННЯ ПРИБУТКОВОСТІ ОКРЕМИХ ПРОДУКТІВ БАНКУ НА ОСНОВІ МАШИННОГО НАВЧАННЯ

Стрельченко Інна, Стогній Дмитро, Стрельченко Анатолій

У статті розглянуто застосування методів машинного навчання для прогнозування прибутковості окремих банківських продуктів. Підкреслено важливість впровадження інтелектуальних алгоритмів у банківському секторі, що зумовлено необхідністю підвищення точності фінансових прогнозів, мінімізації ризиків та покращення стратегічного управління. Обґрунтовано актуальність використання машинного навчання в умовах зростання конкуренції в банківському секторі, посилення регуляторних вимог та необхідності зміцнення фінансової стійкості банківських установ. Показано, що традиційні економетричні моделі мають обмежену здатність враховувати нелінійні залежності, що обмежує їх ефективність у швидкозмінному економічному середовищі. У дослідженні проаналізовано основні детермінанти прибутковості банківських продуктів, зокрема процентну маржу, операційні витрати, кредитний ризик, макроекономічні фактори та регуляторні обмеження. У ньому досліджується використання машинного навчання для побудови адаптивних прогнозних моделей, які можуть виявляти приховані закономірності у фінансових даних і надавати більш точні оцінки майбутньої прибутковості банківських продуктів. Проаналізовано ефективність ключових алгоритмів, включаючи лінійну та логістичну регресію, дерева рішень, ансамблеві методи та нейронні мережі. Показа-

но, що нейронні мережі мають найвищий рівень точності прогнозування, але їх реалізація потребує значних обчислювальних ресурсів. Дослідження доводить, що впровадження машинного навчання в прогнозування прибутковості банківських продуктів сприяє підвищенню точності фінансових оцінок, зниженню ризиків та покращенню стратегічного планування банківських установ.

Ключові слова: прогнозування прибутковості, банківські продукти, машинне навчання, штучний інтелект, нейронні мережі, градієнтний бустинг, фінансові ризики, адаптивні моделі.

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The article examines the application of machine learning methods for forecasting the profitability of certain banking products. The importance of introducing intelligent algorithms in the banking sector is emphasized, which is due to the need to improve the accuracy of financial forecasts, minimize risks and improve strategic management. The relevance of using machine learning in the context of growing competition in the banking sector, tightening regulatory requirements, and the need to strengthen the financial stability of banking institutions is substantiated. It is shown that traditional econometric models have a limited ability to account for nonlinear dependencies, which limits their effectiveness in a rapidly changing economic environment. The study examines the main determinants of the profitability of banking products, including interest margin, operating expenses, credit risk, macroeconomic factors, and regulatory constraints. It explores the use of machine learning to build adaptive predictive models that can identify hidden patterns in financial data and provide more accurate estimates of the future profitability of banking products. The efficiency of key algorithms, including linear and logistic regression, decision trees, ensemble methods and neural networks, is analyzed. It is shown that neural networks have the highest level of predictive accuracy, but their implementation requires significant computational resources. The study proves that the introduction of machine learning in predicting the profitability of banking products helps to improve the accuracy of financial estimates, reduce risks and improve the strategic planning of banking institutions.

Keywords: profitability forecasting, banking products, machine learning, artificial intelligence, neural networks, gradient boosting, financial risks, adaptive models.

REFERENCES

1. Basel Committee on Banking Supervision. (2017). *Implications of fintech developments for banks and bank supervisors.* Bank for International Settlements. Retrieved from https://www.bis.org [in English].

2. Chornovol, A. O., Honcharuk, Y. M., Khelemenyk, Y. I., & Kysylytsia, S. O. (2025). *Vykorystannia shtuchnoho intelektu v upravlinni finansovymy ryzykamy bankiv i strakhovykh kompaniy* [The use of artificial intelligence in managing financial risks of banks and insurance companies]. *Aktualni pytannia ekonomichnykh nauk* [Actual Issues of Economic Sciences]. DOI: https://doi.org/10.5281/zenodo.14887306 [in Ukrainian].

3. Farion, V., & Homotyuk, A. (2024). *Vykorystannia shtuchnoho intelektu dlia prohnozuvannia finansovykh pokaznykiv* [The use of artificial intelligence for financial forecasting]. *Ekonomichnyi analiz* [Economic Analysis], *34*(2), 327. DOI: https://doi.org/10.35774/econa2024.02.327 [in Ukrainian].

4. Krukovets, D. (2020). *Data science opportunities at central banks: Overview. Visnyk of the National Bank of Ukraine, 249*, 13–24. DOI: https://doi.org/10.26531/vnbu2020.249.02 [in English].

5. McKinsey & Company. (2021). *The future of banking: AI-driven strategies for financial institutions.* Retrieved from https://www.mckinsey.com [in English].

6. National Bank of Ukraine. (2023). *Financial stability report*. Retrieved from https://bank.gov.ua/ua/stability/report [in English].

7. National Bank of Ukraine. (2023). *Stratehiia rozvytku finansovoho sektoru Ukrainy* [Strategy for the development of the financial sector of Ukraine]. Retrieved from https://bank.gov.ua/ua/file/download?file=Strategy_finsector_NBU.pdf [in Ukrainian].

8. Oschadbank. (2024). *Shtuchnyi intelekt v ukrainskomu bankivskomu sektori: mozhlyvist chy neobkhidnist?* [Artificial intelligence in the Ukrainian banking sector: Opportunity or necessity?]. Retrieved from https://www.oschadbank.ua/news/stucnij-intelekt-v-ukrainskomu-bankivskomu-sektori-mozlivist-ci-neobhidnist [in Ukrainian].

9. Lukianenko, D., & Strelchenko, I. (2021). *Neuromodeling of features of crisis contagion on financial markets between countries with different levels of economic development.* Neuro-Fuzzy Modeling Techniques in Economics, 10, 136-163. DOI: http://doi.org/10.33111/nfmte.2021.136. Retrieved from https://nfmte.kneu.ua/archive/2021/10.06 [in English].

10. Strelchenko, I., Koczar, J., Pysarkova, V. (2022). Using cluster analysis to assess financial stability as an object of manageriaimpact of regional competitive immunity. *Akademichnyi ohliad – Academy Review, 2(57),* 111-124. DOI: https://doi.org/10.32342/2074-5354-2022-2-57-9. Retrieved from https://ir.duan.edu.ua/handle/123456789/4248 [in English].

11. Pavliuchenko, D. M. (2024). *Vplyv shtuchnoho intelektu ta mashynnoho navchannia na bankivski posluhy* [The impact of artificial intelligence and machine learning on banking services]. *Akademichni vizin* [Academic Visions], *(32).* DOI: https://doi.org/10.5281/zenodo.12936652 [in Ukrainian].

12. World Bank. (2020). *Global financial development report: Bank regulation and supervision a decade after the global financial crisis.* Washington, D.C.: World Bank. Retrieved from https://documents1.worldbank.org/curated/zh/513831574784180010/pdf/Global-Financial- Development-Report-2019-2020-Bank-Regulation-and-Supervision-a-Decade-after-the-Global-Financial-Crisis.pdf [in English].

13. World Economic Forum. (2022). *The future of banking and financial services in the digital age*. Retrieved from https://www.weforum.org [in English].

14. Yakoviev, A. A., & Yatsenko, R. M. (2021). *Zastosuvannia modelei mashynnoho navchannia do otsinky finansovoi stiikosti komertsiinykh bankiv* [Application of machine learning models for assessing the financial stability of commercial banks]. *Suchasni problemy modeliuvannia sotsialno-ekonomichnykh system* [Modern Problems of Modeling Socio-Economic Systems]: *Proceedings of the XIII International Scientific and Practical Conference, April 8-9, 2021.* Bratislava – Kharkiv, VSEM – S. Kuznets National University of Economics. Retrieved from https://mpsesm.hneu.edu.ua/book/2021/thesis04-yaro.html [in Ukrainian].