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NPL COLLECTION PERFORMANCE PREDICTION MODEL – WHAT TO CHOOSE: AHP OR AI?

Prediction of non-performing loan (NPL) recovery rate is a critical component of financial risk management, requiring accurate estimation of recovery likelihood, recovery amounts, and expected timelines. However, forecasting NPL collection performance is challenged by data limitations, market volatility, regulatory constraints, and the heterogeneity of information across institutions. This paper examines two fundamentally different approaches to NPL prediction: the Analytic Hierarchy Process (AHP), a structured multi-criteria decision-making methodology based on expert judgment, and deep learning (DL), a data-driven paradigm capable of capturing complex nonlinear relationships in large-scale datasets. The analysis highlights AHP's strengths in transparency, interpretability, and applicability in contexts with limited or inconsistent data, as well as its limitations arising from subjective judgments and assumptions of criterion independence. Conversely, deep learning offers superior predictive power when trained on extensive, high-quality data, automatically extracting latent patterns and modeling dynamic borrower behavior, yet it depends heavily on the accuracy and representativeness of historical data and suffers from opacity, high computational costs, and vulnerability to concept drift. In light of volatile financial conditions and recurring data limitations, it is difficult to designate any single approach as universally effective. The complementary nature of data-intensive and judgment-based methodologies indicates that integrating multiple analytical paradigms has the potential to enhance the assessment of NPL collection outcomes. The paper provides a comparative overview of the two most common methods with clearly indicated advantages and disadvantages, and thus possible adequate uses in practice.

Key words: *NPL. – Collection Performance. – Data Quality. – Hybrid Modeling (AHP, AI).*

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1. INTRODUCTION

"A non-performing loan (NPL) is a bank loan that is subject to late repayment or is unlikely to be repaid by the borrower in full."[1] The management and prediction of NPL portfolio performance represent critical functions for banks, financial institutions, asset management companies, and investors aiming to optimize recovery rates and minimize losses. Predicting NPL collection performance involves forecasting both the likelihood and magnitude of recovery from delinquent loans, most commonly through the application of data-driven, statistical, and machine learning methodologies. Accurate forecasting is indispensable for financial institutions and NPL servicers seeking to estimate the potential recovery value of their NPL portfolios.

The performance of NPL collection is influenced by a range of factors. Among the most significant are the behavioral characteristics of debtors, including historical response times, volatility of income, and the burden of existing financial obligations. Depending on the approach, many other attributes can be mentioned: "accurate NPL valuation presents considerable methodological challenges, primarily attributable to four factors: market illiquidity and price opacity, uncertainty in collateral recovery rates, pronounced information asymmetries between originating institutions and potential investors, and protracted bureaucratic procedures."[2] In addition, the effectiveness of the collection strategy, such as the timing of intervention measures, the application of cost-benefit considerations, and the extent of potential debt write-offs, plays an essential role. Macroeconomic conditions, encompassing government policies, broader economic indicators, and the institutional environment, also exert substantial influence on recovery outcomes. Emphasizing some of the conditions is immanent to personal thinking: "relationship between non-performing loans and financial development using country and regional data for nonperforming loans"[3].

1 Sanju Kumar Singh, Basuki Basuki, Rahmat Setiawan, "The effect of non-performing loan on profitability: Empirical evidence from Nepalese commercial banks.", *The Journal of Asian Finance, Economics and Business* 8/2021, 709–716.

2 Wanrong Mu, Congjin Zhou, "Indifference valuation of non-performing loan-backed securities", *AIMS Mathematics* 10/2025, 23394–23410.

3 Peterson K. Ozili, "Non-performing loans and financial development: new evidence", *The Journal of Risk Finance* 20/2019, 59–81.

From an investment perspective, key evaluation parameters might include the expected recovery rate, the anticipated recovery time, the costs associated with the recovery process (such as collection fees and legal expenses), and the price of NPL portfolios, which reflects both risk and the time value of money. Despite these established evaluation frameworks, several persistent challenges complicate the prediction of NPL performance. Chief among these are data quality issues, as accurate and reliable portfolio data are often limited; market volatility, as NPL markets remain inherently unpredictable; and regulatory constraints, since valuation and reporting methodologies must comply with evolving regulatory standards. "For financial organization, data quality is looked at terms of comprehensiveness, consistence, and relevance."[4]

Developing a robust and reliable NPL prediction model therefore necessitates the availability of high-quality, standardized data. This requirement raises a fundamental question: how can such data be obtained in practice?

Acquiring consistent and accurate data remains challenging, particularly under the regulatory framework established by Implementing Regulation (EU) 2023/2083 of 26 September 2023[5]. This regulation specifies the technical standards and templates to be used by credit institutions when disclosing information on credit exposures to potential buyers. Inaccuracies or inconsistencies in these datasets significantly undermine predictive accuracy, as the performance of any predictive model is inherently constrained by the quality of its input data.

Prediction methodologies employed in the context of NPL performance can be broadly classified into three main groups: traditional statistical and mathematical models, machine learning approaches, and econometric or hybrid frameworks. Traditional approaches include the Analytic Hierarchy Process (AHP) for estimating recovery amounts

4 Micah Nyabiba Asamba, "Data Quality Challenges for Financial Industry", *https://www.researchgate.net/publication/331374152_Data_Quality_Challenges_for_Financial_Industry#fullTextFileContent*, 10. November 2025.

5 Commission Implementing Regulation (EU) 2023/2083 of 26 September 2023 laying down implementing technical standards for the application of Article 16(1) of Directive (EU) 2021/2167 of the European Parliament and of the Council with regard to the templates to be used by credit institutions for the provision to buyers of information on their credit exposures in the banking book (Text with EEA relevance), C/2023/6306, *OJ* L 241, 29. 9. 2023, 21–63.

from small samples, linear regression or ordinary least squares (OLS) for predicting continuous recovery values, logistic regression for binary outcomes and other mathematical models which can include probability schemas and sample deduction. Machine learning techniques trying to support human reasoning. "First, perception can be achieved through the sensing measurements of the spectrum. This allows the cognitive radio to identify ongoing RF activities in its surrounding environment. After acquiring the sensing observations, the cognitive radio tries to learn from them in order to classify and organize the observations into suitable categories. This can be achieved through different types of learning algorithms that we discuss below in this survey. Finally, the reasoning ability allows the cognitive radio to use the knowledge acquired through learning to achieve its objectives."[6] But still, used data set should be accurate, precise and comparable. Econometric and hybrid models integrate macroeconomic variables, such as GDP and unemployment rates, with borrower-level data to achieve a more comprehensive representation of the recovery process.

Although these methodologies can achieve high levels of precision, their reliability depends fundamentally on the quality and consistency of the underlying data. Enhancing predictive accuracy would be considerably more straightforward if data were standardized across markets and portfolios; however, in practice, data heterogeneity persists, varying not only between different jurisdictions but also across portfolios within the same market.

In this paper, the authors undertake a theoretical examination of the potential predictive performance of deep learning methods compared with the Analytic Hierarchy Process (AHP) mathematical approach in the context of NPL collection performance modeling.

2. AHP AS A SUITABLE MODEL FOR NPL COLLECTION PERFORMANCE PREDICTION

The Analytic Hierarchy Process (AHP) is a structured, multi-criteria decision-making methodology originally developed by Thomas

6 Mario Bkassiny, Yang Li, Sudharman K. Jayaweera, "A survey on machine-learning techniques in cognitive radios", *IEEE Communications Surveys & Tutorials* 15/2012, 1136–1159.

L. Saaty in the 1970s. AHP, as a "multi-criteria decision-making method where criteria are appropriately ranked"[7] provides a systematic framework for analyzing complex decisions that involve multiple, often conflicting, qualitative and quantitative factors[8]. The method decomposes a decision problem into a hierarchy of interrelated elements – typically comprising the overall goal, a set of criteria and sub-criteria, and the available decision alternatives – and then applies pairwise comparisons to determine the relative importance of each element. Through this process, AHP facilitates the quantification of subjective judgments and integrates them into an objective, mathematically consistent decision model[9].

At its core, AHP relies on the principle of pairwise comparison, where decision elements are compared two at a time to evaluate their relative dominance or preference with respect to a higher-level criterion. Each comparison is expressed using a numerical scale, typically ranging from 1 (equal importance) to 9 (extreme importance), reflecting the strength of preference between the elements. The resulting pairwise comparison matrix is then used to derive a set of priority weights or eigenvectors, representing the relative importance of the decision criteria and alternatives. These weights are normalized and aggregated across all levels of the hierarchy to compute an overall ranking of the alternatives.

A distinguishing feature of the AHP method is its ability to assess the consistency of judgments. Because human decision-making is inherently subjective, inconsistencies may arise when evaluating multiple elements. To address this issue, AHP employs a *consistency ratio* (CR) derived from the consistency index (CI) and a random index (RI) benchmark. A CR value of less than 0.10 is generally considered acceptable, indicating that the pairwise comparisons are logically consistent. If the consistency ratio exceeds this threshold, decision-makers are encouraged to revise their judgments to improve reliability[10]. This

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7 Žarko Dimitrijević, Dušan J. Simjanović, "Application of AHP Method in Enforcement Procedures: The Case of Selling Specific Goods", *HARMONIUS* (*Journal for Legal and Social Studies in South East Europe*) 1/2024, 15.

8 Thomas L. Saaty, *The Analytic Hierarchy Process*, McGraw-Hill, New York 1980, 1–118.

9 Thomas L. Saaty, *Decision Making with Dependence and Feedback: The Analytic Network Process*, RWS Publications, Pittsburgh 1996.

10 Mimica Milošević *et al.*, "Fuzzy and interval AHP approaches in sustainable management for the architectural heritage in smart cities", *Mathematics* 9/2021, 304.

mechanism enhances the robustness and transparency of the AHP process, distinguishing it from less formalized decision-making approaches.

In financial applications, AHP has proven to be an effective tool for dealing with multidimensional problems that require the integration of both quantitative data and expert judgment. Within the context of Non-Performing Loan (NPL) management, the AHP method can be applied to predict or prioritize recovery outcomes when data availability is limited or incomplete. For instance, AHP enables analysts to systematically evaluate recovery determinants – such as borrower creditworthiness, collateral quality, macroeconomic conditions, and collection strategies – by assigning relative weights to each factor based on expert knowledge and historical performance data. The resulting hierarchical model provides a structured approach to estimate recovery probabilities or expected recovery amounts, even in the absence of extensive datasets.

Moreover, the AHP framework offers several advantages in comparison with purely statistical or machine learning approaches. It allows for the explicit incorporation of expert intuition and qualitative assessments that are often difficult to capture numerically, such as the perceived reliability of a debtor, the expected efficiency of a collection strategy, or the stability of a particular market segment. It is also computationally less demanding and can be implemented effectively with relatively small samples, making it particularly suitable for early-stage portfolio analysis or when assessing niche segments of NPL portfolios.

However, the AHP method is not without limitations. One of the primary criticisms is its dependence on subjective human judgment, which may introduce bias and variability into the results. Although the consistency ratio helps mitigate this issue, it cannot eliminate it entirely. Additionally, AHP assumes that the decision criteria are independent of one another, an assumption that may not hold in complex financial environments where interdependencies – such as between borrower behavior and macroeconomic trends – are often significant. The method also becomes increasingly cumbersome as the number of criteria and alternatives grows, since the number of pairwise comparisons increases exponentially, potentially leading to decision fatigue and reduced accuracy.

Despite these limitations, the AHP method remains a valuable and widely applied decision-making framework in both academic research and practical finance. Its transparent structure, flexibility, and ability to incorporate both subjective and objective information make it particularly useful for comparative analysis and strategic decision support. When combined with other quantitative approaches – such as regression analysis or machine learning models – AHP can serve as a complementary tool that enhances interpretability and provides a foundation for hybrid modeling approaches.

3. DEEEP LEARNING POSSIBILITIES

"Deep learning is a form of machine learning that enables computers to learn from experience and understand the world in terms of a hierarchy of concepts. Because the computer gathers knowledge from experience, there is no need for a human computer operator formally to specify all of the knowledge needed by the computer. The hierarchy of concepts allows the computer to learn complicated concepts by building them out of simpler ones."[11] Emerging from the foundational principles of artificial intelligence and computational neuroscience, deep learning has become one of the most influential methodologies in predictive analytics, pattern recognition, and data-driven decision support across information-intensive domains. Its primary advantage lies in the ability to autonomously learn hierarchical feature representations directly from raw or minimally processed data, thereby reducing dependence on manual feature engineering and enhancing predictive accuracy in complex, nonlinear settings.

"Deep learning achieves higher power and flexibility due to its ability to process a large number of features when it deals with unstructured data. A deep learning algorithm passes the data through several layers; each layer is capable of extracting features progressively and passes it to the next layer. Initial layers extract low-level features, and succeeding layers combines features to form a complete representation."[12] Through iterative training on large datasets, the

11 Ian Goodfellow, Yoshua Bengio, Aaron Courville, *Deep learning*, MIT Press, Cambridge 2016, 351.

12 Amitha Mathew, P. Amudha, S. Sivakumari, "Deep learning techniques: an overview", *Advances in Intelligent Systems and Computing* (eds. A. Ella Hassanien, R. Bhatnagar, A. Darwish), Springer, Singapore 2021, 599–608.

network continuously refines its internal weights and biases by minimizing a predefined loss function, most commonly using gradient-based optimization algorithms. This training process, known as backpropagation, enables the network to optimize its parameters and generalize learned patterns across data samples. "The performance of classifiers using deep learning improves on a large scale with an increased quantity of data when compared to traditional learning methods."[13]

4. AHP VS DEEP LEARNING IN CONCRETE IMAGINARY DATASET

Deep Learning (DL) represents a data-driven, adaptive, and self-improving modeling paradigm designed to uncover and represent highly complex, nonlinear relationships within large-scale datasets. In the context of Non-Performing Loan (NPL) performance prediction, deep learning methods have emerged as a prominent subset of artificial intelligence due to their ability to process massive amounts of heterogeneous financial data and extract latent patterns that may be inaccessible to traditional statistical or rule-based models. Deep learning algorithms – such as recurrent neural networks (RNNs), convolutional neural networks (CNNs), and long short-term memory (LSTM) architectures – are typically trained on historical datasets that encompass previous loan performance outcomes, borrower credit histories, macroeconomic variables, sectoral indices, and institutional characteristics.

The training process involves iterative adjustment of millions of internal parameters (weights and biases) through backpropagation and gradient descent techniques, aiming to minimize a defined loss function that quantifies prediction error. In this way, the model gradually encodes intricate relationships between independent variables (e.g., borrower income, loan size, interest rate, collateral quality) and the dependent variable (loan performance). Unlike conventional regression models or analytical frameworks such as AHP, deep learning models do not rely on explicit functional forms or pre-specified relationships among variables; instead, they learn autonomously from data, forming internal representations that approximate the true underlying structure of the system.

13 *Ibid.*

This learning capacity enables deep learning to capture non-linearity, feature interactions, and temporal dependencies inherent in credit behavior. For instance, an LSTM model can effectively recognize sequences in time-series data, identifying how evolving macroeconomic pressures – such as inflation or interest rate fluctuations – affect the probability of default over time. Similarly, CNNs can be applied to detect spatial or structural patterns in financial ratios and market indicators. Consequently, DL models are particularly powerful when the relationships between predictors and loan performance are multi-dimensional and not easily quantifiable through pairwise comparisons or linear combinations, as is the case in AHP.

However, this very reliance on historical data and experiential learning introduces a fundamental limitation. While it is undeniably advantageous for deep learning models to "learn" from large datasets – allowing them to detect patterns that would be difficult or impossible for human analysts to discern – the quality and representativeness of these datasets directly determine the quality of the model's learned knowledge. In other words, the predictive "intelligence" of a deep learning system is only as reliable as the data on which it has been trained!

In the financial domain, and particularly in NPL performance prediction, historical datasets often contain inherent inaccuracies, missing values, and biases arising from inconsistent data collection practices, changing accounting standards, or incomplete reporting by financial institutions. Moreover, these datasets frequently reflect historical economic structures and behavioral patterns that may no longer be valid under current or future market conditions. As a result, even though the deep learning model learns complex correlations from these data, it effectively learns from an imperfect representation of reality. Consequently, the model's "knowledge" may also be systematically flawed or contextually outdated, embedding historical distortions that can propagate into future predictions.

This issue becomes especially critical in volatile or rapidly evolving financial environments, where structural breaks, regulatory interventions, or macroeconomic shocks can quickly render past data irrelevant. Thus, deep learning's strength – its capacity to extract insights from historical experience – can simultaneously become its weakness when that experience does not accurately reflect the evolving dynamics of the real-world system it seeks to model.

The global credit system is inherently dynamic and influenced by factors that evolve rapidly, including regulatory reforms, monetary policy adjustments, socio-economic shocks, and sudden shifts in borrower behavior. These changes can alter the statistical properties of the input variables, resulting in what is known as concept drift – a situation where the relationship between predictors and outcomes shifts over time. When such drift occurs, a deep learning model that has "learned" from outdated data may fail to generalize accurately to the current context, leading to significant degradation in predictive performance.

In contrast, the Analytic Hierarchy Process (AHP) does not rely on historical learning or pattern extraction. Instead, it is a deterministic, formula-driven decision-making framework based on present data and expert judgment. In AHP, decision criteria are compared pairwise according to their relative importance, and a priority vector is derived mathematically from the resulting comparison matrix. Because AHP depends on live and context-specific data, it is inherently more transparent and interpretable. It also provides consistent and traceable results, as each weight and consistency ratio can be explicitly justified.

While AHP lacks the capacity to model hidden nonlinearities or adapt to large unstructured datasets, it benefits from stability and contextual validity, especially in environments characterized by rapid change or limited availability of reliable historical data. Its results are not influenced by outdated patterns or statistical noise embedded in prior experiences but are determined by the current conditions and judgments relevant to the decision context. Therefore, AHP can sometimes yield more accurate or relevant outcomes than deep learning, particularly when the financial landscape has shifted substantially compared to the historical training data available to DL systems.

5. CONCLUSION

In the context of NPL collection performance prediction, AHP offers a pragmatic means of bridging the gap between expert-driven assessments and data-driven modeling. It enables financial institutions and asset managers to prioritize recovery efforts, assess portfolio risk, and allocate resources efficiently, even in environments characterized by data scarcity or regulatory uncertainty. As a result, AHP continues to play a relevant role in contemporary financial decision-making, both as a stand-alone methodology and as a component of integrated analytical frameworks aimed at optimizing recovery and risk management outcomes.

Deep learning's primary advantage in NPL prediction lies in its ability to handle large, heterogeneous, and high-dimensional datasets that include both structured data (such as borrower demographics, credit history, and loan parameters) and unstructured data (such as text from collection notes or communication logs). By learning from historical recovery patterns, a deep learning model can generalize and adapt to new portfolios, markets, and macroeconomic conditions. Moreover, it can dynamically adjust to changing relationships between economic variables and debtor behavior—an essential feature in volatile financial environments. Another notable benefit of deep learning is its capacity for representation learning, through which the model automatically extracts the most informative features from raw data. This is particularly valuable in financial contexts where relationships between variables are very complex.

However, despite their strengths, deep learning models also face several challenges and limitations. One of the most significant issues is their dependence on large volumes of high-quality, labeled data for effective training. In the domain of NPL management, data availability is often constrained by regulatory restrictions, inconsistencies in portfolio documentation, and the heterogeneity of information sources. Poor data quality can lead to overfitting, reduced generalizability, and biased outcomes. Moreover, deep learning models are frequently criticized for their lack of interpretability, as the internal decision mechanisms are represented by complex, nonlinear transformations that are not easily understood by human analysts. This "black box" nature poses challenges for regulatory compliance, risk governance, and decision accountability within financial institutions.

Additionally, the computational cost associated with training and tuning deep neural networks is substantial. High-performance computing resources, including graphics processing units (GPUs) and tensor processing units (TPUs), are often required to efficiently process large datasets and optimize network parameters. The selection of appropriate model architectures, hyperparameters, and regularization techniques demands significant technical expertise and experimental calibration.

From a conceptual standpoint, the relationship between AHP and deep learning in NPL prediction represents a trade-off between deterministic precision and experiential learning. Deep learning offers adaptive, data-rich modeling that excels in discovering complex, hidden relationships and long-term dependencies, but its performance is contingent upon the assumption that historical data remain representative. AHP, conversely, emphasizes analytical clarity, contemporaneous relevance, and interpretability, but it does not possess the same predictive power in uncovering deep structural relationships.

Consequently, in practical applications, a hybrid framework that integrates both methodologies could yield optimal outcomes. Deep learning could be employed to identify and quantify latent risk patterns from extensive historical data, while AHP could be used to adjust or validate these insights using current information and expert judgment. Such an integrated model would leverage the adaptive learning capacity of DL and the contextual sensitivity and transparency of AHP, leading to a more balanced and resilient approach to NPL performance prediction in volatile financial systems.

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MODEL PREDVIĐANJA UČINKA NAPLATE NPL-OVA – ŠTA IZABRATI: AHP ILI AI?

Rezime

Predviđanje stope naplate NPL-ova je ključna komponenta upravljanja finansijskim rizicima, koja zahteva tačnu procenu verovatnoće naplate, naplaćenog iznosa i očekivanih vremenskih okvira. Međutim, predviđanje učinka naplate NPL-ova je omeđeno nesavršenim podacima, promenljivošću tržišta, regulatornim ograničenjima i heterogenošću dobijenih informacija. Ovaj rad ispituje dva

fundamentalno različita pristupa predviđanju NPL-ova: Analitički hijerarhijski proces (AHP), strukturiranu metodologiju donošenja odluka na osnovu više kriterijuma zasnovanu na stručnoj proceni, i duboko učenje (DL), paradigmu vođenu podacima sposobnu da obuhvati složene nelinearne odnose u velikim skupovima podataka. Analiza ističe snagu AHP-a u transparentnosti, interpretabilnosti i primenljivosti u kontekstima sa ograničenim ili nedoslednim podacima, kao i njegova ograničenja koja proizilaze iz subjektivnih procena i pretpostavki o nezavisnosti kriterijuma. Nasuprot tome, duboko učenje nudi superiornu prediktivnu moć kada se trenira na opsežnim, visokokvalitetnim podacima, automatski izdvajajući latentne obrasce i modelirajući dinamičko ponašanje zajmoprimaca, ali u velikoj meri zavisi od tačnosti i reprezentativnosti istorijskih podataka i pati od netransparentnosti, visokih troškova računanja i zavisnosti od ponuđenih obrazaca modeliranja. U svetlu nestabilnih finansijskih uslova i ponavljajućih ograničenja podataka, teško je označiti bilo koji pojedinačni pristup kao univerzalno efikasan. Komplementarna priroda metodologija zasnovanih na intenzivnim podacima i procenama ukazuje na to da integracija više analitičkih paradigmi ima potencijal da poboljša procenu ishoda naplate problematičnih kredita. U radu je dat uporedni pregled dva najzastupljenija metoda sa jasno naznačenim prednostima i manama, a time i mogućim adekvatnim upotrebama u praksi.

Ključne reči: *Problematični krediti*. – *Performanse naplate*. – *Kvalitet podataka*. – *Hibridno modeliranje* (*AHP*, *AI*).

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