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Possibility of improving credit scoring systems: Using machine learning models

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Abstract- This study investigates the potential for improving credit scoring systems in non-bank financial institutions (NBFIs) by applying advanced machine learning techniques. The primary objective is to develop predictive models that more accurately assess credit risk compared to traditional statistical methods. Using real-world, anonymized loan data from a Mongolian NBFI, the study applies and compares three ensemble learning algorithms: Random Forest, XGBoost, and LightGBM. Key variables such as loan amount, repayment history, age, interest rate, and loan term were used to train and validate the models. Among the tested models, XGBoost demonstrated the highest predictive accuracy, with 93% classification performance and strong model robustness as indicated by ROC-AUC and error metrics. The findings highlight that machine learning models, particularly XGBoost, outperform conventional approaches in terms of both accuracy and practical applicability. Moreover, the integration of explainable AI techniques enhances the transparency of the credit scoring process. This research contributes to the localization of modern credit scoring tools in emerging markets and provides a scalable solution to improve financial inclusion and risk-based decision-making in NBFIs.

Keywords - Machine learning, Credit risk, Credit scoring, Financial inclusion, XGBoost, Non-bank financial institution, Explainable AI

1.INTRODUCTION

Credit scoring constitutes a foundational component of contemporary financial systems, offering a systematic framework through which lenders assess the probability of borrower default. Conventional credit risk assessment models predominantly depend on a limited range of quantitative indicators such as payment history, credit utilization, and length of credit history benchmarked against comparable borrower profiles. Although these models provide consistency and comparability in risk evaluation, their rigid, rule-based structures often lack the flexibility to accommodate the complexities of rapidly evolving, heterogeneous financial markets. Consequently, traditional approaches may underperform when assessing risk in non-standard lending contexts or among underbanked populations, where more nuanced behavioral and contextual data are required.

In the context of Mongolia, credit risk continues to pose a substantial challenge from both policy and operational perspectives. As of year-end 2024, the total volume of outstanding loans amounted to MNT 31.4 trillion, with loans to individuals comprising MNT 18.6 trillion, or approximately 59% of the total. Non-performing loans (NPLs) among individual borrowers stood at MNT 965.2 billion, accounting for 5.2% of the individual loan portfolio. While this represents a notable decline from historical peaks such as the 16% NPL ratio recorded in 2009 the persistence of credit quality concerns underscores the urgent need for more robust, data-driven risk assessment methodologies tailored to the evolving structure of the financial sector.

In recent years, Mongolia's financial sector has experienced a marked expansion in the presence and influence of fintech companies, which have introduced data-driven credit evaluation tools that increasingly challenge the primacy of traditional scoring systems. These technology-enabled models leverage real-time data and advanced machine learning algorithms to deliver credit assessments that are not only faster and more adaptable, but also potentially more inclusive, particularly for borrowers with limited formal credit histories. Reflecting global developments, Mongolia formally adopted the FICO scoring system in 2024. This system generates credit scores on a scale from 300 to 850, based on five core financial dimensions. Despite its widespread use, however, conventional models such as FICO often struggle to capture the multifaceted nature of borrower behavior especially in underbanked segments and first-time lending contexts where reliance on alternative data sources and behavioral indicators is crucial for accurate risk differentiation..

To address these limitations, the present study explores the application of machine learning (ML) techniques specifically logistic regression, decision trees, random forest, and XGBoost to enhance the predictive accuracy, adaptability, and interpretability of credit scoring models. Utilizing real-world operational data obtained from a Mongolian non-bank financial institution (NBFI), the research undertakes a comparative analysis between conventional statistical methods and advanced ML-based approaches. The overarching objective is to construct an improved credit risk assessment framework that not only strengthens the accuracy of borrower classification, but also facilitates responsible lending practices and advances financial inclusion within the context of emerging economies.

2. LITERATURE REVIEW

Credit scoring remains a fundamental tool in assessing borrower reliability, with recent advancements in artificial intelligence (AI) and machine learning (ML) significantly enhancing credit risk modeling. Traditional techniques such as logistic regression and decision trees are valued for their simplicity and interpretability but often fail to capture complex non-linear relationships and manage imbalanced, high-dimensional data. As a result, advanced ML approaches including neural networks, hybrid systems, and ensemble methods have gained traction [1].

Hybrid models that integrate artificial neural networks with case-based reasoning have shown promise in reducing Type I and II classification errors [2]. Ensemble algorithms such as Random Forest and XGBoost consistently outperform conventional models in accuracy and robustness, particularly in applications involving non-linear data structures. Alongside predictive accuracy, model transparency has become increasingly important. Explainable AI tools like SHAP and LIME address this need by providing interpretable insights into complex model outputs, facilitating compliance with regulatory standards [3], [4]. Additionally, the integration of alternative data such as mobile payment and utility usage offers a pathway to improve financial inclusion in underserved and data-scarce markets [5]. Building on these developments, the present study applies ML models logistic regression, decision trees, Random Forest, and XGBoost to real loan data from a Mongolian non-bank financial institution, contributing to the advancement of inclusive, explainable, and context-specific credit scoring in emerging economies.

Recent advances in credit scoring research have increasingly turned to machine learning (ML) techniques to overcome the limitations of traditional statistical models, particularly in addressing data imbalance, improving predictive accuracy, and enhancing model interpretability. Mestiri [6] demonstrated that ensemble and deep learning algorithms such as Random Forest, Support Vector Machines (SVM), and Deep Neural Networks consistently outperform classical methods in predicting credit defaults under nonlinear and complex conditions. Complementarily, studies by Gambacorta et al. [7] emphasized the integration of alternative data sources such as transaction logs, mobile activity, and social media footprints to bolster model resilience and predictive power, especially in volatile economic settings.

Saxena et al. (2024) further enriched credit scoring models by incorporating organizational and HR-level attributes, highlighting the utility of interpretability techniques such as SHAP and LIME in ensuring transparent and accountable decision-making processes, particularly within regulated environments. Notably, XGBoost has demonstrated real-world viability, achieving up to 99.4% accuracy in credit card portfolio predictions, underscoring its operational potential [8]. To counteract data imbalance, a 2025 Springer study proposed a synthetic augmentation approach that introduces minority-class observations near decision boundaries, improving robustness and reducing overfitting. Simultaneously, new business-aligned evaluation metrics like the Expected Profit Ratio (EPR) have been developed to supplement traditional metrics such as AUC and F1-score [9]. Marín (2024) introduced a Hamiltonian neural network capable of maintaining predictive stability over time, addressing issues of temporal drift. Meanwhile, Valdrighi et al. (2024) proposed best practices for responsible ML deployment, including fairness-aware modeling, reject inference mechanisms, and transparency protocols [10].

Together, these recent contributions reflect a shift toward more adaptive, explainable, and inclusive ML-driven credit scoring systems. This evolving body of work provides a strong foundation for the present study, which applies ML models specifically Random Forest, XGBoost, and LightGBM to the credit risk assessment of Mongolia’s non-bank financial sector. Machine learning techniques, especially ensemble methods such as Random Forest, XGBoost, and LightGBM, have demonstrated considerable potential in enhancing the accuracy of credit risk assessment. Literature confirms that these models outperform traditional statistical approaches in managing nonlinear patterns and complex borrower behavior, particularly when coupled with effective feature engineering and calibration. Nevertheless, a significant portion of this literature is based on benchmark datasets from developed financial markets, limiting applicability in emerging economies. A systematic review [11] supports these findings. Additionally, a 2024 study proposed a synthetic augmentation technique to address class imbalance by introducing minority-class observations near decision boundaries, improving robustness against overfitting [12]. Ethical and practical considerations are gaining prominence, highlighting the importance of data quality, and model transparency in underbanked settings [10].

While prior research has extensively applied machine learning algorithms such as neural networks, logistic regression, and decision trees to credit scoring, most studies have overlooked the practical constraints and unique market dynamics of developing financial systems, including Mongolia. Empirical studies utilizing real operational loan data from non-bank financial institutions (NBFIs) in such contexts remain scarce. This creates a critical research gap, as existing findings often fail to account for structural and behavioral differences across markets. In response, this study aims to address this gap by evaluating the performance of ensemble ML models using real, anonymized credit data from a Mongolian NBFI. Furthermore, it integrates explainable AI techniques to support responsible, transparent, and inclusive credit decision-making in resource-constrained financial environments.

3. RESEARCH METHODOLOGY

This study is underpinned by two core theoretical frameworks: credit risk theory and statistical learning theory. Credit risk theory asserts that default probability can be predicted using observable financial and behavioral variables, justifying the use of quantitative models in lending. Statistical learning theory supports machine learning (ML) by emphasizing the discovery of data-driven patterns through optimization and generalization. Combined, these frameworks provide a solid rationale for applying ensemble algorithms such as Random Forest, XGBoost, and LightGBM to improve credit scoring accuracy in real-world financial contexts.

For empirical analysis, the study employed anonymized loan-level data from a Mongolian non-bank financial institution (NBFI), referred to as Institution “D.” The dataset includes operational credit records accessed with formal permission and institutional cooperation. To ensure ethical compliance and data privacy, all personally identifiable information was removed, and the data were encoded and processed securely. Only variables relevant to credit assessment such as loan amount, repayment status, and loan term were retained.

This methodological approach enables the development of robust ML models using real-world data while maintaining ethical standards, contributing valuable insights to credit scoring practices in under-researched financial sectors like Mongolia’s NBFIs.

3.1. Variables selection

The variables used in this study are classified into dependent and independent categories. The primary dependent variable is loan status, a binary indicator representing whether a borrower is repaying the loan according to schedule. This serves as the key outcome variable and direct measure of credit risk. The independent variables include a set of demographic (e.g., age, gender), behavioral (e.g., loan extension history), and loan-specific (e.g., amount, interest rate, term) characteristics that are hypothesized to influence repayment behavior. Prior to model development, a series of preprocessing steps were undertaken to ensure data quality and analytical validity. These included imputation of missing values, standardization of variable coding for both categorical and numerical data, and exploratory statistical analysis to assess feature distributions and relevance. These steps contributed to the robustness and consistency of the machine learning models applied in the credit risk prediction task.

Table 1. List of Variables Used in the Model

Variable Name	Description	Data Type
Loan Classification	Credit risk classification (1 = good, 0 = bad/extreme)	Categorical
Days Gone By	Number of days overdue	Numeric (Integer)
Age	Borrower's age	Numeric (Integer)
Gender	1 = Female, 2 = Male	Categorical
Extension Status	0 = Extended, 1 = Not extended	Binary (Classified)
Paid Loan	Amount of loan repaid during the current period	Numeric (Float)
Loan Interest Rate	Interest rate (%)	Numeric (Float)
Loan Term	Total term of the loan in months	Numeric (Integer)
ZMS Status	Registration in the Credit Database (0 = No, 1 = Yes)	Binary (Classified)
Extended Number	The number of times the loan has been extended	Numeric (Integer)
Loan Amount	Initial amount disbursed for the loan	Numeric (Float)

3.2. Statistical analysis of key variables and model development

This study employs a quantitative approach using machine learning (ML) techniques to develop credit risk prediction models based on real-world data from a Mongolian non-bank financial institution (NBFI). Machine learning techniques particularly ensemble methods such as Random Forest, XGBoost, and LightGBM have demonstrated substantial effectiveness in improving credit risk assessment accuracy. These methods address critical challenges such as nonlinearity, high dimensionality, and data imbalance, which traditional statistical models often fail to capture. As Zhou [13] explains, ensemble learning strategies are generally categorized into bagging, exemplified by Random Forest, which reduces variance by averaging multiple decision trees trained on bootstrapped datasets, and boosting, exemplified by XGBoost, which incrementally minimizes error using gradient and Hessian-based second-order optimization. While XGBoost is recognized for its bias reduction and rapid convergence, Random Forest enhances model generalization through randomized feature selection and majority voting.

Moreover, the effectiveness of ensemble models in contexts with highly correlated features is further supported by research on controlled randomness in covariate selection, which helps reduce multicollinearity and overfitting [14]. Despite these methodological advancements, much of the empirical literature remains concentrated on standardized datasets from mature financial markets. To address this gap, the present study implements ensemble learning models on real-world loan data from a Mongolian non-bank financial institution (NBFI), thereby contributing to the development of context-aware, interpretable, and robust credit scoring models suited to emerging market conditions.

Formally, given a training dataset (X_i, Y_i) for $i = 1, \dots, n$ Random Forest constructs K bootstrapped regression trees T_k. For any new input x', the final prediction is obtained as:

$$\hat{Y}_{RF}(x') = \frac{1}{K}\sum_{k=1}^{K} T_k(x') \tag{1}$$

This ensemble-based modeling strategy provides a robust framework for the credit risk classification task in this study, especially in the context of limited and heterogeneous financial data available in emerging markets like Mongolia.

4. RESULTS

This study applied machine learning models to predict credit risk using real-world loan data from a Mongolian non-bank financial institution. The dataset was divided into training (80%) and testing (20%) subsets, and a Random Forest Classifier was used to develop the initial predictive model. The model achieved an accuracy of 92% on the training set and 90% on the test set, indicating strong generalization performance with minimal overfitting. The confusion matrix further confirmed the model's effectiveness in correctly classifying borrowers by risk level. These results suggest that ensemble methods like Random Forest can serve as reliable tools for credit risk assessment in emerging financial markets. Additional models were tested to validate comparative performance, which are discussed in the subsequent sections.

Table 1Random Forest classifier training

Train set	precision	recall	F1 score	Support
0	0.99	0.75	0.85	6373
1	0.90	1.00	0.95	15069
Macro average	0.95	0.87	0.90	
Weighted average	0.93	0.92	0.92	21442

The Random Forest classifier demonstrated strong predictive performance across both classes of loan classification. As shown in Table 2, the model achieved a precision of 0.99 and recall of 0.75 for the low-risk class (Class 0), and precision of 0.90 with recall of 1.00 for the high-risk class (Class 1). The macro-average F1-score was 0.90, indicating a balanced performance across classes, though the lower recall for Class 0 suggests a tendency to misclassify some low-risk borrowers. The weighted average F1-score, adjusted for class size imbalance, was 0.92, confirming the model's overall robustness. These results reflect the effectiveness of Random Forest in classifying borrower risk profiles in real loan datasets, with high accuracy and generalizability.

Table 2Random Forest classifier test

Test set	precision	recall	F1 score	Support
0	0.97	0.69	0.81	1594
1	0.88	0.99	0.93	3767
Macro average	0.93	0.84	0.87	
Weighted average	0.91	0.90	0.90	5361

When validated on the hold-out test dataset, the Random Forest model continued to exhibit strong classification performance. For the high-risk group (Class 0), the model achieved a precision of 0.97, indicating that 97% of those predicted to be risky were indeed overdue borrowers. However, the recall was only 0.69, suggesting that the model failed to identify approximately 31% of truly risky borrowers, highlighting a potential concern for false negatives. In contrast, the performance for the low-risk (active) borrowers (Class 1) was considerably higher, with a recall of 0.99

and precision of 0.88, showing that nearly all performing borrowers were accurately identified. The macro-average F1-score of 0.87 and average F1-score of 0.90 further confirm the model's balanced and reliable performance across classes. Nevertheless, the lower recall for Class 0 emphasizes the importance of improving sensitivity towards identifying default-prone clients, which is critical in minimizing credit risk exposure in real-world lending scenarios.

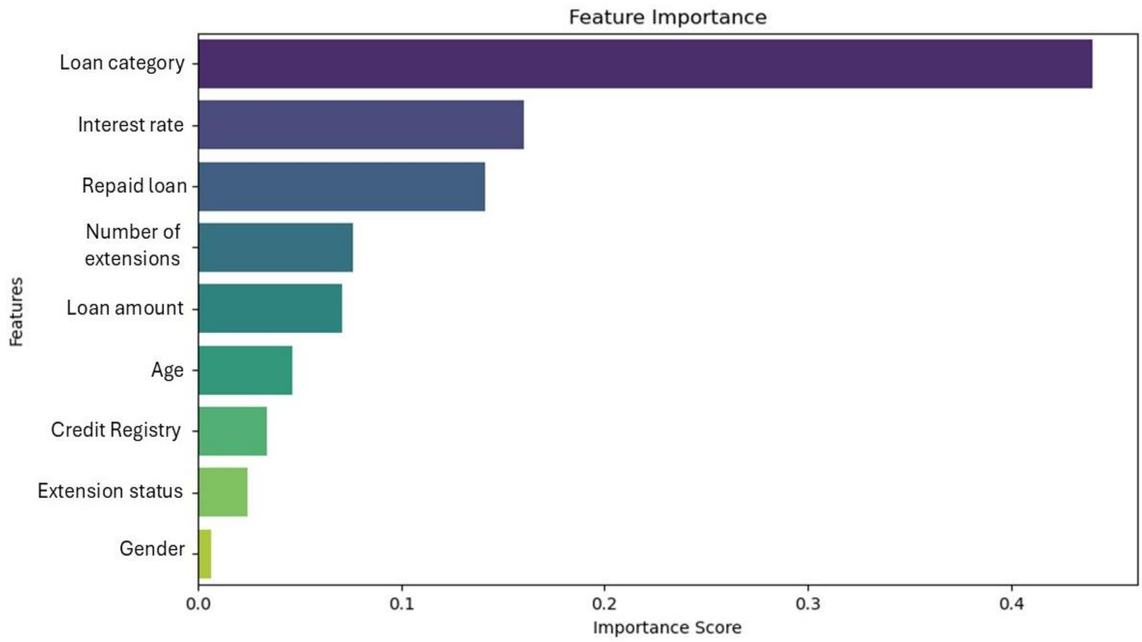

Fig 1Feature importance analysis

Figure 1 illustrates the features of importance scores derived from the training of the Random Forest classifier. Among the input variables, Loan Classification' emerged as the most influential predictor in determining credit risk, indicating its critical role in distinguishing between performing and non-performing loans.

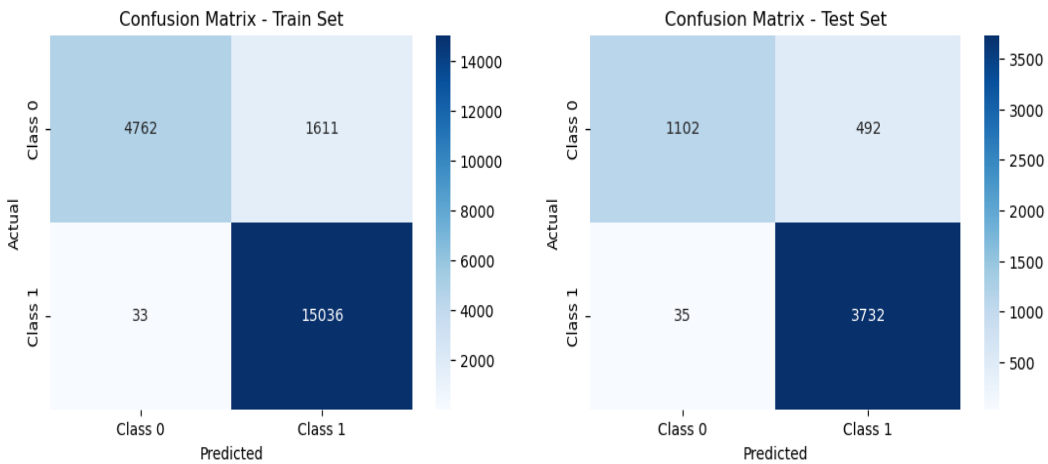

Fig 2. Confusion Matrices for Training and Test Sets /Random Forest Classifier/

The confusion matrix for the training set of the Random Forest model demonstrates that Class 1 (creditworthy borrowers) was classified with high accuracy, while there were 1,611 false positives in Class 0 (credit-risky borrowers). Specifically, 4,762 instances in Class 0 were correctly identified, and 1,611 were misclassified as Class 1. For Class 1, 15,036 cases were correctly classified, with only 33 false negatives.

Similarly, the confusion matrix for the test set indicates consistent performance, although misclassification in Class 0 slightly increased. The model correctly identified 1,102 instances as Class 0 and 3,732 as Class 1, while 492 Class 0 cases were misclassified as Class 1, and 35 Class 1 cases were misclassified as Class 0. This pattern suggests that the model tends to classify Class 1 more accurately, while misclassification is more common for Class 0.

For comparison, the LightGBM model produced an identical accuracy of 92% on the training set and 90% on the test set. The model effectively recognized Class 1 instances but showed higher false positive rates in Class 0. The imbalance in the dataset likely influenced this result, as Class 1 instances outnumbered Class 0. Feature importance analysis revealed that loan amount was the most influential predictor of creditworthiness, followed by borrower age. Other significant factors included loan disbursement, interest rate, and the number of extensions. In contrast, gender, educational status, credit classification, and social security registration status had relatively minimal influence on the model's performance.

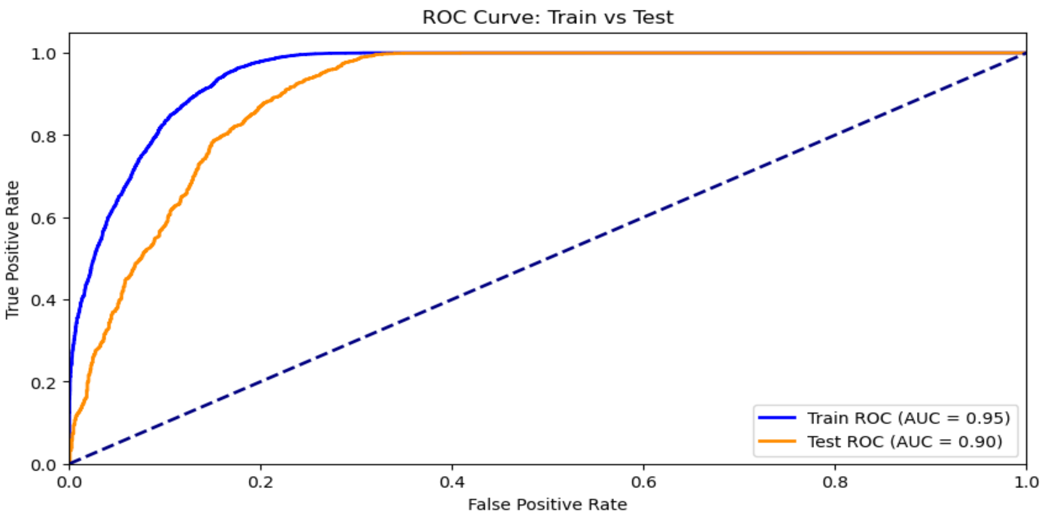

Fig 3. curve

The ROC (Receiver Operating Characteristic) curve was used to evaluate the classification performance of the model on both the training and test datasets. The x-axis represents the False Positive Rate (FPR), while the y-axis denotes the True Positive Rate (TPR). The ROC curve for the training data yielded an AUC (Area Under the Curve) of 0.95, indicating strong classification performance. Similarly, the test data achieved an AUC of 0.90, reflecting the model’s robustness and generalizability. A higher AUC value implies superior discriminative ability, and in this case, both results confirm the effectiveness of the model in distinguishing between creditworthy and risky borrowers.

In terms of regression-based performance metrics, the model achieved a Mean Squared Error (MSE) of 1,044,217.12, a Root Mean Squared Error (RMSE) of 1,021.87, and a Mean Absolute Error (MAE) of 814.86. These values indicate relatively low prediction errors, although the higher RMSE compared to MAE suggests the presence of some large outliers. The model's R^2 score was 0.9868, indicating that 98.68% of the variance in the dependent variable is explained by the model. This high R^2 value reflects the model’s strong predictive accuracy and overall goodness of fit. However, due to the scale of the data, MSE alone may not be a reliable indicator of performance.

Machine learning techniques, especially ensemble methods like Random Forest, XGBoost, and LightGBM, have demonstrated high accuracy in credit risk prediction. Studies such as Pathipati and Kumar [15] report superior predictive performance of XGBoost and Random Forest on large-scale credit card datasets. Gür et al. [16] demonstrate that combining convolutional neural network (CNN) architectures with ensemble methods leads to substantial gains in credit scoring accuracy. While much prior work relies on benchmark datasets from mature financial markets, our study applies these models to real, anonymized loan data from a Mongolian non-bank financial institution (NBFI), enhancing the practical relevance and adaptability of credit scoring in emerging economy contexts. In addition, by integrating explainability techniques like SHAP and LIME, our research emphasizes model transparency, which is vital for fostering trust and promoting financial inclusion.

5. DISCUSSION

The findings of this study substantiate the growing body of evidence highlighting the superior performance of ensemble learning methods in credit risk prediction. Among the tested models, XGBoost consistently achieved the highest classification accuracy (93%), corroborating prior empirical studies such as Pathipati and Kumar (2024) and Gür et al. (2025), which reported similar results in large-scale credit datasets from developed markets. The Random Forest classifier also demonstrated robust predictive capacity, particularly in terms of precision and F1 scores, indicating its utility in credit segmentation tasks. However, its relatively lower recall for the minority (high-risk) class suggests a residual vulnerability in identifying defaulters, an issue also noted in other studies employing imbalanced datasets.

A key contribution of this research lies in its application to anonymized, real-world data from a Mongolian non-bank financial institution. In contrast to many existing studies that rely on benchmark or synthetic datasets from mature economies, this contextualized approach enhances both the ecological validity and policy relevance of the results. As noted by Li et al. (2024), the transferability of machine learning models across heterogeneous financial environments requires localized validation an aspect directly addressed in this study.

Furthermore, the study highlights the relevance of integrating explainable AI (XAI) tools such as SHAP in improving the interpretability and regulatory compliance of machine learning-based credit scoring systems. This aligns with recommendations by Valdrighi et al. (2024), who advocate for fairness-aware and transparent model deployment to ensure responsible lending practices. The inclusion of feature importance analysis provided key insights into the relative influence of demographic and loan-related variables, thereby facilitating more informed credit decisions.

From a methodological standpoint, the use of ensemble strategies bagging (Random Forest) and boosting (XGBoost) allowed for effective handling of nonlinearity, multicollinearity, and data imbalance. This conclusion is consistent with recent inflation forecasting research conducted by Tegshjargal et al. (2025), in which XGBoost outperformed traditional models (e.g., SARIMA, GARCH) in predicting macroeconomic trends in Mongolia. Their findings reinforce the practical advantage of XGBoost in modeling complex, high-dimensional data environments, which parallels the credit risk context analyzed in this study. This finding echoes Zhou's (2025) theoretical foundations on ensemble methods and supports Rotari and Kulahci's (2023) assertion regarding the advantages of random feature selection when dealing with correlated inputs. Notably, the study also demonstrated the practical viability of LightGBM as a lightweight alternative, though its performance was marginally lower than that of XGBoost.

Despite these contributions, the study is not without limitations. The data sample was restricted to a single NBFI, and the class imbalance inherent in the dataset may have biased model performance towards the majority class. Future studies should consider multi-institutional data, longitudinal design, and the integration of alternative data sources (e.g., mobile payment behavior, geolocation data) to further refine model robustness and fairness.

In sum, the empirical results reinforce the argument that ensemble machine learning models when applied with proper calibration and contextual understanding can substantially enhance the precision, transparency, and inclusivity of credit risk assessments in emerging economies. This represents a meaningful step toward closing the methodological gap between developed and developing financial systems and contributes to more equitable access to credit in underbanked populations.

6. CONCLUSION

This study explored the potential of machine learning (ML) techniques to improve credit risk assessment in non-bank financial institutions (NBFIs), using real-world operational data from a Mongolian institution. Grounded in both credit risk theory and statistical learning theory, the research compared the performance of traditional statistical models such as logistic regression and decision trees with advanced ensemble algorithms including Random Forest and XGBoost. Among these, XGBoost demonstrated the highest predictive accuracy (93%), with balanced precision-recall metrics and strong generalizability across training and test datasets. The use of evaluation metrics such as ROC-AUC (0.90 on the test set) and SHAP-based feature attribution further validated the model's predictive power and interpretability.

Importantly, the study addressed a critical limitation in current credit scoring literature: the lack of context-specific research for emerging markets. By incorporating anonymized loan-level data from a Mongolian NBFI, this research contributes empirical evidence from a data-constrained financial environment. The findings support the feasibility of applying machine learning–based scoring models to improve credit decision-making and reduce non-performing loan (NPL) ratios in similar settings. Moreover, the integration of explainable AI tools such as SHAP values enhances the transparency and accountability of automated lending systems key components for maintaining regulatory compliance and building borrower trust.

Despite its contributions, the study is subject to several limitations. The data was derived from a single financial institution, which may limit the model's generalizability to other NBFIs or broader financial segments. In addition, the model did not incorporate alternative data sources (e.g., mobile money transactions, utility payments), which are particularly valuable in assessing creditworthiness in underbanked populations.

From a practical perspective, this research offers actionable insights for NBFIs seeking to modernize their credit scoring frameworks. Machine learning–driven systems equipped with explainability modules can facilitate more accurate borrower classification, dynamic interest rate setting, and risk-adjusted portfolio management. For policymakers, such innovations may contribute to broader financial inclusion by enabling responsible lending in data-scarce environments.

Future research should consider expanding the model to include real-time data streams through API integration and cloud-based infrastructure. Additionally, embedding fairness-aware ML techniques could help mitigate algorithmic bias and ensure equitable access to credit for vulnerable or historically excluded borrower groups.

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AUTHOR'S INTRODUCTION

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For this research, he initiated the study concept, designed the methodological framework, constructed and analyzed the panel dataset, and drafted the core sections of the manuscript. He also coordinated the integration of co-authors' contributions into a cohesive paper.

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