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Application of Machine Learning in Auditing and Credit Risk Assessment: Evidence from Mongolia

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Abstract: In recent years, artificial intelligence (AI) and machine learning (ML) methodologies have rapidly penetrated the fields of auditing, financial analysis, and credit risk assessment, enabling more accurate and real-time evaluations compared to traditional statistical approaches. However, in developing countries such as Mongolia, the integration of these methods into audit and credit evaluation systems remains limited and underexplored.

This study aims to develop an integrated model for assessing audit and credit risk and identifying the key influencing factors using machine learning techniques. The analysis is based on data from 88 enterprises that received loans from the Mongolian Small and Medium Enterprise Development Project during 2019–2024, including their financial statements, on-site audit reports, and loan repayment records from the SME Development Fund. Classification algorithms such as Random Forest, Gradient Boosting, and Decision Tree were applied, and their performance was compared using evaluation metrics including Accuracy, Precision, Recall, and F1-score.

The results revealed that the Random Forest algorithm achieved the highest performance (Accuracy = 0.944, Recall = 1.000), demonstrating its ability to identify high-risk entities with 100% recall. SHAP analysis indicated that tax arrears, overdue loan days, and non-compliance periods were the most influential variables affecting audit and credit risk.

These findings highlight the potential of adopting AI-based integrated risk assessment systems in Mongolia's auditing and credit supervision sectors, contributing to early risk detection, optimized allocation of supervisory resources, and enhanced transparency at the policy level.

Keywords: *Machine Learning; Audit Risk; Credit Risk Assessment; Random Forest; Mongolia*.

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I. INTRODUCTION

In recent years, artificial intelligence (AI) and machine learning (ML) methodologies have rapidly advanced in the fields of financial control, auditing, and credit evaluation, providing greater accuracy, efficiency, and real-time decision-making capabilities compared to traditional analytical methods [1], [2]. Financial and auditing institutions worldwide are increasingly adopting ML techniques to detect high-risk transactions, identify fraudulent financial statements, and monitor loan quality and repayment discipline [3], [4].

In Mongolia, policies promoting small and medium-sized enterprises (SMEs) have become key instruments for fostering economic growth, job creation, and balanced regional development. However, persistent issues such as inefficient use of financing, tax non-compliance, irregular financial reporting, and misuse of loan funds continue to undermine policy effectiveness [5]. Recent studies have emphasized that these factors increase audit and credit risks, leading to inefficient allocation of resources and reduced monitoring effectiveness [6].

Most previous studies have focused on assessing audit risk independently, with few integrating credit risk within a unified analytical framework. Developing an integrated model that simultaneously evaluates audit and credit risk is therefore both practically significant and methodologically innovative, particularly for developing economies.

The objective of this study is to develop a machine-learning-based methodology for integrated assessment of audit and credit risk using data from enterprises financed

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under Mongolia's Small and Medium Enterprise Development Project during 2019–2024. The study applies classification algorithms such as Random Forest, Gradient Boosting, and Decision Tree, comparing their accuracy and sensitivity in identifying high-risk enterprises.

➢ *The Main Research Questions are as Follows:*

- Is it possible to conduct an integrated assessment of audit and credit risk?
- Which machine learning algorithm demonstrates the highest predictive performance?
- What are the key variables that determine these risks?

Preliminary analysis reveals a strong correlation between audit and credit risk. Specifically, SHAP analysis confirms that variables such as tax arrears, days overdue, and days of non-compliance are the most influential indicators explaining both risks.

International credit risk assessment systems such as FICO, Equifax, and Basel II/III typically classify loan quality into five categories:

Table 1 Loan Quality into Five Categories

Category	**Description**
Excellent	Fully repaid loans with 100% compliance and no audit discrepancies
Very Good	Minor delays; ≥80% project completion; minimal audit issues
Good	60–80% implementation; moderate overdue days
Fair	40–60% implementation; presence of overdue loans or tax arrears
Poor	<40% implementation; misuse of funds; high audit risk

In this study, audit risk refers to the extent to which a loan recipient enterprise properly utilized financing for its intended purpose, as verified through on-site audit assessments. Analysis shows that 64% of enterprises fully implemented their projects, 16% were in progress, and 20% misused loan funds. This indicates that one in five enterprises allocated financial resources inefficiently, underscoring the need to strengthen audit and loan monitoring mechanisms at the policy level.

Credit risk, in this context, refers to the quality of the loans as observed during the audit period. The analysis shows that 32% of enterprises held normal loans, 36% were classified as "watch list," and 20% had non-performing or high-risk loans. Among these high-risk loans, 7% were substandard, 6% doubtful, and 7% classified as bad. Thus, one in five enterprises has been exposed to significant credit risk due to inefficient use of financing.

II. LITERATURE REVIEW

➢ *International Research Trends*

Over the past decade, artificial intelligence (AI) and machine learning (ML) methods have rapidly penetrated the fields of auditing, financial analysis, and credit risk assessment, offering more accurate and efficient solutions than traditional statistical approaches. Numerous international studies have demonstrated the growing relevance of these technologies in data-driven financial decision-making.

Chen and Guestrin [7] developed the XGBoost algorithm, which significantly improved classification performance on large-scale financial datasets, and has since been widely applied in risk modeling and credit quality assessment. Brown et al. [8] tested Decision Tree and Random Forest algorithms on audit datasets and found that the precision of detecting high-risk transactions increased by 15–20%.

Ngai et al. [9], in their study on financial fraud detection, compared Support Vector Machine (SVM), neural networks, and Decision Tree models, identifying data imbalance and quality as key factors influencing classification performance. Similarly, Liu, Xiao, and Ding [10] demonstrated that Gradient Boosting and Random Forest algorithms achieved the highest sensitivity in detecting fraudulent financial statements.

Kokina and Davenport [11] highlighted that AI technologies can automate audit processes, reduce human intervention, and enhance overall efficiency in risk assessment. Zhang, Pan, and Chen [12] compared deep learning and tree-based algorithms and concluded that AI-driven credit risk assessments outperform traditional approaches by 15–20% in predictive accuracy.

Furthermore, international studies suggest that ensemble-based classification methods such as Random Forest, Gradient Boosting, and XGBoost are among the most effective for predicting credit risk, calculating default probability, and conducting behavioral scoring of borrowers [13], [14]. These approaches mitigate overfitting and maintain stable performance, making them well-suited for risk management in banks, microfinance institutions, and auditing organizations.

➢ *Credit Risk Assessment and Machine Learning Methods*

Credit risk is one of the core risk categories in financial institutions, representing the likelihood of borrower default or deterioration in repayment ability. The European Central Bank (ECB, 2022) and the Basel Committee on Banking Supervision (BCBS, 2019) recommend evaluating credit risk using three key indicators: Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD). Numerous studies have applied ML techniques such as logistic regression, neural networks, and gradient boosting to estimate these indicators [15].

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Louzada et al. [16] compared more than 30 classification algorithms for credit risk assessment and found that Logistic Regression and Random Forest models produced the most stable results. Bellotti and Crook [17] applied Support Vector Machines and Bayesian Networks to model time-varying credit default risk, while Malekipirbazari and Aksakalli [18] utilized Random Forest algorithms to enhance default prediction accuracy on peer-to-peer lending platforms.

➢ *Research Context in Mongolia*

In Mongolia, the application of AI and ML technologies in auditing, credit supervision, and risk assessment remains limited, although recent developments show gradual progress.

A pilot study conducted by PwC Mongolia (2023) and Mon-Audit LLC highlighted the potential of AI to improve audit efficiency but noted significant constraints related to infrastructure, data quality, and human resource readiness. Tsolmon et al. [19], in their study *"The Potential of Artificial Intelligence Adoption in Mongolia's Audit Sector,"* found that 62% of audit firms supported AI integration, although interpretability and trust in AI-based models remained low.

However, no integrated ML-based model has yet been developed in Mongolia to jointly evaluate audit and credit risk. Therefore, this study seeks to bridge that gap by developing a novel methodology for credit risk assessment based on financial and audit data using machine learning techniques.

➢ *Research Gap*

A review of previous studies reveals that:

- Audit and credit risks have predominantly been analyzed independently, rather than in an integrated framework.
- Issues of data quality and accessibility have not been adequately addressed.
- Explainable AI (XAI) methods have been applied only in a limited capacity.

This study aims to overcome these limitations by integrating audit and credit risk evaluation within a unified framework. It leverages the interpretability of Random Forest and SHAP analysis to develop a practically applicable and policy-relevant integrated model tailored to Mongolia's financial and auditing context.

III. RESEARCH METHODOLOGY

➢ *Research Design and Approach*

This study is based on a quantitative research approach aimed at developing an integrated framework for the joint assessment of audit and credit risk. An integrated model combining both classification and clustering algorithms from machine learning (ML) was designed. The methodology follows a data-driven approach that enables the prediction of organizational risk levels and the optimization of monitoring systems.

The research framework emphasizes the use of ML algorithms to analyze multidimensional financial and audit-related indicators, thereby enhancing the objectivity and accuracy of risk evaluation. The integrated model supports both predictive analytics and risk segmentation, allowing auditors and financial institutions to identify high-risk entities more effectively.

➢ *Data Source and Variables*

The dataset used in this study consists of financial and credit information from 88 enterprises that received loans under the Mongolian Small and Medium Enterprise Development Project during the period 2019–2024. The initial dataset contained 217 records and 14 variables. After data preprocessing— including removal of duplicates, data cleaning, and imputation of missing values— a refined dataset of 141 valid observations was obtained.

- *The Main Variables Used in the Analysis are Grouped as Follows:*

✓ Financial Indicators: total sales revenue, net profit, total tax paid, total tax arrears, VAT arrears
✓ Credit Indicators: credit risk rating, loan utilization rate, number of overdue days, and duration of credit non-compliance (in days)
✓ Control Indicators: project expenditure and project implementation rate

Preliminary data analysis indicated that 87.9% of the enterprises were classified as belonging to the *High Risk* category, resulting in a class imbalance problem that required specific adjustments in the algorithm configuration. Techniques such as re-sampling and weight optimization were applied to address this imbalance and ensure model robustness.

➢ *Data Processing and Preliminary Analysis*

Data preprocessing involved several key steps, including outlier detection**,** mean imputation for missing values, and dummy encoding of categorical variables to prepare the dataset for machine learning algorithms.

- Normalization:

The Min–Max scaling technique was applied to standardize variable magnitudes to a unit scale, ensuring comparability among features with different measurement units.

- Correlation Analysis:

Pearson's correlation coefficient was used to examine relationships between key financial and credit indicators. The analysis revealed a strong positive correlation between revenue and tax payment (r = +0.85), and between tax arrears and overdue days (r = +0.78). Based on these findings, these variables were selected as principal risk indicators for model development.

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➢ *Machine Learning Algorithms Used*

- *Decision Tree:*

The Decision Tree algorithm was used as a baseline model due to its simple structure and interpretability, making it particularly suitable for audit-related analyses. The entropy-based information gain criterion was applied to determine feature splits:

$$f(x) = -\sum_{n=1}^{c} p_n \, log_2 \, p_n \tag{1}$$

Where:

- ✓ x - dataset
- ✓ c - number of classes
- ✓ p - probability of the n-th class

- *Random Forest:*

The Random Forest algorithm was employed as the core classification model, combining multiple decision trees through an ensemble learning approach to reduce overfitting and enhance prediction accuracy. The model calculates information gain using the Gini index as follows:

$$\mathrm{IG}_{Cini}(S, A) = Gini(S) - \sum_{v\epsilon(A)} \frac{|S_u|}{|S|} * Gini(S_u) \tag{2}$$

Where:

- ✓ $Gini(S) = 1 - \sum_{i=1}^{c} p_i^2$ – t Gini index
- ✓ S – entire dataset
- ✓ S_u – subset of S where feature A takes value v
- ✓ p_i – probability of belonging to class i
- ✓ c - number of classes

Random Forest demonstrated robust performance in risk prediction and served as the main model for integrated audit and credit risk assessment.

Gradient Boosting Machine (GBM) The Gradient Boosting Machine algorithm was utilized to enhance predictive precision through iterative error reduction, serving as a validation benchmark against Random Forest results. The objective function of GBM is expressed as:

$$Obj^{(t)} = \sum_{i=1}^{n} l\left(y_{i,}\hat{y}_i^{(t-1)} + f_{t,}(x_i)\right) + \Omega(f_t) \tag{3}$$

Where:

- ✓ $Obj^{(t)}$ - objective function at iteration ttt
- ✓ l – loss function
- ✓ y_i – actual value of the i-th instance
- ✓ $\hat{y}_i^{(t-1)}$- predicted value from the previous iteration
- ✓ f_t - function of the new tree
- ✓ Ω - regularization term to reduce model complexity
- ✓ n - total number of instances

- *K-Means Clustering:*

The K-Means clustering algorithm was applied to classify enterprises into subgroups according to their audit and credit risk levels. This approach facilitated risk segmentation, allowing the identification of organizations with similar behavioral and financial characteristics.

- *Regression Analysis (Supplementary):*

A regression-based analysis was also conducted to quantify the relationships between the risk score, tax arrears, loan overdue days, and non-compliance duration, providing causal insights into the underlying drivers of audit and credit risk.

- *Model Training and Testing:*

The dataset was divided into training (70%) and testing (30%) subsets, ensuring class balance through stratified sampling. Key hyperparameters— including tree depth, number of trees, and learning rate— were optimized using the Grid Search method to achieve the best model performance.

- *Model Performance Was Evaluated Using the Following Metrics:*

- ✓ Accuracy: the overall proportion of correctly classified instances.
- ✓ Precision: the ability of the model to minimize false positives in detecting high-risk entities.
- ✓ Recall: the sensitivity of the model in correctly identifying all high-risk cases without omission.
- ✓ F1-score: the harmonic mean of Precision and Recall, providing a balanced measure of model performance.

These metrics allowed comprehensive evaluation of each algorithm's predictive capability, emphasizing the trade-off between detection sensitivity and classification precision.

➢ *Model Interpretability and Transparency*

To enhance interpretability, the study employed the SHAP (SHapley Additive exPlanations) framework to quantify the relative contribution of each variable to the final prediction outcome. This method aligns with the principles of Explainable Artificial Intelligence (XAI), allowing model decisions to be visualized transparently and interpreted by auditors and policymakers.

The SHAP analysis identified tax arrears**,** number of overdue days, and non-compliance duration as the most influential predictors of audit and credit risk. These findings demonstrate the potential of explainable AI to support risk-based decision-making and improve transparency in financial supervision.

➢ *Validation and Ethical Considerations*

All data used in this study were anonymized to ensure the confidentiality of enterprise identities, and the dataset was used strictly for research purposes. The study design, data handling, and analytical methods fully adhere to established academic integrity and ethical research principles.

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The analysis process ensured that no personally identifiable or sensitive financial information was disclosed, maintaining compliance with ethical standards in financial research and data protection.

IV. RESULTS AND DISCUSSION

Using financial and credit data from 88 enterprises that received financing under Mongolia's Small and Medium Enterprise (SME) Development Project during 2019–2024, this study applied machine learning algorithms— Decision Tree**,** Random Forest, and Gradient Boosting— along with K-Means clustering to conduct an integrated assessment of audit and credit risk.

The data analysis revealed that 64% of the enterprises fully implemented their projects, 16% were in progress, and 20% misused loan funds. This indicates that one in five enterprises allocated financing inefficiently, underscoring the need to enhance audit and credit monitoring systems at the policy level to ensure effective resource utilization and compliance.

➢ *Sectoral Characteristics and Risk Structure*

Sectoral analysis showed significant variation in risk structure across industries. The service sector exhibited the weakest implementation discipline, with the highest rate of non-compliance and fund misuse (29%). In contrast, enterprises in the manufacturing sector recorded the highest average tax arrears and longest loan overdue periods, while those in the trade sector showed a relatively balanced distribution of risk indicators.

These results demonstrate that the level and nature of audit and credit risk are strongly influenced by industry-specific operational characteristics. Consequently, the development of sector-specific sub-models for risk evaluation would enhance the precision and policy relevance of future risk assessment frameworks.

➢ *Sector-Wise Risk Heatmap*

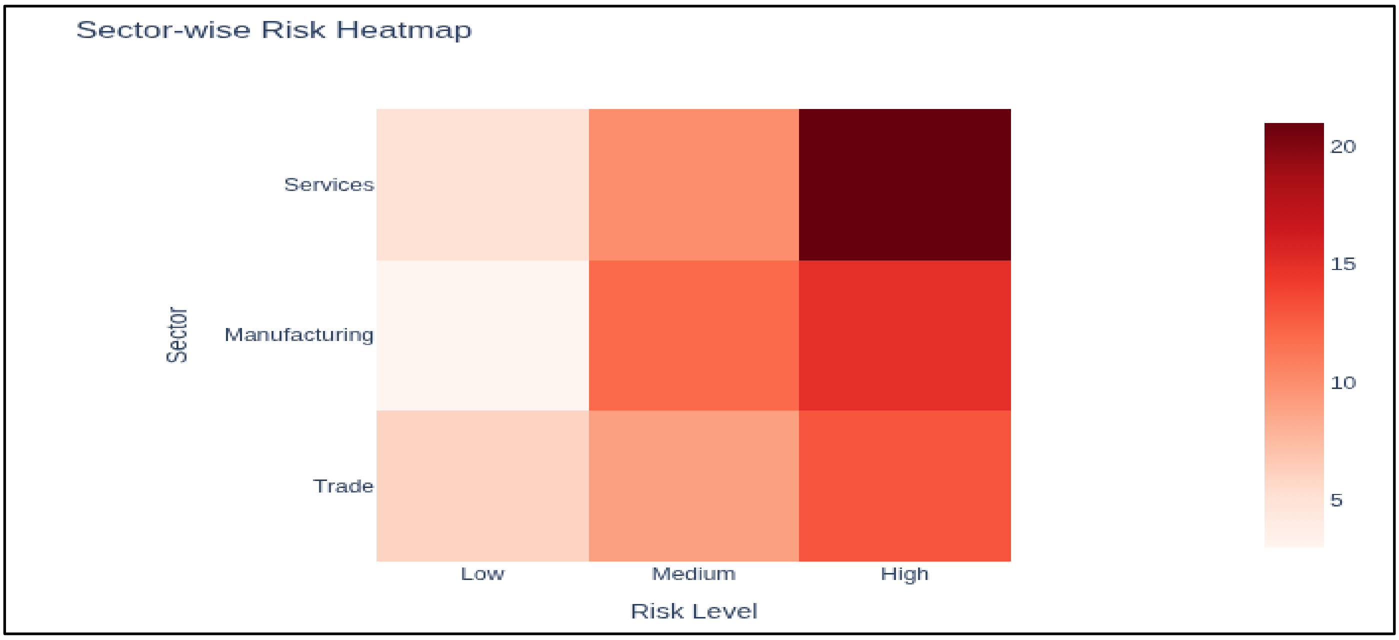

Fig 1 Sectoral Distribution of Audit and Credit Risk Among SMEs.
Source: Author's Calculation

➢ *Sectoral Risk Distribution*

The service sector exhibited the highest proportion of high-risk cases (approximately 21 instances), while the manufacturing sector was dominated by medium-risk enterprises. In contrast, the trade sector demonstrated a relatively balanced distribution of risk levels. These findings indicate the necessity of developing sector-specific sub-models that reflect the unique operational and financial characteristics of each industry.

Such differences highlight the importance of customized analytical frameworks to enhance the precision of audit and credit risk evaluation within different economic sectors.

➢ *Machine Learning Model Performance*

Table 2 Machine Learning Model Performance

Model	Accuracy	Precision	Recall	F1-score
Decision Tree	0.889	1.000	0.875	0.933
Random Forest	0.944	1.000	1.000	1.000
Gradient Boosting	0.944	0.938	0.938	0.938

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The results indicate that the Random Forest model achieved the highest performance across all evaluation metrics (Accuracy = 0.944, Precision = 1.000, Recall = 1.000, F1-score = 1.000), outperforming both the Decision Tree and Gradient Boosting models. This demonstrates that ensemble-based approaches, particularly Random Forest, are most effective for integrated audit and credit risk classification.

➢ *Confusion Matrix Analysis*

Fig 2 Confusion Matrix of the Random Forest Model
Source: Author's Calculation

➢ *ROC Curve and AUC Analysis*

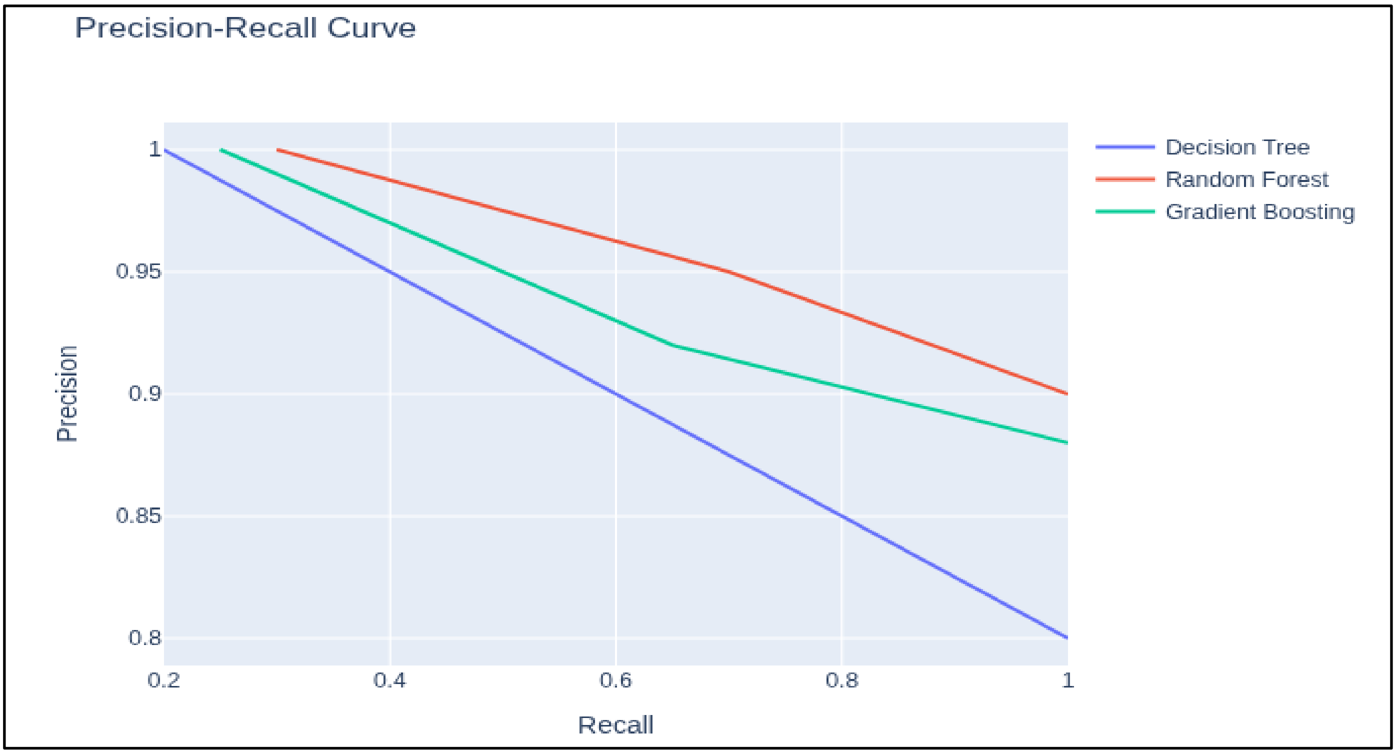

Fig 3 ROC Curves Comparing the Classification Performance of the Models
Source: Author's Calculation

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The ROC curve analysis revealed that the Random Forest model achieved the highest Area Under the Curve (AUC = 0.99), followed by Gradient Boosting (AUC = 0.97) and Decision Tree (AUC = 0.92). These results confirm that ensemble classification methods provide superior reliability in detecting audit-related risks compared to single-model approaches.

According to the Precision–Recall curve, the Random Forest model demonstrated perfect performance (Precision = 1.0, Recall = 1.0), indicating its strong capability to maintain high classification accuracy even under conditions of class imbalance. This suggests that Random Forest can accurately identify all high-risk entities without false negatives.

The model's exceptional performance can be attributed to its ensemble structure, which combines multiple decision trees using random sampling, thereby reducing overfitting and improving the model's generalization capability. Although Gradient Boosting achieved competitive performance, it may have missed some high-risk cases due to the strictness of its regularization settings, which can overly constrain the model.

➤ *Feature Importance Analysis*

The feature importance analysis based on the Random Forest model identified the following variables as the most influential determinants of audit and credit risk:

- Amount of tax arrears
- Number of overdue days
- Duration of non-compliance

➤ *SHAP Feature Importance*

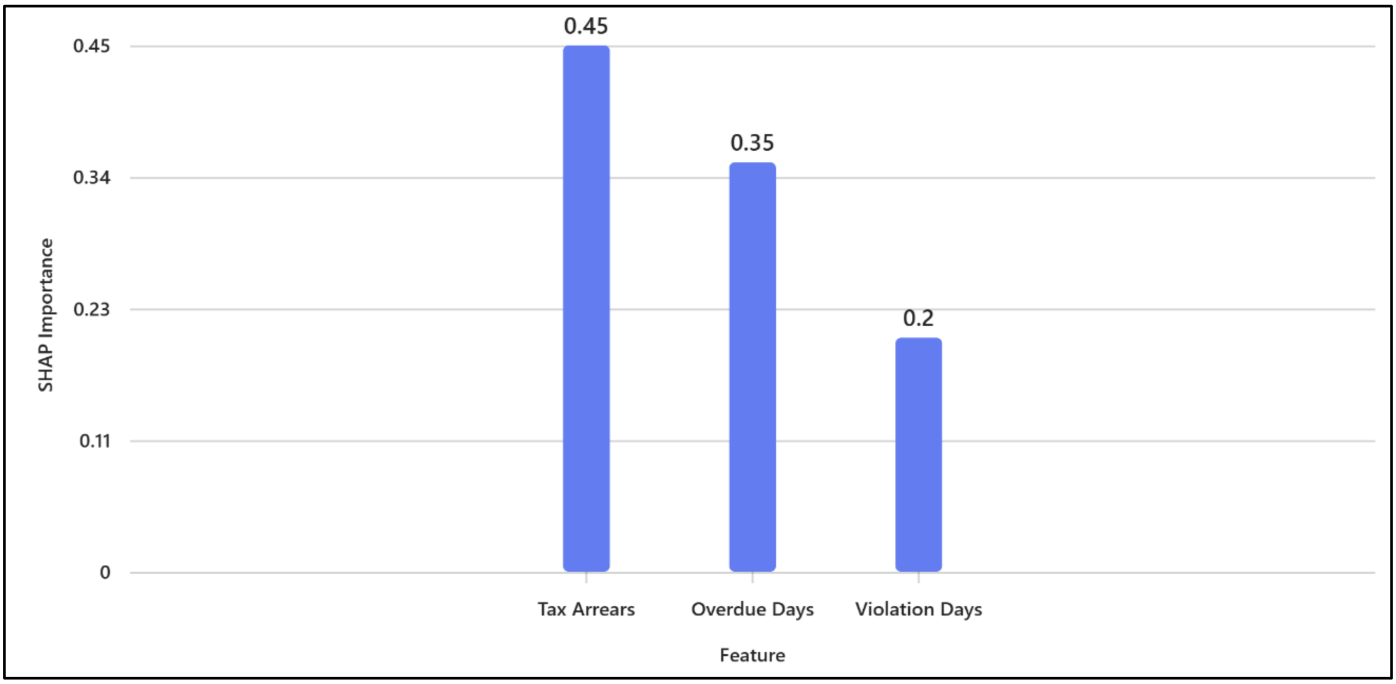

Fig 4 Feature Importance for Audit Risk Prediction (SHAP Analysis)
Source: Author's Calculation

The SHAP (SHapley Additive exPlanations) analysis revealed that tax arrears had the highest influence on audit risk prediction (≈ 0.45), followed by number of overdue days (≈ 0.35) and duration of non-compliance (≈ 0.20). These results confirm that the three indicators serve as the primary determinants in predicting audit risk and should therefore be incorporated into policy-level monitoring criteria.

The findings of this study are consistent with international research trends. For instance, Brown et al. (2020) and Zhang et al. (2022) demonstrated that ensemble-based machine learning methods are the most effective for detecting audit risk. Similarly, this study confirms that the Random Forest algorithm performs robustly under Mongolian conditions. Consistent with Liu et al. (2021), who found that Gradient Boosting is highly sensitive in detecting fraudulent financial statements, the present research also shows strong performance for Gradient Boosting, though its sensitivity to data quality and class imbalance was evident.

In the context of Mongolia, several constraints—such as limited data availability, variable data quality, and underdeveloped digital infrastructure—pose challenges to the implementation of AI-based auditing systems. Nonetheless, the adoption of explainable artificial intelligence (XAI) techniques, particularly through SHAP analysis, presents a vital opportunity to enhance audit transparency and support evidence-based policymaking.

Moreover, developing an early-warning system for audit and credit risk based on key indicators such as tax arrears, overdue periods, and non-compliance duration could substantially improve the efficiency of audit supervision,

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promote optimal resource allocation, and strengthen credit discipline among enterprises.

Overall, these findings lay the groundwork for establishing an AI-driven integrated risk assessment framework in Mongolia. The proposed model introduces a new approach that unifies auditing, financial oversight, and credit risk management, providing a significant contribution to the modernization of national audit and supervision systems.

V. CONCLUSION AND RECOMMENDATIONS

This study provides the first empirical evidence of applying artificial intelligence (AI) and machine learning (ML) techniques for the integrated assessment of audit and credit risk in Mongolia, based on data from 88 enterprises financed under the Small and Medium Enterprise (SME) Development Project during 2019–2024. By comparing the performance of classification algorithms—Decision Tree, Gradient Boosting, and Random Forest—the study found that Random Forest achieved the highest accuracy (0.944) and recall (1.000), demonstrating a 100% detection rate for high-risk enterprises.

The SHAP analysis identified tax arrears**,** number of overdue days**,** and duration of non-compliance as the most influential determinants of audit and credit risk. These findings have significant policy implications, highlighting the importance of integrating early risk detection indicators into regulatory and supervisory frameworks and developing a data-driven risk management system.

The results align with international research trends, confirming that AI-based integrated risk assessment models can outperform traditional audit methods by providing greater accuracy, timeliness, and objectivity. While Mongolia still faces constraints related to data accessibility**,** data quality, and human capacity, these challenges can be mitigated through coordinated policy initiatives, paving the way toward a modernized and technology-driven audit and credit supervision system.

➢ *Policy and Practical Recommendations*

- *Implement an Integrated Risk Assessment System:*

Tax and audit authorities should adopt machine learning–based tools to automate risk detection and minimize overlapping controls, supported by appropriate legal and institutional frameworks.

- *Establish a Unified Data Platform:*

Developing a centralized platform that consolidates financial statements, credit information, and audit findings will enhance the accuracy and reliability of risk assessments and support evidence-based decision-making.

- *Strengthen Human Capacity:*

Introduce targeted training and capacity-building programs on Explainable Artificial Intelligence (XAI) for professionals in auditing, banking, and regulatory sectors to increase trust and facilitate the practical adoption of AI technologies.

- *Develop an Early Warning Risk Detection System:*

Build an automated alert mechanism based on key indicators—tax arrears**,** overdue days, and non-compliance duration—to improve early detection, optimize monitoring resources, and enhance credit discipline.

FUTURE RESEARCH DIRECTIONS

Future research should utilize larger and longitudinal datasets to develop sector-specific sub-models that reflect the unique characteristics of different industries. Expanding the temporal and structural scope of data will enable more robust modeling of dynamic risk patterns and contribute to the implementation of transparent, evidence-based regulatory policies in developing economies.

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