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Article

Determining borrower credit ratings using credit scoring and selected machine learning approaches

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Abstract

The credit rating is major assessment of the creditworthiness of countries and corporates. Creditworthiness of the corporate is significant information for participant in financial markets such as investors, creditors and banks. But in Mongolia, there is no professional credit rating agency and Non-performing loans are still increasing in commercial banks as well. It indicates there is a need for a detailed study in credit rating model, based on the advanced methodology such as technological progress, big data, data mining, machine learning. In addition, the development of the stock market and financial markets, and the steady growth of investment are definitely related with the development and methodology of the credit rating.

The purpose of this study was to develop a corporate credit rating prediction model that would be appropriate for the Mongolian context. In this study, the model was developed by using information of sampled 277 companies, which were selected from the database of commercial bank "X", on the base of the scoring method as traditional and machine learning method as modern in combination. Based on the results of predictive performance indicators, ROC curve, and AUC calculations, Discriminant Analysis was identified as the most optimal model, while the Logit model demonstrated relatively weaker predictive performance. The result showed that the machine learning method have had a higher ability to predict and explain than other methods and models, that assess the borrower's creditworthiness.

Keywords: Credit scoring, Credit Risk Assessment, Machine learning, Neural networks, ROC curve

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Скоринг болон машин сургалтын зарим аргад тулгуурлан зээлдэгчийн зээлжих зэрэглэл тогтоох нь

*Сандагсүрэнгийн **Мөнхцэцэг***

Эдийн засаг, бизнесийн тэнхим, Мандах Их Сургууль, Улаанбаатар хот, Монгол Улс

Хураангуй

Зээлжих зэрэглэл гэдэг нь тухайн улс үндэстэн болон компанийн төлбөрийн чадварыг илэрхийлдэг нэг шалгуур үзүүлэлт юм. Компанийн төлбөрийн чадвартай эсэх нь санхүүгийн зах зээлд оролцогч хөрөнгө оруулагч, банк, зээлдүүлэгчийн хувьд чухал мэдээлэл болж өгдөг. Гэтэл өнөөг хүртэл Монгол улсын хувьд зээлжих зэрэглэл тогтоох мэргэжлийн байгууллага үүсэж хөгжөөгүй, арилжааны банкны олгож буй зээлийн дүнд чанаргүй зээлийн хэмжээ өссөөр байна. Энэ нь зээлжих зэрэглэл тогтоох загварыг техник, технологийн хөгжил, биг өгөгдөл, өгөгдөл тандалт, машин сургалтын арга зэрэг дэвшилтэт арга зүйд тулгуурлан нарийвчлан судлах хэрэгцээ шаардлага байгааг харуулж байна. Түүнчлэн хөрөнгийн зах зээл болон санхүүгийн зах зээлийн хөгжил, хөрөнгө оруулалтын хэмжээ тогтвортой өсөх зэрэг нь зээлжих зэрэглэл тогтоох үйлчилгээний хөгжил, арга зүйтэй салшгүй холбоотой. Энэхүү судалгааны ажлаар Монгол улсын нөхцөлд тохирсон компанийн зээлжих зэрэглэлийг урьдчилан таамаглах загварыг боловсруулахыг зорьсон. Ингэхдээ арилжааны банкуудын хамгийн өргөн ашиглаж буй уламжлалт аргуудын нэг болох скорингийн арга, мөн орчин үед шинээр ашиглагдах болсон машин сургалтын зарим аргуудад тулгуурлан “X” арилжааны банкны мэдээллийн сангаас түүвэрлэсэн 277 зээлдэгчийн мэдээллийг ашиглаж боловсруулав. Таамаглах чадварын үзүүлэлт, ROC муруй болон AUC тооцооллын үр дүнгээр Дискриминантын шинжилгээ нь хамгийн оновчтой загвар болох нь тогтоогдсон бол ложит загварын таамаглах чадвар харьцангуй сул байгааг харуулсан. Судалгааны үр дүнд зээлдэгчийн зээлжих чадварыг үнэлэх арга, загваруудаас машин сургалтын аргуудын хувьд таамаглах болон тайлбарлах чадвар нь илүү өндөр байв.

Түлхүүр үгс: Зээлийн скоринг, Зээлийн эрсдэлийн үнэлгээ, Машин сургалт, Мэдрэлийн сүлжээ, ROC муруй.

1. Introduction

Although banking and financial institutions have diversified their services, lending particularly consumer and corporate loans remains their core activity and primary income source (Vojtek.M & Kocenda.E, 2006). Corporate lending is highly profitable but increasingly faces challenges such as rising non-performing loans and borrowers’ inability to meet repayment obligations. Therefore, a key task for lenders is to distinguish between creditworthy and high-risk borrowers before granting loans.

Credit rating prediction methods are generally divided into traditional statistical approaches and machine learning techniques. Traditional methods include logistic regression (Stepanova.M & Thomas.L.C, 2001), discriminant analysis (Kumar.K & Bhattacharya.S, 2006; Khemakhem.S & Boujelbene.Y, 2015), and Bayesian networks (Hajek.P, Olej.V, & Prochazka.O, 2016). More recent studies apply artificial intelligence models, such as neural networks, which show superior predictive performance on large datasets (Mark.W, Kuldeep.K, & Adrian.G, 2019). Credit rating determinants can be grouped into three categories: (1) financial variables, especially ratios reflecting firm characteristics like leverage, liquidity, and size (Ederington.L, 1985), (Kamstra.M, Kennedy.P, & Suan.T.K, 2001), (Blume.M, Lim.F, & Mackinlay.A, 1998); (2) corporate governance factors, such as ownership structure and board independence (Bhojraj.S & Sengupta.P, 2003) and (Ashbaugh.S.H, Collins.D, & LaFond.R, 2006); and (3) macroeconomic variables, including GDP growth (Amato.J & Furfine.C, 2004).

2. Research Methodology

This study combines traditional credit scoring methods with modern machine learning approaches, including linear discriminant analysis, logistic regression, and artificial neural networks. Credit scoring is a quantitative measure used to evaluate a borrower's ability to repay debt by assigning scores based on financial and behavioral characteristics, thereby estimating default probability and enabling risk based classification (Munkhzaya.B, 2013). In recent years, traditional credit scoring techniques have evolved through the integration of artificial intelligence and machine learning (World Bank Group, 2019). Machine learning focuses on identifying patterns from large datasets, with artificial neural networks being one of its key methods (SAS, 2019). These AI based approaches are now widely applied in advanced fields such as image and speech recognition, autonomous systems, and self driving technologies (Financial Stability Board, 2017).

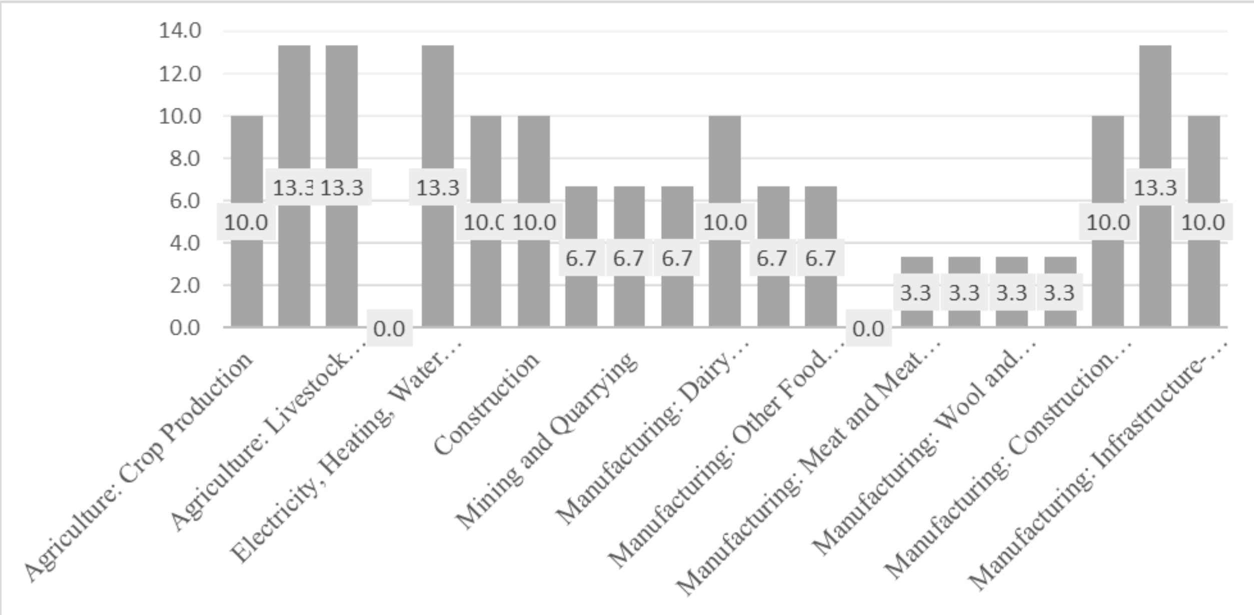
3. Empirical Study

This study proposes a credit rating model for borrowers in Mongolia by integrating credit scoring and machine learning methods, and examines its practical use. The analysis relies on financial and non-financial data from 277 borrowers selected from a commercial bank database. Several classification techniques were applied, including logistic regression, discriminant analysis, decision trees, random forests, support vector machines, and neural networks. The models were implemented using SPSS, EViews, Python, and Excel.

3.1. Development and Results of the Credit Scoring Model

At the initial stage, a credit scoring framework was designed to predict borrower ratings. Creditworthiness was assessed using both quantitative and qualitative factors, including financial indicators, survey data, and macroeconomic variables. Since loan quality is affected by economic cycles and industry performance, sector-level risk was also incorporated. Borrowers were grouped by economic sector, and risk was evaluated based on volatility, current conditions, and future outlook. These were compared against overall sector averages, where above-average sectors were treated as lower risk and below-average sectors as higher risk. (Figure 1.) The results show that construction, construction-related manufacturing, trade, and transportation and warehousing sectors carry higher risk. This aligns with their loan performance, as these sectors also exhibit higher levels of non-performing loans. Sectoral risk was assessed for each borrower and classified into high, medium, and low categories, with a maximum weight of 20% in the overall model. In contrast, sectors such as crop and livestock production, wool and cashmere processing, and textile and leather manufacturing were considered lower risk.

Figure 1. Assessment of Industry-Level Factors



Source: Author's calculations

However, these sectors still show relatively high non-performing loan levels compared to others. To capture qualitative aspects, 48 non-financial variables related to borrower behavior and status were included. Their relevance was tested using correlation analysis, and only statistically significant variables were retained for further modeling.

Table 1. Evaluation of Qualitative Factors

Factor	Sub-category	Notation	Score
Loan Term	Up to 36 months	X10	0
	37–60 months		0.52
	More than 61 months		1.04
Business Experience (Borrower/Company)	Up to 1 year	X13	0
	2–5 years		2.95
	6–10 years		5.9
	More than 11 years		8.85

Gender (Male = 1, Female = 0)	Borrower/Director is male	X7	5.23
	Borrower/Director is female		0
Age of Borrower/Director	Up to 25 years	X14	0
	26–35 years		1.81
	36–50 years		2.71
	Above 51 years		5.42
Geographic Proximity to Market/Customers	Within 300 km	X19	1.07
	More than 300 km		0
Distance to Main Raw Materials	Within 20 km	X20	3.49
	21–60 km		1.75
	More than 61 km		0
Sales Channels (Own store / regular buyers / contracts)	None	X21	0
	1–2 sales channels		1.08
	More than 3 channels		2.17
Business Diversification	Not diversified	X22	0
	2–3 types		0.34
	More than 4 types		0.68
Ownership Share in the Business	Up to 80%	X23	0
	81–99%		0.55
	100%		1.1
Average Revenue Growth (relative to inflation)	Less than 0	X25	0
	0.1–0.5		3.22
	Greater than 0.6		6.43

Source: Author's calculations

For qualitative variables with limited categories, a binary scoring method was applied, assigning full scores when conditions were met and minimum scores otherwise. For quantitatively expressed qualitative variables, scoring thresholds were based on sample statistics such as mean, median, and standard deviation, along with distribution characteristics. The overall weight of qualitative factors was limited to 20%. Financial ratios commonly used in bank credit analysis were also included. Of the 277 borrowers, 242 were performing and 35 were non-performing. An independent sample t-test was conducted to compare the mean values of financial ratios between these two groups. The results show that ratios FR2, FR5, FR7, and FR12 have the strongest differences between groups, indicating their high importance in distinguishing credit risk.

Table 2. Evaluation of Financial Factors

Ratio	Financial Indicator	A_i	B_i	C_i	D_i	Ratio Value	Score
FR2	Current Assets / Total Liabilities	0.1	3	9.12	2.3	9.3	5
FR3	Total Liabilities / Total Assets	0	2	4.72	1.5	0	6
FR5	Net Sales / Total Assets	0	2	4.99	1.5	0.5	3
FR7	Altman Z-score	0.1	4	11.4	3.1	3.4	9.3
FR8	Total Debt / Total Assets	0.1	4	12.3	3.1	0.3	9.3
FR9	Revenue Growth Rate	0.1	4	14.7	3.1	0.3	15.5
FR10	(Inventory, WIP, Receivables) / Total Liabilities	0	1	2.98	0.8	0.6	2.4
FR11	Net Income (Current Period) / Total Assets	0	1	2.86	0.8	0	0

FR12	Post-loan Debt / Total Assets	0.2	5	36.9	3.8	1.2	0
Total		0.6		26	100		50.5*

Note: *The total score (50.5) represents the sum of scores obtained by borrower i across all financial ratio indicators.*

Source: Author's calculations

Here, A_i represents represents the correlation between each financial ratio and credit risk, while B_i reflects its relative importance on a scale of 1 to 5. The proportional contribution C_i and assigned weight D_i were calculated based on these values. Since the impact of financial ratios varies, their appropriate ranges were determined using statistical measures such as mean, median, standard deviation, and one-way tabulation. The total contribution of financial factors in the credit scoring model was capped at 40%.

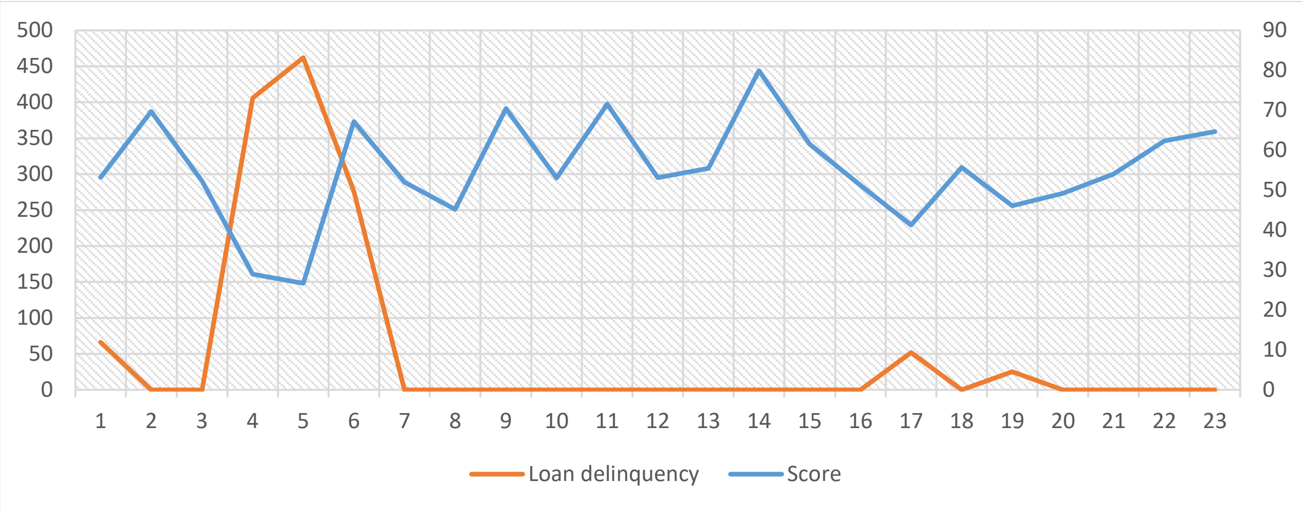
Table 3. Evaluation of Survey-Based Factors

No.	Question	Response	Score
1	What is your business experience?	Up to 1 year	1
		1–2 years	2
		2–3 years	3
		3–5 years	4
		More than 5 years	5
2	What is the main reason for initiating this business project?	Expansion of current operations or diversification of business activities	3
		Possesses professional experience in this field	2
		The sector is expected to receive policy or market support	1
3	Is the applicant's (or co-applicant's) professional background aligned with the proposed business activity?	Fully aligned	3
		Not aligned	-1
		Partially related	1
		Not aligned but has relevant experience	2
…	…	…	…
21	Is it possible to control and manage product distribution channels?	One sales outlet	1
		2–4 outlets	2
		5–10 outlets	3
		More than 11 outlets	4
22	Information regarding suppliers	Low dependency: abundant availability of raw materials and finished goods	1
		High dependency: reliant on a limited number (1–2) of suppliers	-1
23	If previous loans were obtained, how were they utilized?	Primarily used for consumption purposes with a good repayment history	3
		Small business loans used appropriately and repaid on time	2
		Small business loans repaid on time but used for unintended purposes	1
24	Taxpayer status	Compliant taxpayer	2
		Individual taxpayer with unverifiable income	1
		Not a taxpayer	-1

Source: Author's calculations

A questionnaire was used to assess borrowers' business profiles, including past performance, current conditions, and future prospects. Scoring followed a risk-based approach, where lower scores indicate higher risk. The questionnaire varied by business size, start up, micro, small, and medium enterprises with the total weight capped at 20%. Key credit risk variables were selected through comparative analysis and the methodology was tested on data from 23 borrowers of a commercial bank in Mongolia.

Figure 2. Relationship between Loan Delinquency and Qualitative Assessment for the 23 Sampled Borrowers



Source: Author's calculations

The empirical findings indicate an inverse relationship between the total credit score and loan delinquency, whereby lower overall scores are associated with higher levels of delinquency. For instance, Borrower 5 recorded the lowest total score (26.68 points), while simultaneously exhibiting the highest level of loan delinquency (462 days).

Table 4. Credit Scoring Results for the 23 Sampled Borrowers

№	Industry Sector	I	II	III	IV	Score	Credit Assessment
		Quantitative	Qualitative	Questionnaire based	Sectoral		
		40	20	20	20	100	AAA
1	Services	23.4	19.32	18.1	13	73.82	BBB
2	Services	23.5	19.65	17.6	13	73.75	BBB
3	Trade: Food, Consumer Goods, and Pharmaceuticals	27.12	17.4	19.87	3	67.39	BB+
4	Manufacturing: Infrastructure	0	9.43	8.94	10	28.37	C
5	Agriculture: Crop Production	12.34	13.56	19.6	13	58.5	B
6	Trade: Food, Consumer Goods, and Pharmaceuticals	18.5	19.9	18.7	3	60.1	BB-
7	Manufacturing: Textiles, Footwear, and Leather	15.3	19.73	19.48	13	67.51	BB+
8	Trade: Food, Consumer Goods, and Pharmaceuticals	26.71	19.91	18.99	3	68.61	BBB-
9	Manufacturing: Construction Support Materials	18.74	19.87	19.94	0	58.55	B
10	Services	25.67	19.4	19.81	13	77.88	A-

11	Manufacturing: Wool and Cashmere	20.12	19.65	18.95	10	68.72	BB+
12	Manufacturing: Dairy Products	19.78	19.56	13.21	20	72.55	BBB+
13	Manufacturing: Other	10.92	15.46	20.97	10	57.35	B
14	Manufacturing: Other	8.23	19.61	18.65	10	56.49	B
15	Manufacturing: Other	20.96	18.53	18.65	10	68.14	BB+
16	Manufacturing: Other	17.83	19.36	19.84	10	67.03	BB+
17	Manufacturing: Textiles, Footwear, and Leather	10.87	13.78	19.67	13	57.32	B+
18	Agriculture: Livestock	15.74	27.68	19.56	10	72.98	BBB
19	Agriculture: Livestock	15.31	25.45	19.76	10	70.52	BBB-
20	Manufacturing: Dairy Products	13.45	15.46	11.58	20	60.49	BB-
21	Trade: Other	22.03	19.99	18.7	3	63.72	BB
22	Construction	12.45	19.5	19.82	0	51.77	CCC-
23	Manufacturing: Dairy Products	10.01	21.06	36.08	20	87.15	AA

Source: Author's calculations

The 23 borrowers were classified by economic sector and evaluated using the credit scoring model. Results show that 26.09% were rated "BBB," while 34.78% fell into the "BB" category, indicating lower credit quality. Only 8.67% achieved a high rating ("AA"), and another 8.67% were classified as high-risk ("C"). Borrowers in construction, construction materials manufacturing, and trade sectors received relatively weaker ratings, consistent with earlier sectoral risk assessments and supporting the model's validity.

3.2. Development and Results of Machine Learning Models

This section develops borrower credit rating models using several machine learning methods, including discriminant analysis, logistic regression, support vector machines, decision trees, random forests, and neural networks. To identify the most influential variables, Levene's test and one-way ANOVA were applied. The results show that, out of 58 variables (48 qualitative, 9 financial, and 1 sectoral), 18 were statistically significant in explaining credit rating outcomes.

Table 5. Results of Levene's Test for X25

Test of Homogeneity of Variances					
X25	Based on Mean	8.498	1	198	0.004***
	Based on Median	4.607	1	198	0.033**
	Based on Median and with adjusted df	4.607	1	177.9	0.033**
	Based on trimmed mean	6.866	1	198	0.009***
Note: The symbols (***), (**), and (*) indicate the rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.					

Source: Author's calculations

For instance, Levene's test shows that the variance of variable X25 (revenue growth relative to inflation) differs significantly between groups, indicating its strong effect on credit ratings. This implies that changes in a borrower's income level are an important factor in determining creditworthiness.

Table 6. One-Way ANOVA Results for X25

		Sum of Squares	df	Mean Square	F	Sig.
X25	Between Groups	57.067	1	57.067	4.97	0.027**
	Within Groups	2273.429	198	11.482		
	Total	2330.496	199			
Note: The symbols (***), (**), and (*) indicate the rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.						

Source: Author's calculations

The ANOVA results for X25 (F = 4.97) reject the null hypothesis at the 5% level, indicating a significant difference in mean income between performing and delinquent borrowers. Further testing using ANOVA and Levene's test identified 18 variables (X2, X3, X10, X13, X14, X15, X17, X23, X25, X31, X33, X38, X41, X42, X45, FR2, FR5, FR6) as statistically significant for credit rating. The dataset of 277 borrowers was split into training and testing sets (80:20). Models were trained on 80% of the data and evaluated on the remaining 20% to determine the best-performing approach. Although decision tree and random forest models achieved 100% accuracy on the training data, their performance dropped below 90% on the test data, making them less reliable than other models.

Table 7. Comparison of Predictive Performance of Models

Model	Decision Tree				Random Forest				Support Vector Machine			
Count	Training		Testing		Training		Testing		Training		Testing	
	BB	GB	BB	GB	BB	GB	BB	GB	BB	GB	BB	GB
Bad Borrower /BB/	32	0	6	2	31	1	4	4	9	23	1	7
Good Borrower /GB/	0	191	7	38	0	191	3	42	0	191	0	45
Percentage	Decision Tree				Random Forest				Support Vector Machine			
	Training		Testing		Training		Testing		Training		Testing	
Bad Borrower /BB/	14%	0%	11%	4%	14%	0%	8%	8%	4%	10%	2%	13%
Good Borrower /GB/	0%	86%	13%	72%	0%	86%	6%	79%	0%	86%	0%	85%
Overall Predictive Accuracy	100%		83%		100%		87%		90%		87%	
Bad Borrower Accuracy	100%		75%		97%		50%		28%		13%	
Good Borrower Accuracy	100%		84%		100%		93%		100%		100%	
Model	Logistic Regression				Discriminant Analysis				Artificial Neural Network			
Count	Training		Testing		Training		Testing		Training		Testing	
	BB	GB	BB	GB	BB	GB	BB	GB	BB	GB	BB	GB
Bad Borrower /BB/	16	16	4	4	17	15	7	1	20	12	7	1
Good Borrower /GB/	7	184	1	44	7	184	1	44	7	184	3	42
Percentage	Logistic Regression				Discriminant Analysis				Artificial Neural Network			
	Training		Testing		Training		Testing		Training		Testing	
Bad Borrower /BB/	7%	7%	8%	8%	8%	7%	13%	2%	9%	5%	13%	2%
Good Borrower /GB/	3%	83%	2%	83%	3%	83%	2%	83%	3%	83%	6%	79%
Overall Predictive Accuracy	90%		91%		90%		96%		92%		93%	
Bad Borrower Accuracy	50%		50%		53%		88%		63%		88%	
Good Borrower Accuracy	96%		98%		96%		98%		96%		93%	

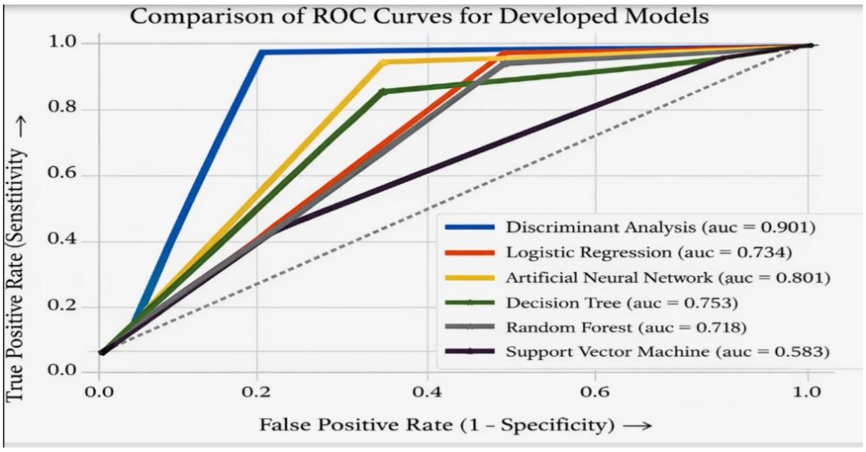
Source: Author's calculations

From the overall predictive performance of the developed models, the decision tree and random forest models show 100% accuracy in correctly predicting both normal and overdue borrowers in the training sample. However, in the test sample, their accuracy drops to below 90%, indicating weaker predictive performance compared to other models. In contrast, the logit, discriminant analysis, and artificial neural network models achieve 90% or higher accuracy in correctly predicting outcomes in both the training and test samples.

For instance, the discriminant analysis model correctly classified 7 out of 8 delinquent borrowers (88%) and 44 out of 45 performing borrowers (98%) in the testing dataset.

Similarly, the artificial neural network model achieved an accuracy of 88% in identifying delinquent borrowers and 93% in correctly classifying performing borrowers. As a result, the overall classification accuracy of these models in distinguishing between good and bad borrowers reached approximately 93% and 96%, respectively, which is relatively higher than that of the other models. Given that several models exhibited similarly high predictive performance, the Receiver Operating Characteristic (ROC) curve was employed as a comparative evaluation tool to assess the relative effectiveness of the developed models. The ROC curve is widely regarded as one of the most appropriate metrics for evaluating classification performance, as it measures model accuracy across different threshold levels. In this context, the Area Under the Curve (AUC) serves as a key indicator, where higher values reflect a stronger ability of the model to correctly distinguish between performing and delinquent borrowers.

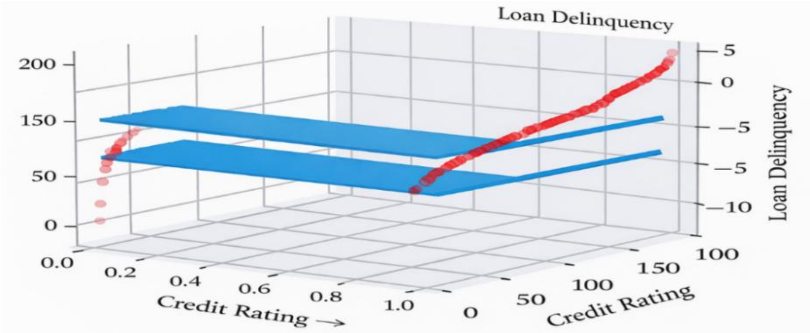
Figure 3. Comparison of ROC Curves for Developed Models



Source: Author's calculations

The relatively high performance of the discriminant analysis and artificial neural network models suggests that adjusting the classification threshold of the target variable beyond the conventional 0.5 level may further enhance predictive accuracy. Based on the combined evidence from accuracy metrics, ROC curve analysis, and AUC calculations, discriminant analysis is identified as the most optimal model. In contrast, the logistic regression model demonstrates comparatively weaker predictive performance.

Figure 5. AUC of Developed Models: 3D Scatter Plot



Source: Author's calculations

The three-dimensional model classifies borrower creditworthiness into three regions. The upper plane represents the threshold for good borrowers, while the lower plane defines high-risk borrowers. The area between them indicates uncertainty, where repayment ability is unclear.

Based on this, creditworthiness is classified as:

1. $CR \geq 1.8908139$ Good borrower
2. $-1.8345232 \leq CR < 1.8908139$ Uncertain borrower
3. $CR < 0.020966$ бол Poor borrower

Table 8. Comparative Analysis of Machine Learning and Credit Scoring Models

Model	Machine Learning Model				Credit Scoring Model			
Count	Training		Testing		Training		Testing	
	BB	GB	BB	GB	BB	GB	BB	GB
Bad Borrower /BB/	17	15	7	1	13	19	5	3
Good Borrower /GB/	7	184	1	44	21	170	5	40
Percentage	Machine Learning Model				Credit Scoring Model			
	Training		Testing		Training		Testing	
Bad Borrower /BB/	7.8%	6.5%	13.5%	2.7%	5.8%	8.5%	9.4%	5.7%
Good Borrower /GB/	3.2%	82.5%	2.7%	81.1%	9.4%	76.2%	9.4%	75.5%
Overall Predictive Accuracy	90.3%		94.6%		82.1%		84.9%	
Bad Borrower Accuracy	54.55%		83.33%		40.63%		62.50%	
Good Borrower Accuracy	96.21%		96.77%		89.01%		88.89%	

Source: Author's calculations

The comparative results between the traditional credit scoring model and commonly used machine learning models for rating prediction indicate that machine learning approaches exhibit superior overall predictive performance.

4. Conclusion

Recent studies on corporate financial risk and credit rating have gained importance with technological progress, supporting both firm-level evaluation and policy decisions. This research developed a credit rating model tailored to Mongolia by identifying key determinants and testing predictive approaches. The main findings are:

- Using data from 277 borrowers, a credit scoring model was constructed based on four factor groups: sectoral, financial, qualitative, and questionnaire-based variables.

- A 100-point weighting system was designed considering factor characteristics, prior studies, and variable importance.
- Financial indicators were found to be the most influential, as they also reflect underlying non-financial effects.
- Sectoral and macroeconomic risks were incorporated, highlighting their significant impact on borrower performance.
- Machine learning models outperformed traditional methods in predictive accuracy and practical use.

Recommendations

- Update indicators dynamically by adjusting or removing less relevant variables.
- Credit rating systems can improve capital structure, efficiency, and borrower–lender trust, while helping firms focus on key performance factors.
- For banks and investors, such systems support firm classification, sector analysis, lending decisions, regulatory oversight, transparency, and reduction of non-performing loans.

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