Eduvest – Journal of Universal Studies
Volume 4 Number 6, June, 2024
p- ISSN 2775-3735- e-ISSN 2775-3727

THE MACHINE LEARNING METHODS FOR MICRO-CREDIT SCORING: THE CASE OF MICRO-FINANCING IN MONGOLIA

Bayarmaa Dashnyam[1], Gerelt-Od Uvgunkhuu[2]*, Burmaa Sosorbaram[3]
[1,2] Department of Finance, National University of Mongolia, Mongolia
[3]MBA, Department of Finance, National University of Mongolia, Mongolia
Email: gereltod.u@num.edu.mn

ABSTRACT

As a result of growing digital technologies in the financial sector, the traditional slow lending process is being replaced by fast and easy digital lending systems that can make decisions in real time. Both lenders and borrowers have experienced the benefits of digital lending, the activities of microfinance institutions have expanded rapidly and the volume of digital microloans has increased significantly worldwide, including Mongolia. At the same time with the growing volume of digital microloans in Mongolia, the rationality of credit risk management has been becoming more critical. Credit quality is the most important factor in optimal credit risk management. It depends on determining the customer's creditworthiness and making accurate credit decisions. This research focuses on a credit scoring system to improve the digital loan evaluation system of the Mongolian microfinance institute. This study aims to contribute to the development of possible credit scoring systems for Mongolian microfinance institutions by comparing several machine-learning approaches based on loan datasets of a non-banking microfinance institute in Mongolia. The result shows the ensemble methods Random Forest and XGBoost Tree's accuracies are higher than other machine learning models for the microloan borrowers' repayment status prediction.

KEYWORDS *Micro-Credit; Micro-Finance; Credit Scoring; Microloan; Machine Learning*

INTRODUCTION

Due to the rapid development of technology, many types of digital services have emerged in the financial sector creating a lot of opportunities for financial institutions to deliver higher-quality services to their customers quickly and easily. Among financial services, digital lending services are rapidly developing and many

How to cite:	Bayarmaa Dashnyam, et al. (2024). The Machine Learning Methods For Micro-Credit Scoring: The Case Of Micro-Financing In Mongolia. *Journal Eduvest*. *4*(5), 4489-4503
E-ISSN:	2775-3727
Published by:	https://greenpublisher.id/

digital lending platforms are being introduced from banks and microfinance institutions. Allied Marketing Research estimated the global digital lending market value as $12.6 billion in 2022 and forecasts that the market will reach $71.8 billion by 2032 (Pradeep R., 2023).

Pradeep (2023) defined it as a digital platform for providing customers with loans and credit without needing in-person interactions. It has become increasingly popular in recent years due to advancements in technology. In terms of borrowers and customers, it can offer a more convenient service for them with faster approval times and reduced paperwork (Pradeep R., 2023).

Along with the expansion of the digital lending market, the volume of microloans is growing fast, since most microloans are offered by digital lending. So, there is still a risk that borrowers will be burdened with debt, and the quality of the loan portfolio of financial institutions will deteriorate in the long term in Mongolia. Financial institutions can improve their credit decision with data-driven digital experiences. Credit scoring systems play an important role in the credit decisions of financial institutes. Credit scoring is used to evaluate an individual's creditworthiness and determine whether an individual's application is approved or rejected (Thomas Lyn, 2017). Nowadays, the use of machine learning approaches in credit scoring systems becoming more popular and improving credit decision quality (Bhilare, 2018), (Pan, 2021), (Anil Kumar, 2021).

In Mongolia, as a result of the effect of fintech service, the volume of digital microloans of nonbank financial institutions(NBFI) has significantly increased and a total of thirty-seven NBFIs provide digital lending services. According to the Financial Market Review report, the total digital loan portfolio of Mongolian non-banking financial institutes' has reached 461.0 billion MNT in 2022 which is a 1.5-fold increase from 2021. This amount is 17% of the total loan portfolio and 79% of the total number of borrowers of Mongolia's NBFIs. This indicates that 79% of all NBFC customers are digital loan borrowers and its portfolio will grow further (Financial Regulatory Commission, 2022). Although digital lending demand has grown fast, financial institutes must be aware of the risk of increased debt burden and the deterioration of the quality of the loan portfolio. In 2021, 5.6% of the digital loan portfolio was categorized as attention and non-performing loans, but this amount has increased to 10.0% in 2022. (Financial Regulatory Commission, 2022).

Although the risk of digital credit is at the attention of the regulatory body and the Financial Regulatory Commission of Mongolia has issued some regulations on digital credit services, the monitoring of implementation and setting the right requirements for digital borrowers is still not enough. Solving this issue has been becoming more and more important for the NBFIs. For Mongolia's NBFIs, the use of the credit scoring model for credit risk management is relatively weak, and insufficient requirements for borrowers affect credit risk. The solution to reducing the risk of digital credit is to improve the digital lending evaluation system to treat customers equally and assess their creditworthiness. There is a lack of studies related to credit scoring in the case of the Mongolian microfinance environment. Therefore, the purpose of this research is to develop possible credit scoring systems by comparing several machine learning models based on microloan datasets of a non-banking financing institute in Mongolia.

There are numerous of literature on credit scoring (Apostolos Ampountolas, 2021), (Pan, 2021), (Bhilare, 2018), (Gernmanno Teles, 2020). Apostolos et al. (2021) demonstrated that off-the-shelf multi-class classifiers can perform at classifying borrowers' various credit categories. The researchers conducted this study for borrowers of a micro-lending organization. Yi Wu et al. (2021) demonstrated that a logistic regression method is more fits to the credit evaluation model for individual customers. Bhilare (2018) conducted an empirical analysis and compared ensemble tree learning techniques with a base decision tree. The results suggested that ensemble models show the better performance than individual models. Gernmanno (2020) compared the results between fuzzy sets and artificial neural network models. The researchers pointed out that the fuzzy logic approach is more accurate in modeling uncertainty.

There are very few studies on credit scoring that use machine learning models on microfinance digital lending services in Mongolia. (Ganbat M., 2021) predicts an individual's credit risk by applying the empirical data using logistic regression. The researchers predicted a borrower's credit risk based on psychological factors such as self-discipline, diligence, selflessness, and cost-effective decision-making, etc.

In this research, we used a Mongolian nonbanking finance institute's borrowers' dataset. From the dataset, we initially extracted 37 possible features and examined them to select optimal features. After the feature selection process, a total of 15 explanatory variables which are customers' general and credit history data, and 1 response variable are chosen for the scoring model. We compared ten classification models with highly predictive accuracy that are used by researchers (Keramati, 2011). Among these models, XGBoost Tree(76.13), Random Forest(75.40), CHAID (70.33), and Random Tree (70.06) methods have 70% higher accuracy and we discussed the detailed results of these for classifiers in our research. All of these models are tree-based models and it might be because our dataset has many categorical features. The top two methods were the XGBoost Tree and Random Forest models which are ensemble methods. Therefore, it is shown that the ensemble methods have better performance in terms of microloan.

The remainder of this paper is structured as follows. The literature review section presents the theoretical background of the credit scoring and machine learning models and reviews the related literature; the Data and Methodology section describes the data and methodologies used in this study, followed by the Result section in which detailed results are explained, finally, Discussion & Conclusion section.

Literature Review

In 1956, engineer William Fair and mathematician Earl Isaac introduced a new branch of research into science by developing an algorithm for making predictions about borrower behavior. They have developed a 2-page scorecard containing borrower information (Poon, 2007). In the recent, there are various studies have introduced for credit scoring (Apostolos Ampountolas, 2021), (Anil Kumar, 2021) (Pan, 2021), (Bhilare, 2018), (Gernmanno Teles, 2020). Keramati & Yousefi (2011) proposed data mining classification techniques in credit scoring and identified parametric and non-parametric methods. (Anil Kumar, 2021) presented the various machine learning algorithms that rural borrowers. Apostolos et al. (2021) compared several models and showed that standard multi-class classifiers work well in classifying various credit categories of customers. The researchers conducted their study in a micro-lending organization in which there is a lack of data related to customer creditworthiness. Gernmanno (2020) compared the results between fuzzy sets and artificial neural network models. The researchers pointed out that the fuzzy logic approach is more accurate in modeling uncertainty. An-Hsing Chang (2022) built the credit scoring model for peer-to-peer loans by using an artificial neural network approach. Several studies demonstrate that ensemble methods predict better than individual models (Bhilare, 2018) (Breiman, 2001) (Munkhdalai L., 2019). Bhilare (2018) conducted an empirical analysis and compared ensemble tree learning techniques with a basic decision tree. The results of this study showed that the ensemble models predict higher prediction accuracy than individual models. The existing literature suggests that several classification models are proven with good performance for prediction such as Decision tree (Bhilare, 2018), Ensemble methods such as XGBoost, Random Forest (Bhilare, 2018)), Logistic regression (Pan, 2021), (Ganbat M., 2021), Neural network(NN) (Chang A.H., 2022), Bayesian network (Germanno Teles, 2020), and Support vector machine (J. Vaidya, 2007).

There are few studies related to credit scoring using machine learning for the case of microfinance digital lending in Mongolia. (Ganbat M., 2021) predicted an individual's credit risk using logistic regression based on empirical data. The researcher used customers' psychological data such as self-discipline, diligence, selflessness, cost-effective decision-making, etc.

The result of the research shows that the tree-based classification models XGBoost (extreme gradient boosting method), Random Tree, Random Forest, and CHAID models perform the predictions with higher accuracies in our dataset. We briefly reviewed some of these machine-learning models below.

Decision trees are non-parametric supervised learning algorithms. A hierarchical tree structure consists of root nodes, branches, internal nodes, and leaf nodes. The ensemble method constructs more than one decision tree. An ensemble method XGBoost or Extreme Gradient Boosting method which is was proposed by Chen and Guestrin (2016). It is a gradient algorithm based on scalable tree boosting. Boosting trees are built into regression and classification trees while optimizing the prediction result.

The Random Forest classifier is also an ensemble algorithm of decision trees wherein each tree depends on randomly selected samples trained independently, with a similar distribution for all the trees in the forest (Breiman, 2001). Thus, a random forest is a classifier containing a collection of tree-structured classifiers, which reduces overfitting and increases overall accuracy (Geurts, 2006). A random forest classifier is a special type of bootstrap that builds multiple decision trees by repeatedly resampling and permuting the training data and voting on a consensus prediction.

Random Trees is a tree-based classification and prediction method based on the Classification and Regression Tree methodology (Loh, 2011). A random tree randomly selects a certain number of predictors and uses the best one from the selection to split the nodes. Each tree in the random tree is fully grown until each leaf node has one record. Therefore, the depth of the tree can be very large.

One of the tee-based classification methods is CHAID(Chi-squared Automatic Interaction Detection) uses chi-square statistics for optimal splits to achieve the best outcome for the target variable (Gilbert, 2013).

RESEARCH METHOD

Data Collection

We conducted our study using the microloan borrowers' dataset of nonbanking finance institutes in Mongolia. Initially, we extracted 12450 borrowers' data. In the data preparation stage, we analyzed and cleaned data, and a total of 6947 customer data remained for model building.

Feature Selection

From the NBFI's database, we initially extracted 37 possible variables and excluded the variables that were not relevant to our research and with a low ability to explain the response variable. Moreover, we eliminated the features that have a high positive linear correlation between the variables. It helps to remove the confounding effect which is a result of the presence of multicollinearity. The presence of the multicollinearity leads to the models' overfitting or underfitting where a small change in the data leads to a drastic effect on the model in question. In this step, a total of 15 explanatory variables that represent customers' general and credit history information and 1 response variable are chosen for the scoring model. The variables used in our research are listed in Table 1.

Table 1. Definitions of variables

Variables	Definition
Age	Age of customer
Gender	Gender of a customer. Female code as 0 and male as 1;
Mobile number value	Mobile phone number value: Valuable, Average valuable, No valuable;
Is our customer	If the customer has ever taken a loan from this institute before, the value is 1, and otherwise 0;
Loan count	Number of active loans;
Application loan	Number of active digital loans
Property loan	Customer's mortgage loan status: If a customer has a mortgage loan is coded as 1, and if not as 0;
Debt income ratio	Debt-to-income ratio of customer
Property	Real estate ownership status of a customer. If a customer owns at least one real estate is coded as 1, and if not as 0;
Vehicle	A customer's vehicle status. If a customer owns at least one vehicle is coded as 1, and if not as 0;

Mobile phone type	The customer's mobile phone type: iPhone, Samsung, and Other;
Marital status	Marital status of customer: Single, Married, and Not specified
Job-status	Customer's job. If a customer employs at least one job is coded as 1, and if not as 0;
More than one job	If a customer employs more than one job is coded as 1, and if not as 0;
Living area	Living area of customer: Capital, Other area, and Unknown
Result	The target variable or result class. If the customer is overdue his/her loan for more than 30 days is coded as 1(considered as "bad" class label), and if not 0 (considered as "good" class label);

In this study, we categorized our response(result) variable into two classes "Good" customer and "Bad" customer. if the customer is not overdue his or her loan payment, or overdue for less than 30 days belongs to the "Good" class label, if the customer is in arrears for more than 31 days and classified into the "Bad" class.

We recalculated the correlation between these variables using Pearson's R, Correlation ratio, and Cramer's V methods and examined whether there the highly correlated variables or one replacing or negating the other. As a result of the examination, there were no such results and therefore, it was possible to continue to use the selected features in the model building.

Data Balancing

While classifying all customer data, we faced unbalanced data with 72.03% of the entire data set belonging to the "Good" customer class. The problem with models trained on unbalanced data is that when the model is applied to a real-world scenario, it can achieve high accuracy by consistently predicting the majority class, even if accepting the minority class is equally or more important. Therefore, we used to balance our result class the machine learning synthetic minority over-sampling technique (SMOTE) to over-sample the minority classes to achieve balanced representation for each class. After using this approach, the "Bad" class constituted 50% of the data set. Figure 1 shows the nature of the data set before and after applying the SMOTE algorithm.

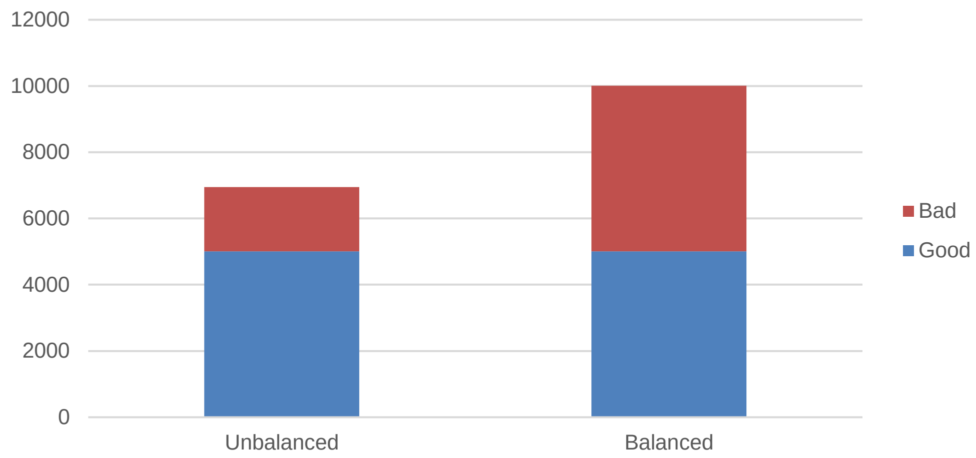


Figure 1. The balancing of the "Result" class labels

Training–Test Set Split. We split our dataset into 70% for the training set and 30% for the testing set (validation).

RESULT AND DISCUSSION

To predict whether a borrower will overdue his/her loan of more than 30 days, we initially run 10 highly predictive classification models in our database that are used by other researchers for credit scoring (Anil Kumar, 2021), (Khalil Masmoudi, 2019), (Keramati, 2011) based on our intense examination of pre-existing literature. All model evaluation metrics in this paper are based on the validation/testing set. All analyses presented in this paper were done using the IBM SPSS Modeler 18.4 software.

Prediction Accuracy

In the first step, we considered each model's prediction accuracy to determine which model performs best with our data. A model's prediction accuracy is the ratio of correct predictions to the total number of input samples. From Table 2 we can see the best-performing models in terms of prediction accuracy were the ensemble classifiers Random Forest and XGBoost Tree. These models had slightly higher accuracy than the next models than CHAID and Random Trees which is by around +5%.

Table 2. The prediction accuracy

Model	Overall Accuracy (%)
Random Forest (boosting)	76.13
XGBoost Tree	75.40
CHAID	70.33
Random Trees	70.06
LSVM	66.73
Bayesian Network	64.66

Logistic regression	64.00
XGBoost Linear	63.00
Neural Net	62.97
Decision List	60.95

From Table 2, we can see the Random Forest (with boosting), XGBoost Tree, CHAID, and Random Trees models with higher than 70% accuracy. Also, other model evaluation and diagnostic metrics such as Precision, Recall, ROC curve, and AUC of these four classifiers showed better performance than the rest of the other models. Therefore, we chose these four models and will explain the detailed results of these classifiers in the rest of this research.

There are several metrics to test a classification model's quality such as confusion matrix, overall prediction accuracy, precision, recall, lift, and area under the curve (AUC) values.

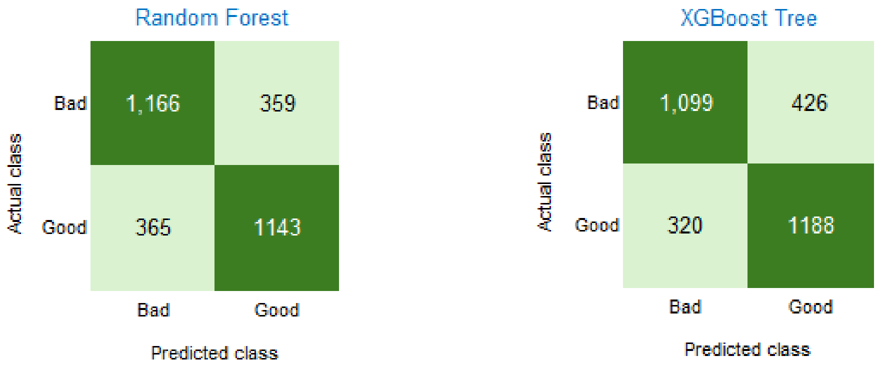
Confusion Matrix

Classification performance is best described by a *confusion matrix or truth table* which is a performance evaluation tool in machine learning, representing the accuracy of a classification model. It displays the number of true positives, true negatives, false positives, and false negatives as shown in Table 3.

Table 3. *Confusion matrix*

		Predicted class (expectation)	
		Positive	Negative
Actual class (Observation)	Positive	TP (correct result)	FN (missing result)
	Negative	FP (unexpected result)	TN (correct absence of result)
TP - true positive; FP - false positive; FN - false negative; TN- true negative.			

To evaluate the classification quality of a classification model, it is necessary to look at the confusion matrix. For an ideal confusion matrix, it is expected to get values only on the main diagonal that are correct class values. The misclassified values are located off the diagonal. Figure 2 illustrates the confusion matrix for each of our models.



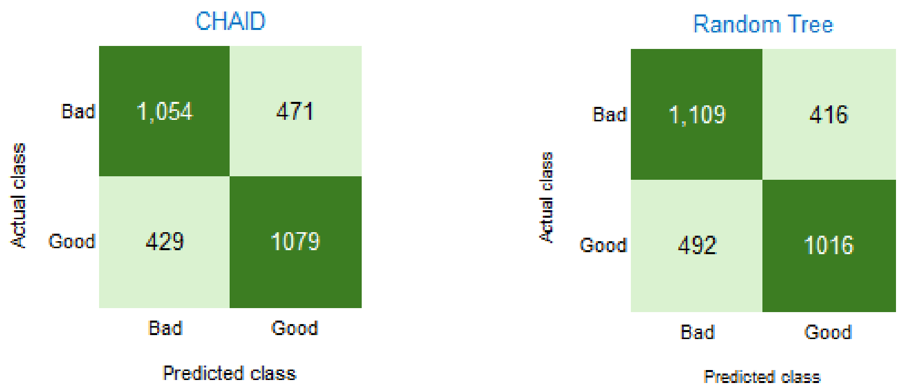


Figure 2. The confusion matrix for each model

The Evaluation Metrics

In this subsection, we examine each model's other evaluation metrics such as precision, recall, and f1-score.

Table 4. The description of the evaluation metrics of a classification model

Metrics		Estimation
Precision	The proportion of cases found that were relevant data points. For our classification task, it is the ratio of predicted values of a "bad" class to all values that belong to it.	TP/(TP+FP)
Recall	True positive rate which is the proportion of all relevant cases that were found. On the other hand, it is a ratio of the actual values of a "bad" class label that was predicted as belonging to that class.	TP/(TP+FN)
F1 -score	The harmonic mean between the model's precision and recall.	$\frac{2 * \text{Precison} * \text{Recall}}{\text{Precision} + \text{Recall}}$

These evaluation metrics of each model are shown in Table 5. We can see the Random Forest classifier is evenly good performance for every metric. The precision of the XGBoost Tree is 0.774 which is a slightly higher value than the Random Forest model (0.762), but we can not say that the XGBoost Tree is better than Random Forest, since the precision differences are very small between models that are 0.012. However, since precision is a measure of how accurate the positive predictions of a model are, it is shown that the XGBoost Tree model slightly more accurately predicted the positive class than the Random Forest method.

Table 5. The evaluation metrics of each model

Model	Precision	Recall	F1-score
Random Forest (boosting)	0.762	0.765	0.763

XGBoost Tree	0.774	0.721	0.747
CHAID	0.711	0.691	0.701
Random Tree	0.693	0.727	0.710

While the precision metrics of Random Forest and XGBoost Tree are very close, the value of recall is a little different between these two models. Precision and recall usually have inverse relations. In terms of recall metrics, the Random Forest classifier is better than the XGBoost Tree model which is the same as the Random Tree model. Since recall shows whether a model can find all objects of the target class, therefore we can say that the Random Forest classifier predicts a “bad” class label better than other models.

For the F1 score, the Random Forest model is still higher than the other models at 0.763. F1-score is a metric that measures both precision and recall and provides a balance of precision and recall. The value of F1-score is always between 0 and 1 and close to 1 indicates high precision and recall of the model.

Sensitivity Analysis

Here, we present the receiver operating characteristic (ROC) curves and their areas under the curve (AUCs) of the classification models. ROC curve and AUC are used to measure the quality of the classifier's output. It is useful to look at different metrics to see if there is a trade-off situation. The TP detection rate of the model can be checked and compared to its FP detection ability. ROC curve shows this and it was originally developed in signal detection (Green, 1966). *Sensitivity* is true positive rate (TPR) that the ability to select what needs to be selected (TP/(TP+FN)) and while *Specificity i*s true negative rate(TNR) that ability to reject what needs to be rejected (TN/(TN+FP)).

Movement along the ROC curve is typically a trade-off between the classifier’s sensitivity, and the steeper the curve, the better. For the ROC curve, sensitivity increases as we move up, and specificity decreases as we move right. The ROC curve of each classifier is presented in Figure 3. Figure shows the ROC curve of both the training and testing set.

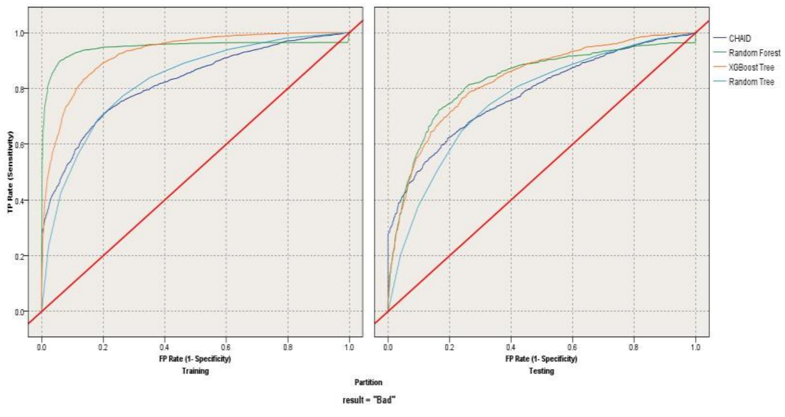


Figure 3. The receiver operating characteristic (ROC) for the models (training and testing set)

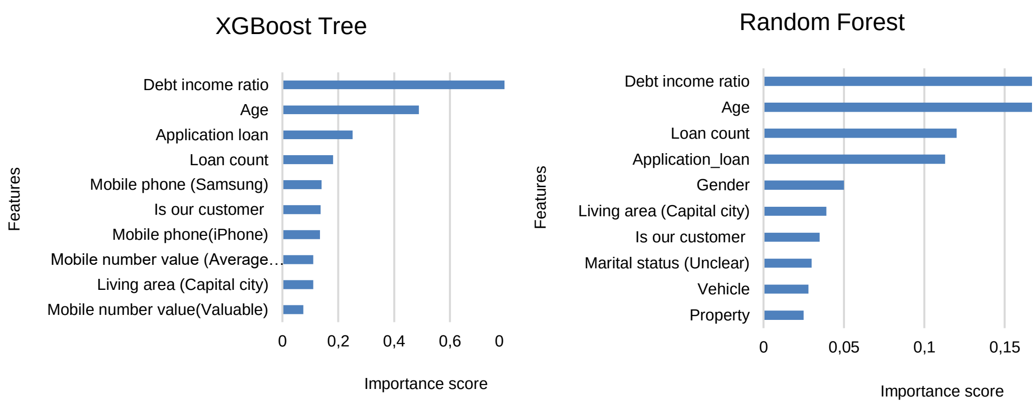
From the figure, we can observe the ROC curves for all the classifiers look good as the ROC curves are high above the 0.5 threshold which is a random guess along with 45° degree line. We can see from Figure 3. that the Random Forest model curve is the best, much steeper ROC curve among these models. The second is the XGBoost Tree classifier's ROC curve. Moreover, the ROC curves of the training set for each model did not decrease significantly in the test set, indicating that our trained models were not overfitted. The area under the curve (AUC) is a measure of the discrimination between classes of a binary classifier. The results of the AUC metrics are shown in Table 6. The higher the AUC, the better the model's ability to discriminate between true and false classes. If AUC is equal to 1, it means that the model is the best and perfect.

Table 6. Evaluation metrics of the models(AUC and Gini)

Model	**AUC**
Random Forest (boosting)	0.865
XGBoost Tree	0.829
CHAID	0.780
Random Trees	0.760

Feature Importance

In this subsection, we evaluate the relative importance of each feature (predictive variables) in predicting borrower loan repayment default. The feature importance determines the features/predictors that have the biggest impact on predictions. The feature importance scores of each model are shown in Figure 4.



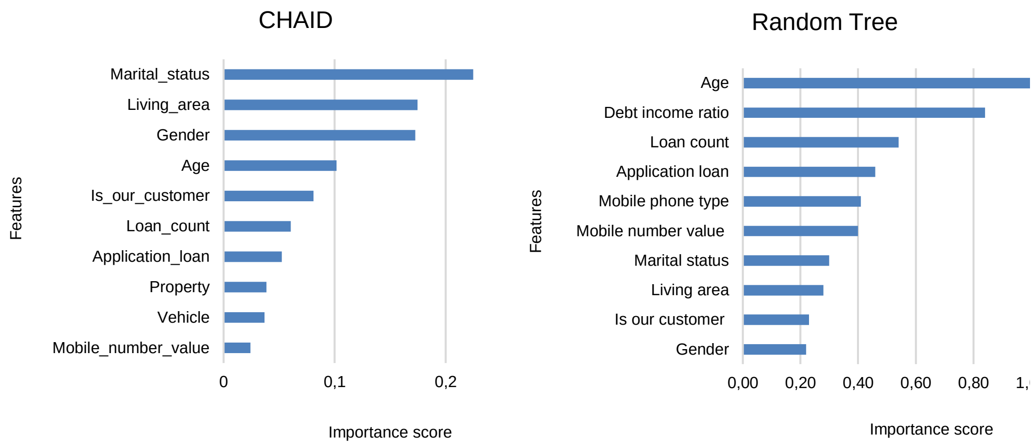


Figure 4. Feature importance for classifier models

From the XGBoost Tree, Random Forest, and Random Tree models, it can be seen that the *Debt-to-Income ratio, Number of Loans, Age, and Number of Digital Loans* have the greatest influence on the borrower's loan repayment. We can say that if a borrower's Debt-to-Income ratio becomes higher, it is more risky to overdue his or her loan payment. The higher Debt-to-Income ratio might mean that a borrower has more loans or digital loans. For all models including CHAID, we can see that the borrower's Age is one of the important predictors. There is one interesting feature which is the Mobile Number Value. In Mongolia, there are expensive and more valuable mobile phone numbers that some people deem to represent the phone number holder's reputation. Thus, this feature also contributes to the prediction since the number is expensive, it is shown as an important feature in three models. We also realized that numerical features have more relative importance in predicting a borrower's loan repayment than categorical features for all the classifiers.

CONCLUSION

In Mongolia, however, microloan products by digital lending services have been developed for a short period, and the growth is very intense. With this fast growth, the rationality of credit risk management has been becoming more critical. The monitoring and determining the customer's creditworthiness is relatively weak and leads to the risk of increased debt burden and the deterioration of the quality of the loan portfolio. Compared to commercial banks, NBFIs have weak credit risk prevention and credit scoring development systems, so it is important to develop and use appropriate credit scoring methods to ensure efficient credit decision-making. Thus, this research focused on a credit scoring system to improve the evaluation of the digital lending system for Mongolian microfinance institutes.

In this research, we compared several machine learning models to predict borrower's loan repayment status based on real microloan datasets of a non-banking financing institute of Mongolia. In the data preparation stage, we faced unbalanced data in terms of our response variable. The proportion of the "Bad" customers which is our main focus class label was only less than 30% among the target(response variable). This unbalancing data situation in the original data set was solved using the SMOTE oversampling algorithm which is used to handle unbalanced data.

Through intense exploration of the related works of literature, initially, we chose ten common models good fit for credit scoring problems and trained models in our dataset. However, there were four models with an overall accuracy of 70% or higher on the validation set and we discussed the results of these four models in our research. All analyses presented in this paper were done using the IBM SPSS Modeler 18.4 software. The four models that are Random Forest, XGBoost, Random Tree, and CHAID models have higher accuracy and all these models are tree-based algorithms. The reason tree-based models have better performance in our dataset is they might cause many categorical features of our dataset. The tree-based classifiers have been known to generally work better with such data sets. Among the models reported in this paper, the top two best-performing classifiers which are Random Forest and XGBoost are both ensemble classifiers. These two classifiers predicted an overall accuracy of at least 75% on the validation set. Other performance measures adopted also revealed that the classifiers have good predictive power in assessing defaults in microloans such as the Confusion matrix (Sec. 4.2), The result of the evaluation metrics (Sec. 4.3), and Sensitivity analysis (Sec. 4.4). In section 4.5, we presented the feature importance for each model. From the feature importance analysis, it can be seen that the Number of Loans, Debt-to-Income Ratio, Age, and Number of Digital Loans have more impact on the prediction borrower's loan repayment status. The result of this research shows that ensemble methods such as Random Forest and XGBoost Tree classifiers better predict than other models on the Mongolian microcredit and digital credit dataset.

There are very few studies that apply machine learning algorithms to credit scoring in the case of Mongolian microloans and digital lending environment. Therefore, the result of this research makes an important contribution to Mongolian nonbanking financing institutes that offer microloans by digital lending service to improve their digital lending evaluation system to the solution to reducing the risk of digital credit.

It can be an interesting future research direction to conduct a study to improve credit scoring methodology by taking into account the realism of different types of income such as income outside of current job and business income. It might have an important impact on improving credit scoring, thus preventing risks and making an optimal decision for digital lending for customers with any type of income. It is also possible to improve the credit scoring model by adding external factors that reflect economic and sector risks.

REFERENCES

An-Hsing Chang, L.-K. Y.-H.-K. (2022). Machine learning and artificial neural networks to construct P2P lending credit-scoring model: A case using Lending Club data . Quantitative Finance and Economics, 6(2), 303-325. doi:10.3934/QFE.2022013

Anil Kumar, S. S. (2021). Machine Learning (ML) Technologies for Digital Credit Scoring in Rural Finance: A Literature Review. Risks, 9(192). doi:https://doi.org/10.3390/risks9110192

Apostolos Ampountolas, T. N. (2021). A Machine Learning Approach for Micro-Credit Scoring. Risks, 9(3), 50. doi:https://doi.org/10.3390/risks9030050

B. Ghaddar and J. Naoum-Sawaya. (2018). High dimensional data classification and feature selection using support vector machines. European Journal of Operational Research,, 265(3), 993–1004.

Bhilare, A. C. (2018). Application of Ensemble Models in Credit Scoring Models. Business Perspectives and Research, 6(2), 129–141.

Breiman, L. (2001). Random Forests. Machine Learning, 45(5-32).

Chau, C. W. (2011). Rainfall–runoff modeling using artificial neural network coupled with singular spectrum analysis. Journal of Hydrology, 399(3-4), 394-409.

Chen, T. a. (2016). Xgboost: A scalable tree boosting system. 22nd ACM Sigkdd International International Conference on Knowledge Discovery and Data Mining, 13–17, pp. 785–94. San Francisco, CA, USA.

Dumitrescu E., ,. H. (2022). Machine learning for credit scoring: Improving logistic regression with non-linear decision-tree effects. European Journal of Operational Research, 297(3), 1178-1192. doi:https://doi.org/10.1016/j.ejor.2021.06.053

Financial Regulatory Commission. (2022). FInancial Market Review 2022. Ulaanbaatar, Mongolia: Financial Regulatory Commission. Retrieved from http://www.frc.mn/resource/frc/Document/2023/03/31/0gt0qm9v25qrpo9z/MARKET%20REVIEW%202022.pdf

Germanno Teles, J. J. (2020). Artificial neural network and Bayesian network models for credit risk prediction. Journal of Artificial Intelligence and Systems, 2, 118-132. doi:https://doi.org/10.33969/AIS.2020.21008

Gernmanno Teles, J. J. (2020). Machine learning and decision support system on credit scoring. Neural Computing and Applications, 32, 9809–9826. doi:https://doi.org/10.1007/s00521-019-04537-7

Geurts, P. D. (2006). Extremely randomized trees. Machine Learning, 63, 3-42.

Gilbert, R. (2013). CHAID and Earlier Supervised Tree Methods. Contemporary Issues in Exploratory Data Mining in the Behavioral Sciences, 48–74.

Green, D. S. (1966). Signal detection theory and psychophysics. New York: John Wiley and Sons.

J. Vaidya, H. Y. (2007). “Privacy-preserving SVM classification. Knowledge and Information Systems, 14(2), 161–178.

Keramati, A. &. (2011). A proposed classification of data mining techniques in credit scoring. In Proc. 2011 Int. Conf. on Industrial Engineering and Operations Management, (pp. 416-424). Kuala Lumpur, Malaysia . Retrieved 2011

Khalil Masmoudi, L. A. (2019). Credit risk modeling using Bayesian network with a latent variable. Expert Systems with Applications, 127, 157–166.

Leong, C. (2016). Credit Risk Scoring with Bayesian Network Models. Computional Economics, 423–446. doi:https://doi.org/10.1007/s10614-015-9505-8

Lkhagvadorj M., O.-E. N. (2018). Credit Scoring with Deep Learning. 4th International Conference on Information, System and Convergence

Applications. Bangkok, Thailand.

Lkhagvadorj Munkhdalai, T. M.-E. (2019). An Empirical Comparison of Machine-Learning Methods on Bank Client Credit Assessments. Sustainability, 11(3), 699. doi:https://doi.org/10.3390/su11030699

Loh, W.-Y. (2011). Classification and regression trees. Data Mining and Knowledge Discovery, 1(1), 14-23. doi:https://doi.org/10.1002/widm.8

Mandukhai Ganbat, E. B.-E. (2021). Effect of Psychological Factors on Credit Risk: A Case Study of the Microlending Service in Mongolia. Behavioral Sciences, 11(4). doi:https://doi.org/10.3390/bs11040047

Mohammad Amini, J. R. (2015). A Cluster-Based Data Balancing Ensemble Classifier for Response Modeling in Bank Direct Marketing. International Journal of Computational Intelligence and Applications, 14(04), 1550022. doi:https://doi.org/10.1142/S1469026815500224

Pan, Y. W. (2021). Application Analysis of Credit Scoring of Financial Institutions Based on Machines Learning Model. Complexity, 2021, 12. doi:https://doi.org/10.1155/2021/9222617

Poon, M. (2007). Scorecards as Devices for Consumer Credit: The Case of Fair, Isaac & Company Incorporated. The Sociological Review , 55(2), 284-306. doi:https://doi.org/10.1111/j.1467-954X.2007.00740.x

Pradeep R., ,. K. (2023). Digital Lending Market Research, Global Opportunity Analysis and Industry Forecast, 2023-2032. Allied Market Research.

Shin, S. K. (2022). Two stage credit scoring using Bayesian approach. Journal of Big Data, 9, 106. doi:https://doi.org/10.1186/s40537-022-00665-5

Shobana A., K. N. (2023). Bank loan prediction using KNN algorithm. International Research Journal of Modernization in Engineering Technology and Science, 5(03). doi:https://www.doi.org/10.56726/IRJMETS34927

Somvanshi M., a. C. (2016). A review of machine learning techniques using decision tree and support vector machine. Proceedings of the 2016 International Conference on Computing Communication Control and Automation (ICCUBEA) , (pp. 1–7). Pune, India.

V. Anantha Nageswaran, S. K. (2021). White paper on Digital Lending: Issues, Challenges and Proposed Solutions. Indicus Centre for Financial Inclusion. Retrieved from https://indicus.org/admin/pdf_doc/White-Paper-DIgital-Lending-April-2021.pdf

Vapnik, V. N. (1997). The Support Vector method. Artificial Neural Networks — ICANN'97 (pp. 261–271). Berlin: Springer. doi:https://doi.org/10.1007%2FBFb0020166

Zhang, G. B. (1998). Forecasting with artificial neural networks: The state of the art. International Journal of Forecasting, 14, 35-62.