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# Classifying Credit Card Payment Risk among Senior Citizens using Machine Learning on Limited Data

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**Abstract**

Sri Lanka is experiencing a significant demographic transition in view of lower fertility, enhanced life expectancy, and international migration, all of which have accounted for a higher proportion of senior citizens. The credit risk associated with a rising percentage of elderly population demands an investigation into the payment habits of senior citizens using credit facilities, for their own benefits and the sustainability of financial institutions. Addressing this issue, machine learning techniques are employed in this study in order to develop a viable model for classifying the credit card payment risk posed by the senior citizens based on their demographic and financial metrics at a leading private bank in Sri Lanka. Predictive dual-category classifications comprising of on-time payers and risky payers that include both late payers and dormant users are achieved using the machine learning algorithms of Logistic Regression, Random Forest, Support Vector Machine, Naïve Bayes, Extreme Gradient Boosting, and Multi-Layer Perceptron Neural Networks. Hyperparameter tuning and model performance optimization were accomplished using Grid Search Cross-Validation, with models being assessed by Accuracy, Precision, Recall, F1 Score, and AUC-ROC. Of those modelling techniques, the Random Forest excelled with 85% Accuracy, 85% Precision, 85.45% Recall, 84.99% F1 Score, and a high AUC-ROC score of 88 in classifying the risk posed by senior citizens, identifying payment settlement, average monthly credit card spending, average monthly debit, and number of credit card transactions as the key contributing variables. This classification method could be recommended for financial institutions with limited databases in setting credit limits tailored to senior citizens' payment behaviour, reducing risk and promoting sustainable financial management for seniors.

***Keywords***: Credit Risk, Limited Data, Random Forest, Senior Citizen

## Introduction

Senior citizens, in particular, have increasingly adopted credit cards in recent decades due to convenient application processes, enhanced security, and financial benefits such as cashback offers and instalment plans. The ability to make bill payments and to shop online without physical visits has further encouraged credit card usage among this demographic. As the global aging population continues to rise (United Nations, 2023), the utilization of financial services, in particular credit cards, among senior citizens has also risen leading to heightened credit risk for banks. Commensurate with this global trend, Sri Lanka is also experiencing a significant rise in the proportion of senior citizens, who are projected to make up 27% of the total population by the year 2050 (Population Trends Asia Pacific, 2024). This demographic shift is accounted for by factors like declining fertility rates, rising life


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expectancy, and labour migration and emigration. By the year 2041, one in four citizens is predicted to be elderly in Sri Lanka, making it the country with the highest proportion of senior citizens in South Asia (World Bank, 2012). With the increasing proportion of senior citizens, many Sri Lankan financial institutions have introduced appealing credit card systems, tailor-made for retirees and pensioners. Such incentives strengthen financial flexibility while supporting senior citizens' continued participation in economic activities. However, fixed incomes, unexpected medical expenses, inflationary pressures, and wide-ranging financial literacy complicate credit card settlements while increasing the risk of late payments and defaults. Further, poor financial literacy also contributes to increase dormant credit card users.

The banking sector in Sri Lanka is also confronted with high risks of payment delays and defaults, despite some fluctuations reported in late 2023 (Central Bank of Sri Lanka, 2023). This compels banks to reassess their strategies to align with the financial status, spending habits, and priorities of senior citizens that differ significantly from those of the other demographic groups. Sustaining credit cards as a long-term profitable venture requires a deeper understanding of senior citizens' repayment patterns based on their demographics and financial metrics. A reliable classification mechanism would not only help banks better understand senior citizens' financial behaviour but also implement personalized financial services to meet their specific needs and manage high-risk user profiles.

Machine learning approaches are particularly effective for this purpose, as they accommodate classification of complex datasets using various algorithms. Several studies can be cited for exploring credit risk prediction using machine learning techniques. Yeh & Lien (2009) compared six data mining methods for forecasting credit card defaults among Taiwanese clients and found that artificial neural networks outperformed traditional classifiers. Wu & Wang (2018) applied the Self-Organizing Map technique to segment clients based on credit card information by using age, gender, marital status, and education as key attributes for feature extraction. According to Husejinovic et al. (2018), Naïve Bayes model achieved a success rate exceeding 71%, while logistic regression provided the highest accuracy in prediction of credit card default payments. Liu (2018) demonstrated that Feedforward Neural Networks outperformed Long Short-Term Memory networks and conventional machine learning models in credit risk prediction. Further, Ma (2020) developed an Extreme Gradient Boosting credit-score model that identified key financial variables for predicting default probabilities, achieving a high AUC-ROC score.

Most existing credit risk assessment models have focused on broad client classifications related to credit card defaults, often overlooking the specific financial behaviours and risk factors associated with aging individuals *aka* senior citizens. However, a targeted analysis of senior citizens' payment behaviour can offer deeper insights, as their financial stability often depends on pensions, fixed deposits, and unforeseen expenses, particularly for healthcare, making their credit repayment patterns both unique and complex. Lack of comprehensive studies on this topic, especially in Sri Lanka, where research has primarily focused on bank loans and lease defaults by ordinary clients (Perera et al., 2022), highlights a critical research gap that must be addressed to enhance financial management for aging individuals and improve risk mitigation strategies for banks. The present study aims to address this gap by utilizing machine learning techniques to develop a predictive model that accurately classifies senior citizens' credit card repayment behaviour based on their demographic and financial characteristics. A key challenge in this process is the difficulty faced by financial institutions in sharing client data due to confidentiality issues. Therefore, this study is aimed at identifying the most effective machine learning model capable of categorizing seniors' repayment behaviour, even when working with incomplete or imperfect information of limited capacity. This classification will benefit banks in identifying consistent on-time payers with no risk and late payers with higher risk well in advance, allowing for tailored solutions to reduce the risk of default. Moreover, this prior classification technique will help recognize financially inactive or dormant users as risky payers, enabling the implementation of awareness

programs to encourage active credit usage and drive profitable business. Ultimately, data-driven decision-making should benefit banks to mitigate credit card payment risks while ensuring that financial services remain inclusive and accessible to senior citizens.

## Materials and Methods

The dataset used in this study was obtained from a reputed private bank in Sri Lanka on the agreement of safeguarding the confidentiality of the source of information, which includes information on the credit cardholders who were aged over 55 years over the five years (2019-2023) and it comprises of 100 observations each being characterized by 9 variables. The target variable was the Payer Type (On-time and Risky payers) while the eight independent variables were Gender, Monthly Average Balance, Main Income Source, Average Monthly Debit, Average Monthly Credit Card Spending, Credit Card Spending Purpose, Number of Credit Card Transactions, and Percentage of Payment Settlement.

Initially, basic frequency analysis for each categorical variable was carried out. During data pre-processing, categorical variables were appropriately encoded using Label Encoder, Ordinal Encoder, and OneHot Encoder. The numerical variable was normalized using the "MinMaxScaler" technique (De Amorim et al.,2023). All variables sans the Payer Type were selected as feature variables for the analysis of this dataset. The selected features and target variable were further split into the training and validation sets at the ratio of 4:1. A total of six different machine learning algorithms *viz.* Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), Bernoulli Naïve Bayes (NB), Extreme Gradient Boosting (XGBoost), and Multi-Layer Perceptron Neural Networks (MLP), appropriate for binary classification (Liu, 2018), were trained in this study to predict the payment settlement type of a senior citizen. For RF and XGBoost, the importance of each feature of the respective model was obtained for its onward assessment of the model. After training the models, respective predictions from each model were obtained using the testing portion of the dataset and the trained models were evaluated using evaluation metrics. Further, hyperparameter optimization and cross validation techniques were applied for each base model fitted from each classifier. Accuracy, Precision, Recall, F1-score, and AUC-ROC score were used in the evaluation process, assuming that the categories of the target variable were balanced. In the classification, Precision, Recall, and F1-score were calculated individually for each class. In order to evaluate the overall performance of a model, the average of the above metrics across both classes was used as the net indicator. This study employed macro-averaged Precision, Recall, and F1-score to ensure that both classes of the target variable were treated equally in the evaluation. Moreover, this study applied a combination of Grid Search and K-Fold Cross-Validation (GridSearchCV) across all machine learning models to generalize results to unseen data and fine-tune hyperparameters for optimal performance. The Python (3.13) language was used for the study in PyCharm Community Edition (2024.3.5).

## Results

The distribution of payer type of senior credit card users was approximately balanced as 56% of users represented risky payers and the rest on-time payers. The majority of customers were found to be female senior citizens (59%) and, on average, 63% of the payments were settled by customers within the range of 24% to 100% of the settlements. However, the standard deviation of 19.73% demands that a more comprehensive classification is needed to identify the senior citizens belonging to the risky category as described below. The evaluation metric scores of baseline models of each classifier are presented in Figure 1.

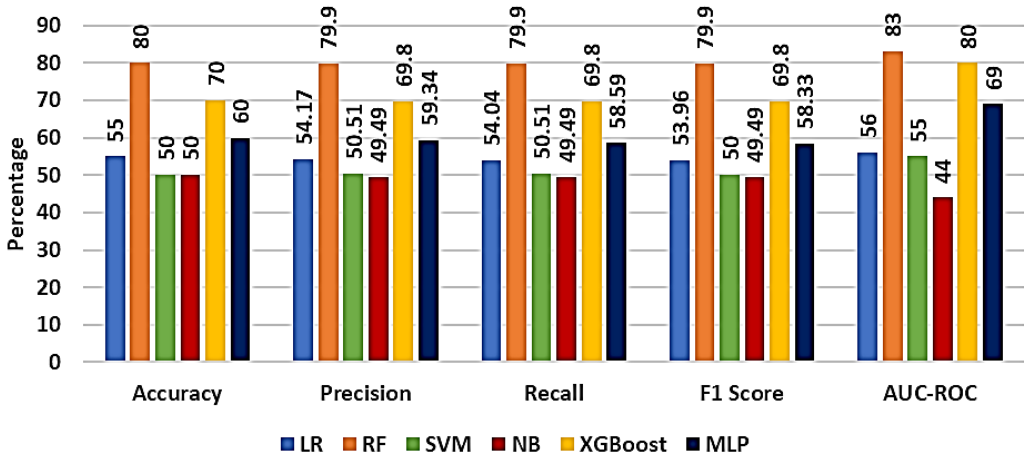


**Figure 1:** *Comparison of percentage performance of baseline models*

Random Forest (RF) consistently performed consistently better than other models, as shown by the clustered bar chart in Figure 1. It achieved the greatest scores in all measures, especially in Accuracy (80%), Precision (79.9%), Recall (79.9%), F1 Score (79.9%), and AUC-ROC (83%). Moreover, XGBoost operates commendably, though achieving somewhat lower scores than RF. MLP neural networks function moderately well, outperforming certain models. Other models range from 49% to 60%. Figure 2 illustrates each classifier's evaluation metric scores upon the application of Grid Search with 2-Fold Cross Validation.

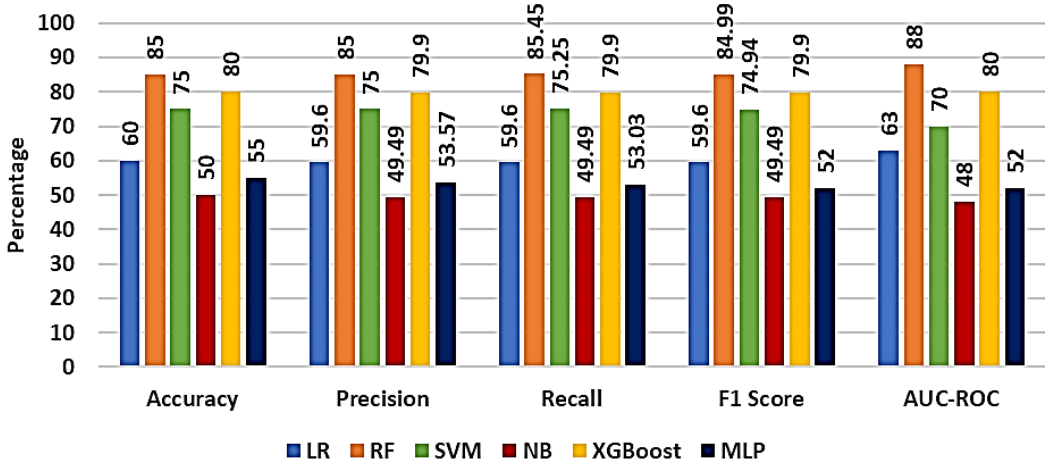


**Figure 2:** *Comparison of percentage performance of models after applying GridSearchCV*

It can be seen in Figure 2 that SVM emerged with much improved performance after hyperparameter tuning and validation. In comparison, the Random Forest model showed notable improvement with the application of Grid Search and 2-Fold Cross-Validation, boosting its accuracy from the baseline to an impressive 85%. Similarly, XGBoost also benefitted from tuning, with its performance improving significantly, resulting in an accuracy improved to 80%. These enhancements highlight the value of optimizing hyperparameters to achieve better model performance across some algorithms.

According to the above model comparison, the highest classification performance measured by accuracy, precision, recall, F1 score, and AUC-ROC score (85%, 85%, 85.45%, 84.99%, and 88%, respectively) was achieved by the RF model after applying Grid Search with 2-Fold Cross-Validation. Since the Random Forest is a decision tree-based model, the importance of each feature was also examined. It was revealed that the most important feature of the classification is the percentage of payment settlement followed by average monthly credit card spending, average monthly debit, and

the number of credit card transactions in the bank account. However, other financial and demographic features appeared to be much less impactful on the classification of a senior citizen based on his credit card payment settlement pattern using aforementioned RF model.

## Discussion

According to the findings, RF consistently outperformed the other classifiers across all the techniques applied. In Grid Search with 2-Fold Cross-Validation, the Random Forest (RF) model achieved the highest scores compared to the RF in baseline fitting. Random Forest is a viable technique that provides good performance for classification tasks with limited data, as it is more robust to overfitting compared to other classifiers. However, since the dataset in this study was quite small, overfitting might still occur, particularly due to insufficient examples for training each class in the classification task. XGBoost showed stable performance across both models, indicating its robustness in handling binary classifications with limited data. Although LR, SVM, NB, and MLP neural networks still performed below RF and XGBoost models, they appeared to be somewhat better with hyperparameter optimization techniques when compared to the baseline models. This implies that Grid Search hyperparameter tuning can greatly improve the model performance. The application of 2-Fold Cross Validation helped achieve robust performance estimates and ultimately reduced overfitting in agreement with Ma's work (2020), the XGBoost model in the present study too yielded reasonably good performance with limited data. While the present results showed that LR and NB were moderate classifiers for complicated structures with limited data, the study of Husejinovie et al. (2018) revealed that these methods performed well in binary scenarios with a large dataset. The limited dataset used here might have affected the model performance, as it was barely sufficient to be divided between training and testing the machine learning models. The restricted number of financial variables and the absence of diverse demographic features may have further limited each classifier's ability to comprehensively analyse the credit card settlement behaviour of senior citizens. To gain a deeper understanding of this behaviour, it is necessary to access a larger dataset that includes more instances, along with additional financial and demographic information.

## Conclusions

It could be concluded that Random Forest excelled in performance particularly with Grid search 2-fold cross validation, emerging as the best classifier for limited data to capture complex patterns and interactions with feature variables. The most important feature of this model was the percentage of payment settlement followed by average monthly credit card spending, average monthly debit, and the number of credit card transactions in the bank account, which can be identified as financial metrics of a person. Grid search with 2-fold cross validation proved to be an effective technique, emphasizing the importance of hyperparameter tuning and validation for optimal model performance. By using this RF model for binary classification of senior citizens, banks can tailor their services, products, and policies to meet specific needs of senior citizens, leading to greater operational efficiency, better financial product management and risk management, customer satisfaction, and higher profits. Moreover, the ability to detect early warning signs of payment failure allows banks to take timely actions, such as offering personalized financial guidance or modifying credit terms to suit individual customer needs. Such interventions can not only mitigate financial risks but also enhance customer satisfaction and trust in banking services. The best modelling techniques emerged from this study may also be applied to classify senior citizens using credit cards issued by any financial institution operating under similar circumstances, prompting to review their strategies on how best to serve senior citizens while reducing the upcoming payment default risk.

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