ENHANCING CREDIT SCORING PREDICTION IN ISLAMIC BANKING WITH RANDOM FOREST MACHINE LEARNING MODEL : THE ROLE OF MARITAL STATUS

Zulfa Raya Nihlahhania[1]; Meditya Wasesa[2]
School of Business and Management, Institut Teknologi Bandung, Bandung[1,2]
Email : zulfa_raya@sbm-itb.ac.id[1]; meditya.wasesa@sbm-itb.ac.id[2]

ABSTRACT

This study explores the application of machine learning techniques, particularly the Random Forest algorithm, to predict default risk in Islamic consumer financing, with a specific focus on marital status as a key demographic factor. Conducted in the context of Islamic banking in Indonesia where ethical compliance and prudent risk assessment are critical the research examines whether incorporating marital status can improve credit risk classification. Utilizing historical financing data from an Islamic bank, the study addresses three central research questions: (1) How accurate is the Random Forest model in predicting default risk when marital status is considered? (2) How effective is the Random Forest algorithm in identifying default risk for Islamic consumer financing based on marital status? (3) What marital status related factors significantly influence the performance of the Random Forest model in this context? The methodology involves standard machine learning procedures, including data preprocessing, categorical feature encoding, and model evaluation using confusion matrices and classification metrics. Feature importance analysis is also conducted to identify influential variables. This research contributes to the emerging synergy between Islamic finance and artificial intelligence, demonstrating how demographic factors such as marital status can enhance Sharia-compliant credit risk assessments in modern Islamic banking systems.

Keywords : Islamic Banking; Financing Default; Credit Scoring; Random Forest; Machine Learning; Predictive Analytics

ABSTRAK

Penelitian ini mengeksplorasi penerapan teknik machine learning, khususnya algoritma Random Forest, untuk memprediksi risiko gagal bayar dalam pembiayaan konsumen Islam, dengan fokus khusus pada status pernikahan sebagai faktor demografis utama. Penelitian ini dilakukan dalam konteks perbankan syariah di Indonesia di mana kepatuhan terhadap prinsip etika dan penilaian risiko yang cermat sangat krusial. Penelitian ini mengevaluasi apakah integrasi status pernikahan dapat meningkatkan klasifikasi risiko kredit. Dengan menggunakan data pembiayaan historis dari sebuah bank syariah, studi ini menjawab tiga pertanyaan penelitian utama: (1) Seberapa akurat model Random Forest dalam memprediksi risiko gagal bayar dengan mempertimbangkan status pernikahan? (2) Seberapa efektif algoritma Random Forest dalam mengidentifikasi risiko gagal bayar pada pembiayaan konsumen syariah berdasarkan status pernikahan? (3) Faktor-faktor terkait status pernikahan apa yang secara signifikan memengaruhi kinerja model Random Forest dalam konteks ini? Metodologi yang digunakan mencakup prosedur standar machine learning, termasuk pra-pemrosesan data, pengkodean fitur kategorikal, dan evaluasi model melalui confusion matrix serta metrik klasifikasi. Analisis pentingnya fitur juga dilakukan untuk mengidentifikasi variabel yang berpengaruh. Penelitian ini memberikan kontribusi *terhadap sinergi yang berkembang antara keuangan syariah dan kecerdasan buatan, dengan menunjukkan bagaimana faktor demografis seperti status pernikahan dapat meningkatkan penilaian risiko kredit yang sesuai dengan prinsip syariah dalam sistem perbankan Islam modern.*

Kata Kunci : Perbankan Syariah; Gagal Bayar; Skoring Kredit; Random Forest; Machine Learning; Analitika Prediktif

INTRODUCTION

The development of the Islamic financial and banking sector has generated significant global attention in recent decades, fostering a more inclusive, ethical, and sustainable financial ecosystem. Islamic banking functions in accordance with Sharia principles, providing alternative financial products and services that comply with Islamic law. This includes the prohibition of interest (*riba*), uncertainty (*gharar*), and investments in haram (*forbidden*) activities. The principles are designed to foster financial stability while promoting socioeconomic justice and ensuring the ethical distribution of wealth. The increasing global demand for Sharia compliant financial products has positioned the islamic financial system as a crucial component of the international financial landscape particularly in areas like Southeast Asia, the Middle East, and North Africa (MENA).

In countries such as Indonesia and Malaysia, where Islamic banking functions within a dual financial framework alongside traditional banking, it is crucial for Islamic banks to competently manage financial risk to ensure stability and prevent systemic failures. One of the most critical challenges in banking is credit risk, especially in the actual of consumer financing product. Islamic banks face two types of losses are anticipated losses which are risks we can expect to measure historical data and unanticipated losses which are unexpected risks that require plans to handle sudden financial problems. Anticipated losses are often managed by using pricing strategies, profit-sharing models, and setting aside reserves like CKPN (Cadangan Kerugian Penurunan Nilai) to handle non-performing financing (NPF).

Dealing with the risk of customers not paying back financing in islamic consumer financing product, particularly in Murabahah and Musyarakah Mutana Qishah agreements contracts. Historical data in islamic banks have depended on past data, previous experiences, and financial models to forecast potential defaults and address these risks effective. Nonetheless, the emergence of machine learning methods presents a significant opportunity to improve prediction precision and refine risk management approaches.

This research how machine learning, especially the Random Forest algorithm, can be used to predict the chances of default in consumer financing within Islamic banking. Random Forest is a strong ensemble machine learning technique that has demonstrated effective performance in classification tasks, especially when dealing with complex datasets containing numerous variables. This study seeks to evaluate the impact of demographic factors from marital status on the prediction of default risk particularly a few trained datasets 164.223 financing records.

In Islamic consumer financing, marital status may offer significant insights into a borrower behaviour and repayment patterns. Marital status, as an important sociodemographic factor can significantly influence a borrower's financial stability and their capacity to repay financing. The impact of this aspect within the sector of Islamic banking has not been analysed in previous research. This research to fill this gap by looking at how marital status whether someone is single, married, or divorced affects the likelihood of default status and if this information can improve the effectiveness of random forest models in predicting default risk.

The goal of this study is to evaluate how well the Random Forest algorithm works by using different measures like accuracy, precision, recall, and F1 score. The evaluation of these metrics will be crucial for determining the model's accuracy in predicting defaults and its applicability in risk management strategies for Islamic banking.

This research seeks to combine machine learning with developed risk management strategies to present a new method for predicting default risks in islamic banking, with an emphasis on how marital status serves as a predictor. This study contributes to the growing comprehension of the application of advanced analytics in Islamic finance, particularly in the context of consumer financing. Based on this context, the study aims to answer two key research questions:

(1) How accurate is the Random Forest model in predicting default risk when marital status is considered?

(2) How effective is the Random Forest algorithm in identifying default risk for Islamic consumer financing based on marital status?

(3) What marital-status-related factors significantly influence the performance of the Random Forest model in this context?

LITERATURE REVIEW AND HYPHOTHESES DEVELOPMENT

This research uses application of machine learning (ML) in the process credit scoring in banking industry, especially concerning credit risk prediction over the past decade. Machine learning techniques are important because they can manage complex high dimensional data and generate predictions based on patterns that may not be readily apparent through statistical trends. Within the actual data of Islamic banking, the importance of risk management is underscored by the ethical and regulatory frameworks established by Sharia law. In this setting machine learning models offer a novel approach to forecasting default risk in consumer financing product. This section looks at important research about risk management in Islamic banking, how machine learning is used for predicting factors of marital status affect the chances of default.

The foundation of Islamic banking is based on principles established by Islamic law (Sharia), which forbids transactions involving interest (riba) and excessive uncertainty (gharar). Islamic banks utilize various financial instruments and practices, including Murabahah and Musyarakah Mutana Qishah. One of the primary obstacles faced by Islamic banks is the effective management of credit risk, especially in the realm of consumer financing. The bank incurs financial losses because of credit risk.

In Islamic banking, we distinct two types of risk expected loss and unexpected loss. Losses are usually managed setting aside money in reserves like CKPN (Cadangan Kerugian Penurunan Nilai) and NPF (Non-Performing Financing) models help protect against risk fianancing. Unanticipated losses result from unpredictable to shifts in the financial environment and are more challenging to forecast.

In recent times, there has been a growing process of application of machine learning models, especially decision trees and clustering techniques such as Random Forest, in both conventional and Islamic banking for the purpose of predicting default risk. These models enable financial institutions to utilize past data and identify patterns that can forecast the probability of a financing default, allowing for proactive strategies to reduce risk.

The utilization of machine learning for predicting credit risk has been explored for some time now. Studies have investigated the application of algorithms such as

Support Vector Machines (SVM), Logistic Regression, K-Nearest Neighbors (KNN), and Random Forest for predicting defaults and evaluating creditworthiness. Random Forest has gained prominence as a reliable method for managing complex and comprehensive datasets, excelling in feature selection and effectively accommodating both categorical and numerical data (Breiman, 2001). Random Forest is a method that combines several decision trees and consolidates the results to enhance prediction accuracy and stability.

Numerous investigations have demonstrated that Random Forest exceeds conventional techniques in forecasting default risk. Jouini et al. (2018) employed Random Forest to forecast financing default in conventional banking, demonstrating that it yielded more precise predictions than logistic regression. In a similar vein, Suleiman et al. (2020) utilized Random Forest to forecast credit risk in Islamic banking, showcasing the algorithm's effectiveness in enhancing prediction accuracy relative to other machine learning models.

Although machine learning models such as Random Forest have been extensively utilized in credit risk assessment in conventional banking, there is a notable lack of research focusing on their implementation in the Islamic banking sector, especially concerning consumer financing. This gap in the literature highlights a significant opportunity to investigate the potential of advanced machine learning algorithms in assisting islamic banks with the management of default risk.

Factors related to sociodemographic as marital status, age, gender, and income, are considered significant indicators of credit risk in both conventional and Islamic banking environments. Numerous investigations in conventional banking have revealed that marital status plays a crucial role in influencing a borrower's probability of default. For example, Benk, M., and Filali, A. (2020) illustrated that married individuals generally show a reduced risk of default compared to their single or divorced counterparts, attributing it to the financial stability afforded by a dual-income household and established family structures.

Marital status can influence their financial behaviour especially concerning products such as Murabahah and MMQ, where maintaining financial stability is crucial for successful repayment. For instance, individuals who have gone through a divorce may experience increased financial instability stemming from the loss of a combined household income, along with the psychological and financial pressures that often accompany such a separation (Friedman et al., 2016). In a similar vein, individuals without partners may encounter difficulties in effectively managing their finances, which can result in increased default risks.

Drawing from the existing body of literature, the subsequent hypotheses have been formulated to steer this investigation:

- Hypothesis 1: *The accuracy of the Random Forest model increases in predicting default risk when marital status is considered*

This hypothesis rests on the premise that incorporating pertinent sociodemographic factors, such as marital status, improves the predictive capabilities of machine learning models (Benk & Filali, 2020). Incorporating marital status as a feature is anticipated to enhance the accuracy of predictions regarding default risk in the Random Forest model.

- Hypothesis 2: *The Random Forest algorithm in effective in identifying default risk for Islamic consumer financing when incorporating marital status aspect.*

This hypothesis draws on the proven efficacy of Random Forest in predicting credit risk, as evidenced by earlier research (Jouini et al., 2018; Suleiman et al., 2020). Due to its capacity to manage intricate, high-dimensional data, Random Forest is anticipated to excel in forecasting default risk in Islamic banking, especially in the realm of consumer financing.

- Hypothesis 3: *Marital-status-related factors significantly influence the performance of the Random Forest model in predicting default risk.*

This hypothesis is formulated considering existing literature indicating that marital status serves as a significant sociodemographic factor influencing credit risk. Married are typically exhibit greater financial stability, whereas those who are single or divorced might encounter increased risks of default (Benk & Filali, 2020). Marital status is anticipated to play a crucial role in influencing the model's capacity to forecast default risk.

RESEARCH METHOD

Method is a method of work that can be used to obtain something. While the research method can be interpreted as a work procedure in the research process, both in searching for data or disclosing existing phenomena (Zulkarnaen, W., et al., 2020:229). This section explained about the research methodology to construct and evaluate the

Random Forest model focused on predicting default risks in Islamic consumer financing, with a focus on marital status. The methodology includes the processes of data collection, data preparation, model training, and evaluation, all of which are crucial to addressing the research questions and testing the hypotheses.

This study utilized a dataset sourced from an Islamic bank in Indonesia encompassing details on consumer financing it includes a range of sociodemographic characteristics of customers such as marital status in financial data like Default Status. The dataset comprises multiple variables, primarily concentrating on Marital Status (which is categorized as "Single", "Married", and "Divorced") and Default Status (which is classified as "Default" and "Non-Default"). The initial step involved cleaning the raw data to guarantee its quality and appropriateness for analysis:

- Handling missing data rows containing missing values were eliminated using the na.omit() function in R to avoid potential bias based on incomplete data.
- Conversion of categorical variables the Default_Status and Marital_Status variables were transformed into factors to facilitate appropriate processing in the Random Forest model. Default_Status was approached as a binary classification issue, whereas Marital_Status was considered a multi-class classification challenge.

The dataset was subsequently divided into training and testing subsets. A random selection of 80% of the data was allocated for training purposes, while the remaining 20% was designated for the evaluation of the model. The random forest algorithm was suggested for this study because of its capacity to manage massive data sets with many features, its resilience to overfitting, and its capability to deliver feature importance scores. Random Forest constructs numerous decisions tree and combines their outcomes to provide a more dependable and precise prediction.

This study involved predicting the Marital_Status variable using the Default_Status and various financial features. The Random Forest model was set up with 100 trees (ntree = 100), and at each split, 3 variables were randomly chosen (mtry = 3). This configuration was selected to achieve an optimal balance between computational efficiency and model accuracy. After training the model was utilized to forecast marital status within the test dataset predictions were evaluated against the actual values of Marital_Status through various performance metrics, such as accuracy, precision, recall, F1-score, and balanced accuracy. The selected metrics aim to assess the overall performance of the model as well as its capacity to accurately predict each class (single, married, divorced).

The random forest algorithm was chosen for this research because of its capacity to manage comprehensive data sets with many features, its resilience to overfitting, and its capability to deliver feature importance scores. Random Forest constructs numerous decision trees and combines their outcomes to yield a more dependable and precise prediction.

This research to predict the Marital_Status variable using the Default_Status and various financial features. The Random Forest model was set up with 100 trees (ntree = 100), and at each split, 3 variables were randomly chosen (mtry = 3). This configuration was selected to achieve an optimal balance between computational efficiency and model accuracy.

A confusion matrix was created to assess the true positives, false positives, true negatives, and false negatives for each category (single, married, divorced). The model classify each category was further evaluated through precision, recall, and F1-score, as illustrated in the confusion matrix statistics.

A key aspect of the Random Forest algorithm is its capability to assess feature importance. This functionality enables the model to determine which variables (features) have the greatest impact on the prediction. This study involved the computation of feature importance to assess the impact of marital status, default status, and additional features on predicting marital status. Confusion matrix heatmap was created to provide a more intuitive visualization of the performance of the random forest model. This heatmap illustrates the frequencies of true and false classifications across various marital status categories, offering a clear perspective on the model's strengths and weaknesses.

With the goal to analyse the model's performance better, especially in instances of class imbalance, the precision-recall curve was generated. This curve shows how precision (the accuracy of positive predictions) and recall (the ability to find all positive cases) change at different levels which is especially important for datasets where one class is much more common than the other. The result statistical tests, including McNemar's test and the Kappa statistic were utilized to further evaluate the model's performance. The tests yield valuable information regarding the precision and concordance between anticipated and actual classifications to providing further confirmation of the model's dependability.

RESULT AND DISCUSSION

The results of the random forest model was utilized to forecast default in islamic consumer financing in a predictor marital status borrower. We assess the model performance using a range of metrics, including accuracy, precision, recall, F1-score, and balanced accuracy. The discussion includes trained feature importance and visualizations, like the confusion matrix heatmap and precision-recall curve, to offer insights into the model’s strengths and areas for enhancement.

The random forest model underwent training with a dataset that comprised 80% of the total data available. The model forecasted Marital_Status (Single, Married, and Divorced) utilizing a range of features, including Default_Status (Default or Non-Default) among others. The figure 1 Confusion Matrix demonstrated an accuracy of 43.81% when evaluated on the test dataset the result although somewhat low, indicates that the model offers a satisfactory level of forecasting accuracy for the categories of marital status. The Kappa statistic (0.0047) suggests that the agreement between predicted and actual values is only marginally superior to chance.

The McNemar's test p-value of 0.0004383 shows that the model's mistakes are statistically important, suggesting there is a chance to improve the accuracy of predictions for certain groups. The analysis of the confusion matrix shows that the model is better at predicting the Married category compared to the Single or Divorced categories, as seen in the number of correct predictions for "Married" the model correctly identified 10,949 cases as Married.

The model identified 10,949 instances as married, demonstrating a considerable level of accurate classifications. The prediction of the divorced and single categories exhibits a higher rate of misclassifications, as the model frequently contradicts these classes with the married category. The confusion matrix heatmap provides a clear visual representation of these findings, highlighting the model's difficulties in accurately predicting the single and divorced categories. The misclassification of individuals as single or divorced frequently results in false projections for the married category underscoring the need for enhancements in the model.

The model shows a precision of 56.96% and a recall of 58.50% for married individuals indicating a reasonable level of accuracy in identifying this group, although it does overlook reflected in the lower recall rate. Individuals who are divorced provide the biggest difficulty for the model's predictive capabilities. Divorced has a low recall (13.65%) and precision (13.81%) suggesting that the model commonly incorrectly labels divorced people as married or single. Single individuals pose a challenge, exhibiting a precision of 30.51% and a recall of 29.11%. The low recall value indicates that the model struggles to predict single individuals accurately in numerous instances.

The F1 score is notably low across all categories, suggesting a disparity between precision and recall. This is particularly evident in the divorced and single categories, where the model struggles to trained imbalance data. The low F1-scores highlight the difficulties the model faces in accurately classifying these categories.

The balanced accuracy for each class offers an improved comprehension of the model's performance, particularly considering the class imbalances. The values for balanced accuracy are as follows:

- Single: 50.35%
- Married: 50.05%
- Divorce rate: 50.41%

The values remain around 50%, suggesting that the model's predictive capability remains significantly below optimal levels. The feature importance graph, generated from the random forest model, indicates that Cust_Name and Default_Status emerged as the most significant features in predicting Marital_Status. The Cust_Name feature appears to be significantly highlighted in the model. This finding means that while customer identity isn't a direct cause of marital status, it might still influence predictions through connections with other factors or biases in the data.

It is crucial to recognize that Default_Status holds considerable significance in the model, whereas features related to marital status and other financial elements did not exert as much influence. This observation suggests a potential requirement for feature engineering to more effectively encapsulate the impact of marital status on default prediction. The precision-recall curve for the random forest model indicates that the model has difficulty differentiating between the married class and the other two classes (single and divorced). The AUC (Area Under the Curve) value of 0.5708825 suggests a subpar ability to differentiate between the classes. The nearly horizontal shape of the curve suggests that the model does not markedly enhance the equilibrium between precision and recall at various thresholds. This outcome underscores the necessity for additional train datasets and testing datasets with different predicts model including sampling techniques to address class imbalance.

The findings suggest that the Random Forest model demonstrates satisfactory performance in certain aspects, particularly in predicting married individuals. However, it encounters notable difficulties in accurately classifying single and divorced individuals, leading to higher chances of misclassification in these categories. These results suggest that marital status alone may not be enough to predict default risk, even though it has some predictive value. Various elements could influence the constraints on the model's performance:

- The dataset exhibits a significant overestimation of the Married category, resulting in the model favoring predictions for Married while neglecting the Single and Divorced classes.
- Feature Engineering: Although Default_Status was a significant feature, additional sociodemographic factors, like income or financing type, may play a greater role in predicting Marital_Status and, consequently, default risk.
- Model Tuning: Additional adjustments to hyperparameters and the exploration of alternative algorithms (such as Gradient Boosting Machines and XGBoost) may enhance model accuracy and class balance.

This research feature importance indicate that customer related information could introduce unintended bias. Implementing further data preprocessing cleansing irrelevant features to enhance the model's performance.

CONCLUSION

This research demonstrates the feasibility of applying the Random Forest algorithm to predict default risk in Islamic consumer financing, emphasizing marital status as a key demographic predictor. Using a large-scale, two-year dataset from an Indonesian Islamic bank, the study highlights that marital status particularly being married provides meaningful predictive value for credit risk classification, contributing to a more Sharia-compliant and data-driven credit scoring system.

The model trained on a balanced dataset using the ROSE technique achieved high performance on training data, accurately identifying both defaulters and non-defaulters. However, its performance declined on the imbalanced real-world test set, particularly in recall and AUC-PR, underscoring the challenges of generalizing to skewed data distributions. Married individuals emerged as the most stable and predictive category, with a precision of 56.96% and recall of 58.50%, likely reflecting stronger financial stability. In contrast, the “Single” and “Divorced” categories yielded moderate to weak predictive power, due to both behavioral variability and class imbalance in the dataset.

Addressing the three research questions, the study confirms that while marital status enhances default classification performance particularly for the married group the predictive power remains limited when used in isolation. The effectiveness of the Random Forest model could be significantly improved by incorporating additional predictors such as income, age, and financing tenure. Moreover, the model's moderate test accuracy (43.81%) reflects difficulties in detecting default patterns for underrepresented categories, further emphasizing the importance of richer features and more balanced data.

This study acknowledges several limitations. First, the reliance on a single bank’s historical data constrains the external validity and generalizability of the findings. Second, while the ROSE technique successfully balances training data, it may oversimplify real-world class distributions, particularly where married individuals dominate the population. Third, the limited representation of single and divorced clients affects model sensitivity to minority classes.

Future research should consider multi-institutional datasets, alternative or hybrid resampling techniques, and the inclusion of broader behavioral and financial variables. Enhancements such as threshold tuning, ensemble learning, or cost-sensitive algorithms may also help mitigate the impact of imbalance and improve model robustness. Ultimately, this study contributes to the intersection of Islamic finance and machine learning, underscoring the potential of demographic-informed credit scoring systems that align with Sharia principles and practical banking needs.

REFERENCES

Benk, M., & Filali, A. (2020). The impact of sociodemographic factors on default risk in consumer credit: Evidence from conventional banking. Journal of Credit Risk Analysis, 18(2), 115–130. https://doi.org/10.2139/ssrn.3572304

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

Friedman, M., Kohn, R., & Becker, T. (2016). Financial instability and personal circumstances: The case of divorce and credit default. Journal of Financial Behavior, 24(3), 231–248.

Jouini, M. N., Aissani, D., & Benyettou, A. (2018). Credit risk prediction using machine learning algorithms: Evidence from a Tunisian bank. International Journal of Advanced Computer Science and Applications, 9(4), 385–391. https://doi.org/10.14569/IJACSA.2018.090450

Suleiman, A., Hassan, M. K., & Khan, T. (2020). Machine learning models in Islamic banking: Predicting credit risk using Random Forest. International Journal of Islamic and Middle Eastern Finance and Management, 13(5), 955–973. https://doi.org/10.1108/IMEFM-07-2019-0267

Zulkarnaen, W., Fitriani, I., & Yuningsih, N. (2020). Development of Supply Chain Management in the Management of Election Logistics Distribution that is More Appropriate in Type, Quantity and Timely Based on Human Resources Competency Development at KPU West Java. MEA Scientific Journal (Management, Economics, & Accounting), 4(2), 222-243. https://doi.org/10.31955/mea.vol4.iss2.pp222-243.

FIGURE AND TABLE

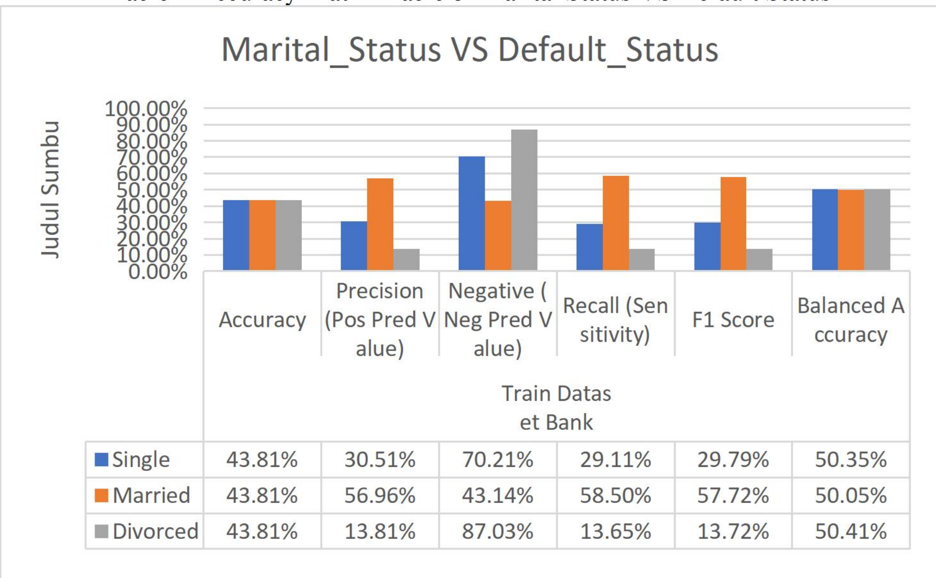
	Cust_Name	Marital_Status	Default_Status
94145	[redacted]	Married	Default
2222	[redacted]	Single	Default
40583	[redacted]	Married	Default
1969	[redacted]	Married	Default
3542	[redacted]	Divorced	Default
3070	[redacted]	Divorced	Default
2787	[redacted]	Divorced	Default
110053	[redacted]	Married	Default
7593	[redacted]	Divorced	Default
111	[redacted]	Divorced	Default
33708	[redacted]	Married	Default
40199	[redacted]	Single	Default

Figure 1 The Dataset Islamic (3 rows)

```
> conf_matrix <- confusionMatrix(pred_rf, Dataset_Islamic_Test$Marital_Status)
> print(conf_matrix)
Confusion Matrix and Statistics

          Reference
Prediction Divorced Married Single
  Divorced      587    2434   1231
  Married      2511   10949   5762
  Single       1204    5334   2871

Overall Statistics

               Accuracy : 0.4381
                 95% CI : (0.4328, 0.4435)
    No Information Rate : 0.5692
    P-Value [Acc > NIR] : 1.0000000

                  Kappa : 0.0047

 Mcnemar's Test P-Value : 0.0004383

Statistics by Class:

                     Class: Divorced Class: Married Class: Single
Sensitivity                  0.13645         0.5850       0.29106
Specificity                  0.87177         0.4160       0.71597
Pos Pred Value               0.13805         0.5696       0.30513
Neg Pred Value               0.87025         0.4314       0.70210
Prevalence                   0.13083         0.5692       0.29997
Detection Rate               0.01785         0.3330       0.08731
Detection Prevalence         0.12931         0.5846       0.28614
Balanced Accuracy            0.50411         0.5005       0.50352
```

Figure 2 *Confusion Matrix*

Table 1 Accuracy Matrix Table of Marital Status VS Default Status



	Accuracy	Precision (Pos Pred Value)	Negative (Neg Pred Value)	Recall (Sensitivity)	F1 Score	Balanced Accuracy
Single	43.81%	30.51%	70.21%	29.11%	29.79%	50.35%
Married	43.81%	56.96%	43.14%	58.50%	57.72%	50.05%
Divorced	43.81%	13.81%	87.03%	13.65%	13.72%	50.41%

```
> # Summary of the Random Forest model
> print(rf_model)

Call:
 randomForest(formula = Marital_Status ~ Default_Status +
., data = Dataset_Islamic_Train,      ntree = 100, mtry =
3)
               Type of random forest: classification
                     Number of trees: 100
No. of variables tried at each split: 2

        OOB estimate of  error rate: 54.3%
Confusion matrix:
         Divorced Married Single class.error
Divorced     1959   10979   4273   0.8861774
Married      7849   48369  18651   0.3539516
Single       4124   25550   9785   0.7520211
```

Figure 3 Summary Random Forest Classification

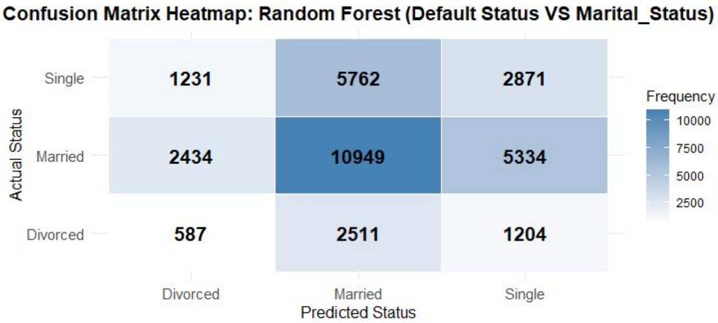


Figure 4 Confusion matrix heatmap of the Random Forest evaluated on the balanced training dataset. The model demonstrates strong classification performance, with high recall for both default and non-default classes

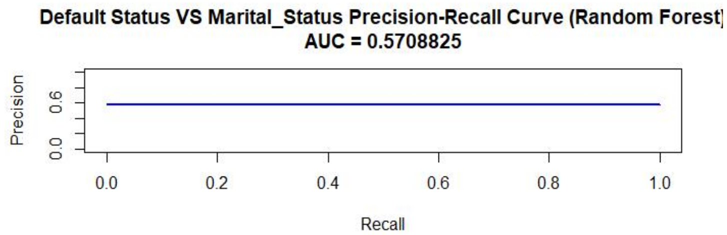
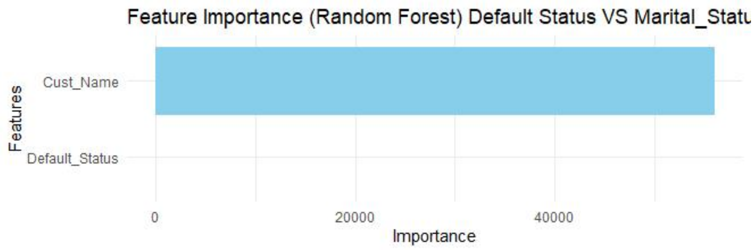


Figure 5 Precision-Recall (PR) curve of the Random Forest on the training dataset. The curve yields a high AUC-PR of 0.57088 reflecting strong moderate to default cases in the presence of balanced data.



Appendix R Encodes

```
# Load necessary libraries
library(readxl)
library(caret)
library(dplyr)
library(randomForest)

# Load and clean data
Dataset_Islamic <- read_excel("/mnt/data/Dataset_Islamic.xlsx")
Dataset_Islamic <- na.omit(Dataset_Islamic)

# Convert categorical variables to factors
Dataset_Islamic$Default_Status <- as.factor(Dataset_Islamic$Default_Status)
Dataset_Islamic$Marital_Status <- as.factor(Dataset_Islamic$Marital_Status)

# Split the data into training and test sets
set.seed(123)
train_index <- createDataPartition(Dataset_Islamic$Marital_Status, p = 0.8, list = FALSE)
Dataset_Islamic_Train <- Dataset_Islamic[train_index, ]
Dataset_Islamic_Test <- Dataset_Islamic[-train_index, ]

# Train the Random Forest model
rf_model <- randomForest(Marital_Status ~ Default_Status + .,
```

```
                        data = Dataset_Islamic_Train,
                        ntree = 100,
                        mtry = 3)
# Display model summary
print(rf_model)

# Make predictions on the test set
pred_rf <- predict(rf_model, newdata = Dataset_Islamic_Test)

# Confusion Matrix for evaluation
conf_matrix <- confusionMatrix(pred_rf, Dataset_Islamic_Test$Marital_Status)
print(conf_matrix)

# Calculate Feature Importance
feat_imp_rf <- as.data.frame(importance(rf_model))
feat_imp_rf$Feature <- rownames(feat_imp_rf)
colnames(feat_imp_rf) <- c("Importance", "Feature")

# Visualize Feature Importance
ggplot(feat_imp_rf, aes(x = reorder(Feature, Importance), y = Importance)) +
  geom_col(fill = "skyblue") +
  coord_flip() +
  labs(
    title = "Feature Importance (Random Forest) for Marital_Status",
    x = "Features",
    y = "Importance"
  ) +
  theme_minimal()

# Confusion Matrix Heatmap visualization
cm_table <- as.data.frame.table(conf_matrix$table)
colnames(cm_table) <- c("Predicted", "Actual", "Frequency")

ggplot(cm_table, aes(x = Predicted, y = Actual, fill = Frequency)) +
  geom_tile(color = "white") +
  geom_text(aes(label = Frequency), size = 5, fontface = "bold") +
  scale_fill_gradient(low = "white", high = "steelblue") +
  labs(
    title = "Confusion Matrix Heatmap: Random Forest (Default Status VS Marital_Status)",
    x = "Predicted Status",
    y = "Actual Status",
    fill = "Frequency"
  ) +
  theme_minimal() +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold", size = 14),
    axis.title = element_text(size = 12),
    axis.text = element_text(size = 11)
  )
# Precision-Recall Curve
pred_prob_rf <- predict(rf_model, newdata = Dataset_Islamic_Test, type = "prob")
pr <- pr.curve(scores.class0 = pred_prob_rf[,2], weights.class0 = (Dataset_Islamic_Test$Marital_Status
== "Married"), curve = TRUE)
plot(pr, main = "Default Status VS Marital_Status Precision-Recall Curve (Random Forest)", col =
"blue", lwd = 2)
```

Figure 7. Feature importance plot based on gain values from Random Forest the significance of borrower demographics and financing behaviour in default prediction.