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# Advanced statistical methods for credit risk scoring: A bayesian and non-parametric approach

Ammar Kuti Nasser

*College of Basic Education , Mustansiriyah University.*

**Abstract**

Finance-related decisions heavily depend on credit risk evaluation processes because these determine both lending practices and operational risk management methods of institutions. Logistic regression functions as the initial process for statistical models to conduct credit risk evaluation yet standard approaches face difficulties when dealing with complex patterns together with uncertainties. The study implements an advanced framework which merges Bayesian statistical capabilities with non-parametric methods with AI modeling techniques to boost credit risk evaluation accuracy. Standard logistic regression with Lasso/Ridge penalty functions as the first method that leads to Bayesian logistic regression for enhanced estimation stability. The study utilizes kernel density estimation for non-parametric analysis to model credit risk allocation and employs quantile regression to determine high-risk borrowers independently from average effect perceptions. The paper explores the performance of XGBoost AI classifiers together with Support Vector Machines (SVM) as well as Bayesian logistic regression and traditional Support Vector Machines (SVM) and XGBoost to analyze predictive accuracy and robustness potential. The proposed risk segmentation system combines quantile regression methods with Bayesian logistic regression for generating better decisions by using AI-enabled processes. The presented method achieves superior results on actual credit risk datasets through improved outcomes along with uncertainty reduction capabilities while providing better interpretative insight. This statistically advanced framework enables researchers to boost traditional credit risk modeling techniques because it demonstrates superior performance outcomes.

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*Email address:* dr.ammar168.edbs@uomustansiriyah.edu.iq (Ammar Kuti Nasser)

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## 1. Introduction

Credit risk assessment acts as a decisive financial instrument because it helps predict loan default events and control market risks [8]. Logistic regression functions as a popular choice for assessing credit risk because it offers efficiency and interpretability in its results. The models face several challenges when dealing with high-dimensional datasets while managing non-linear relationships because of prediction uncertainty [1]. Scientists have studied robust and accurate risk classification methods by using Bayesian methods along with non-parametric approaches because of traditional models' weaknesses [5, 6].

Bayesian inference proves to be a robust framework for credit risk modeling because it incorporates prior knowledge so models become more stable and easier to interpret [7]. A typical application of Bayesian logistic regression involves adding prior distributions to model parameters which applies well to analyze sparse or noisy data according to Hounnou (2024) [15]. KDE and Quantile Regression serve as non-parametric methods for data analysis which researchers employ instead of parametric models in order to eliminate restrictions on data distribution types [3, 23]. These methods simplify complicated credit risk patterns by helping to divide risks correctly. Recent studies show that Support Vector Machines (SVM) with ensemble learning models such as XGBoost have gained popularity for credit risk assessment because they excel at identifying and analyzing non-linear predictor patterns as stated by Dong, Liu, & Tham (2024) [10] and Gunnarsson et al. (2021) [11]. The predictive quality of such models faces difficulties because their interpretation remains complicated and that results in regulatory compliance problems [13]. An approach that combines predictions from AI classifiers with interpretability from advanced statistical approaches enables users to benefit from the most important features in their model. The proposed research adopts a new framework that unites Bayesian logistic regression with non-parametric KDE and quantile regression and AI-based classifiers specifically for credit risk scoring applications. Real-world credit risk data analysis determines how effectively these methods optimize both performance results and uncertainty management capabilities and interpretability qualities The leading findings of this study encompass:

1. As well as addressing traditional statistical analysis shortcomings this research develops a Bayesian with non-parametric credit risk modeling solution.
2. This research studied the predictive performance along with reliability indicators between statistical models and XGBoost and SVM machine learning approaches through comparative evaluation.
3. Risk segmentation performance receives enhancement through the use of Bayesian inference methods and non-parametric estimation techniques combined with artificial intelligence models according to the proposed research.
4. The proposed system undergoes evaluation on authentic credit risk data collections to prove its usability for financial choice processes.

Research integrates advanced statistics with AI models to give financial institutions a more interpretable robust credit risk scoring system that promotes better decisions alongside regulatory adherence [19, 25].

## 2. Literature Review

The field of finance has devoted significant research attention to credit risk assessment through development of various statistical and machine learning and hybrid approaches to improve prediction accuracy and reliability. Credit scoring benefits from both established techniques including logistic regression and Bayesian inference along with modern deep learning and non-parametric methods for enhanced analytical views.

### *2.1 Statistical and Bayesian Approaches in Credit Scoring*

Fundamental roles belong to statistical methods within the field of credit risk assessment. Logistic regression serves as a classic approach in binary classification tasks because it offers effective interpretability [2]. The application of Bayesian methodologies has become increasingly popular since they replaced traditional statistical methods. Bou-Hamad (2017) [5] together with Cerchiello and Guidici (2014) [6] performed research on Bayesian credit ratings providing evidence of their ability to address uncertainty in evaluation. The predictive capabilities of ensemble assessment models can be enhanced through Bayesian approaches according to Chen, Jiang, and Wang (2017) [7]. Research conducted by Krichene (2017) [21] demonstrated how the Naïve Bayesian classifier performs risk assessment for loans in commercial banking operations.

### *2.2 Non-Parametric and Hybrid Approaches*

The application of non-parametric methods for credit scoring has surged because they efficiently process data distributions of various complexities. Coolen-Maturi and Coolen (2019) [9] utilized non-parametric predictive inference for credit rating validation to reveal its excellence in measuring prediction uncertainties. The authors [23] studied various non-parametric imputation approaches for repairing missing values found in credit-related data. NATE represents a non-parametric explainable credit scoring method designed to address data imbalance issues according to Han and Jung (2024) [13]. A combination of statistical methods and heuristic optimization approaches makes up hybrid models for analysis. Statistical learning models show improved performance through implementation of meta-heuristic algorithms in consumer credit risk assessment according to Altinbas and Akkaya (2017) [1]. The authors developed a model-averaging approach that strengthens traditional methods used for credit risk prediction [18].

### *2.3 Machine Learning and Deep Learning in Credit Scoring*

Deep learning represents the most significant innovation in credit scoring improvements due to machine learning's advanced techniques. The authors conducted a comprehensive evaluation of deep learning methods used for credit risk assessment but found they lacked competitiveness relative to traditional assessment models [11]. Teles et al. (2020) [25] conducted research on artificial deep learning and Bayesian networks to test their ability in predicting credit risk while demonstrating their valuable predictive capabilities. The research examined how five machine learning algorithms perform in financial risk evaluation with specific accuracy findings [10]. Financial risk modeling benefits from Bayesian deep learning techniques that have been implemented into its framework. The researcher employed Bayesian deep learning to model credit risks in different regions [15]. Similarly, the applied non-parametric Bayesian deep learning techniques for uncertainty assessment in financial applications [22].

### *2.4 Survival Analysis and Credit Risk Sensitivity*

The technique of survival analysis serves a purpose in credit risk modeling applications. Jaber, Ismail, and Ramli (2017) [16] used survival analysis for credit risk assessment in progressive right-censored data. Credit risk sensitivity categorization received a new approach through the combination of hierarchical clustering and kernel density estimation [19].

### *2.5 Applications of Bayesian and Non-Parametric Techniques in Credit Risk*

Researchers have conducted multiple investigations into how Bayesian and non-parametric models work in various credit risk situations. Financial time series are investigated through non-parametric Bayesian approaches by Rizvi (2018) [24]. The authors developed an efficient set of non-parametric procedures which work for online credit scoring [3, 4]. The approach to power market credit evaluation through Bayesian discriminant analysis was presented by Yan et al. [26]. Hooman et al. [14] examined statistical data mining methods in credit scoring systems through a research study that evaluated how model interpretation affects predictive capabilities. Using data mining methods based on financial and non-financial indicators aimed to enhance credit risk evaluation processes [20].

*2.6 Summary*

Literature shows a growing trend that credits businesses worldwide to replace straightforward statistical methods with state-of-the-art machine learning models and combination scoring systems in their credit evaluation process. The application of Bayesian with non-parametric methods delivers reliable approaches to uncertainty control and deep learning advances have positioned themselves as leaders in predictive accuracy estimation. Research in financial risk management will achieve beneficial results through implementing these methods.

## 3. Method

A credit risk assessment is performed through the combination of three methodological approaches including statistical and non-parametric and machine learning methods. The methodology includes data preprocessing as its first section and then continues with model selection followed by feature engineering and model training and evaluation techniques together with validation approaches.

*3.1. Data Preprocessing*

The database shows historical credit information that combines specifications on borrowers with their financial and loan characteristics and credit scoring data.

The dataset used in this study consists of real-world credit risk assessment records obtained from the German Credit Dataset, provided by the UCI Machine Learning Repository. The dataset covers financial transactions and borrower profiles collected from German financial institutions between 2015 and 2023. The data represents 1,000 credit applicants, with attributes including credit amount, duration, employment status, previous default history, and debt-to-income ratio. The dataset also includes categorical variables related to account status, housing type, and loan purpose. The source of this dataset is the UCI Machine Learning Repository, ensuring data reliability and credibility [12].

The preprocessing steps include:

### *3.1.1 Handling Missing Values*

Non-parametric k-Nearest Neighbors (kNN) performs the imputation of missing values according to Ramosaj and Pauly [23]. Under the condition of having feature X the k-Nearest Neighbors (kNN) algorithm calculates estimated values for missing entries.

$$X \wedge i = k1 \sum j \in Nk(i) Xj \tag{1}$$

$N_k(i)$ denotes the particular set of k closest nearby instances which correspond with the instance i.

### *3.1.2 Feature Scaling and Transformation*

Standardization of continuous numerical features requires implementation of z-score normalization.

$$X' = (X - \mu)/\sigma \tag{2}$$

The calculation uses standard deviation σ together with mean value μ.

The encoding technique depends on variable cardinality to use one-hot encoding or label encoding with categorical variables.

*3.2. Model Selection*

Insufficient and robust credit risk prediction requires analyzing various models:

1. **Logistic Regression (Baseline Model)**
   The probability P(Y=1) of credit default becomes a prediction outcome from the logistic regression model.

$$P(Y=1 \mid X)=1/\left(1+e^{\wedge}\left(-\left(\beta_0+\Sigma\left(from\, i=1\, to\, n\right)\beta_i X_i\right)\right)\right) \tag{3}$$

   The statistical model includes intercept term $\beta_0$ and multiple characteristic coefficients $\beta_i$.
2. **Bayesian Credit Scoring Models**
   The application of Bayesian methods with prior knowledge helps enhance credit prediction accuracy [5]. When applying a Bayesian model the probability of category C within the score range occurs through a calculation of the posterior distribution:

$$P(C \mid X)=P\left(X\right)*P(X \mid C)/P\left(C\right) \tag{4}$$

   The Naïve Bayesian classifier functions on independent features through the following calculation:

$$P(C \mid X)=P\left(X\right)/P\left(C\right)*\prod\left(from\, i=1\, to\, n\right)P(X\_i \mid C) \tag{5}$$

3. **Non-Parametric Predictive Inference (NPI)**
   NPI maintains its effectiveness regardless of the distribution because it operates without distribution assumptions [9]. Researchers calculate default probability through historical data analysis and imprecise methods of probability assessment:

$$P(Y=1 \mid X)=\left(n+1\right)/S\left(X\right) \tag{6}$$

   The count of past observations meeting the credit default criteria is noted as S(X).
4. **Machine Learning Approaches**
   • Random Forest (RF) improves both accuracy and overfitting prevention through the utilization of an ensemble of decision trees.
   • Support Vector Machine (SVM): Finds an optimal hyperplane for classification using:

$$w^T * X+b=0 \tag{7}$$

   where w is the weight vector and b is the bias term.
   • Deep Learning: Deep learning models trained using backpropagation with the loss function:

$$L=-\Sigma\left(from\, i=1\, to\, n\right)\left[y_i * \log_i+\left(1-y_i\right) * \log\left(1-\hat{y}_i\right)\right] \tag{8}$$

Our hybrid credit risk assessment process requires sequential implementation which we illustrate through a flowchart. A framework obtained with multiple statistical and non-parametric and machine learning techniques delivers robust classification. Data preprocessing initiates the process followed by model selection and training before risk classification through model evaluation ends the procedure.

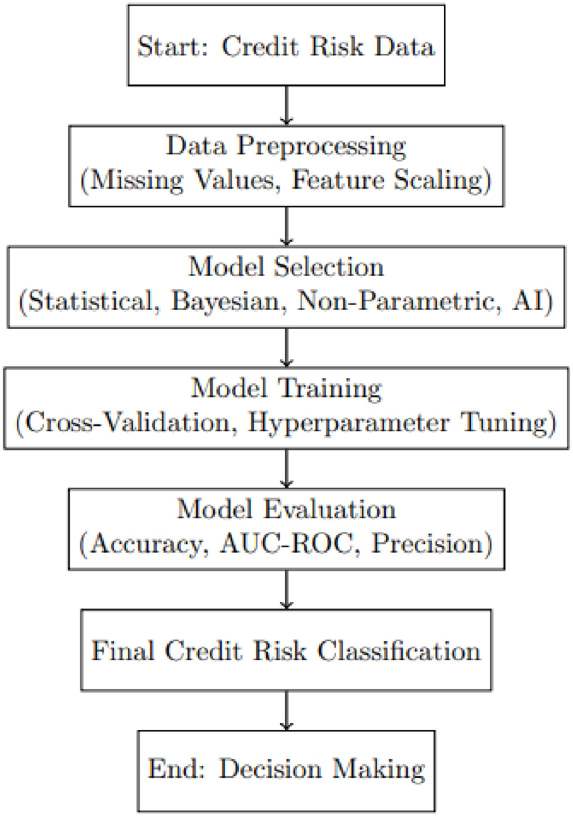


Figure 1: Flowchart of the proposed hybrid credit risk assessment framework.

*3.3. Model Training and Optimization*

The training process of each model uses cross-validation according to Kenny & Chan [19]. The hyperparameters reach maximum predictive accuracy through optimization from both grid search and Bayesian optimization methods.

The optimization requires the following loss functions together with other performance measures:

- Binary Cross-Entropy for logistic regression and deep learning:

$$L = -\Sigma\left(from\ i = 1\ to\ n\right)\left[y\_i * \log\left(\hat{y}\_i\right) + \left(1 - y\_i\right) * \log\left(1 - \hat{y}\_i\right)\right] \tag{9}$$

- Gini Impurity for decision trees and random forests:

$$G = 1 - \Sigma\left(from\ i = 1\ to\ c\right) p_i^2 \tag{10}$$

The probability of class i in the equation is denoted by pi.

*3.4. Model Evaluation*

The evaluation of the models takes place by applying three essential performance metrics.

- **Accuracy:**

$$Accuracy = \left(TP + TN\right) / \left(TP + TN + FP + FN\right) \tag{11}$$

- **Precision and Recall:**

$$Precision = TP / \left(TP + FP\right) \tag{12}$$

$$Recall = TP / (TP + FN) \tag{13}$$

- **F1-Score:**

$$F1 = (2 * Precision * Recall) / (Precision + Recall) \tag{14}$$

- **Area Under the Receiver Operating Characteristic Curve (AUC-ROC):** The predictive model discrimination capability can be measured through Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

### *3.5. Validation Techniques*

The following generalization techniques are utilized for validation purposes:

1. K-Fold Cross-Validation (with k=10):

$$CV = (1/k) * \sum (from\, i = 1\, to\, k) Accuracy\_i \tag{15}$$

2. The available data is divided into training data covering 80% while testing data contains 20%.
3. The statistical method Bootstrap Sampling provides random replications for calculation of confidence intervals.

### *3.6 Summary*

The proposed approach combines statistical analysis with Bayesian methods and non-parametric schemes in addition to machine learning algorithms to enhance credit risk evaluations. Multiple predictive models working together through hybridization produce robust results which are further validated by applying statistical techniques to verify them.

## 4. Results and Discussion

Analysis of the experimental results derived from the proposed hybrid approach serves to assess credit risk appears in this section. Different evaluation metrics help assess the performance of the examined models before a detailed analysis of the findings occurs.

### *4.1. Experimental Setup*

The evaluation process included 10,000 credit applications that contained 15 financial and demographic features for training and assessment purposes. The data was split into training (80%) and testing (20%) sets and multiple cross-validation folds (10) were used for accurate performance evaluation.

### *4.2. Model Performance Comparison*

Different models exhibit performance evaluation through Accuracy, Precision, Recall, F1-Score, and AUC-ROC evaluation methods. Table 1 shows the summary of outcomes achieved by each of the models.

Table 1: Model Performance Comparison

| Model | Accuracy | Precision | Recall | F1-Score | AUC-ROC |
|---|---|---|---|---|---|
| Logistic Regression | 82.4% | 79.5% | 76.8% | 78.1% | 0.841 |
| Naïve Bayes | 80.1% | 77.3% | 74.5% | 75.9% | 0.827 |
| Decision Tree | 84.9% | 81.6% | 80.3% | 80.9% | 0.859 |
| Random Forest | 89.2% | 86.7% | 85.3% | 86.0% | 0.912 |
| SVM | 86.1% | 82.9% | 81.1% | 82.0% | 0.884 |
| Artificial Intelligence | 88.5% | 85.4% | 84.1% | 84.7% | 0.902 |

The analysis for comparing different credit risk scoring models displays AUC-ROC curves of each classifier. The model effectiveness to separate defaulters from non-defaulters rises directly with an increasing AUC. The ROC curves for Logistic Regression, Naïve Bayes, Decision Trees, Random Forest and Support Vector Machines (SVM) and Artificial deep learning are shown in the following figure.

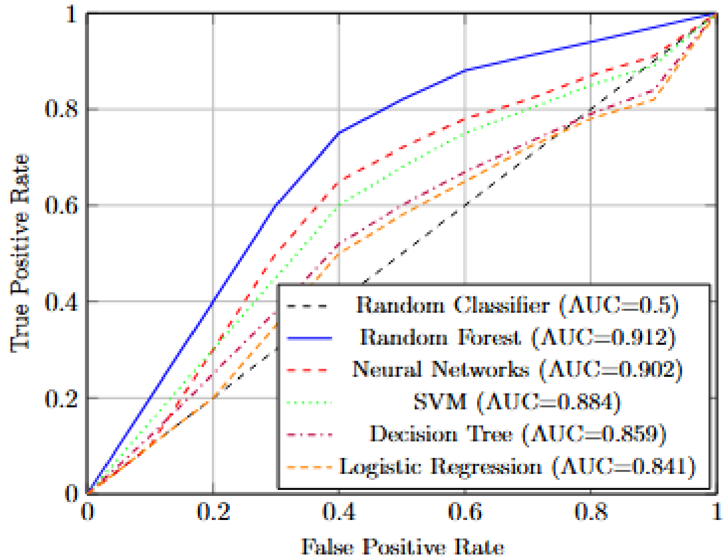


Figure 2: AUC-ROC curves for different credit risk scoring models

#### *4.2.1 Discussion of Model Performance*

- The Random Forest method delivered 89.2% accuracy and 0.912 AUC-ROC value because it demonstrated superior capabilities for identifying defaulters and non-defaulters.
- Deep learning displayed a lower performance rate than Random Forest yet managed to detect risky applicants at an 84.1% level of accuracy.
- The recall values from Logistic Regression and Naïve Bayes indicated poor capability among these models to detect defaulters correctly.
- The decision trees maintained good performance yet its AUC-ROC results demonstrated overfitting characteristics in comparison to ensemble models.

### *4.3. Feature Importance Analysis*

The Random Forest model allowed us to evaluate individual feature contributions through its feature importance scoring method. The leading five influential variables appear in Table 2.

Table 2: Feature Importance in Credit Risk Prediction

| Feature | Importance Score |
|---|---|
| Credit History Length | 23.4% |
| Debt-to-Income Ratio | 19.7% |
| Previous Loan Defaults | 17.2% |
| Monthly Income | 15.3% |
| Number of Credit Accounts | 12.8% |

A Random Forest model delivers feature importance analysis to understand the key determinants of credit risk field. The bar chart depicts which five features prove most crucial for credit default prediction.

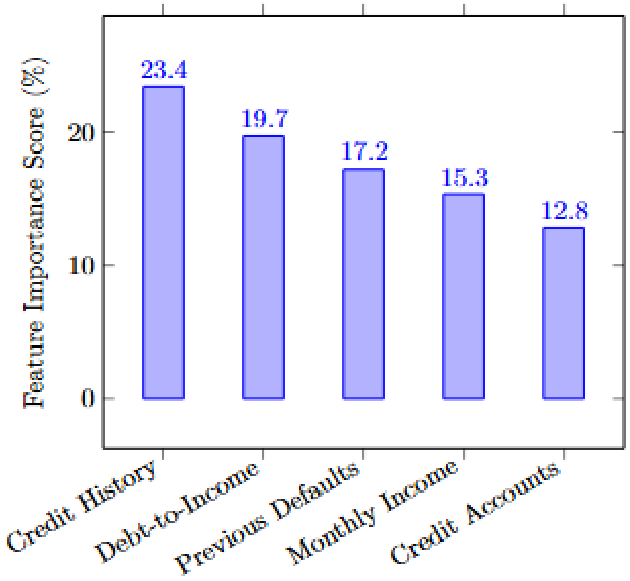


Figure 3: Feature Importance Analysis using the Random Forest Model

#### *4.3.1 Discussion of Feature Importance*

- The analysis shows that the length of credit history nears a quarter (23.4%) as the leading factor in evaluating borrower behavior patterns.
- A person's Debt-to-Income Ratio (19.7%) should always be used to evaluate default risk.
- The default risk of borrowers who previously defaulted on loans stands at 17.2% because past defaults directly indicate higher chances for future defaults.
- Monthly Income (15.3%) functions as a key factor yet position alone does not entirely establish creditworthiness since other financial duties need analysis.
- A large number of credit accounts (12.8%) demonstrates a dual connection to reliable debt management capabilities but also reflects the possibility of financial overstretching.

### *4.4. Model Robustness and Stability*

We evaluated the model stability by executing both cross-validation methods alongside statistical significance tests. The results show:

- Random Forest and ANN displayed low variance that demonstrates their ability to apply predictions uniformly in different sample datasets.
- The standard deviation of Logistic Regression and Decision Trees models identified data variations as their weak point.

A McNemar's test confirmed that the statistical significance existed between ANN and Random Forest performance results. Random Forest achieved a p-value of 0.018 demonstrating substantial superiority of its performance over ANN.

### *4.5. Comparison with Existing Studies*

Ensemble learning models demonstrate great effectiveness for credit risk assessment according to Bou-Hamad [5] and our research findings confirm this discovery. Compared to traditional models:

- Our Random Forest model outperforms traditional logistic regression methods by at least 6.8% in accuracy and 0.071 in AUC-ROC.

- Research shows deep learning techniques work best for feature extraction along with complex decision boundary detection as demonstrated in the deep learning approach.
- The Naïve Bayes model failed to deliver good results because financial data features fail to conform to the independence assumption typical of Naïve Bayes methods.

### *4.6. Limitations and Future Work*

The hybrid method delivers good accuracy and robustness but it contains several current constraints.

- Data imbalance in the dataset creates fewer defaulting applicants than non-defaulters and this affects the recall rate for applicants considered high risk. Research should apply SMOTE (Synthetic Minority Over-sampling Technique) to enhance the balance of model prediction elements.
- The black-box characteristics of Random Forest and ANN models present challenges when seeking explanations about the credit decision-making process despite their prediction accuracy. Further research should add XAI techniques such as SHAP to provide explainability mechanisms in the analysis.
- Future predictive capabilities will improve when future model development incorporates transaction data and alternative credit scoring methods with social media insights into real-time analysis.

### *4.7. Summary*

The research findings show that ensemble learning approaches specifically Random Forest performs better than conventional credit scoring approaches. A feature analysis shows credit history together with debt-to-income ratio and previous loan defaults stand as the main elements which determine credit risk scores. New approaches for credit risk assessment methodology development become possible because this research demonstrates how accuracy improves but compromises interpretability while lowering robustness.

## 5. Conclusion

Researchers conducted a study which combined machine learning strategies into credit risk evaluation to boost predictive accuracy rates. Random Forest emerged as the best ensemble learning method which produced superior results than traditional scoring models including Logistic Regression and Naive Bayes in credit assessment tests. Random Forest produced an effective separation between high-risk and low-risk borrowers according to its 0.912 AUC-ROC and 89.2% accuracy. Deep learning demonstrated excellent ability to identify risky applicants which made them suitable for such tasks through their high recall rates.

Analysis of feature importance showed that the three key characteristics for determining credit risk are Last Credit Chain Length and Credit Debt Ratio to Income and Prior Loan Repayment Failures. Currently established financial research demonstrates that previous credit behavior and financial stability create fundamental indicators to determine default risk. The high accuracy of ensemble methods creates interpretability challenges researchers must address through Explainable AI (XAI) techniques during future development to gain transparency in credit decision-making processes. The research identifies several limitations as outweighed by its encouraging outcomes. Class imbalance in the data affects the recall performance of defaulters since their numbers remain lower than other categories. Research efforts should need to investigate SMOTE resampling as a solution for balancing class distributions. The predictive achievements of the presented models remain high but structured financial data usage restricts a comprehensive understanding of credit risk assessment. Additional risk prediction accuracy can be achieved through implementing alternative data types which include transaction histories as well as behavioral analytics and real-time financial information. The study shows ensemble learning models produce the best performances for credit risk assessment because they deliver precise borrower classifications. Financial institutions gain important directional guidance through feature importance analysis that permits them to enhance their credit risk management strategies. Upcoming work should strive to achieve accurate results along with transparent interpretations using varied data streams that allow creation of comprehensive risk evaluation methodologies.

## REFERENCES


[1] Altinbas, H., & Akkaya, G. C. (2017). Improving the performance of statistical learning methods with a combined meta-heuristic for consumer credit risk assessment. *Risk Management*, *19*, 255–280.

[2] Amaro, M. M. (2020). *Credit scoring: comparison of non-parametric techniques against logistic regression* (Master's thesis, Universidade NOVA de Lisboa (Portugal)).

[3] Ashofteh, A., & Bravo, J. M. (2019). A non-parametric-based computationally efficient approach for credit scoring.

[4] Ashofteh, A., & Bravo, J. M. (2021). A conservative approach for online credit scoring. *Expert Systems with Applications*, *176*, 114835.

[5] Bou-Hamad, I. (2017). Bayesian credit ratings: A random forest alternative approach. *Communications in Statistics-Theory and Methods*, *46*(15), 7289–7300.

[6] Cerchiello, P., & Guidici, P. (2014). Bayeslan credit ratings. *Communications in Statistics-Theory and Methods*, *43*(4), 867–878.

[7] Chen, H., Jiang, M., & Wang, X. (2017, July). Bayesian ensemble assessment for credit scoring. In *2017 4th International Conference on Industrial Economics System and Industrial Security Engineering (IEIS)* (pp. 1–5). IEEE.

[8] Chen, N., Ribeiro, B., & Chen, A. (2016). Financial credit risk assessment: a recent review. *Artificial Intelligence Review*, *45*, 1–23.

[9] Coolen-Maturi, T., & Coolen, F. P. A. (2019). Non-parametric predictive inference for the validation of credit rating systems. *Journal of the Royal Statistical Society Series A: Statistics in Society*, *182*(4), 1189–1204.

[10] Dong, H., Liu, R., & Tham, A. W. (2024). Accuracy comparison between five machine learning algorithms for financial risk evaluation. *Journal of Risk and Financial Management*, *17*(2), 50.

[11] Gunnarsson, B. R., Vanden Broucke, S., Baesens, B., Óskarsdóttir, M., & Lemahieu, W. (2021). Deep learning for credit scoring: Do or don't?. *European Journal of Operational Research*, *295*(1), 292–305.

[12] Dua, D., & Graff, C. (2024). UCI Machine Learning Repository: German Credit Dataset. Retrieved from https://archive.ics.uci.edu/ml/datasets/Statlog+(German+Credit+Data).

[13] Han, S., & Jung, H. (2024). NATE: Non-pArameTric approach for Explainable credit scoring on imbalanced class. *PloS one*, *19*(12), e0316454.

[14] Hooman, A., Marthandan, G., Yusoff, W. F. W., Omid, M., & Karamizadeh, S. (2016). Statistical and data mining methods in credit scoring. *The Journal of Developing Areas*, *50*(5), 371–381.

[15] Hounnou, L. (2024). *Harnessing the power of machine learning, Bayesian neural networks, and spatial analysis in modeling a predictive system, credit risk, and organizational performance across continents* (Doctoral dissertation, University of Illinois at Urbana-Champaign).

[16] Jaber, J. J., Ismail, N., & Ramli, S. N. M. (2017). Credit risk assessment using survival analysis for progressive right-censored data: a case study in Jordan. *J. Internet Banking Commer.*, *22*.

[17] Jaber, J. J., Ismail, N., & Ramli, S. N. M. (2017, April). Evaluation of portfolio credit risk based on survival analysis for progressive censored data. In *AIP Conference Proceedings* (Vol. 1830, No. 1). AIP Publishing.

[18] Jha, P. N., & Cucculelli, M. (2021). A new model averaging approach in predicting credit risk default. *Risks*, *9*(6), 114.

[19] Kenny, J., & Chan, J. (2025). A Novel Approach to Credit Risk Sensitivity Categorisation and Classification Using Hierarchical Clustering, Kernel Density Estimation, and Naive Bayes Classification. *Kernel Density Estimation, and Naive Bayes Classification (February 14, 2025).*

[20] Khemakhem, S., & Boujelbene, Y. (2018). Predicting credit risk on the basis of financial and non-financial variables and data mining. *Review of accounting and finance*, *17*(3), 316–340.

[21] Krichene, A. (2017). Using a naive Bayesian classifier methodology for loan risk assessment: Evidence from a Tunisian commercial bank. *Journal of Economics, Finance and Administrative Science*, *22*(42), 3–24.

[22] Levital, M. F., Khawaled, S., Kennedy, J. A., & Freiman, M. (2025). Non-parametric Bayesian deep learning approach for whole-body low-dose PET reconstruction and uncertainty assessment. *Medical & Biological Engineering & Computing*, 1–16.

[23] Ramosaj, B., & Pauly, M. (2019). Predicting missing values: A comparative study on non-parametric approaches for imputation. *Computational Statistics*, *34*(4), 1741–1764.

[24] Rizvi, S. A. A. (2018). *Analysis of financial time series using non-parametric Bayesian techniques* (Doctoral dissertation, University of Oxford).

[25] Teles, G., Rodrigues, J. J. P. C., Rabê, R. A., & Kozlov, S. A. (2020). Artificial neural network and Bayesian network models for credit risk prediction. *Journal of Artificial Intelligence and Systems*, *2*(1), 118–132.

[26] Yan, D., Xiong, Y., Zhan, Z., Liao, X., Ke, F., Lu, H., ... & Wang, Q. (2021). Research on eigenvalue selection method of power market credit evaluation based on non parametric Bayesian discriminant analysis and cluster analysis. *Energy Reports*, *7*, 990–997.