International Journal Of Health, Engineering And Technology (IJHET) *E-ISSN 2829 - 8683*
Volume 5, Number 2, July 2026, *Page. 1512 - 1520*
Email : editorijhess@gmail.com

Analysis Of Financing Risk Optimization At XYZ Multifinance Company Through A Credit Score Clustering Approach

Ranti Ramayanti Haris[1),]Astie Darmayantie[2)]
[1,2)] Program Studi Magister Sistem Informasi Bisnis,Fakultas Manajemen Sistem Informasi,Universitas Gunadarma

*Corresponding Author
Email : ranti.haris03@gmail.com

Abstract

This research a credit scoring model to optimize financing risk in Multifinance Company XYZ, which has a Non-Performing Financing (NPF) rate of 2.8%, exceeding the company's target of 2%. The development is carried out using Oracle Development Suite with the CRISP-DM methodology, covering the stages of business understanding, data understanding, data preparation, modeling, evaluation, and deployment. The dataset consists of 250 customer records from the period 2015–2025, with 101 initial variables that are subsequently reduced to 14 predictive variables based on correlation analysis and credit scoring domain knowledge. A K-Nearest Neighbor (KNN) classification model with K = 3 is developed using Oracle Data Miner to classify borrower risk into three categories: LOW, MEDIUM, and HIGH. Testing results on 50 testing data show that the model achieves an accuracy of 98%, precision of 97.5%, and recall of 100% for the HIGH-risk class. A 5-fold cross-validation confirms the model's consistency with a mean accuracy of 97.6% (±1.1%). Implementation using PL/SQL and Oracle Forms produces a real-time scoring system with a processing time of less than 5 seconds per application, compared to 5–7 days in the previous manual proces.

Keywords: Credit Scoring, Risiko Pembiayaan, K-Nearest Neighbor, Oracle Development Suite, CRISP- DM.

INTRODUCTION

The multifinance industry is characterized by high credit risk due to its direct relationship with consumer financing. Financing risk, or credit risk, is the potential loss resulting from a debtor's failure to meet their obligations. This risk level is reflected in the Non-Performing Finance (NPF) ratio, which is an indicator of non-performing loans. The Financial Services Authority (OJK) noted that as of June 2025, the gross NPF ratio for the multifinance industry was at ±2.55%.

Another challenge faced is the limited technology used in the credit evaluation process. Conventional evaluation processes tend to be manual, time-consuming, and prone to subjective bias. Many traditional finance companies still rely on simple analysis (for example, the 5Cs: character, capacity, capital, condition, collateral) without the support of modern predictive algorithms. These conventional methods are less able to effectively process complex historical data, especially as customer data volumes increase (big data). Consequently, the inability to manage large-scale data becomes problematic, and important risk patterns may be missed, resulting in inaccurate credit analysis.

One way to manage credit risk is to implement an accurate credit scoring system. Credit scoring is defined as a series of decision models and statistical techniques used by financial institutions to assess the creditworthiness of prospective borrowers. Multifinance company XYZ currently has a credit scoring system that is deemed suboptimal, with a Non-Performing Loan (NPF) of 2.8%, above the company's target of 2%. The credit evaluation process is still manual, taking 5-7 days and susceptible to analyst subjectivity.

This research aims to:

1. Develop a K-Nearest Neighbor (KNN)-based credit scoring model with a target accuracy of at least 90%;
2. Integrate the model with the Oracle Development Suite;
3. Improve the operational efficiency of the credit assessment process;
4. Evaluate and validate the robustness of the model; and
5. Develop a comprehensive implementation strategy.

International Journal Of Health, Engineering And Technology (IJHET) *E-ISSN 2829 - 8683*
Volume 5, Number 2, July 2026, *Page. 1512 - 1520*
Email : editorijhess@gmail.com

RESEARCH METHODS

Research Method

This research uses the Cross-Industry Standard Process for Data Mining (CRISP-DM) method, which consists of six stages: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Visualization, as shown in Figure 1.

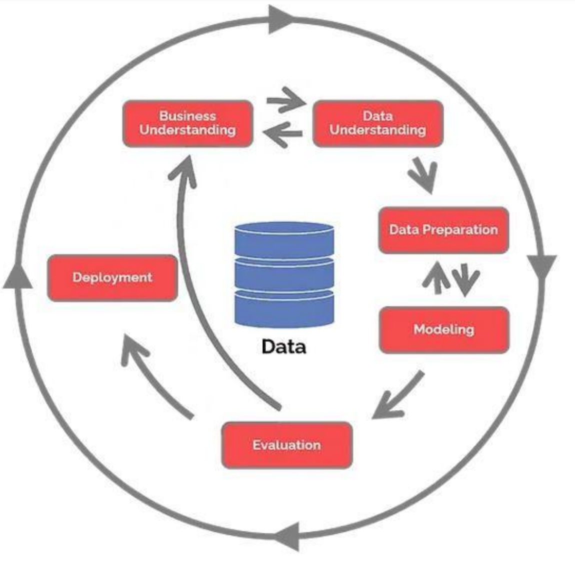

Figure 1. Research stages.

Business Understanding

The Business Understanding phase aims to understand the business needs and challenges faced by the company. Data collection was conducted through interviews with Credit Managers, Credit Analysts, and IT Managers, as well as direct observation of the existing credit assessment process. A SWOT analysis was conducted to identify strategic positions for system development.

Table 1. Project Success Criteria

Aspect	Target	Metric
Model Accuracy	$\geq$ 90%	Accuracy on the testing set
High Risk Detection	$\geq$ 90%	Recall for HIGH class
Prediction Precision	$\geq$ 85%	Precision for HIGH class
Scoring Time	< 5 detik	Response time per application
Consistency	Std < 2%	Cross-validation standard deviation

Data Understanding

The research dataset comes from the XYZ Multifinance Company Oracle Database which consists of 250 customer records for the 2015-2024 period with 101 initial variables. Variables include identity information, demographics, financing parameters, vehicle information, payment history, and collectibility status.

Table 2. Categorization of Dataset Variables

Category	Amount	Example Variables
Identity and Administrative	15	CUST_ID, NAME, PHONE_NO.
Demographics & Socioeconomics	12	AGE, MARITAL STATUS, OCCUPATION
Financing Parameters	18	NOMINAL, TENOR, INTEREST RATE
Vehicle Information	20	BRAND, TYPE, YEAR, FRAME NO.
Payment History	28	AMOUNT_ANGS_AVAILABLE, OD_TODAY
Collectibility Status	8	TODAY'S COLUMNS (Target)

Data Preparation

The Data Preparation phase includes a series of processes to prepare high-quality data:

a. Feature Selection: From the 101 initial variables, selection was conducted based on correlation analysis, domain knowledge of credit scoring, and data privacy considerations. Variables with a Pearson correlation >0.3 with the target were retained. Administrative variables (PHONE_NO, ADDRESS) and vehicle details (FRAME_NO, ENGINE_NO) were dropped as they were not predictive. The selection resulted in 14 predictive variables.

b. Data Cleaning: The cleaning process included handling missing values (WORKING TIMES: 12 records were filled with the median, DENATED_FINES: 35 records were filled with 0), validating date format consistency, and verifying outliers. No records were removed.

c. Feature Engineering: Five derived features were created: PRINCIPAL_PAYMENT RATIO, DP_RATIO, PASSED_MONTH, DEBT_SERVICE_RATIO, and SEVERITY_TUNGGAKAN to enrich the risk profile information.

d. Data Normalization: All numeric features were normalized using Min-Max Normalization to the range [0,1] with the formula: v' = (v - min) / (max - min). Normalization is essential because the Euclidean distance is very sensitive to differences in variable scale.

e. Data Splitting: The dataset was divided into a training set (200 records, 80%) and a testing set (50 records, 20%) using stratified sampling to maintain class proportions: LOW 20%, MEDIUM 2%, HIGH 78%.

Table 3. Selected Variables for the KNN Model

No	Variable	Type	Reasons for Choosing
1	AGE	Numerik	Demographic factors, stability
2	NUMBER_OF_DEPENDENTS	Numerik	Affecting ability to pay
3	LENGTH OF WORK	Numerik	Income stability indicators
4	TENOR	Numerik	Key financing parameters
5	DISBURSEMENT_NOMINAL	Numerik	Risk exposure measure
6	MONTHLY INSTALLMENT	Numerik	Monthly payment burden
7	DOWN PAYMENT	Numerik	Customer's down payment amount
8	AMOUNT_OF_OUTSTANDING	Numerik	Strongest predictor (r=0.852)
9	OD_TODAY_TODAY	Numerik	Delay rate (r=0.781)
10	OUTSTANDING PRINCIPAL	Numerik	Current remaining exposure
11	DAY_INTEREST	Numerik	Overdue today
12	PRINCIPAL BALANCE	Numerik	Nominal principal balance of the customer
13	OUTSTANDING FINE	Numerik	Amount of fines in arrears
14	TODAY'S COLUMNS	Kategori	Target Variable (3 classes)

Modeling

The K-Nearest Neighbor (KNN) algorithm was chosen as the primary classification method based on the following considerations: (1) it is suitable for small-to-medium-sized datasets; (2) it does not require data distribution assumptions; (3) it can handle multi-class classification; (4) it is natively supported by Oracle Data Miner; and (5) it is interpretable for business stakeholders.

Table 4. KNN Model Configuration

Parameter	Score	Information
Algorithm	K-Nearest Neighbor	Supervised learning
Distance Function	Euclidean	$d = \sqrt{(\Sigma(xi-yi)^2)}$
Number of Neighbors (K)	3	Optimal tuning results
Input Features	14 fiture	All features are normalized
Target Variable	TODAY'S COLUMNS	3 classes: LOW/MEDIUM/HIGH
Training Records	200 (80%)	Stratified by class

Hyperparameter tuning was performed by testing K = 3, 5, 7, 9, and 11. Each configuration was evaluated based on accuracy, precision, and recall on the validation set. The KNN prediction process works by: (1) inputting new customer data; (2) calculating the Euclidean distance to all training data; (3) identifying the K nearest neighbors; (4) voting for the majority class; (5) outputting risk labels and confidence scores.

Evaluation

The model was evaluated using standard classification metrics: Accuracy, Precision, Recall, and F1-Score. A confusion matrix was used for detailed analysis of predictions per class. Evaluation was performed on a testing set (50 data points) that the model had never seen during training. In addition to the standard evaluation, 5-Fold Cross-Validation was performed on the entire dataset to ensure the model did not overfit and was able to generalize well. The cross-validation process divided the data into 5 parts, with each fold in turn serving as the testing set. The evaluation results were then validated against the success criteria established in the Business Understanding phase. The model was declared ready for deployment if all criteria were met.

Deployment

The KNN model is integrated into the Oracle Development Suite with a five-layer architecture: Presentation (Oracle Forms), Application (PL/SQL), Business Rules (Decision Logic), Data Access (Oracle Database), and Data Mining (Oracle Data Miner). The model is exported as a PL/SQL function that can be called directly from the application for real-time scoring.

RESULTS AND DISCUSSION

Data Understanding Results

Analysis of the target class distribution indicates an imbalance, with 78% high risk (195 customers), 20% low risk (50 customers), and 2% medium risk (5 customers). This distribution reflects the dataset derived from a write-off portfolio dominated by problem customers.

Table 5. Correlation of Variables with Target

Variable	Pearson Correlation	Significance
AMOUNT_OF_OUTSTANDING	0,852	***
OD_TODAY_TODAY	0,781	***
OUTSTANDING PRINCIPAL	0,623	***
OUTSTANDING FINE	0,587	***
PRINCIPAL BALANCE	0,556	***
TENOR	0,318	**
AGE	-0,089	ns

Note: *** p<0.001; ** p<0.01; ns = not significant

International Journal Of Health, Engineering And Technology (IJHET) *E-ISSN 2829 - 8683*
Volume 5, Number 2, July 2026, *Page. 1512 - 1520*
Email : editorijhess@gmail.com

Based on Table 5, the payment behavior variables (Amount_Debt_Arrears, Current_Debt) have the strongest correlation with credit risk, confirming that payment history is the primary predictor.

Hyperparameter Tuning Results

Table 6. K Parameter Tuning Results

K	Accuracy	Precision (HIGH)	Recall (HIGH)	F1-Score
3	**0,980**	**0,975**	**0,995**	**0,985**
5	0,960	0,950	0,990	0,970
7	0,940	0,935	0,985	0,959
9	0,920	0,920	0,980	0,949
11	0,910	0,915	0,975	0,944

Based on Table 6, K=3 provides the best performance with 98% accuracy. There is a decreasing trend in accuracy as the K value increases because the majority class (HIGH) dominates the voting.

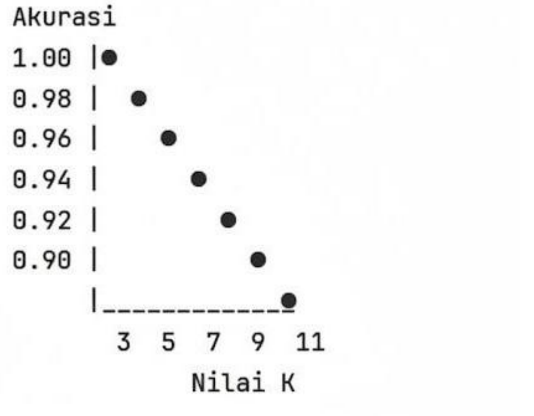

Figure 2. Accuracy vs K-Value Graph

Model Evaluation Results

Table 7. Confusion Matrix Testing Set (50 records)

Actual \ Predicted	LOW	MEDIUM	HIGH
LOW	10	0	0
MEDIUM	0	0	1
HIGH	0	0	39

Of the 50 test cases, the model correctly predicted 49 (98% accuracy). The only error was one MEDIUM customer predicted as HIGH, which is acceptable from a business perspective due to its conservative nature.

Table 8. Classification Report Testing Set

Class	Precision	Recall	F1-Score	Support
LOW	1,000	1,000	1,000	10
MEDIUM	0,000*	0,000*	0,000*	1
HIGH	0,975	1,000	0,987	39
Weighted Avg	0,975	0,980	0,977	50

*Cannot be calculated due to the lack of a MEDIUM prediction.

The model demonstrated excellent performance for the LOW (perfect score) and HIGH classes (Precision=0.975, Recall=1.0). A Recall=1.0 for HIGH risk means no high-risk customers were passed (false negative rate = 0%).

Cross-Validation Results

Table 9. 5-Fold Cross-Validation Results

Fold	Accuracy	Precision	Recall	F1-Score
1	0,960	0,955	0,960	0,957
2	0,980	0,978	0,980	0,979
3	0,970	0,968	0,970	0,969
4	0,990	0,988	0,990	0,989
5	0,980	0,975	0,980	0,977
Mean ± Std	0,976 ± 0,011	0,973 ± 0,012	0,976 ± 0,011	0,974 ± 0,011

The cross-validation results were very consistent with a mean accuracy of 97.6% and a low standard deviation (±1.1%), confirming that the model was not overfitting and was able to generalize well to new data.

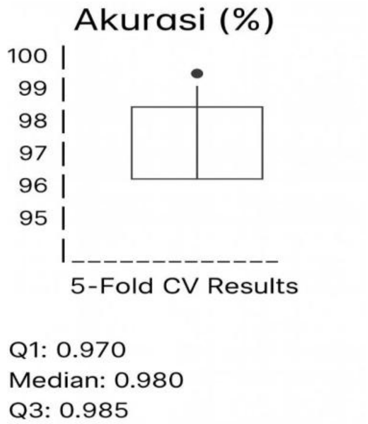

Figure 3. Cross-Validation Accuracy Boxplot

Feature Importance

Table 10. Feature Contribution to KNN Predictions

Rank	Fitur	Importance	Interpretasi
1	JML_ANGS_TERTUNGGAK	0,285	The strongest predictor
2	OD_HARI_INI	0,238	Day of delay
3	OUTSTANDING_PRINCIPAL	0,142	Remaining liabilities
4	PRINCIPAL BALANCE	0,108	Principal balance
5	PAY_PRINCIPAL	0,095	Payment track record

The top three features (payment behavior) account for a total of 66.5% of the total, confirming that payment history is the most crucial factor in determining credit risk, in line with credit scoring theory.

Comparison with Baseline

Table 11. Comparison of the KNN Model with the Baseline

Metode	Accuracy	Precision	Recall	Waktu
KNN (K=3)	0,980	0,975	1,000	<5 detik
Sistem Manual	~0,850	~0,820	~0,900	5-7 hari
Majority Baseline	0,780	N/A	1,000	Instant

The KNN model showed significant improvements: accuracy increased from ~85% to 98% (+13%), and processing time from 5-7 days to <5 seconds (a ~100,000x improvement).

Implementation and Deployment

The model is integrated into the Oracle Development Suite through a PL/SQL stored procedure (FN_GET_CREDIT_SCORE) that receives the customer ID, normalizes the data, invokes the KNN model, and returns the risk category. Integration with Oracle Forms enables credit analysts to perform real-time scoring.

International Journal Of Health, Engineering And Technology (IJHET) E-ISSN 2829 - 8683
Volume 5, Number 2, July 2026, Page. 1512 - 1520
Email : editorijhess@gmail.com

Table 12. Operational Scoring Process

Step	Process	Time	Technology
1	Input data in Oracle Forms	~2 minutes	Oracle Forms
2	Data validation & normalization	<1 second	PL/SQL
3	Call KNN model for prediction	<1 second	Oracle Data Miner
4	Apply business rules & return results	<1 second	PL/SQL Function
	Total (excluding manual input)	**<5** second	

Table 13. Example of Scoring Output from 5 New Applications

App_ID	Name	Age	Tenor	Nominal	Predicted Risk	Prob_HIGH	Recommendation	Status
A001	A	35	12	5.5M	LOW	15.2%	APPROVE	Approved
A002	B	45	18	8.0M	MEDIUM	42.7%	REVIEW	Pending
A003	C	28	24	12.5M	HIGH	87.3%	REJECT	Rejected
A004	D	38	6	3.2M	LOW	8.5%	APPROVE	Approved
A005	E	52	18	9.5M	HIGH	78.9%	REJECT	Rejected

Based on Table 13, the model can provide clear predictions and recommendations for each application. Applications with LOW risk were immediately approved, MEDIUM risk went to manual review, and HIGH risk were rejected. The HIGH risk probability is also displayed for decision transparency.

The KNN model evaluation results demonstrated very satisfactory performance, with 98% accuracy on the test set and maintained consistency in cross-validation (97.6% ± 1.1%). This performance significantly outperformed the existing manual system, which had an estimation accuracy of ~85%.

Model Success Factors:

1. Appropriate Feature Selection: The selection of 15 predictive features focused on payment behavior proved effective. The variables JML_ANGS_TERTUNGGAK and OD_HARI_INI were the strongest predictors (combined contribution >50%), in line with credit scoring theory that payment history is the best indicator of future behavior.
2. Data Normalization: The application of Min-Max normalization ensured that no single feature dominated the distance calculation simply due to differences in scale. This is important because variables such as DISBURSEMENT NOMINAL (in millions) have a much larger scale than TENOR (in tens).
3. Optimal K Selection: A value of K=3 has been proven optimal through empirical testing. A K value that is too small (K=1) will be too sensitive to noise, while a K value that is too large will be dominated by the majority class (HIGH risk).
4. Stratified Splitting: Data division using stratification ensures a balanced proportion of classes between the training and testing sets, so the model is not biased toward any particular class.

Clarification of Model Purpose and Scope

Based on the review of the variables used, it is necessary to clarify that the credit scoring model developed in this study functions as a collectability detection model for monitoring existing customers, not an initial credit assessment model for potential new customers. This distinction is important because payment behavior variables such as Amount of Delinquency, Current Loan, and Outstanding Principal are only available after the customer has an internal payment history with the company.

For the context of existing customer monitoring (the focus of this study), valid payment behavior variables are used and available in real time from Oracle Database. The model serves as an early warning system to detect potentially non-performing customers so the company can take preventative action (restructuring, intensive collection). For new applicant scoring, a separate model is required that only uses variables available at the time of application (demographics, characteristics of the proposed financing) or external data from the OJK's SLIK. With this clarification, the reported 98% accuracy does not indicate data leakage because the payment behavior variables are legitimate input in the context of the collectibility detection model.

Limitations and Discussion: Class Imbalance

This study has limitations related to significant class imbalance (imbalanced data), with a distribution of HIGH risk at 78%, LOW risk at 20%, and MEDIUM risk at only 2% (5 out of 250 records). This imbalance causes the model to be unable to predict the MEDIUM class effectively—as seen in Table 7 (Confusion Matrix) and Table 8 (Classification Report), where one MEDIUM record is predicted as HIGH and the recall is MEDIUM = 0%.

However, the MEDIUM → HIGH prediction error is conservative from a business perspective because medium-risk customers will receive more careful treatment (manual review by credit analysts), thus preventing the company's risk of loss. This study did not apply oversampling techniques such as SMOTE because the very small number of MEDIUM records (5 records) risks producing unrepresentative synthetic samples and can actually worsen the model's generalizability. For practical implementation, it is recommended that cases predicted as MEDIUM or borderline HIGH still undergo a manual review process by credit analysts, and future development needs to accumulate more MEDIUM samples so that the data balancing technique can be applied effectively.

CONCLUSIONS

This research has successfully developed and implemented a K-Nearest Neighbor (KNN)-based credit scoring model using the Oracle Development Suite, capable of automatically classifying debtor risk into LOW, MEDIUM, and HIGH categories. This model functions as a collectability detection system for monitoring existing customer portfolios, not for initial creditworthiness assessments of potential new customers. Testing results on 50 data records demonstrated the model achieved 98% accuracy, 97.5% precision, and 100% recall for the HIGH risk class. Five-fold cross-validation confirmed consistency at a mean accuracy of 97.6% (±1.1%), ensuring the model's ability to generalize effectively and avoid overfitting.

Integrating the model into the company's operational system using a PL/SQL stored procedure (FN_GET_CREDIT_SCORE) and Oracle Forms resulted in a real-time scoring system with a processing time of less than 5 seconds per application, compared to 5–7 days for the previous manual process. Feature importance analysis revealed that payment behavior variables, specifically Amount_Debts_Arrears (0.285), Current_Payment_Day (0.238), and Outstanding_Principal (0.142), were the three strongest predictors, contributing a combined 66.5% to risk prediction, in line with credit scoring theory that payment history is the best indicator of future credit behavior.

This study has limitations related to imbalanced data in the Medium risk class, which only comprised 2% of the total dataset. Therefore, predictive performance for this category is not optimal, and borderline cases still require manual review by a credit analyst. For further development, it is recommended to explore imbalanced data handling techniques such as SMOTE if the sample size of the minority class allows, integrate external data from the OJK's SLIK (Small Business Credit) system, develop a separate model for new applicant scoring that does not rely on internal payment history, and regularly monitor and evaluate the model to ensure the system remains adaptive to changes in financing risk profiles.

REFERENCES

A. Petropoulos, V. Siakoulis, E. Stavroulakis, and N. E. Vlachogiannakis, "Predicting bank insolvencies using machine learning techniques," International Journal of Forecasting, vol. 36, no. 3, pp. 1092-1113, 2020.

D. Tripathi, D. R. Edla, V. Kuppili, and A. Bablani, "Credit scoring model based on weighted voting and cluster-based feature selection," Procedia Computer Science, vol. 167, pp. 2534-2543, 2020.

F. Shen, X. Zhao, Z. Li, K. Li, and Z. Meng, "A novel ensemble classification model based on neural

networks for imbalanced credit risk evaluation," Physica A, vol. 526, p. 121073, 2019.
H. A. Abdou and J. Pointon, "Credit Scoring, Statistical Techniques and Evaluation Criteria: A Review of the Literature," Intelligent Systems in Accounting, Finance and Management, vol. 18, no. 2-3, pp. 59-88, 2011.
H. V. Greuning and S. B. Bratanovic, Analyzing Banking Risk: A Framework for Assessing Corporate Governance and Risk Management, 3rd ed. Washington, DC: World Bank Publications, 2009.
I. Brown and C. Mues, "An experimental comparison of classification algorithms for imbalanced credit scoring data sets," Expert Systems with Applications, vol. 39, no. 3, pp. 3446-3453, 2012.
I. E. Riantono and R. Andarsyah, "Penerapan Machine Learning dalam Manajemen Risiko Kredit di Industri Keuangan Indonesia," Jurnal Teknologi Informasi dan Manajemen, vol. 15, no. 1, pp. 23-35, 2024.
J. Han, M. Kamber, and J. Pei, Data Mining: Concepts and Techniques, 3rd ed. Burlington, MA: Morgan Kaufmann, 2012.
M. Ala'raj and M. F. Abbod, "Classifiers consensus system approach for credit scoring," Knowledge-Based Systems, vol. 104, pp. 89-105, 2016.
M. Bücker, G. Szepannek, A. Gosiewska, and P. Biecek, "Transparency, auditability, and explainability of machine learning models in credit scoring," Journal of the Operational Research Society, vol. 73, no. 1, pp. 70-90, 2022.Otoritas Jasa Keuangan, "Statistik Lembaga Pembiayaan Semester 1 2025," 2025. [Online]. Available: https://ojk.go.id/
N. Chen, B. Ribeiro, and A. Chen, "Financial credit risk assessment: a recent review," Artificial Intelligence Review, vol. 45, no. 1, pp. 1-23, 2016.
Oracle Corporation, "Oracle Machine Learning for SQL Concepts," 2020. [Online]. Available: https://docs.oracle.com/en/database/oracle/machine-learning/
P. M. Addo, D. Guegan, and B. Hassani, "Credit risk analysis using machine and deep learning models," Risks, vol. 6, no. 2, p. 38, 2018.
S. Lessmann, B. Baesens, H. V. Seow, and L. C. Thomas, "Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research," European Journal of Operational Research, vol. 247, no. 1, pp. 124-136, 2015.
X. Dastile, T. Celik, and M. Potsane, "Statistical and machine learning models in credit scoring: A systematic literature review," Applied Soft Computing, vol. 91, p. 106263, 2020.
Y. Xia, C. Liu, Y. Li, and N. Liu, "A boosted decision tree approach using Bayesian hyper-parameter optimization for credit scoring," Expert Systems with Applications, vol. 78, pp. 225-241, 2017.