International Journal Software Engineering and Computer Science (IJSECS)
6 (1), 2026, 53-60
Published Online April 2026 in IJSECS (http://www.journal.lembagakita.org/index.php/ijsecs)
P-ISSN: 2776-4869, E-ISSN: 2776-3242. DOI: https://doi.org/10.35870/ijsecs.v6i1.6618.

RESEARCH ARTICLE Open Access

Data Mining for Predicting Creditworthiness in Credit Card Approval: A Systematic Literature Review

Wahyu Purnama Magribi [1*], **Muhammad Fazly Qusyairy** [2], **Tino Saputra** [3]

[1*,2,3] Department of Computer Science, Universitas Esa Unggul, West Jakarta City, Special Capital Region of Jakarta, Indonesia.

**Corresponding author*: wahyupurnamaa@gmail.com

Received: February 18, 2026; Accepted: March 25, 2026; Published: April 1, 2026.

Abstract: The growing volume of credit card applications has led financial institutions to seek faster and more reliable methods in the approval process. Manual evaluation is not only time-consuming but also susceptible to human error, which can result in poor credit decisions and measurable financial losses. This study conducts a Systematic Literature Review (SLR) to examine data mining techniques applied to creditworthiness prediction. Five research questions were formulated to identify: (1) commonly used data mining techniques, (2) frequently used datasets, (3) performance evaluation metrics, (4) algorithms with the strongest performance, and (5) recurring challenges and practical recommendations. A structured search across three academic databases — Scopus, Google Scholar, and GARUDA — yielded 8 relevant articles (7 primary experimental studies and 1 secondary study) published between 2021 and 2025. The findings show that Naïve Bayes, Decision Tree, Random Forest, Support Vector Machine, and K-Nearest Neighbors are the most widely applied methods. Tree-based algorithms such as Decision Tree and Random Forest consistently yield high accuracy, while K-Nearest Neighbors also delivers strong results in specific experimental settings. Naïve Bayes appears most frequently across studies, and its performance can be improved through metaheuristic approaches such as Particle Swarm Optimization (PSO). Standard evaluation metrics include accuracy, precision, recall, F1-score, and AUC-ROC. The review underscores the importance of data preprocessing, class imbalance handling, and hyperparameter tuning in building reliable prediction models — findings with direct implications for financial institutions seeking to reduce non-performing loan rates.

Keywords: Credit Card Prediction; Credit Approval; Data Mining; Creditworthiness; Machine Learning; Systematic Literature Review.

1. Introduction

Creditworthiness assessment is a fundamental element in risk management in the banking sector, particularly in minimizing the potential of non-performing loans and financial losses (Andriani *et al.*, 2025; Babu *et al.*, 2024; Kusnaeni *et al.*, 2024). As the volume of credit applications continues to grow, the traditional manual evaluation process faces increasingly significant challenges. Beyond being time-consuming and resource-intensive, manual assessment is inherently vulnerable to subjectivity and human error — two factors that can produce inconsistent eligibility decisions across analysts and institutions (Oktafriani *et al.*, 2023; Sutedja *et al.*, 2024). When unqualified applicants are approved due to flawed assessment, the consequences extend beyond individual transactions: non-performing loan rates rise, capital reserves are strained, and institutional credibility is undermined (Sutedja *et al.*, 2024; Putri *et al.*, 2024). These structural weaknesses in manual credit evaluation have created a clear demand for more systematic, scalable, and objective approaches. Data mining and machine learning respond directly to that demand by enabling financial institutions to analyze historical applicant data at scale, with consistent decision logic that is not subject to fatigue or cognitive bias (Oktafriani *et al.*, 2023; Bagja *et al.*, 2023; Andriani *et al.*, 2025). Through classification algorithms, banks can automate significant portions of the approval process, identify complex patterns in applicant profiles, and substantially improve the accuracy of creditworthiness prediction (Sutedja *et al.*, 2024; Religia *et al.*, 2021).

A wide range of classification algorithms has been implemented and compared for this purpose. Decision Tree, Random Forest, Naïve Bayes, Support Vector Machine (SVM), and Logistic Regression are among the most consistently evaluated methods, applied to categorize prospective borrowers into "eligible" or "ineligible" groups (Abdussomad *et al.*, 2023; Sutedja *et al.*, 2024; Andriani *et al.*, 2025). Ensemble methods such as Random Forest and probabilistic models such as Logistic Regression tend to generalize well with lower overfitting risk, while instance-based methods like K-Nearest Neighbors (K-NN) and rule-based approaches like Decision Tree have demonstrated strong performance in specific experimental settings (Oktafriani *et al.*, 2023; Abdussomad *et al.*, 2023; Sutedja *et al.*, 2024). The variation in reported performance across these studies is not incidental — it reflects genuine differences in dataset characteristics, preprocessing strategies, and evaluation protocols, which makes cross-study comparison both necessary and non-trivial. Despite the growing volume of individual experimental studies, a consolidated synthesis covering publications from 2021 to 2025 remains limited. Prior reviews such as Sutedja *et al.* (2024) provide a useful methodological baseline, but the field has continued to evolve, and an updated synthesis is needed to capture recent algorithmic developments, shifting dataset practices, and emerging challenges in the domain.

This study addresses that gap by conducting a Systematic Literature Review (SLR) that synthesizes findings from 8 relevant studies, providing a structured overview of techniques, datasets, evaluation metrics, performance comparisons, and practical challenges in credit card approval prediction using data mining. The specific objectives are: (1) to identify data mining techniques commonly used for building credit card approval prediction models; (2) to determine the datasets frequently used in credit approval prediction research; (3) to examine how algorithm performance is evaluated in the context of creditworthiness prediction; (4) to determine which algorithms consistently demonstrate the best performance; and (5) to identify common challenges and recommendations for improving prediction models. The remainder of this paper is organized as follows. Section 2 reviews related work in credit scoring, classification algorithms, and SLR methodology. Section 3 describes the methodology, including the planning, search and selection strategy, and data extraction protocol. Section 4 presents the results and discussion. Section 5 concludes the paper with key findings and directions for future research.

2. Related Work

This section reviews previous studies related to data mining techniques for credit approval prediction, providing context for the systematic literature review conducted in this study. Classification algorithms have been extensively studied for credit scoring and approval prediction, with methods tested across varied institutional settings and dataset types. Andriani *et al.* (2025) compared Decision Tree, K-NN, Naïve Bayes, and Random Forest for creditworthiness prediction at Bank BRI, reporting that K-NN achieved the highest accuracy at 97.83%. That figure is notable, but it should be read in context — K-NN is sensitive to the choice of k and the distance metric used, and high accuracy on one institutional dataset does not guarantee equivalent results elsewhere. Babu *et al.* (2024) developed a credit card approval prediction system using multiple machine learning methods, finding that Logistic Regression achieved an AUC of 0.99 after careful preprocessing, which suggests that classical statistical models remain competitive when data quality is adequately controlled. Oktafriani *et al.* (2023) compared C4.5, Naïve Bayes, K-NN, and Random Forest for credit eligibility determination, finding that tree-based algorithms generally performed well across multiple evaluation metrics. Bagja *et al.* (2023) narrowed the comparison to Naïve Bayes and SVM for loan eligibility classification, offering a direct view of the trade-offs between probabilistic and margin-based classifiers — two fundamentally different learning strategies that each carry distinct assumptions about the data distribution.

Beyond standard classification, several studies have examined ways to extend baseline algorithm performance. Religia *et al.* (2021) applied Particle Swarm Optimization (PSO) to Naïve Bayes for credit bank application classification and reported measurable gains in both accuracy and recall. This finding is significant because it challenges the common practice of treating algorithm selection as the primary lever for performance improvement — preprocessing quality and optimization strategy can matter just as much. Abdussomad *et al.* (2023) implemented a standard Decision Tree without optimization extensions and still achieved an accuracy of 93.49%, which confirms the algorithm's practical utility in credit classification tasks. Kusnaeni *et al.* (2024)

applied Naïve Bayes to bank customer data for credit eligibility classification, further supporting the algorithm's broad applicability across different institutional contexts. Putri *et al.* (2024) approached the problem from a different angle entirely, applying a qualitative 5C framework — Character, Capacity, Capital, Collateral, and Condition — to credit decision-making at PT Bank BTN Syariah. The study does not use machine learning, but it raises a point worth acknowledging: statistical models learn from historical patterns, while qualitative frameworks account for contextual and relational factors that structured numerical data rarely captures. Both approaches address the same problem from different vantage points, and neither is fully sufficient on its own. In the domain of systematic reviews, Sutedja *et al.* (2024) conducted a literature review on credit card approval prediction that established a useful reference point for understanding the range of techniques and methodologies applied in this field. Their review drew from multiple databases but was anchored to an earlier publication window, which leaves room for an updated synthesis that accounts for more recent experimental work and shifts in algorithmic practice. Table 1 presents a comparative summary of the studies reviewed in this section, reflecting the diversity of algorithms, datasets, and reported findings across the literature.

Table 1. Comparative summary of previous studies on credit approval prediction.

Study	Algorithm(s)	Dataset	Key Finding
Andriani *et al.* (2025)	DT, K-NN, NB, RF	Bank BRI Tegal	K-NN highest accuracy (97.83%)
Babu *et al.* (2024)	RF, SVM, LR	Credit data	LR achieved AUC 0.99; ensemble methods effective
Oktafriani *et al.* (2023)	C4.5, NB, K-NN, RF	Credit data	Tree-based algorithms perform well
Bagja *et al.* (2023)	NB, SVM	Loan data	Comparison of NB vs SVM
Religia *et al.* (2021)	NB + PSO	Credit bank data	PSO improves NB performance
Abdussomad *et al.* (2023)	Decision Tree	Credit data	DT accuracy 93.49%
Sutedja *et al.* (2024)	SLR (multiple)	Various	Systematic literature review
Kusnaeni *et al.* (2024)	Naïve Bayes	Bank customer data	NB effective for credit classification
Putri *et al.* (2024)	Qualitative (5C)	Bank BTN Syariah	Qualitative credit analysis

3. Methodology

This systematic literature review was conducted through three main stages: planning, search and selection, and data extraction for synthesis.

3.1 Planning

The planning stage follows the guidelines of Kitchenham and Charters (2007) and the PRISMA 2020 framework, with the aim of defining the research scope, formulating research questions, and establishing selection criteria that ensure a transparent and reproducible review process. The central focus of this SLR is to examine how data mining techniques are applied to creditworthiness prediction. To achieve this, five research questions (RQ) were formulated, as presented in Table 2. Inclusion and exclusion criteria were also established to ensure that only relevant and methodologically sound articles are included in the final synthesis (Table 3).

Table 2. Research questions for the systematic literature review.

Research Question	Motivation and Expected Results
RQ1: What data mining techniques are used to build credit card approval prediction models?	To obtain references on the application of various data mining techniques in credit scoring and approval prediction.
RQ2: What datasets are commonly used in credit card approval prediction research?	To identify commonly used data sources and benchmark datasets.
RQ3: How is algorithm performance evaluated in the context of creditworthiness prediction?	To understand evaluation metrics and validation methods used.
RQ4: Which algorithm consistently shows the best performance for credit card approval prediction?	To determine the most effective algorithms across different studies.
RQ5: What are the common challenges and recommendations for improving prediction models?	To identify practical issues and future research directions.

Table 3. Description and rationale for eligibility criteria.

Criteria	Description
Inclusion	Papers in any language; publications from 2021–2025; focus on data mining/machine learning for credit scoring or approval prediction; published in peer-reviewed journals or conferences.
Exclusion	Papers not focusing on credit scoring/approval; non-peer-reviewed publications; duplicate studies; papers without clear methodology; studies using purely qualitative methods (e.g., 5C analysis without ML/DL implementation).

3.2 Search and Selection Strategy

A structured search was applied across three databases — Scopus, Google Scholar, and GARUDA (Indonesian Scientific Journal Database) — using keyword combinations derived from the research questions. The core search terms covered credit-related concepts ("Credit Approval", "Credit Eligibility", "Credit Scoring"), algorithmic methods ("Data Mining", "Machine Learning", "Decision Tree", "Naive Bayes"), and task descriptors ("Prediction", "Classification"). Search strings were adapted to the syntax and filtering capabilities of each database, as detailed in Table 4.

Table 4. Application of the search string in the information sources and preliminary results.

No.	Database	Research String Format	Results
1	Scopus	TITLE-ABS-KEY(("Scoring" OR "Credit" OR "CARD") AND ("predictive modeling" OR "predictive credit") AND ("data mining" OR "machine learning" OR "regression" OR "classification" OR "clustering" OR "Naive Bayes" OR "decision tree")) AND (PUBYEAR > 2020 AND PUBYEAR < 2026)	247
2	Google Scholar	("credit scoring" OR "credit approval" OR "credit eligibility") AND ("data mining" OR "machine learning" OR "Naive Bayes" OR "decision tree") AND ("prediction" OR "classification") — Custom range: 2021–2025	35
3	GARUDA	"kelayakan kredit" AND ("data mining" OR "machine learning") — Tahun: 2021–2025	16

The selection process followed the PRISMA 2020 protocol across four stages: (1) *Identification* — retrieving records from each database using the defined search strings; (2) *Screening* — removing duplicates and assessing title and abstract relevance; (3) *Eligibility* — conducting full-text review against the inclusion and exclusion criteria in Table 3; and (4) *Inclusion* — finalizing the set of studies for data extraction. From 298 initial records, 45 duplicates were removed, leaving 253 unique records for screening. After title and abstract assessment, 220 records were excluded for irrelevance, leaving 33 articles for full-text review. Of these, 25 were excluded for the following reasons: not focused on credit prediction (n = 10), no data mining technique used (n = 7), review or survey paper (n = 4), and insufficient methodological reporting (n = 4). The final set comprised 8 studies (see Fig. 1).

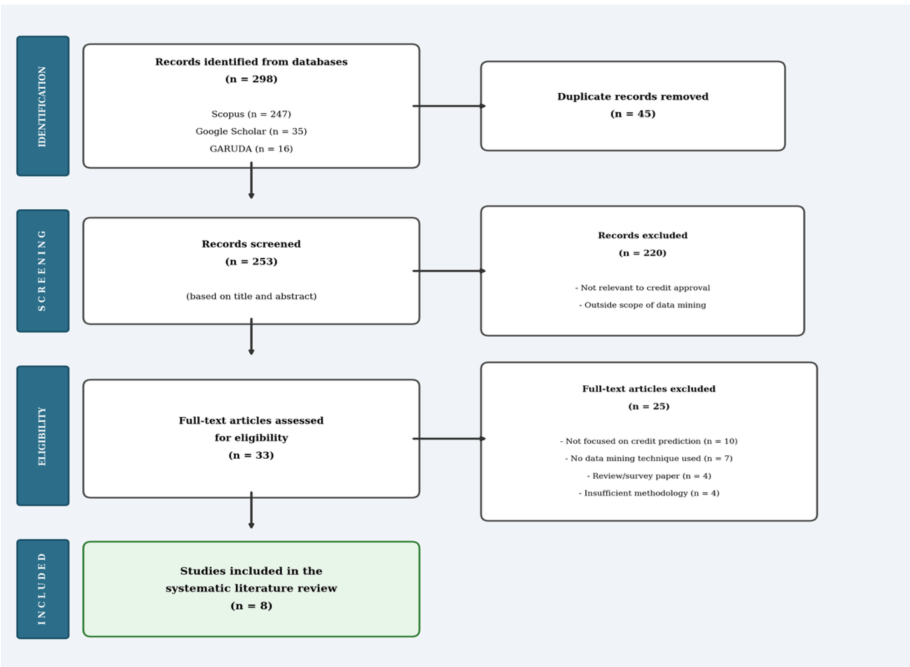

Figure 1. PRISMA 2020 flow diagram of the study selection process.

3.3 Data Extraction Protocol

Data extraction was guided by five criteria covering the most analytically relevant aspects of each selected study, including problem identification, research contribution, data type, algorithm applied, and evaluation method. These criteria are presented in Table 5, and the full list of included studies is presented in Table 6.

Table 5. Data extraction criteria.

Criteria	Description
C1. Problem Analysis	Identifying the problem discussed and its relevance to credit scoring prediction.
C2. Contribution	The novelty and contribution of the study to the field.
C3. Data Type	The type of data used (public dataset, private dataset, etc.).
C4. Algorithm	The data mining or machine learning algorithm applied.
C5. Evaluation	Evaluation metrics and validation methods used.

Table 6. Full-text studies included in the SLR.

ID	Title	Authors & Year	Source / Database
P1	Analysis of Data Mining Applications for Determining Credit Eligibility Using Classification Algorithms C4.5, Naïve Bayes, K-NN, and Random Forest	Oktafriani *et al.*, 2023	Journal / Google Scholar
P2	Comparative Analysis of Naïve Bayes and SVM for Loan Eligibility Classification	Bagja *et al.*, 2023	Journal / GARUDA
P3	Application of Naïve Bayes in Bank Customer Creditworthiness Classification	Kusnaeni *et al.*, 2024	Conference / Google Scholar
P4	Smart Credit Card Approval Prediction System using Machine Learning	Babu *et al.*, 2024	Conference / Scopus
P5	Credit Card Approval Prediction: A Systematic Literature Review	Sutedja *et al.*, 2024	Journal / Scopus
P6	Analysis of the Use of PSO on Naïve Bayes for Classification of Credit Bank Applications	Religia *et al.*, 2021	Journal / GARUDA
P7	Comparative Analysis of Machine Learning for Creditworthiness Prediction at Bank BRI	Andriani *et al.*, 2025	Journal / Google Scholar
P8	Implementation of the Decision Tree Algorithm to Determine Creditworthiness	Abdussomad *et al.*, 2023	Journal / GARUDA

4. Result and Discussion

4.1 Results

Analysis of the 8 selected studies reveals a clear concentration around a small set of classification algorithms. Of these, 7 are primary experimental studies and 1 (P5, Sutedja *et al.*, 2024) is a secondary study — a systematic literature review. P5 is excluded from the technique frequency count in Table 8 to avoid double-counting methods that were reviewed rather than directly applied. To assess the quality and contribution of each article, scoring was conducted based on two dimensions: approach (clarity of objectives and algorithm suitability) and content (depth of analysis and reporting quality), as presented in Table 7.

Table 7. Quality evaluation results of primary studies.

ID	Approach Score (%)	Content Score (%)
P1	85	80
P2	80	85
P3	75	70
P4	90	85
P5	85	90
P6	80	75
P7	90	85
P8	80	80

Studies with higher scores generally provide more substantive methodological detail and more rigorous discussion of results. Table 8 summarizes the distribution of data mining techniques across the primary experimental studies.

Table 8. Summary of data mining techniques used.

Category	Frequency	Description	References
Decision Tree (DT)	3	Including C4.5 and standard DT implementations.	P1, P7, P8
Naïve Bayes (NB)	5	Used both independently and with optimization such as PSO.	P1, P2, P3, P6, P7
Random Forest (RF)	3	Used as ensemble classifier for comparison.	P1, P4, P7
Support Vector Machine (SVM)	2	Applied for binary classification comparison.	P2, P4
K-Nearest Neighbors (K-NN)	2	Instance-based learning for credit scoring.	P1, P7
Logistic Regression (LR)	1	Achieved high accuracy in specific conditions.	P4

As shown in Table 8, Naïve Bayes is the most frequently applied technique across primary studies (5 studies), followed by Decision Tree and Random Forest (3 studies each), and SVM and K-NN (2 studies each). The prevalence of Naïve Bayes reflects its computational simplicity and interpretability — qualities that are particularly valued in institutional settings where model transparency is expected. Tree-based models appear less frequently but tend to report stronger absolute performance figures.

4.2 Discussion

The following discussion addresses each research question based on the synthesis of the 8 selected studies. The analysis covers the range of techniques applied, the data sources used, the evaluation practices adopted, the relative performance of algorithms, and the practical challenges encountered across the reviewed literature.

1) RQ1 — Data Mining Techniques Used
   Classification algorithms dominate the reviewed literature. Naïve Bayes is the most widely applied technique, appearing in 5 of the 7 primary studies, followed by Decision Tree and Random Forest (3 studies each), and SVM and K-NN (2 studies each). Several studies also apply optimization methods — notably PSO on Naïve Bayes (Religia *et al.*, 2021) — to extend baseline classifier performance, pointing to a productive direction that remains underexplored in the broader literature. The absence of deep learning or gradient boosting methods across all selected studies is worth noting, and likely reflects either a preference for interpretable models or a gap that future research should address.
2) RQ2 — Commonly Used Datasets
   Public datasets, particularly the South German Credit dataset from Kaggle and the UCI Credit Approval Dataset, are the most frequently used, facilitating cross-study comparison and reproducibility. Several studies draw on private institutional data from banks such as Bank BRI and Bank BTN Syariah, which limits direct comparison across studies but increases the practical relevance of reported findings. The reliance on public benchmark datasets, while methodologically convenient, may not fully reflect the distributional characteristics of credit portfolios in specific regional or institutional contexts.
3) RQ3 — Evaluation Metrics
   All quantitative studies use the confusion matrix as the basis for performance evaluation. Accuracy, precision, recall, and F1-score are reported consistently across studies, while AUC-ROC is applied in studies where class discrimination is the primary concern (Babu *et al.*, 2024; Sutedja *et al.*, 2024). The near-universal use of accuracy as the headline metric is problematic in class-imbalanced datasets, as it can produce inflated scores that obscure poor performance on the minority class. Reporting F1-score and AUC-ROC alongside accuracy provides a more complete and honest picture of model behavior.
4) RQ4 — Algorithms with the Best Performance
   No single algorithm consistently outperforms the others across all studies. Decision Tree achieved 93.49% accuracy in Abdussomad *et al.* (2023), outperforming both SVM and Naïve Bayes in that setting. K-NN reached 97.83% accuracy in Andriani *et al.* (2025), the highest figure reported across the reviewed studies. Logistic Regression achieved an AUC of 0.99 in Babu *et al.* (2024) following intensive preprocessing. Naïve Bayes shows more variable performance, though PSO-based optimization demonstrably improves both accuracy and recall (Religia *et al.*, 2021). Taken together, these results suggest that dataset quality and preprocessing decisions carry more weight than algorithm selection alone — a well-configured simpler model can outperform a more complex one applied to poorly prepared data.
5) RQ5 — Challenges and Recommendations
   Four recurring challenges were identified across the reviewed studies:
   a) Imbalanced Data: Credit datasets typically contain far more approved applicants than rejected ones, causing models to favor the majority class and produce misleading accuracy scores. Resampling techniques such as SMOTE are recommended as a standard step in the preprocessing pipeline.

b) Feature Selection and Preprocessing: Irrelevant or redundant features reduce model reliability. Normalization and systematic feature selection are consistently associated with better classification performance across the reviewed studies.
c) Hyperparameter Tuning: Algorithms such as SVM and Random Forest are sensitive to hyperparameter configurations. Grid Search or cross-validated tuning procedures are recommended to avoid suboptimal settings that understate a model's true performance.
d) Model Validation: K-fold cross-validation (typically k = 10) is preferred over a single train-test split, as it produces more stable performance estimates and reduces the risk of results that are artifacts of a particular data partition.

This review has three notable limitations. First, the search was restricted to three databases — Scopus, Google Scholar, and GARUDA — which means relevant studies indexed in other repositories may have been missed. Second, variations in methodological quality and reporting standards across the included studies affect the consistency of cross-study comparisons. Third, the 2021–2025 publication window, while recent, may not capture the most current developments in areas such as gradient boosting or transformer-based approaches for tabular credit data.

5. Conclusion and Recommendations

This study identified and analyzed data mining techniques used for credit card approval prediction through the synthesis of 8 relevant articles. The findings confirm that traditional classification and ensemble algorithms — Decision Tree, Naïve Bayes, Random Forest, Support Vector Machine, and K-Nearest Neighbors — remain the primary methods in the literature for predicting applicant creditworthiness. The five research questions formulated in this study were addressed as follows.

1) RQ1: Naïve Bayes is the most frequently applied technique, followed by Decision Tree and Random Forest. Classification algorithms dominate the reviewed literature, with deep learning and gradient boosting methods largely absent.
2) RQ2: Public datasets from UCI and Kaggle serve as the primary data sources, enabling reproducible and comparable model evaluation across studies.
3) RQ3: Model performance is consistently evaluated using accuracy, precision, recall, F1-score, and AUC-ROC. Accuracy alone is insufficient for imbalanced datasets, and the combined use of these metrics provides a more reliable assessment of model behavior.
4) RQ4: No single algorithm universally outperforms the others. Decision Tree, Random Forest, and K-NN frequently demonstrate strong and stable accuracy across different experimental settings, though results remain sensitive to dataset characteristics and preprocessing decisions.
5) RQ5: Class imbalance is the most frequently cited challenge. The main recommendations center on systematic data preprocessing, hyperparameter tuning, and the use of K-fold cross-validation for more reliable model validation.

These findings indicate that data mining techniques have a measurable role in improving the accuracy and consistency of credit card approval decisions. As banking systems generate larger volumes of applicant data, the case for adopting well-validated predictive models in credit risk management becomes increasingly difficult to ignore. Future research should pursue four directions: (1) testing deep learning architectures designed for tabular data against the classical methods reviewed here; (2) examining the effect of feature engineering on model performance across different institutional datasets; (3) developing prediction models that satisfy regulatory interpretability requirements without sacrificing accuracy; and (4) conducting longitudinal evaluations to measure how model performance shifts as credit behavior patterns change over time.

References

Abdussomad, Kurniawan, I., & Wibowo, A. (2023). Implementation of the Decision Tree algorithm to determine creditworthiness. *COMPILER: Jurnal Ilmiah Teknik Informatika*, *12*(2), 103–108. https://doi.org/10.28989/compiler.v12i2.1911

Andriani, W., Gunawan, N., & Naja, N. N. P. W. (2025). Analisis perbandingan machine learning untuk prediksi kelayakan kredit perbankan pada Bank BRI Tegal. *IT-Explore: Jurnal Penerapan Teknologi Informasi dan Komunikasi*, *4*(1), 82–92. https://doi.org/10.24246/itexplore.v4i1.2025

Babu, K., Prabhakaran, S., Marikkannu, P., Roobini, R., Rai, P., & Singh, A. P. (2024). Smart credit card approval prediction system using machine learning. *E3S Web of Conferences*, *540*, Article 13001. https://doi.org/10.1051/e3sconf/202454013001

Bagja, A., Kusrini, & Arief, M. R. (2023). Komparasi algoritma Naïve Bayes dan Support Vector Machine (SVM) untuk klasifikasi kelayakan pemberian pinjaman. *Infotek: Jurnal Informatika dan Teknologi*, *6*(2), 513–523.

Kitchenham, B., & Charters, S. (2007). *Guidelines for performing systematic literature reviews in software engineering* (Technical Report EBSE-2007-01). Keele University & Durham University.

Kusnaeni, H., Husain, & Nisardi, M. R. (2024). Penerapan Naïve Bayes dalam klasifikasi kelayakan kredit nasabah bank. In *Prosiding Seminar Nasional Statistika Aktuaria III* (pp. 1–5).

Oktafriani, Y., Firmansyah, G., Tjahjono, B., & Widodo, A. M. (2023). Analysis of data mining applications for determining credit eligibility using classification algorithms C4.5, Naïve Bayes, K-NN, and Random Forest. *Asian Journal of Social and Humanities*, *1*(12), 1139–1158. https://doi.org/10.59888/ajosh.v1i12.119

Putri, Y. E., Halmia, Irmawati, I., & Harun, S. (2024). Analisis kelayakan kredit calon debitur sebagai dasar dalam pengambilan keputusan pemberian Kredit Usaha Rakyat: Studi kasus pada PT Bank BTN Syariah. *AKSIOMA: Jurnal Sains Ekonomi dan Edukasi*, *1*(12), 964–975.

Religia, Y., Pranoto, G. T., & Suwancita, I. M. (2021). Analysis of the use of Particle Swarm Optimization on Naïve Bayes for classification of credit bank applications. *JISA: Jurnal Informatika dan Sains*, *4*(2), 133–137.

Sutedja, I., Lim, J., Setiawan, E., & Adiputra, F. R. (2024). Credit card approval prediction: A systematic literature review. *Journal of Theoretical and Applied Information Technology*, *102*(3), 1198–1206.