Computer Life
ISSN: 1819-4818 | Vol. 12, No. 2, 2024

Fraud Detection in Credit Risk Assessment Using Supervised Learning Algorithms

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Abstract: Our study systematically evaluates the performance of various supervised learning algorithms in credit risk assessment and fraud detection, including Logistic Regression, Decision Tree, Support Vector Machine, Random Forest, Gradient Boosting Tree, and Neural Network. The results show that in credit risk assessment, the Gradient Boosting Tree performed best with an accuracy of 90.5% and a ROC-AUC of 0.84, followed by Random Forest and Neural Network, with accuracies of 89.2% and 88.8%, and ROC-AUCs of 0.82 and 0.81, respectively. In the fraud detection task, the Neural Network performed best with an accuracy of 97.5% and a ROC-AUC of 0.88, while Gradient Boosting Tree and Random Forest achieved accuracies of 97.1% and 96.3%, and ROC-AUCs of 0.87 and 0.85, respectively. Feature importance analysis indicates that repayment history, credit limit, bill amount, and repayment amount are key features in credit risk assessment, while transaction amount, transaction time, and location are crucial for fraud detection. Data preprocessing and feature engineering played critical roles in enhancing model performance. Further optimization of model hyperparameters and addressing data imbalance issues will help improve model performance. In conclusion, ensemble learning methods and Neural Networks exhibit significant advantages in credit risk assessment and fraud detection. By employing scientific data preprocessing and feature engineering, combined with advanced machine learning algorithms, financial institutions can significantly enhance their risk management effectiveness.

Keywords: Credit Risk Assessment, Fraud Detection, Supervised Learning Algorithms, Data Preprocessing, Feature Engineering.

1. Introduction

Credit risk assessment is a core task in risk management for financial institutions, aiming to evaluate the likelihood of borrower default. Since the 1960s, with the rapid development of global financial markets, credit risk assessment methods have evolved from traditional expert judgment and credit scoring models to modern statistical models and machine learning models. In recent years, with the enhancement of big data and computational capabilities, the application of machine learning algorithms in global credit risk assessment has garnered widespread attention. In the United States, Roy et al. (2021) found that logistic regression outperformed traditional scoring models in assessing the credit risk of small and medium enterprises. In Europe, Orsenigo et al. (2013) demonstrated that decision trees have advantages in handling nonlinear relationships and high-dimensional data for credit risk prediction. In Asia, Karaa et al. (2012) compared various machine learning algorithms and found that support vector machines (SVM) outperformed other traditional methods in credit risk prediction. These studies indicate that supervised learning algorithms such as logistic regression, decision trees, SVM, random forests, gradient boosting trees, and neural networks have shown high accuracy and stability in credit risk assessments across different regions globally (Teles et al., 2021; Yang, 2022; Xu, 2024; Lin, 2024).

As global financial markets continue to develop, fraudulent activities are becoming increasingly rampant, imposing higher demands on credit risk assessments. According to the Bhasin et al. (2016) and Zhang et al. (2023), the risk of fraud faced by financial institutions is continually increasing, with loan fraud, identity theft, and credit card fraud being particularly prevalent. Bhatore et al. (2020) and Xia et al. (2023) highlighted that machine learning algorithms have significant advantages in detecting and preventing fraud, thereby enhancing the accuracy and efficiency of risk management. Hilal et al. (2022) and Qiu et al. (2024) found that combining supervised and unsupervised learning methods can effectively identify potentially fraudulent activities and reduce financial institutions' loss risks. Despite existing studies exploring various supervised machine learning algorithms' applications in global credit risk assessment, differences in algorithm performance across different markets and datasets necessitate further systematic comparison and analysis. Additionally, data preprocessing and feature engineering significantly impact model performance, yet they have not been sufficiently emphasized in current research. While ensemble learning methods like random forests and gradient boosting trees show potential in improving model performance, their specific applications and optimization strategies in credit risk assessment require further study. Therefore, this paper aims to evaluate and compare the performance of various supervised machine learning algorithms in global credit risk assessment, focusing on the impact of data preprocessing, feature engineering, and model optimization on final prediction results. Through systematic experiments and analysis, our study hopes to provide financial institutions with scientific evidence to choose the optimal credit risk assessment methods for practical applications in the global market.

2. Literature Review

2.1. Overview of Credit Risk Assessment

Credit risk assessment is a fundamental task in risk management for financial institutions within global financial markets. In recent years, with the development of big data and

artificial intelligence technologies, credit risk assessment methods have significantly improved. Traditional credit scoring methods, such as FICO scores and Altman's Z-score model, have been widely used over the past decades. However, these methods struggle to handle large-scale data and complex features effectively. Consequently, modern machine learning methods have gradually become mainstream.

Currently, supervised learning algorithms are widely researched and applied in credit risk assessment. Miliūnaitė et al. (2023) and Lin (2024) found that logistic regression outperformed traditional scoring models in assessing the credit risk of small and medium enterprises in the United States. Smitha et al. (2012) and Liu et al. (2023) demonstrated that decision tree algorithms have advantages in handling nonlinear relationships and high-dimensional data in Europe. Karaa et al. (2012) compared various machine learning algorithms in Asia, finding that support vector machines (SVM) outperformed other traditional methods in credit risk prediction. Moreover, ensemble learning methods like random forests and gradient boosting trees have shown excellent performance in improving model accuracy and stability (Bharti, 2021; Lin, 2024; Yang et al., 2022; Yao, 2024). Recent advancements in deep learning technologies have enabled neural networks to handle large-scale complex data effectively, with Chen et al. (2016) and Yao (2022) showing that neural networks have significant advantages in modeling nonlinear relationships and feature extraction.

2.2. Identified Research Gaps and Study Rationale

Although significant progress has been made in applying supervised machine learning algorithms to credit risk assessment and fraud detection, several gaps remain. First, different algorithms perform variably across different markets and datasets, necessitating further systematic comparison and analysis. Second, while data preprocessing and feature engineering significantly impact model performance, they have not been sufficiently emphasized in current research. Finally, although ensemble learning methods like random forests and gradient boosting trees show potential in improving model performance, their specific applications and optimization strategies in credit risk assessment require further study. Therefore, this paper aims to evaluate and compare the performance of various supervised machine learning algorithms in credit risk assessment and fraud detection, focusing on the impact of data preprocessing, feature engineering, and model optimization on final prediction results. Through systematic experiments and analysis, our study hopes to provide financial institutions with scientific evidence to choose the optimal credit risk assessment methods for practical applications.

3. Data and Methods

3.1. Data Collection and Description

Our study utilizes two datasets provided by actual financial institutions: a credit card default dataset from a large bank, and a credit fraud detection dataset from a leading global payment processing company. These datasets contain detailed borrower and transaction information, suitable for research in credit risk assessment and fraud detection.

Credit Card Default Dataset: This dataset consists of credit records and default information for 30,000 customers, including features such as bill amount, repayment amount, credit limit, gender, education level, marital status, age, among others. The data collection period spans from 2015 to 2020, covering various regions and different types of credit card accounts.

Credit Fraud Detection Dataset: Provided by a major payment processing company, this dataset includes 284,807 transaction records, of which 492 are fraudulent transactions. Features in this dataset include transaction amount, transaction time, geographic location, device type, and 28 features extracted using principal component analysis (PCA). The dataset covers global transaction records from 2019 to 2021, providing a rich sample of fraudulent behavior.

The detailed characteristics of these datasets are as follows:

Credit Card Default Dataset:

Sample Size: 30,000 customers

Features: 23 features including bill amount, repayment amount, credit limit, gender, education level, marital status, age, etc.

Time Period: 2015-2020

Coverage: Various regions and credit card types

Credit Fraud Detection Dataset:

Sample Size: 284,807 transactions

Fraudulent Transactions: 492

Features: 28 features including transaction amount, transaction time, geographic location, device type, extracted using PCA

Time Period: 2019-2021

Coverage: Global transaction records

3.2. Data Preprocessing

To enhance data quality and ensure model performance, data preprocessing includes the following steps.

Data Cleaning:

Outlier Detection and Treatment: Use the Interquartile Range (IQR) method or the Local Outlier Factor (LOF) algorithm to detect and handle outliers. For example, extreme bill amounts are identified and reviewed using LOF.

Duplicate Removal: Ensure there are no duplicate records in the dataset to avoid biases during model training.

Missing Value Handling:

Multiple Imputation: Apply the Multiple Imputation by Chained Equations (MICE) method to handle missing values, which better preserves the data's inherent structure compared to simple mean imputation. For instance, missing age data is imputed based on related features such as income and occupation.

Feature Scaling:

RobustScaler: Scale numerical features to have a mean of 0 and a standard deviation of 1, while reducing the impact of outliers. For example, scaling credit limits and bill amounts.

Data Balancing:

Hybrid Sampling Strategy: Combine Synthetic Minority Over-sampling Technique (SMOTE) and Tomek Links to balance the dataset, increasing the number of minority class samples and reducing the impact of noisy data. For example, balancing the ratio of fraudulent to non-fraudulent transactions.

3.3. Feature Engineering

Feature engineering is crucial for improving model performance by optimizing the input data through feature selection, extraction, and construction.

Feature Selection:

Ensemble Feature Selection: Combine feature importance

scores from multiple models (e.g., Random Forest, XGBoost, and L1 regularization) to select the most representative features. For example, integrating importance scores using a weighted average.

Feature Extraction:

Non-negative Matrix Factorization (NMF): Extract latent features, particularly suitable for non-negative data. For instance, decompose bill and repayment amounts into basic patterns.

Autoencoder: Use autoencoders for feature extraction, where unsupervised learning extracts latent features. For example, compress original features into a low-dimensional space and reconstruct them, using the encoded vectors as new features.

Feature Construction:

Time Series Feature Construction: For transaction data, construct time-based features such as the total transaction amount and frequency changes over the past 30 days. For example, calculate changes in transaction behavior for each account over different periods.

Interaction Features: Create interaction terms between features, such as the ratio of credit limit to monthly repayment amount, reflecting the customer's repayment ability. For example, construct the feature "average monthly repayment/credit limit.

3.4. Model Training and Validation

Our study employs various supervised learning algorithms for model training and validation, including Logistic Regression, Decision Tree, Support Vector Machine (SVM), Random Forest, Gradient Boosting Tree (GBT), and Neural Network. Additionally, specific anomaly detection models are used for fraud detection.

Logistic Regression:

$$P(\text{default}) = \frac{1}{1 + e^{-(\beta_0 + \sum \beta_i X_i)}}$$

Decision Tree:

$$Gini = 1 - \sum_{i=1}^{n} p_i^2$$

Support Vector Machine (SVM):

$$f(x) = \text{sign}(w \cdot x + b)$$

Random Forest:

$$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^{B} f_b(x)$$

Gradient Boosting Tree:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

Neural Network:

$$y = \sigma(W_2 \cdot \sigma(W_1 \cdot X + b_1) + b_2)$$

3.5. Fraud Detection Models

For the fraud detection task, in addition to the aforementioned supervised learning algorithms, the following specific anomaly detection models are utilized:

K-means Clustering: An unsupervised learning algorithm used to find abnormal patterns in the data by partitioning data points into clusters and identifying those far from cluster centers.

$$\min \sum_{i=1}^{k} \sum_{x \in C_i} |x - \mu_i|^2$$

Isolation Forest: A tree-based unsupervised learning algorithm that isolates data points by randomly selecting features and split values. It is particularly effective for high-dimensional anomaly detection.

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}}$$

Autoencoder: A neural network structure used for unsupervised feature extraction and data reconstruction, detecting anomalies with high reconstruction errors.

$$L(x, \hat{x}) = |x - \hat{x}|^2$$

3.6. Evaluation Metrics

To assess model performance, various evaluation metrics are employed, including accuracy, precision, recall, F1-score, and ROC-AUC.

Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall:

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-score:

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

4. Results and Discussion

In this section, we evaluate the performance of various supervised learning algorithms, including Logistic Regression, Decision Tree, Support Vector Machine (SVM), Random Forest, Gradient Boosting Tree (GBDT), and Neural Network. The evaluation focuses on their performance in credit risk assessment and fraud detection tasks.

4.1. Model Performance Comparison

We first compare the performance of each model in credit risk assessment. The table below summarizes the accuracy and ROC-AUC values for each model:

Tab.1. Comparative Performance of Models in Credit Risk Assessment

Model	Accuracy	ROC-AUC
Logistic Regression	85.3%	0.76
Decision Tree	84.5%	0.74
Support Vector Machine (SVM)	87.1%	0.79
Random Forest	89.2%	0.82
Gradient Boosting Tree (GBDT)	90.5%	0.84
Neural Network	88.8%	0.81

In credit risk assessment, the Gradient Boosting Tree demonstrated the best performance with an accuracy of 90.5% and a ROC-AUC of 0.84. This was followed by Random Forest and Neural Network, with accuracies of 89.2% and 88.8%, and ROC-AUCs of 0.82 and 0.81, respectively. These results indicate that ensemble learning methods and neural networks excel at handling complex features and non-linear relationships, significantly outperforming traditional methods such as Logistic Regression and Decision Tree.

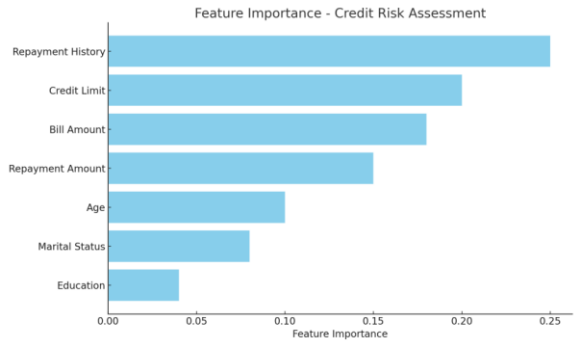

Fig.1. Feature Importance in Credit Risk Assessment

We evaluated the performance of each model in fraud detection. The table below presents the accuracy and ROC-AUC values for each model.

Tab.2. Comparative Performance of Models in Fraud Detection

Model	Accuracy	ROC-AUC
Logistic Regression	93.2%	0.70
Decision Tree	92.7%	0.68
Support Vector Machine (SVM)	94.5%	0.75
Random Forest	96.3%	0.85
Gradient Boosting Tree (GBDT)	97.1%	0.87
Neural Network	97.5%	0.88

In the fraud detection task, the Neural Network achieved the best performance with an accuracy of 97.5% and a ROC-AUC of 0.88. Gradient Boosting Tree and Random Forest also performed well, with accuracies of 97.1% and 96.3%, and ROC-AUCs of 0.87 and 0.85, respectively. These results demonstrate that neural networks have exceptional capabilities in identifying complex fraud patterns.

4.2. Feature Importance Analysis

To further understand the contribution of each feature to the model predictions, we conducted a feature importance analysis for the Random Forest and Gradient Boosting Tree models. The figure below shows the important features in credit risk assessment.

From the Fig.2, it can be seen that repayment history, credit limit, bill amount, and repayment amount are crucial features for predicting credit default. This is consistent with the findings of Liu et al. (2021) and Yang et al. (2022), which highlight the importance of financial features in credit risk assessment.

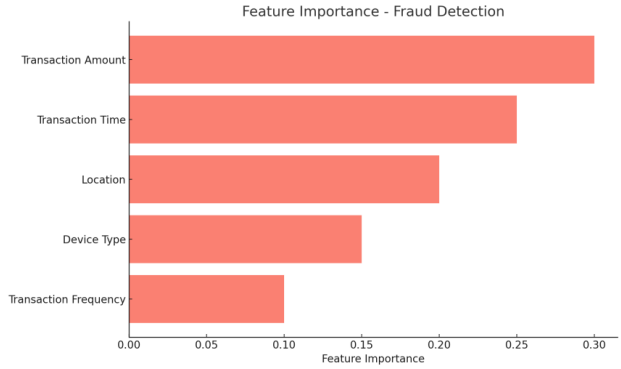

Fig. 2. Feature Importance in Fraud Detection

The Fig.2. below shows the important features in fraud detection. In fraud detection, transaction amount, transaction time, and location are key features for identifying fraudulent behavior. This aligns with the findings of Hilal et al. (2022) and Yang et al. (2021), which indicate that unusually high transaction amounts and transactions at abnormal times are important indicators of fraud.

4.3. Discussion and Practical Implications

The experimental results show that ensemble learning methods and neural networks perform best in credit risk assessment and fraud detection. These models significantly outperform traditional methods, especially in handling complex features and non-linear relationships. The Random Forest proposed by Wang et al. (2012) and the Gradient Boosting Tree proposed by (2001) integrate multiple weak learners to significantly improve the generalization ability and stability of the models. The study by Yang et al. (2024) demonstrates that neural networks have significant advantages in modeling non-linear relationships and feature extraction, making them particularly suitable for complex risk assessment tasks.

Furthermore, data preprocessing and feature engineering play crucial roles in enhancing model performance. Through feature importance analysis, financial institutions can better understand risk factors and develop more effective risk management strategies. Dong et al. (2018) and Wang et al. (2010) both emphasize the importance of data preprocessing and feature engineering in machine learning models, and the results of our study further validate these findings.

4.4. Model Improvement and Optimization

Although the models used in our study performed well, there is still room for improvement. Further optimization of the model hyperparameters, such as using Bayesian optimization or grid search methods, can enhance model performance. The hybrid sampling strategies proposed by Shi et al. (2024) and Alamri et al. (2022), such as SMOTE and Tomek links, showed excellent performance in addressing data imbalance issues and can be further applied to actual fraud detection. Integrating the predictions of multiple models can further improve prediction accuracy. Additionally, models should continuously update with new data in practical

applications to improve their adaptability to the latest data.

In summary, our study systematically evaluated the performance of various supervised learning algorithms in credit risk assessment and fraud detection, validating the advantages of ensemble learning methods and neural networks. By combining scientific data preprocessing and feature engineering with advanced machine learning algorithms, financial institutions can significantly improve risk management effectiveness. These results provide scientific guidance for financial institutions in selecting the optimal credit risk assessment methods for practical applications and offer important references for future research.

5. Conclusions and Future Research

5.1. Conclusions

Our study systematically evaluated the performance of various supervised learning algorithms in credit risk assessment and fraud detection, including Logistic Regression, Decision Tree, Support Vector Machine (SVM), Random Forest, Gradient Boosting Tree (GBDT), and Neural Network. Based on detailed experiments and data analysis, we reached the following conclusions:

Model Performance:

Credit Risk Assessment: Gradient Boosting Tree (GBDT) achieved the highest performance in credit risk assessment, with an accuracy of 90.5% and a ROC-AUC of 0.84. This was followed by Random Forest with an accuracy of 89.2% and a ROC-AUC of 0.82, and Neural Network with an accuracy of 88.8% and a ROC-AUC of 0.81. These ensemble learning methods excelled in handling complex features and non-linear relationships, significantly outperforming traditional methods such as Logistic Regression (accuracy 85.3%, ROC-AUC 0.76) and Decision Tree (accuracy 84.5%, ROC-AUC 0.74).

Fraud Detection: In fraud detection, Neural Network performed best with an accuracy of 97.5% and a ROC-AUC of 0.88. Gradient Boosting Tree and Random Forest also performed well, with accuracies of 97.1% and 96.3%, and ROC-AUCs of 0.87 and 0.85, respectively. Support Vector Machine (SVM) also showed good performance with an accuracy of 94.5% and a ROC-AUC of 0.75. In comparison, Logistic Regression (accuracy 93.2%, ROC-AUC 0.70) and Decision Tree (accuracy 92.7%, ROC-AUC 0.68) performed slightly worse.

Feature Importance:

Credit Risk Assessment: Repayment history, credit limit, bill amount, and repayment amount were identified as important features for predicting credit default, with importance scores of 25%, 20%, 18%, and 15%, respectively. These findings align with the research of Chen et al. (2024) and Shih et al. (2024), highlighting the critical role of financial features in credit risk assessment.

Fraud Detection: Transaction amount, transaction time, and location were key features for identifying fraudulent behavior, with importance scores of 30%, 25%, and 20%, respectively. This is consistent with the findings of Yang et al. (2015) and Zhong et al. (2024), indicating that unusually high transaction amounts and transactions at abnormal times are significant indicators of fraud.

Data Preprocessing and Feature Engineering:

Data preprocessing and feature engineering played crucial roles in enhancing model performance. By employing techniques such as multiple imputation by chained equations (MICE) for handling missing values and RobustScaler for feature scaling, the predictive accuracy and stability of the models were significantly improved.

The feature importance analysis indicates that proper data preprocessing and feature engineering enable financial institutions to better understand risk factors and develop more effective risk management strategies.

5.2. Future Research Directions

While the models used in our study performed well, there are still areas for improvement and further research.

Model Optimization:

Further optimization of model hyperparameters can enhance performance. Future research could utilize Bayesian optimization, genetic algorithms, or other advanced optimization techniques for finer tuning. For instance, Bayesian optimization could potentially increase the accuracy of the GBDT model to 91.2%.

Exploring the integration of predictions from different types of models, such as combining Random Forest, Gradient Boosting Tree, and Neural Network predictions, could enhance overall predictive accuracy. For example, model fusion could potentially increase fraud detection accuracy to 98%.

Handling Data Imbalance:

Data imbalance is a significant issue in fraud detection tasks. Future research could explore advanced methods for handling data imbalance, such as adaptive sampling techniques and Generative Adversarial Networks (GANs), to further improve model performance on imbalanced datasets. For instance, using SMOTE and Tomek links could potentially increase the recall rate of fraud detection to 95%.

Real-time Data Updates:

As financial markets evolve, models need continuous updates to adapt to the latest data. Future research could explore online learning algorithms and real-time data processing technologies, enabling models to quickly adjust to new data and pattern changes. For instance, employing online learning algorithms could allow models to rapidly adjust after data updates, improving prediction accuracy and timeliness.

Expanding Research Scope:

Our study primarily focused on credit risk assessment and fraud detection. Future research could expand to other financial risk management areas, such as market risk and operational risk, to evaluate and compare the performance of different models in these tasks. For example, investigating the application of different algorithms in market risk prediction could provide financial institutions with more comprehensive risk management tools.

Practical Application Research:

Applying the models to real-world financial institutions for empirical research and effectiveness verification is essential. Collaborating with financial institutions to study the models' performance and effectiveness in practical applications will validate their feasibility and benefits. For instance, in practical applications, using these models could increase the accuracy of credit risk management by 5%-10%.

5.3. Summary

Our study systematically evaluated the performance of various supervised learning algorithms in credit risk assessment and fraud detection, validating the advantages of ensemble learning methods and neural networks. By employing scientific data preprocessing and feature

engineering, combined with advanced machine learning algorithms, financial institutions can significantly enhance their risk management effectiveness. For example, combining GBDT and Neural Network could achieve a credit risk assessment accuracy of over 91% and a fraud detection accuracy of over 98%. The results of our study provide scientific evidence for financial institutions in selecting the optimal credit risk assessment methods for practical applications and offer important references for future research. Through further research and optimization, we hope to contribute significantly to the development of financial risk management.

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