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EFFECTIVENESS OF MACHINE LEARNING ALGORITHMS IN CREDIT RISK DETECTION

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Abstract

Credit risk detection is one of the most significant tasks in the banking and financial sector because inaccurate assessment of borrowers may lead to substantial financial losses and instability in financial institutions. Traditional statistical approaches such as logistic regression have been widely used in credit scoring systems for decades. However, the growth of digital banking, large-scale financial datasets, and computational technologies has encouraged the adoption of machine learning algorithms for more accurate prediction of default risk. This article analyzes the effectiveness of major machine learning algorithms in credit risk detection, including Logistic Regression, Decision Trees, Random Forest, Support Vector Machines, Artificial Neural Networks, and XGBoost. The study is based on recent scientific literature, comparative experimental findings, and empirical evidence from financial datasets. Research findings demonstrate that ensemble learning methods such as Random Forest and XGBoost generally outperform traditional statistical models in predictive accuracy, Area Under Curve (AUC), recall, and precision metrics. At the same time, issues related to interpretability, fairness, regulatory compliance, and imbalanced datasets remain important challenges in practical implementation. The paper also discusses the significance of explainable artificial intelligence (XAI) methods in improving transparency in machine learning-based credit scoring systems. The study concludes that machine learning algorithms significantly improve credit risk detection performance when combined with appropriate preprocessing techniques, feature engineering, and interpretability frameworks.

Keywords

Credit risk detection, machine learning, credit scoring, logistic regression, Random Forest, XGBoost, artificial neural networks, financial technology, predictive analytics, explainable artificial intelligence.

Introduction

Credit risk refers to the probability that a borrower will fail to meet debt obligations according to agreed conditions. Financial institutions rely on credit risk assessment systems to reduce losses and improve lending decisions. Traditional credit scoring models were mainly based on statistical techniques such as Logistic Regression because of their simplicity and interpretability. However, these models often struggle to capture nonlinear relationships and complex interactions among variables in large financial datasets.

The rapid growth of financial technologies and digital transactions has generated enormous amounts of structured and unstructured data. As a result, machine learning algorithms have become increasingly important in credit risk prediction. Unlike conventional statistical approaches, machine learning methods can automatically identify hidden patterns in datasets and improve predictive accuracy. Studies show that ensemble methods such as Random Forest and XGBoost frequently achieve better performance compared to traditional Logistic Regression models.

Financial institutions are particularly interested in improving the prediction of loan defaults, non-performing loans, and borrower behavior. Effective credit risk detection enables banks to optimize capital allocation, reduce financial losses, and comply with international regulatory frameworks such as Basel III and IFRS 9. According to recent research, machine learning

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models provide higher discrimination power and better handling of nonlinear relationships than classical econometric methods.

Among the most widely used algorithms in credit risk analysis are Logistic Regression, Decision Trees, Random Forest, Support Vector Machines (SVM), Artificial Neural Networks (ANN), Gradient Boosting Machines, and XGBoost. Each method has advantages and limitations regarding predictive accuracy, interpretability, computational efficiency, and regulatory acceptance. Logistic Regression remains attractive because of its transparency, while XGBoost and Random Forest are favored for higher predictive performance.

Recent studies also emphasize the importance of handling imbalanced datasets in credit scoring. Since default cases are usually much smaller than non-default cases, oversampling methods such as SMOTE and SMOTETomek are frequently used to improve model performance. Research demonstrates that combining oversampling techniques with ensemble learning models significantly improves classification outcomes.

Therefore, this article aims to evaluate the effectiveness of machine learning algorithms in credit risk detection by examining comparative research findings, methodological approaches, and practical challenges in the banking sector.

Methodology

This study uses a qualitative and comparative research methodology based on scientific literature analysis and empirical findings from peer-reviewed publications related to machine learning applications in credit risk detection. The research focuses on evaluating the predictive effectiveness of major machine learning algorithms commonly used in financial institutions.

The primary algorithms analyzed in this study include:

- Logistic Regression (LR)
- Decision Trees (DT)
- Random Forest (RF)
- Support Vector Machines (SVM)
- Artificial Neural Networks (ANN)
- XGBoost
- CatBoost
- Gradient Boosting Machines (GBM)

The evaluation criteria considered in this analysis include:

- Accuracy
- Precision
- Recall
- F1-score
- Area Under the Curve (AUC)
- Interpretability
- Computational efficiency

Most reviewed studies used publicly available credit datasets such as LendingClub, Home Credit datasets, and banking supervisory datasets. Researchers commonly applied preprocessing techniques including missing value imputation, normalization, feature selection, and categorical encoding.

An important methodological issue in credit risk prediction is class imbalance. In most banking datasets, default events represent a relatively small percentage of total observations. To address this problem, studies used oversampling methods such as Synthetic Minority Oversampling Technique (SMOTE) and SMOTETomek. These methods generate synthetic samples for minority classes and improve the model's ability to identify default borrowers.

Cross-validation methods were also widely used to avoid overfitting and ensure model generalization. Ensemble methods such as Random Forest and XGBoost were often optimized through hyperparameter tuning processes involving tree depth, learning rate, and number of estimators.

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In addition, recent studies incorporated Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME to improve transparency and interpretability of machine learning models. These techniques help financial analysts understand the contribution of individual variables in credit risk predictions.

Results

The reviewed studies consistently demonstrate that machine learning algorithms outperform traditional statistical methods in credit risk detection tasks. Ensemble learning algorithms, particularly Random Forest and XGBoost, achieved the highest predictive performance across most evaluation metrics.

Research comparing Logistic Regression, Random Forest, XGBoost, and CatBoost found that XGBoost and CatBoost achieved superior accuracy and AUC values in imbalanced credit datasets. In one comparative analysis, XGBoost achieved training AUC values above 99%, while Random Forest achieved nearly perfect training performance. However, Random Forest also showed signs of overfitting in some experiments.

Another study analyzing credit registry data found that Random Forest and One-Class Classification models significantly outperformed Logistic Regression in identifying default cases within imbalanced datasets. The application of oversampling methods such as SMOTE improved recall and minority class classification.

Deep learning models also demonstrated strong predictive capabilities, especially when large datasets were available. Research conducted on corporate loan portfolios showed that deep neural networks and XGBoost improved default classification accuracy compared to conventional econometric approaches.

Studies comparing traditional and advanced methods indicate that Logistic Regression remains competitive in terms of interpretability and regulatory compliance. However, its predictive performance is generally lower than nonlinear machine learning models.

Research findings further indicate that feature engineering and preprocessing significantly influence model performance. Variables such as borrower income, employment duration, repayment history, and external credit scores were identified as critical predictors in many studies.

Analysis and Discussion

The growing use of machine learning in credit risk detection reflects the transformation of modern financial systems into data-driven environments. Machine learning algorithms provide important advantages over traditional statistical models because they can process high-dimensional datasets and capture nonlinear interactions among variables.

Random Forest and XGBoost have become particularly popular because of their strong classification performance and robustness. Random Forest reduces overfitting by combining multiple decision trees, while XGBoost improves predictive accuracy through gradient boosting and regularization mechanisms.

However, increased model complexity creates significant interpretability challenges. Financial regulators often require transparency in lending decisions to prevent discrimination and ensure fair treatment of borrowers. Logistic Regression remains widely accepted because its coefficients can be directly interpreted by financial analysts and regulators. In contrast, complex ensemble models are often described as “black-box” systems.

Explainable Artificial Intelligence techniques provide potential solutions to this problem. SHAP and LIME methods help explain individual predictions by identifying the contribution of each variable to the final decision. Recent research demonstrates that combining machine learning models with explainability frameworks improves trust and regulatory compatibility.

Another important issue is dataset imbalance. In most credit datasets, default cases are relatively rare, which may cause models to favor majority classes. Oversampling techniques such as SMOTE and SMOTETomek help improve recall and minority class detection. Nevertheless, excessive oversampling may increase the risk of overfitting.

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Model fairness and ethical concerns are also increasingly important. Machine learning algorithms may unintentionally reproduce biases existing in historical financial data. Therefore, financial institutions must implement fairness testing and governance mechanisms before deploying automated credit scoring systems.

Overall, current evidence suggests that machine learning algorithms substantially improve predictive performance in credit risk detection. However, successful implementation requires balancing predictive accuracy with interpretability, fairness, and regulatory compliance.

Conclusion

Machine learning algorithms have significantly transformed credit risk detection in the financial industry. Compared with traditional statistical methods, advanced machine learning techniques such as Random Forest, XGBoost, and Artificial Neural Networks provide higher predictive accuracy and better handling of complex nonlinear relationships within large financial datasets.

The findings reviewed in this study indicate that ensemble learning models consistently outperform Logistic Regression in metrics such as AUC, precision, recall, and F1-score. Techniques such as SMOTE and feature engineering further improve the effectiveness of machine learning models in handling imbalanced datasets.

Despite these advantages, interpretability and regulatory compliance remain major challenges. Financial institutions continue to rely on transparent models such as Logistic Regression because regulatory authorities require understandable and explainable decision-making systems. The integration of Explainable Artificial Intelligence methods such as SHAP and LIME represents an important step toward resolving these concerns.

Future developments in credit risk detection will likely focus on hybrid approaches that combine the predictive strength of machine learning with the transparency required by financial regulations. As digital banking and financial technologies continue to evolve, machine learning will play an increasingly important role in improving the accuracy, efficiency, and reliability of credit risk management systems.

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