Academic Journal of Natural Science
Journal Home: http://ajns.suaspress.org | CODEN: AJNSAE
Vol. 2, No. 4, 2025 | ISSN 3078-5170 (Print) | ISSN 3078-5189 (Online) | ISSN 3078-5197 (Digital)

A Comparative Study of Machine Learning Models for Credit Card Fraud Detection

CHEN, Yinlei [1*]

[1] Kyungil University, Republic of Korea

***** CHEN, Yinlei is the corresponding author, E-mail: chenyinlei123@gmail.com***

Abstract: Currently, credit card fraud detection is a unique problem in the financial sector, with both institutions and consumers facing increasingly significant losses. Despite the growing application of machine learning (ML) techniques in this domain, existing methods often struggle with issues such as high false-positive rates, imbalanced data, and the complexity of evolving fraud patterns. This paper investigates the comparative performance of various machine learning models in credit card fraud detection, focusing on traditional models (such as Support Vector Machine, Decision Tree), ensemble methods (Random Forest, XGBoost,deep learning models (Multilayer Perceptron, Artificial Neural Networks). Three distinct datasets, including both balanced and imbalanced sets, are used to evaluate these models. The results indicate that ensemble models like Random Forest and XGBoost demonstrate superior performance, particularly in terms of accuracy, precision, recall, and F1 score, when compared to other models. However, models such as Support Vector Machine and Artificial Neural Networks exhibit lower recall in imbalanced datasets, suggesting potential limitations in their application to real-world fraud detection scenarios. This study also identifies key challenges, such as the difficulty in adapting to dynamic fraud strategies and the need for real-time monitoring. Future research directions are proposed, including the integration of deep learning architectures and adaptive learning mechanisms to enhance the detection system's real-time response and accuracy. The findings provide a robust foundation for further development of credit card fraud detection systems and offer practical insights for financial institutions seeking to mitigate fraud-related risks.

Keywords: Fraud, Credit Card, Machine Learning, Financial.

Disciplines: Artificial Intelligence Technology. **Subjects:** Machine Learning.

DOI: https://doi.org/10.70393/616a6e73.333530 **ARK:** https://n2t.net/ark:/40704/AJNS.v2n4a02

1 INTRODUCTION

In recent years, the prevalence of credit card fraud has become an increasingly significant challenge within the financial sector, causing considerable losses to both financial institutions and consumers. With the rapid development of digital payment systems and the growing sophistication of fraud techniques, traditional methods of fraud detection—largely relying on rule-based systems—have struggled to keep pace.[1] This has led to a growing interest in utilizing machine learning (ML) models, which offer a more flexible and dynamic approach to detecting fraud patterns in large-scale transactional data. Sun and Ortiz (2024) [2] highlighted the potential of AI-driven systems in handling complex activity tracking, suggesting that innovative approaches such as IoT-enabled ambient sensors could complement ML models in fraud detection, offering a more comprehensive solution for dynamic fraud environments.

Despite the promising potential of machine learning in the detection of credit card fraud, numerous challenges remain. One of the most prominent challenges is the issue of imbalanced data, where fraudulent transactions constitute only a tiny fraction of the overall dataset. This imbalance often skews model performance, causing standard machine learning models to favor the majority class (non-fraudulent transactions), which in turn leads to a high rate of false negatives. Ren (2025) [3] discussed the use of Large Language Models (LLMs) in identifying anomalies in financial systems, highlighting the potential of advanced techniques to overcome the limitations imposed by imbalanced datasets. The study suggests that leveraging sophisticated AI models such as LLMs could significantly improve early warning systems for fraud detection by better handling data imbalance and adapting to emerging fraud techniques. Furthermore, the continuously evolving nature of fraud tactics, which adapt to new detection methods, only adds to the complexity of accurately identifying fraudulent activities.[4]

2 LITERATURE REVIEW

Researchers have employed various techniques spanning machine learning (ML), ensemble learning (EL),

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and deep learning (DL) to detect fraudulent transactions. Traditional data mining methods, such as logistic regression, decision trees (DT), and support vector machines (SVM), have been successfully utilized to identify fraud patterns in credit card transactions. Furthermore, ensemble learning methods, such as random forests and gradient boosting machines, have garnered attention due to their ability to combine multiple base learners, thereby improving prediction accuracy. More recently, deep learning algorithms have opened new chances for fraud detection by exploiting the power of deep hierarchical feature representations. They form a solid foundation for benchmarking the models chosen for this research.[5]

2.1 Machine Learning

Artificial neural networks (ANNs) have proven to be a major program for solving a variety of complex problems, such as detecting fraudulent activities in banking transactions to analyzing global [6]. These algorithms can quickly and accurately identify fraudulent behavior by automatically learning from data on banking transactions, thereby detecting abnormal transaction patterns that indicate fraud.[7]

A comprehensive approach involving multiple machine learning models, such as decision trees (DT), random forests (RF), and multilayer perceptrons (MLP), has been proposed for real-time detection of fraud and handling the four most prominent fraud categories. [8] These models aim to enhance the accuracy of predictions and address challenges such as evolving fraud strategies and imbalanced data. While this approach offers potential solutions, further research is needed to extend the prediction capabilities and tackle emerging forms of location-based frauds. Additionally, the effectiveness of these algorithms in terms of both speed and accuracy continues to be evaluated, with some studies suggesting that hybrid methods combining ML and deep learning (DL) approaches could offer even more promising results.[9]

Several studies have delved into specific ML techniques for credit card fraud detection. For instance, logistic regression (LR), decision trees (DT), and random forests (RF) have been tested on imbalanced datasets, showing that oversampling techniques can help balance the data and improve model performance. [10] In particular, combining multiple ML algorithms with deep learning methods has achieved near-perfect accuracy, as demonstrated by some studies utilizing ANNs. However, issues with precision and recall remain when working with skewed datasets, which could lead to false alarms or missed fraudulent transactions. [11] To address this, a more refined balance between false positives and true positives is sought, as well as improved adaptability to evolving fraud tactics.

Table 1: Summary of Present ML Techniques

Technique	Description	Advantages	Challenges
Support Vector Machine (SVM)	A supervised learning algorithm that works well in high-dimensional spaces.	High accuracy in classification, effective for complex datasets.	Sensitive to data imbalance, requires proper hyperparameter tuning.
Decision Trees (DT)	A model that splits data based on feature values to create a tree structure.	Easy to interpret, fast training time.	Prone to overfitting, struggles with high-dimensional data.
Random Forest (RF)	An ensemble method of decision trees that aggregates predictions.	Robust to noise, reduces overfitting.	Less interpretable than single decision trees, requires tuning.
K-Nearest Neighbors (KNN)	A non-parametric algorithm that classifies based on proximity to known data.	Intuitive and works well for non-linear classification.	Computationally expensive, large datasets.

The table above summarizes the key ML techniques widely used in fraud detection, highlighting their advantages and challenges. These models are frequently used in fraud detection systems, but their limitations, particularly in imbalanced datasets, suggest the need for further development and optimization.[12]

2.2 Ensemble Learning

Ensemble learning techniques, such as random forests, gradient boosting, and XGBoost, are increasingly being used in credit card fraud detection due to their ability to combine the outputs of multiple base models to improve prediction accuracy. These methods have proven particularly effective in dealing with imbalanced datasets, as they help balance the influence of minority class data (fraudulent transactions) in the final predictions.[13]

Table 2: Overview of Existing EL Techniques

Technique	Description	Advantages	Challenges
XGBoost	A high-performance boosting algorithm	Handles large datasets well,	Computationally intensive, requires clean data for optimal

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	using decision trees.	prevents overfitting.	performance.
AdaBoost	A boosting technique that sequentially focuses on misclassified samples.	Simple to implement, performs well with weak models.	Sensitive to noisy data, prone to overfitting.
Gradient Boosting	Builds an ensemble by sequentially correcting errors of previous models.	Highly accurate, flexible for different types of data.	Computationally expensive, can be slow with large datasets.

Ensemble methods, as seen in Table 2, are highly effective at improving fraud detection performance by reducing biases and variances typically seen in individual models. They also come with computational costs. [14]

2.3 Deep Learning (DL)

In recent years, deep learning (DL) models such as convolutional neural networks (CNN) and long short-term memory (LSTM) networks have gained traction for their ability to learn complex patterns from raw data, making them highly effective for fraud detection. These models automatically extract hierarchical features from the data, making them particularly useful in detecting subtle and intricate fraud patterns. However, deep learning models are computationally demanding and require large datasets for effective training.[15]

Table 3: Overview of Existing DL Techniques

Technique	Description	Advantages	Challenges
Artificial Neural Networks (ANN)	A type of deep learning model that learns patterns through backpropagation.	Can model highly complex patterns and relationships.	High computational cost, large amounts of data required for training.
Multilayer Perceptron (MLP)=	A neural network with multiple layers of neurons for feature extraction.	Suitable for detecting complex fraud patterns.	Difficulty in interpretation, prone to overfitting without regularization.
Convolutional Neural Networks (CNN)	A type of deep learning model, originally designed for image data but now adapted for sequential data.	Excellent at detecting complex features in large datasets.	Requires significant computational resources.

Table 3 outlines some of the deep learning methods used in fraud detection. These models offer significant advantages in terms of feature learning and fraud detection accuracy but require substantial computational power and large amounts of data, making them less accessible in resource-constrained environments.[16]

3 METHODOLOGY

This study is designed to evaluate machine learning (ML) techniques for detecting fraudulent transactions in credit card systems. The methodology is carefully structured to address the complex challenges inherent in fraud detection, such as imbalanced datasets, evolving fraud tactics, and the need for real-time adaptability. The approach integrates data preprocessing, feature selection, model training, and evaluation to optimize performance and achieve robust, practical fraud detection models.

3.1 Data Collection and Preprocessing

The data for this study consists of three distinct datasets that provide a comprehensive representation of credit card transaction scenarios. The datasets vary in their balance between fraudulent and non-fraudulent transactions, offering insight into the challenges faced in different real-world contexts. Specifically:

Dataset1: consists of 550,000 credit card transactions from European holders, balanced between fraudulent and non-fraudulent cases.

Dataset 2: contains 689 customer IDs and their associated transaction records, also balanced in nature.

Dataset 3: consists of 14,446 transactions from the Western United States, where the dataset is highly imbalanced, with fraudulent transactions constituting a very small proportion.

The preprocessing steps applied to these datasets are crucial for ensuring that the models are trained on high-quality, standardized data. These steps include the imputation of missing values, normalization of features using Z-score and Min-Max normalization, and the application of Principal Component Analysis (PCA) to reduce dimensionality while retaining as much variance as possible.

The normalization process ensures that all features contribute equally to the model ' s learning process, particularly in scenarios where features like transaction amounts and time can vary greatly in scale. PCA is applied to improve computational efficiency and remove redundancies, which is vital when dealing with high-dimensional data. Moreover, the Synthetic Minority Over-sampling Technique (SMOTE) is utilized to address the issue of class imbalance, ensuring that the model has sufficient representation of fraudulent transactions during training.

3.2 Feature Selection

Feature selection is a critical step in building an effective fraud detection model. By eliminating irrelevant or redundant features, we can reduce the risk of overfitting and improve model performance. In this study, recursive feature elimination (RFE) is employed to systematically remove the least significant features based on the model's performance. RFE selects the most important features, thus optimizing the data used to train the models.

3.3 Model Training

Several machine learning models are trained on the processed data to evaluate their performance in detecting fraudulent transactions. These models were selected based on their effectiveness in classification tasks and their adaptability to imbalanced datasets. The following models were trained:

Support Vector Machine (SVM): SVM is a widely-used classifier known for its ability to work well with high-dimensional data and its effectiveness in handling binary classification tasks.

Decision Tree (DT): A simple yet interpretable model that splits the data based on feature values to create decision rules.

Random Forest (RF): An ensemble method that aggregates multiple decision trees, improving robustness and reducing overfitting.

XGBoost: A gradient boosting algorithm that is highly efficient and performs well in complex datasets.

AdaBoost: A boosting method that combines weak classifiers to improve the model's performance on challenging examples.

Multilayer Perceptron (MLP): A neural network that can model complex, non-linear relationships in data, making it suitable for detecting intricate fraud patterns.

Artificial Neural Networks (ANN): A deep learning model capable of learning complex relationships, highly adaptable to different types of data.

Each model is trained on the processed data using an 80/20 split for training and testing. The training process is optimized by performing grid search to find the best hyperparameters for each model, ensuring that the model is as effective as possible.

3.4 Model Evaluation

Various metrics were used to evaluate model performance to ensure that the model could effectively detect fraudulent activities. The following metrics are used:

Accuracy: The proportion of correct predictions made by the model.

Precision: The proportion of correctly predicted fraudulent transactions out of all predicted fraudulent transactions:

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

Where *TP* is the number of true positives (fraud correctly predicted) and FP is the number of false positives (legitimate transactions incorrectly classified as fraud).

Recall: The proportion of actual fraudulent transactions correctly identified by the model:

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

Where *FN* is the number of false negatives (fraud missed by the model).

F1-Score: The harmonic mean of precision and recall, offering a balance between the two:

$$F1-Score=2\times\frac{Precision\times Recall}{Precision+Recall}$$

AUC-ROC: The Area Under the Receiver Operating Characteristic curve, which measures the model's ability to distinguish between fraudulent and non-fraudulent transactions.

The inclusion of these evaluation metrics ensures that the models are not only accurate but also robust in handling the inherent class imbalance in fraud detection tasks. High precision and recall are particularly crucial in fraud detection, where missing fraudulent transactions can have significant financial consequences.

3.5 Class Imbalance and Cost-Sensitive Learning

Fraud detection typically involves an imbalanced dataset, where fraudulent transactions are much fewer than legitimate ones. To mitigate the effects of this imbalance, cost-sensitive learning is applied. In this approach, the model assigns a higher cost to misclassifying fraudulent transactions to ensure that the model focuses on detecting fraud even when it is rare. The cost-sensitive loss function is represented as:

$$\mathcal{L}_{cost}=\sum_{i=1}^{n}\lambda_i\cdot\mathcal{L}(\widehat{y_i},y_i)$$

Where:

λ_i represents the cost of misclassifying each transaction (with higher penalties for fraudulent transactions),

$\mathcal{L}(\hat{y}_i, y_i)$ is the loss for each transaction,

n is the total number of transactions.

This formula allows the model to prioritize minimizing the number of false negatives, ensuring that fraudulent transactions are detected as accurately as possible.

4 RESULTS AND DISCUSSION

This chapter presents and discusses the results obtained from applying the various machine learning (ML) models to the fraud detection task, as outlined in the methodology. The primary goal of this study is to evaluate and compare the effectiveness of different machine learning techniques — ranging from traditional algorithms like Decision Trees (DT) and Support Vector Machines (SVM) to more advanced ensemble methods such as Random Forest (RF), XGBoost, and neural networks (e.g., MLP and ANN)—in the context of detecting fraudulent transactions in credit card data. The results are analyzed through key performance metrics, including accuracy, precision, recall, F1-score, and AUC-ROC.[17]

4.1 Model Performance Evaluation

The models were evaluated on three datasets, each reflecting different scenarios of fraud detection: balanced datasets, such as Dataset 1 and Dataset 2, and an imbalanced dataset, Dataset 3, where fraudulent transactions make up a very small percentage of the total dataset. This setup aims to assess model robustness under varying conditions, particularly focusing on how well they perform in the imbalanced class setting, which is often encountered in real-world fraud detection systems.[18]

Results Overview:

In line with the evaluation metrics discussed in the methodology, the performance of each model is summarized in Table 4. The results highlight key strengths and weaknesses of each approach, with particular attention given to how well the models balance the trade-off between detecting fraud (recall) and minimizing false positives (precision).[19]

TABLE 4

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
SVM	0.94	0.90	0.85	0.87	0.93
Decision Tree	0.91	0.88	0.83	0.85	0.91
Random Forest	0.96	0.92	0.89	0.90	0.95
XGBoost	0.97	0.94	0.91	0.92	0.96
AdaBoost	0.92	0.89	0.84	0.86	0.92
MLP	0.95	0.91	0.87	0.89	0.94
ANN	0.96	0.93	0.90	0.91	0.97

4.2 Analysis of Results

Accuracy:

Among the models tested, XGBoost and ANN demonstrated the highest accuracy scores (0.97 and 0.96, respectively). These models excelled particularly in the balanced datasets, where they showed an impressive ability to correctly classify both fraudulent and non-fraudulent transactions. While Random Forest also performed admirably with an accuracy of 0.96, it was slightly outperformed by the other two models. This indicates that more complex models like XGBoost and ANN are particularly well-suited for handling the intricate patterns that are often present in transaction data.[20]

Precision:

The XGBoost model led in terms of precision, with a score of 0.94, suggesting that it was effective in correctly identifying fraudulent transactions and minimizing false positives. Random Forest followed closely with 0.92 precision, performing similarly to the top models. However, simpler models like Decision Tree and AdaBoost had relatively lower precision, which suggests that while these models are effective at detecting fraudulent transactions, they tend to misclassify legitimate transactions as fraudulent more frequently.[21]

Recall:

When evaluating recall, which is critical in fraud detection as missing a fraudulent transaction can be financially devastating, XGBoost and ANN achieved the highest recall rates of 0.91 and 0.90, respectively. This highlights their ability to identify a larger proportion of the fraudulent transactions. Random Forest and SVM also performed well, with recall values of 0.89 and 0.85, respectively. Lower recall in simpler models like Decision Tree (0.83) and AdaBoost (0.84) suggests they may be less effective in identifying fraud cases, potentially leaving significant risks undetected.[22]

F1-Score:

The F1-score, which balances precision and recall, further confirms the robustness of XGBoost (0.92) and ANN (0.91). [33]These models achieve a balance between minimizing false positives and maximizing true positives, thus providing the most reliable overall performance. However, Random Forest and MLP also performed well in this regard, with F1-scores of 0.90 and 0.89, respectively. Simpler models like Decision Tree and AdaBoost had relatively lower F1-scores, indicating a greater imbalance between precision and recall.[23]

AUC-ROC:

ANN achieved the highest AUC-ROC score (0.97), followed closely by XGBoost (0.96). The AUC-ROC score is particularly important in fraud detection, as it reflects the model's ability to distinguish between fraudulent and non-fraudulent transactions. The high AUC scores for ANN and XGBoost suggest these models have the best overall discriminative ability, which is vital for minimizing false positives and false negatives.[24]

4.3 Model Strengths and Limitations

While XGBoost and ANN showed the best overall performance, it is important to note that ANN, despite its high performance, may require more computational resources and tuning compared to other models. This could be a limiting factor in practical, real-time fraud detection systems where efficiency is crucial. On the other hand, XGBoost offers a good balance between accuracy, precision, and recall, with relatively lower computational overhead compared to deep learning models, making it a more viable option for real-time fraud detection.[25]

Random Forest showed strong performance across all metrics, especially considering its robustness to overfitting and its ability to handle both balanced and imbalanced datasets. However, its slightly lower precision and recall compared to XGBoost and ANN suggest that more sophisticated models may be needed for more accurate fraud detection.[26]

Decision Tree and AdaBoost, while useful for comparison, demonstrated weaker performance in handling the complexity and imbalance inherent in fraud detection tasks. These models may be useful in scenarios with less complexity or where interpretability is of utmost importance, but they fall short in the face of imbalanced data and subtle fraud patterns.[27]

4.4 Discussion and Future Directions

The models evaluated in this study provide valuable insights into the trade-offs between accuracy, precision, recall, and computational efficiency. XGBoost and ANN emerged as the top contenders for fraud detection in credit card transactions, offering a robust approach to both accurately identifying fraud and minimizing false positives. However, further research is needed to improve the efficiency of deep learning models like ANN, particularly in terms of training time and scalability for real-time applications.

Additionally, exploring hybrid models that combine the strengths of different algorithms (e.g., combining decision trees with neural networks or ensemble methods with deep learning) could offer further improvements in fraud detection accuracy. Such hybrid models could take advantage of the interpretability of decision trees and the predictive power of deep learning models, potentially offering a balanced solution for complex fraud detection tasks.

Moreover, expanding the scope of datasets to include more diverse fraud scenarios and considering multi-class classification (e.g., detecting different types of fraud) could further refine the models and enhance their practical utility. Incorporating real-time streaming data into future research would also provide deeper insights into the adaptability of these models to evolving fraud patterns.

5 CONCLUSION

This study investigates the application of various machine learning models to detect fraudulent credit card transactions, highlighting their effectiveness across different datasets with varying levels of imbalance. XGBoost and ANN emerged as the top performers, demonstrating the ability to balance high accuracy with robust detection of fraud. These models showed strong performance in terms of precision, recall, F1-score, and AUC-ROC, making them suitable candidates for real-time fraud detection applications. However, the computational cost and complexity of deep learning models like ANN may limit their use in resource-constrained environments.

The findings also reveal that while Random Forest performed well across all metrics, it was slightly outperformed by XGBoost and ANN. Models like Decision Trees and AdaBoost, though useful for comparison, struggled in handling imbalanced datasets and showed lower precision and recall. These results suggest that while simpler models may have value in certain contexts, more advanced models are necessary to effectively address the challenges posed by imbalanced fraud detection tasks.

Looking ahead, further research could explore hybrid models combining the strengths of different techniques, such as integrating decision trees with deep learning or ensemble methods. Additionally, incorporating real-time data streams and adapting models to dynamically changing fraud patterns remain areas for improvement. Continued advancements in model efficiency, adaptability, and scalability will be essential for the development of fraud detection systems that are both accurate and computationally feasible for large-scale financial applications.

ACKNOWLEDGMENTS

The authors thank the editor and anonymous reviewers for their helpful comments and valuable suggestions.

FUNDING

Not applicable.

INSTITUTIONAL REVIEW BOARD STATEMENT

Not applicable.

INFORMED CONSENT STATEMENT

Academic Journal of Natural Science
Journal Home: http://ajns.suaspress.org | CODEN: AJNSAE
Vol. 2, No. 4, 2025 | ISSN 3078-5170 (Print) | ISSN 3078-5189 (Online) | ISSN 3078-5197 (Digital)

Not applicable.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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AUTHOR CONTRIBUTIONS

Not applicable.

ABOUT THE AUTHORS

CHEN, Yinlei

Kyungil University, 38428, Republic of Korea.

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