IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

AI-Powered Credit Card Fraud Detection: A Comparative Analysis of Machine Learning and Deep Learning Techniques

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Abstract : This study evaluates the efficacy of AI techniques in credit card fraud detection amidst the growing digital economy, where financial fraud, particularly credit card fraud, has surged. Traditional fraud detection methods like rule-based systems and manual verification are increasingly inadequate against sophisticated fraud tactics. We compare machine learning (ML) and deep learning (DL) models using a publicly available dataset, focusing on metrics such as accuracy, precision, recall, and F1-score. Deep learning models, notably LSTM and ANNs, demonstrated superior performance, with LSTM achieving the highest accuracy at 98.3%. However, ML models like XGBoost also showed competitive results, suggesting their utility for real-time applications due to lower computational demands. The findings underscore the need for AI solutions that balance efficiency, accuracy, and adaptability to counter evolving fraud patterns, highlighting areas for future research including model optimization, interpretability, and security enhancements against adversarial attacks.

Keywords: Credit Card Fraud, Fraud Detection, Machine Learning (ML), Deep Learning (DL), Artificial Intelligence (AI).

I. INTRODUCTION

The digital economy has witnessed rapid growth over the past decade, leading to an exponential increase in online financial transactions. The convenience of credit card payments in e-commerce, digital banking, and mobile wallets has significantly enhanced consumer experiences. However, this surge in digital transactions has also led to a rise in financial fraud, particularly credit card fraud. Fraudsters employ increasingly sophisticated methods, including identity theft, card skimming, phishing attacks, and account takeovers, to exploit vulnerabilities in financial systems. As a result, financial institutions face mounting pressure to implement robust fraud detection systems that can identify and prevent fraudulent activities in real time[1].

Credit card fraud is a significant concern for banks, payment processors, and regulatory bodies worldwide. According to recent financial reports, global losses due to payment fraud are projected to reach **$40.62 billion by 2027**, with credit card fraud accounting for a substantial share of these losses[2]. Traditional fraud prevention methods, including static rule-based systems and manual verification, have proven inadequate in detecting evolving fraud patterns. As fraudsters develop more advanced techniques, such as synthetic identity fraud and deepfake-based identity manipulation, the need for intelligent, automated fraud detection systems has become more critical than ever.

Beyond financial losses, credit card fraud has far-reaching consequences:

- **Customer Trust and Reputation Damage**: Frequent fraudulent transactions erode consumer confidence in financial institutions and payment service providers.
- **Regulatory Compliance Challenges**: Financial institutions must comply with stringent regulations such as the Payment Card Industry Data Security Standard (PCI DSS) and General Data Protection Regulation (GDPR) to protect consumer data and mitigate fraud risks.
- **Operational Costs and Chargebacks**: Fraudulent transactions result in costly chargebacks, legal disputes, and operational inefficiencies for banks and merchants[3].

Given these challenges, advanced fraud detection mechanisms must be fast, accurate, and adaptive to new fraud tactics. Artificial Intelligence (AI) has emerged as a powerful tool to enhance fraud detection, offering automated decision-making, real-time anomaly detection, and self-learning capabilities.

1.1 Limitations of Traditional Fraud Detection Methods

Conventional fraud detection methods, including rule-based systems and manual audits, have historically played a crucial role in mitigating fraud. However, these approaches exhibit significant drawbacks in handling high-dimensional, real-time transaction data and rapidly evolving fraud patterns.

- **Rule-Based Systems:** These rely on predefined rules to flag suspicious transactions, such as setting thresholds for transaction amounts or detecting unusual geographic locations.
  Limitations: These systems lack adaptability, leading to high false positive rates and inefficiency against dynamic fraud strategies.
- **Manual Audits:** Human experts analyze financial records to detect irregularities.
  Limitations: Labor-intensive and prone to errors, manual audits cannot scale efficiently to process millions of transactions in real time.
- **Statistical Methods:** Techniques such as regression analysis and clustering identify anomalies in transaction data.
  Limitations: These methods struggle with high-dimensional data and fail to capture non-linear fraud patterns effectively[4].

Given these limitations, AI-based fraud detection methods offer a more scalable and adaptive approach by learning from historical data and identifying evolving fraud patterns dynamically.

1.2 AI-Based Techniques in Fraud Detection

AI has transformed fraud detection by enabling real-time anomaly detection, reducing false positives, and improving adaptability to new fraud tactics. AI-driven fraud detection methods fall into three primary categories: Machine Learning (ML), Deep Learning (DL), and Anomaly Detection.

1.2.1 Machine Learning Algorithms

Machine learning (ML) techniques enhance fraud detection by identifying intricate transaction patterns that are difficult to detect using traditional approaches.

- **Supervised Learning Models**: These models are trained on labeled datasets containing both fraudulent and legitimate transactions.
  - **Decision Trees:** Generate interpretable fraud detection rules.
  - **Random Forest (RF):** Uses multiple decision trees to enhance detection accuracy and reduce overfitting.
  - **Support Vector Machines (SVM):** Effective in high-dimensional data but computationally intensive for large datasets.
  - **XGBoost**: An optimized gradient boosting technique known for its high predictive accuracy.
- **Unsupervised Learning Models:** Used when labeled fraud data is limited.
  - **K-Means Clustering**: Groups transactions into clusters and identifies outliers as potential fraud.
  - **Isolation Forest:** Specializes in anomaly detection by isolating rare fraudulent transactions.
- **Reinforcement Learning:** An adaptive AI approach that improves detection over time by learning from transaction outcomes[5].

1.2.2 Deep Learning Techniques

Deep learning has significantly enhanced fraud detection by utilizing advanced neural networks that can identify intricate fraudulent patterns within large-scale transactional datasets. These techniques improve accuracy, adaptability, and efficiency in detecting fraudulent activities across various domains. Some key deep learning techniques used for fraud detection:

- **Artificial Neural Networks (ANNs):** It is one of the powerful tools for fraud detection, capable of identifying complex patterns in financial transactions. Comprising input, hidden, and output layers, they process data using activation functions and optimize accuracy through backpropagation and gradient descent. ANNs effectively detect anomalies in credit card transactions, banking activities, and e-commerce fraud, identifying unusual spending, suspicious withdrawals, and fake accounts. Their high accuracy and adaptability make them valuable for evolving fraud patterns, but they require large datasets and high computational power, posing challenges for real-time detection[6].
- **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks:** Designed to analyze sequential data, making them highly effective in fraud detection. RNNs utilize a feedback loop to retain information from past transactions, enabling the detection of suspicious behavior. LSTMs improve upon RNNs by incorporating input, forget, and output gates to manage long-term dependencies in transaction sequences. These models are widely applied in detecting financial fraud by tracking user transactions, identifying anomalies in online payments, and monitoring cybersecurity threats such as unauthorized login attempts. Their main advantage lies in efficiently capturing temporal fraud patterns and handling sequential data better than traditional models. However, they require extensive training data and can be computationally expensive for real-time fraud detection[7].
- **Autoencoders:** Unsupervised neural network technique used for fraud detection by identifying anomalies in transaction patterns. They consist of an encoder, which compresses data, and a decoder, which reconstructs it, learning normal transaction behaviors. Any significant deviation from these learned patterns is flagged as fraudulent. Autoencoders are widely applied in credit card fraud detection (spotting unusual spending behaviors), insurance fraud (detecting false claims), and healthcare fraud (finding billing discrepancies). Their key advantages include the ability to work with unlabeled data, reducing manual effort, and detecting previously unknown fraud patterns. However, they may generate false positives if legitimate transactions vary widely and require careful tuning to optimize detection accuracy [8].

1.3 Challenges in AI-Based Fraud Detection

While AI-based fraud detection techniques offer substantial advantages, they also introduce challenges:

- **Data Imbalance:** Fraudulent transactions are rare compared to legitimate ones, leading to biased model predictions. Techniques like SMOTE (Synthetic Minority Over-sampling Technique) and cost-sensitive learning are often used to mitigate this issue.
- **False Positives vs. False Negatives:** AI models must balance high recall (detecting fraud accurately) with precision (reducing false alarms) to prevent legitimate transaction declines.
- **Real-Time Detection Requirements**: Many AI models require significant computational power, limiting their deployment in high-speed financial systems.
- **Adversarial Attacks:** Fraudsters manipulate AI models using adversarial techniques to evade detection, necessitating robust security measures.
- **Explain ability and Transparency**: AI models, especially deep learning techniques, often function as "black boxes," making it difficult to interpret fraud detection decisions[9].

The study provides comprehensive insights into how AI-powered models enhance fraud detection while addressing scalability, adaptability, and real-time processing constraints.

1.4 Objective of the Study

The objective of the study is to compare the performance of various AI-based techniques—machine learning (ML) and deep learning (DL)—in credit card fraud detection, using a publicly available dataset. This involves:

- Evaluating the effectiveness of different models in terms of accuracy, precision, recall, and F1-score.
- Investigating how these models handle issues like class imbalance in fraud detection.
- Providing insights into the practical application of these models in real-world scenarios

II. LITERATURE REVIEW

The detection of credit card fraud has become a critical area of research due to the increasing reliance on digital transactions and the associated risks. Over the years, various machine learning (ML) and deep learning (DL) techniques have been proposed to address this challenge. This literature review synthesizes findings from 14 key studies published between 2017 and 2024, highlighting the evolution of methodologies, comparative analyses, and advancements in fraud detection systems.

Awoyemi et al. (2017) conducted one of the earliest comparative studies on credit card fraud detection using machine learning techniques. They evaluated algorithms such as Decision Trees, Random Forests, and Support Vector Machines (SVMs) on a real-world dataset. Their findings indicated that ensemble methods, particularly Random Forests, outperformed other models in terms of accuracy and fraud detection rates. This study laid the groundwork for subsequent research by emphasizing the importance of model selection and feature engineering[10]. Dal Pozzolo et al. (2017) introduced a realistic modeling approach for fraud detection, addressing the issue of imbalanced datasets, which is a common challenge in fraud detection. They proposed a novel learning strategy that adapts to the changing nature of fraud patterns over time. Their work highlighted the significance of dynamic model updating and the use of resampling techniques to improve detection performance[11]. Varmedja et al. (2019) explored various machine learning methods, including Logistic Regression, k-Nearest Neighbors (k-NN), and Naive Bayes, for credit card fraud detection. They emphasized the importance of preprocessing steps such as normalization and feature selection in enhancing model performance. Their study provided a comprehensive comparison of traditional ML algorithms, offering insights into their strengths and limitations[12]. Asha and KR (2021) focused on the use of Artificial Neural Networks (ANNs) for credit card fraud detection. They demonstrated that ANNs, with their ability to model complex non-linear relationships, could achieve high accuracy in detecting fraudulent transactions. However, they also noted the challenges associated with training ANNs, such as the need for large datasets and computational resources[13]. Voican (2021) explored the use of deep learning techniques, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, for credit card fraud detection. The study demonstrated that deep learning models could capture temporal dependencies in transaction data, leading to improved detection rates compared to traditional ML methods[14]. Zioviris et al. (2022) proposed a multistage deep learning model for credit card fraud detection. Their approach involved multiple layers of feature extraction and classification, which significantly improved the model's ability to detect sophisticated fraud patterns. This study underscored the potential of combining multiple deep learning architectures for enhanced performance[15]. Bin Sulaiman et al. (2022) provided a comprehensive review of machine learning approaches for credit card fraud detection. They discussed the evolution of techniques from traditional ML to deep learning and highlighted the importance of explainability and interpretability in fraud detection models. Their review also emphasized the need for continuous model evaluation and adaptation to emerging fraud patterns[16]. Ashraf et al. (2022) conducted a comparative analysis of machine learning and deep learning techniques for credit card fraud detection. They found that deep learning models, particularly CNNs and LSTMs, outperformed traditional ML models in terms of detection accuracy. However, they also noted that deep learning models require more computational resources and longer training times[17]. Mienye and Sun (2023) proposed a deep learning ensemble approach combined with data resampling techniques to address the class imbalance problem in fraud detection. Their study demonstrated that ensemble methods, such as stacking and boosting, could significantly improve the robustness and accuracy of fraud detection systems[18]. Paulraj (2024) explored the use of 1D Convolutional Neural Networks (1D-CNNs) for credit card fraud detection. The study highlighted the ability of 1D-CNNs to capture local patterns in transaction data, leading to improved detection rates. This work introduced a novel approach to leveraging CNNs for sequential data in fraud detection[19]. Chang et al. (2024) investigated advanced machine learning techniques, including Gradient Boosting Machines (GBMs) and XGBoost, for credit card fraud detection. Their study emphasized the importance of hyperparameter tuning and model interpretability in developing effective fraud detection systems[20]. Gandhar et al. (2024) provided a comprehensive overview of fraud detection using both machine learning and deep learning techniques. They discussed the integration of ML and DL models to create hybrid systems that leverage the strengths of both approaches. Their study also highlighted the importance of real-time fraud detection and the challenges associated with deploying these systems in production environments[21]. Aslam and Hussain (2024) conducted a performance analysis of various machine learning techniques for credit card fraud detection. They compared traditional ML models, such as Decision Trees and SVMs, with more advanced techniques like XGBoost and LightGBM. Their findings indicated that advanced ensemble methods consistently outperformed traditional models, particularly in handling imbalanced datasets[22].

The literature reviewed demonstrates a clear evolution in credit card fraud detection techniques, from traditional machine learning models to advanced deep learning architectures. Key themes that emerge include the importance of addressing class imbalance, the need for dynamic model updating, and the potential of hybrid and ensemble approaches.

III. RESEARCH METHODOLOGY

This study aims to compare the performance of various AI-based techniques—machine learning (ML) and deep learning (DL)—in credit card fraud detection. The methodology involves the use of a publicly available credit card transaction dataset to train, evaluate, and compare different models. The study is structured into several key phases: data pre-processing, model training, evaluation metrics, and comparison of results.

3.1 Dataset

The dataset used in this study is the publicly available Credit Card Fraud Detection Dataset from Kaggle, which consists of anonymized transaction data, including features such as transaction amount, user demographics, and transaction time. The dataset contains both legitimate and fraudulent transactions, with a class imbalance, as fraudulent transactions represent a small proportion of the total.

3.2 Data Pre-processing

The raw dataset undergoes several pre-processing steps:

- **Handling Imbalanced Data**: Since fraudulent transactions are underrepresented, techniques like **SMOTE** (Synthetic Minority Over-sampling Technique) are employed to balance the dataset.
- **Feature Selection**: The dataset contains many features, but not all are relevant. We use feature selection techniques such as **Recursive Feature Elimination (RFE)** to identify the most important features for model training.
- **Normalization**: To ensure that all features contribute equally to the model, the dataset is normalized using standard scaling methods to transform each feature to a range suitable for ML and DL models.
- **Splitting the Dataset**: The dataset is split into a training set (80%) and a test set (20%) for model evaluation.

3.3 Machine Learning Models

Several machine learning models are trained and evaluated on the pre-processed dataset. These models include: Random Forest (RF), Support Vector Machine (SVM), XGBoost, K-Nearest Neighbors (KNN). Each model is evaluated using cross-validation to ensure stability and robustness in performance.

3.4 Deep Learning Models

For deep learning techniques, the following models are trained and evaluated: Artificial Neural Networks (ANNs), Autoencoders, Long Short-Term Memory (LSTM). These models are trained using backpropagation, with hyper-parameters tuned via grid search to optimize performance.

3.5 Evaluation Metrics

To evaluate the performance of the models, the following metrics are used:

- **Accuracy**: The overall percentage of correctly classified transactions.
- **Precision**: The proportion of true positives out of all positive predictions, indicating how many of the flagged transactions are indeed fraudulent.
- **Recall**: The proportion of true positives out of all actual fraudulent transactions, reflecting the model's ability to detect fraud.
- **F1-Score**: The harmonic mean of precision and recall, providing a balanced measure of model performance, especially in imbalanced datasets.
- **AUC-ROC (Area Under the Curve - Receiver Operating Characteristic)**: Preferred metric for anomaly detection, indicating the model's ability to distinguish between fraudulent and legitimate transactions.

3.6 Experimental Setup

The experiments are conducted using Python with libraries such as scikit-learn, TensorFlow, and Keras for model implementation. All models are trained on a single machine, and hyper-parameter optimization is performed using grid search with cross-validation. To mitigate overfitting, early stopping and dropout techniques are applied in the deep learning models.

IV. RESULT AND DISCUSSION

The experimental results are based on evaluating multiple machine learning (ML) and deep learning (DL) models on the credit card fraud detection dataset. The models were assessed using four key performance metrics: Accuracy, Precision, Recall, and F1-Score, along with the AUC-ROC score, which measures the model's ability to distinguish between fraudulent and non-fraudulent transactions.

Table 1 presents a comparative analysis of the evaluated models. The LSTM model achieved the highest accuracy **(98.3%)**, followed closely by XGBoost **(98.2%)** and ANNs **(98%).** Among the traditional ML models, XGBoost performed best, while Random Forest **(97.5%)** and SVM **(96.8%)** demonstrated slightly lower accuracy. These results indicate that deep learning models outperform traditional machine learning models in fraud detection. Precision, which measures the ability to minimize false positives, was highest for LSTM (**95.8%**) and XGBoost (**95.3%**), suggesting that these models effectively reduce incorrect fraud classifications. In terms of recall, which indicates the model's ability to correctly identify fraudulent transactions, LSTM (**92.1%**) and ANNs (**91.2%**) performed the best.

Table 1: Performance Comparison of Machine Learning and Deep Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Random Forest (RF)	97.5	94.2	88.1	91	97.2
Support Vector Machine (SVM)	96.8	92.1	85.4	88.6	96.5
XGBoost	98.2	95.3	90.5	92.8	98
Artificial Neural Networks(ANNs)	98	94.7	91.2	92.9	97.8
Recurrent Neural Networks(RNNs)	97.8	94.5	90.8	92.6	97.6
Long Short-Term Memory (LSTM)	98.3	95.8	92.1	93.9	98.2

The **F1-score**, which balances precision and recall, was also highest for LSTM (**93.9%**), followed by ANNs (**92.9%**) and XGBoost (**92.8%**). Additionally, the AUC-ROC score, which evaluates the model's ability to distinguish between fraudulent and non-fraudulent transactions, was **98.2%** for LSTM and **98%** for XGBoost, confirming their strong performance.

The comparative analysis suggests that deep learning models, particularly LSTM and ANNs, are highly effective in detecting fraudulent activities. However, XGBoost, an ensemble-based machine learning model, demonstrated competitive performance, making it a strong alternative for real-time fraud detection, especially in scenarios where computational efficiency is a concern. While deep learning models excel in capturing complex fraud patterns, they require significant computational resources, which may limit their practicality in certain applications.

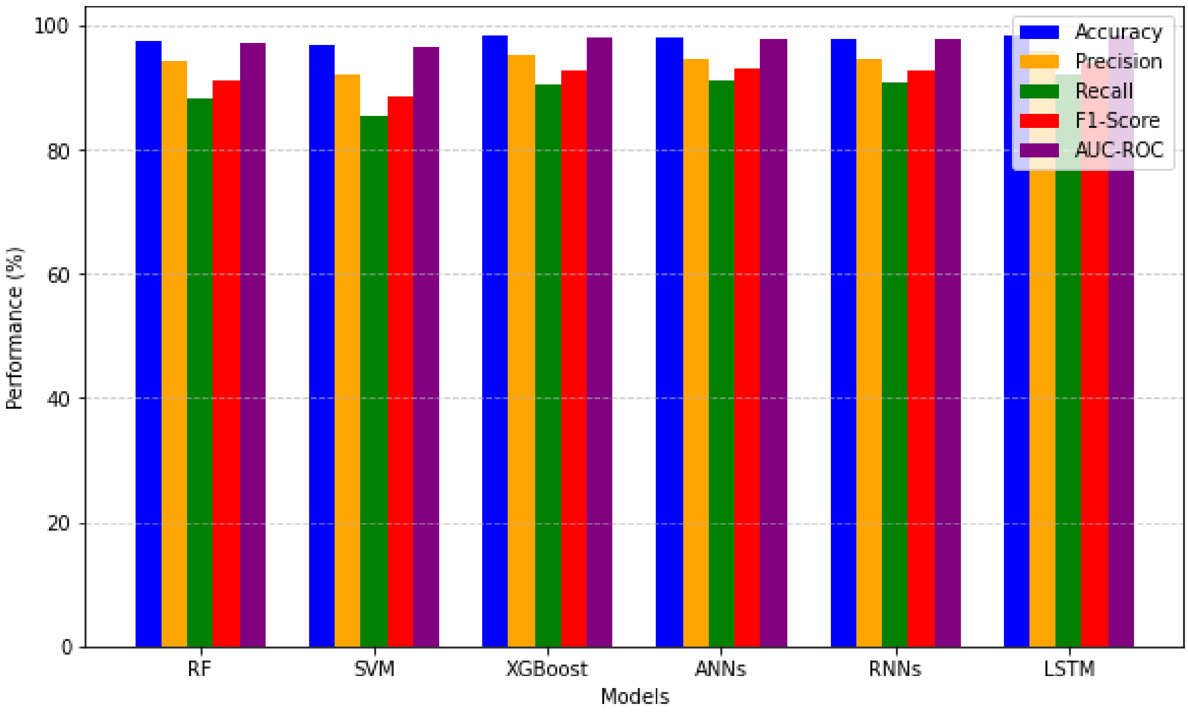

Figure1. Performance Comparison of Machine Learning and Deep Learning Models

The graphical representation in Figure 1 further illustrates the performance of these models, emphasizing the superiority of deep learning techniques. However, trade-offs between precision and recall must be considered. Some models, such as Random Forest, achieved high precision but slightly lower recall, leading to potential false negatives, which can be costly in fraud detection. Overall, the results indicate that financial institutions and fraud detection systems should carefully balance accuracy, computational efficiency, and real-time processing capabilities when selecting an optimal model for fraud detection.

V. Conclusion and Future Scope

This study compared machine learning and deep learning models for credit card fraud detection using accuracy, precision, recall, and F1-score. The results show that deep learning models, particularly LSTM and ANNs, achieved higher accuracy and recall than traditional models. LSTM performed the best with 98.3% accuracy, followed by XGBoost (98.2%) and ANNs (98%), demonstrating the effectiveness of deep learning. However, machine learning models like RF and SVM remain suitable for real-time applications due to their lower computational cost.

Future research should focus on optimizing deep learning models for real-time fraud detection while maintaining accuracy. Hybrid models combining machine learning and deep learning can improve efficiency. Enhancing model interpretability through explainable AI (XAI) will increase trust in automated systems. Additionally, addressing adversarial attacks can improve security. Technologies like block-chain and federated learning could further enhance privacy and decentralization.

In summary, while deep learning models excel in fraud detection, improving their efficiency, transparency, and robustness is crucial for real-world implementation.

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