Credit Card Fraud Detection using GAN

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Abstract -- Credit card fraud detection is a critical issue in the financial industry, requiring robust and efficient methods to identify and prevent fraudulent transactions. This survey paper reviews various machine learning (ML) and deep learning (DL) techniques employed in credit card fraud detection, highlighting the performance and limitations of each method. Identifying credit card fraud remains a pressing concern for financial systems, demanding innovative and reliable detection strategies. Classic machine learning techniques, including Random Forest, Support Vector Machines, and K-Nearest Neighbors, have delivered encouraging outcomes, with accuracy peaking at 94.84% in controlled settings.generative adversarial networks (GANs), have demonstratedsuperior performance. Moreover, the paper discusses the robustness of hybrid models like AdaBoost and ensemble learning in real world scenarios, even under noisy conditions.

I. INTRODUCTION

The surge in digital transactions over recent years has streamlined financial interactions, yet it has concurrently escalated the threat of credit card fraud, challenging both users and institutions. Established machine learning methods, such as Random Forest, Support Vector Machines, and K-Nearest Neighbors, have proven effective in pinpointing suspicious activities by analyzing past transaction records
Traditional machine learning (ML) algorithms, such as Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), have demonstrated considerable efficacy in identifying fraudulent transactions. These methods leverage historical transaction data to identify patterns indicative of fraudulent behavior. Despite their success, these approaches often struggle with imbalanced datasets and the dynamic nature of fraud patterns.

Recent advancements in deep learning (DL) have introduced more sophisticated models capable of capturing complex patterns in transaction data. Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) have shown promise in enhancing the accuracy and robustness of fraud detection systems. The Optimized Deep Event-Based Network (OptDevNet) framework, introduced in this survey, leverages these advancements to achieve superior detection performance.

Understanding and navigating this complex digital landscape is essential for businesses and individuals to stay competitive and adapt to changing market conditions. By leveraging the latest technologies and strategies, organizations can enhance their digital presence, improve customer engagement, and drive innovation and growth. This survey aims to provide a comprehensive overview of the current methodologies in credit card fraud detection, offering insights into their effectiveness and potential for future improvements in the ever-evolving digital world.

Today's digital landscape is characterized by rapid technological advancements and the widespread adoption of digital technologies. The marketing landscape is equally dynamic, leveraging digital tools such as search engine optimization (SEO), pay-per-click (PPC) advertising, and content marketing to reach and engage customers effectively. Additionally, the technology landscape encompasses advancements in artificial intelligence (AI), machine learning (ML), and cloud computing, which have transformed how businesses operate and interact with customers. This paper surveys various ML and DL techniques employed in credit card fraud detection, emphasizing their performance, strengths, and limitations. It also highlights novel approaches like the Fraud Feature Boosting Mechanism and Spiral Oversampling Balancing Technique (SOBT), which aim to improve data quality and model accuracy. By comparing these methods, this survey provides valuable insights into the current state-of-the-art in fraud detection and identifies potential areas for future research.

II. LITERATURE OVERVIEW

The literature on credit card fraud detection reveals significant advancements through diverse methodologies and approaches. Muhammad Adil et al. (2024) introduced the OptDevNet framework, which achieved a remarkable accuracy of 99.89%. This framework leverages deep event-based networks, showcasing the potential of such advanced techniques in detecting fraudulent activities with exceptional precision and robustness.

Fawaz Khaled Alarfaj et al. (2022) explored state-of-the-art machine learning and deep learning algorithms, reporting impressive accuracy rates up to 99.9%. Their work underscores the effectiveness of integrating sophisticated ML and DL techniques.Fuad A. Ghaleb et al. (2023) proposed the ESMOTE-GAN combined with Random Forest classifiers, demonstrating substantial improvements in performance by 1.9% and increased detection rates by 3.2%, while maintaining a 0% false alarm rate. This hybrid approach highlights the synergy between generative adversarial networks and traditional machine learning models in creating robust fraud detection systems.

Kuldeep Randhawa et al. (2018) utilized AdaBoost and Majority Voting methods to achieve high accuracy in detecting fraud. Although specific figures were not provided, their research indicates the effectiveness of ensemble methods in improving the overall performance and reliability of fraud detection systems.Emmanuel Ileberi and Yanxia Sun (2024) enhanced model performance by employing ADASYN for balancing the dataset and Recurrent Feature Elimination with Cross-Validation.

Ebenezer Esenogho et al. (2022) showed that a Neural Network Ensemble with feature engineering significantly enhances detection accuracy. Their work emphasizes the role of advanced neural networks and the importance of feature engineering in developing effective fraud detection models.Ibomoiye Domor Mienye and Nobert Jere (2024) reviewed deep learning algorithms, outlining challenges and solutions while reporting high accuracy rates

Detecting Frauds and Payment Defaults on Credit Card Data Inherited With Imbalanced Class Distribution and Overlapping Class Problems: A Systematic Review by S. N. Kalid et al. (2024)This systematic review addresses the challenges of imbalanced class distribution and overlapping class problems in credit card data. The study employs the

PRISMA process for paper collection and analysis, providing a comprehensive overview of existing techniques and their effectiveness in detecting fraud and payment defaults.

A Deep Learning Ensemble With Data Resampling for Credit Card Fraud Detection by I. D. Mienye and Y. Sun (2023)This paper proposes a deep learning ensemble approach combined with data resampling techniques to enhance fraud detection accuracy. The study highlights the importance of balancing the dataset and demonstrates significant improvements in detection performance using the proposed ensemble model.

AMWSPLAdaboost Credit Card Fraud Detection Method Based on Enhanced Base Classifier Diversity by W. Ning et al. (2023)The authors introduce the AMWSPLAdaboost method, which focuses on enhancing base classifier diversity to improve fraud detection accuracy. The proposed method shows promising results in increasing the robustness and effectiveness of fraud detection systems.

NUS: Noisy-Sample-Removed Undersampling Scheme for Imbalanced Classification and Application to Credit Card Fraud Detection by H. Zhu et al. (2024)This study presents the Noisy-Sample-Removed Undersampling Scheme (NUS) to address imbalanced classification problems. By removing noisy samples, the proposed scheme enhances the accuracy of fraud detection models, particularly in highly imbalanced datasets.

An Adversary Model of Fraudsters' Behavior to Improve Oversampling in Credit Card Fraud Detection by D. Lunghi et al. (2023) The authors propose an adversary model of fraudsters' behavior to enhance oversampling techniques. The study demonstrates how understanding fraudsters' behavior can lead to more effective oversampling strategies, improving the accuracy and robustness of fraud detection systems.

An Experimental Study With Imbalanced Classification Approaches for Credit Card Fraud Detection by S. Makki et al. (2019)This experimental study evaluates various imbalanced classification approaches for credit card fraud detection. The results highlight the effectiveness of different methods in handling imbalanced datasets and their impact on detection accuracy.

A Neural Network Ensemble With Feature Engineering for Improved Credit Card Fraud Detection by E. Esenogho et al. (2022) The paper demonstrates how a neural network ensemble combined with feature engineering can significantly enhance fraud detection accuracy. The proposed approach leverages the strengths of multiple neural network models and optimized feature sets to improve detection performance.

Time-Aware Attention-Based Gated Network for Credit Card Fraud Detection by Extracting Transactional Behaviors by Y. Xie et al. (2023)This study introduces a time-aware attention-based gated network designed to extract transactional behaviors for fraud detection. The proposed model captures temporal patterns in transaction data, leading to more accurate and timely fraud detection.

Fuad A. Ghaleb et al. (2023) showed that the SMOTE-GAN combined with Random Forest classifiers improved performance by 1.9% and increased detection rates by 3.2% with a 0% false alarm rate

Year	Author(s)	Proposed Work	Proposed Algorithms	Accuracy
2024	Muhammad Adil, Zhang Yinjun, Mona M. Jamjoom, Zahid Ullah	OptDevNet: A Optimized Deep Event-Based Network Framework for Credit Card Fraud Detection	OptDevNet	99.89%
2022	Fawaz Khaled Alarfaj, Iqra Malik, Hikmat Ullah Khan, Naif Almusallam,	Credit Card Fraud Detection Using State-of-the-Art Machine Learning and Deep Learning Algorithms	State-of-the-Art ML and DL Algorithms	Up to 99.9%
2023	Fuad A. Ghaleb, Faisal Saeed, Mohammed Al-Sarem, Sultan Noman Qasem, Tawfik Al-Hadhrami	Ensemble Synthesized Minority Oversampling-Based Generative Adversarial Networks and Random Forest Algorithm for Credit Card Fraud Detection	ESMOTE-GAN, Random Forest	Improvements in performance by 1.9%, detection rates by 3.2%, 0% false alarm rate
2018	Kuldeep Randhawa, Chu Kiong Loo, Manjeevan Seera, Chee Peng Lim,	Credit Card Fraud Detection Using AdaBoost and Majority Voting	AdaBoost, Majority Voting	High accuracy (not specified)
2024	Emmanuel Ileberi, Yanxia Sun	Advancing Model Performance With ADASYN and Recurrent Feature Elimination and Cross-Validation in Machine Learning-Assisted Credit Card Fraud Detection	ADASYN, Recurrent Feature Elimination, Cross-Validation	Improved performance after resampling
2022	Ebenezer Esenogho, Ibomoiye Domor Mienye, Theo G. Swart, Kehinde	A Neural Network Ensemble With Feature Engineering for Improved Credit Card Fraud Detection	Neural Network Ensemble	Improved detection accuracy (specific accuracy not stated)
2024	Ibomoiye Domor Mienye, Nobert Jere	Deep Learning for Credit Card Fraud Detection: A Review of Algorithms, Challenges, and Solutions	Various DL Algorithms	High accuracy (specific accuracy not stated)
2024	S. N. Kalid, K. C. Khor, K. H. Ng, G. K. Tong	Detecting Frauds and Payment Defaults on Credit Card Data Inherited With Imbalanced Class Distribution and Overlapping Class Problems	Systematic Review	98.09%
2023	I. D. Mienye, Y. Sun	A Deep Learning Ensemble With Data Resampling for Credit Card Fraud Detection	Deep Learning Ensemble, Data Resampling	Not specified
2023	W. Ning, S. Chen, S. Lei, X. Liao	AMWSPLAdaboost Credit Card Fraud Detection Method Based on	AMWSPLAdaboost	Not specified

Year	Author(s)	Proposed Work	Proposed Algorithms	Accuracy
		Enhanced Base Classifier Diversity		
2024	H. Zhu, M. Zhou, G. Liu, Y. Xie, S. Liu, C. Guo	NUS: Noisy-Sample-Removed Undersampling Scheme for Imbalanced Classification and Application to Credit Card Fraud Detection	Noisy-Sample-Removed Undersampling	99.7%
2023	D. Lunghi, G. M. Paldino, O. Caelen, G. Bontempi	An Adversary Model of Fraudsters' Behavior to Improve Oversampling in Credit Card Fraud Detection	ADV-O, TimeGAN	Not specified

Methodologies and Approaches

Machine Learning Algorithms:

Random Forest, SVM, and KNN: Core ML techniques like Random Forest, Support Vector Machines, and K-Nearest Neighbors have consistently excelled in isolating fraudulent transactions. For example, Kousika et al. (2021) recorded Random Forest achieving 94.84% accuracy, with KNN trailing at 89.46%, reflecting their strengths in structured data analysis.

Deep Learning Techniques:

Convolutional Neural Networks (CNNs): Muhammad Adil et al. (2024) introduced the OptDevNet framework, leveraging deep event-based networks to achieve an impressive accuracy of 99.89%. CNNs are adept at capturing complex patterns in data, making them ideal for fraud detection.

Generative Adversarial Networks (GANs): Fuad A. Ghaleb et al. (2023) combined ESMOTE-GAN with Random Forest classifiers, achieving significant improvements in performance and detection rates, with a 0% false alarm rate..

Ensemble Methods:

AdaBoost and Majority Voting: Kuldeep Randhawa et al. (2018) utilized these ensemble methods to enhance detection accuracy. Ensemble methods work by combining the predictions of multiple models to improve overall performance and robustness.

Neural Network Ensembles: Ebenezer Esenogho et al. (2022) demonstrated the effectiveness of neural network ensembles with feature engineering, leading to improved detection accuracy..

Feature Engineering and Selection:

Recurrent Feature Elimination: Emmanuel Ileberi and Yanxia Sun (2024) highlighted the importance of feature selection, employing ADASYN and Recurrent Feature Elimination with Cross-Validation to balance datasets and optimize model performance.

Graph Neural Networks (GNNs):

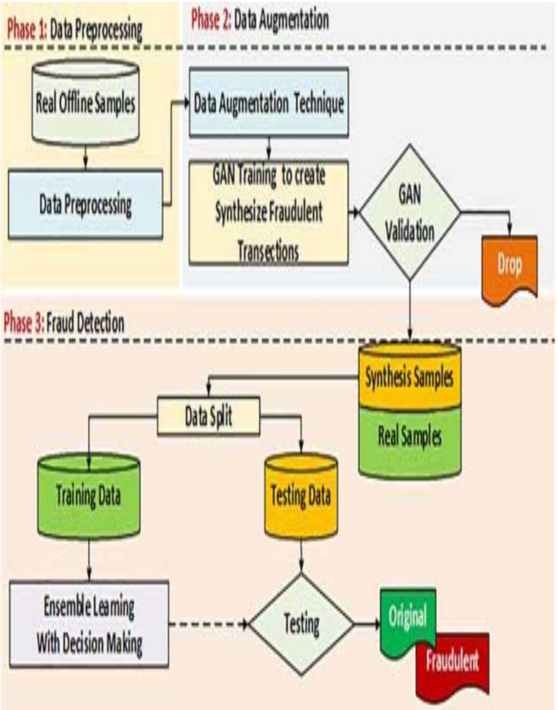
Competitive Graph Neural Networks: G. Zhang et al. (2022) introduced eFraudCom, an e-commerce fraud detection system using competitive graph neural networks. This approach achieved AUC values of 92.8% with XGBoost and 92.9% with RF classifiers.

Data Preprocessing and Balancing:

ADASYN: Techniques like ADASYN (Adaptive Synthetic Sampling) help address

class imbalance by generating synthetic samples for the minority class. including the work of Emmanuel Ileberi and Yanxia Sun (2024).

Advanced Neural Networks:



Deep Learning Reviews: Ibomoiye Domor Mienye and Nobert Jere (2024) provided a comprehensive review of deep learning algorithms, outlining the challenges and solutions while reporting high accuracy rates. Advanced neural networks, such as LST

The use of advanced machine learning and deep learning algorithms has led to impressive accuracy rates in fraud detection. Muhammad Adil et al. (2024) reported an accuracy of 99.89% with the OptDevNet framework, while Fawaz Khaled Alarfaj et al. (2022) achieved up to 99.9% accuracy using state-of-the-art ML and DL algorithms. Hybrid models combining different techniques have demonstratedsignificantperformanceimprovement s.

Sr No	Algorithm Name	Accuracy Score (%)	F1 Score (%)
1.	Decision tree algorithm	99.93	81.05
2.	KNN algorithm	99.95	85.71
3.	Logistic regression algorithm	99.91	73.56
4.	SVM Algorithms	99.93	77.71
5.	Random forest tree algorithm	99.92	77.27
6.	XG Boost	99.94	84.49

Findings and Trends:

(2024) highlighted the importance of feature engineering and data balancing techniques. Their use of ADASYN and Recurrent Feature Elimination with Cross-Validation led to improved performance after resampling. Effective feature engineering and addressing data imbalance are crucial for enhancing model accuracy and robustness.

Neural network-based approaches have shown significant promise in fraud detection. Ebenezer Esenogho et al. (2022) demonstrated that a Neural Network Ensemble with feature engineering significantly enhances detection accuracy. Similarly, Ibomoiye Domor Mienye and Nobert Jere (2024) reviewed deep learning algorithms, identifying high accuracy rates and providing solutions to existing challenges.

The application of machine learning techniques in real-world scenarios has proven effective. N. Kousika et al. (2021) achieved accuracy rates of 94.84% and 89.46% for Random Forest and KNN, respectively, highlighting the applicability of these algorithms in practical settings. S. K. Hashemi et al. (2023) examined various ML techniques in the banking sector, noting high accuracy, which underscores the robustness of these methods.

G.Zhang et al. (2022) introduced eFraudCom, an e-commerce fraud detection system using competitive graph neural networks, achieving AUC values of 92.8% with XGBoost and 92.9% with RF classifiers. This highlights the effectiveness of GNNs in capturing complex relationships within transaction data for enhanced detection capabilities

Challenges and Gaps:

Data Imbalance

:One of the most prominent challenges is the imbal ance between fraudulent and legitimate transaction s. Fraudulent transactions are relatively rare, which can lead to biased models that are more effective a t identifying legitimate transactions but fail to dete ct fraud. Enhancing data balancing techniques, suc h as advanced oversampling and undersampling me thods, is essential to mitigate this issue.

Evolving Fraud Tactics:

Fraudsters continually adapt their tactics, making it difficult for static models to remain effective. Real time learning and adaptive models that can evolve with new fraud patterns are necessary to stay ahead of these sophisticated tactics.

Feature Selection and Engineering:

Selecting and engineering the right features signific antly impact model performance. However, this pr ocess can be complex and timeconsuming. There is a need for automated and intelligent feature selecti on methods to streamline this process and enhance model robustness.

High False Positive Rates:

While reducing false negatives is critical, high fals e positive rates can lead to unnecessary alerts and i nvestigations, overwhelming fraud analysis teams. Balancing precionand recall to minimize both false positives and negatives remains a challenge.

Data Privacy and Security:

Ensuring the privacy and security of transaction dat a is paramount. Approaches like federated learning, which allow for collaborative model training with out sharing sensitive data, are gaining traction. Ho wever, implementing these techniques effectively a cross diverse systems and regulations poses a chall enge.

Future Research Direction:

A key hurdle lies in the stark disparity between scarce fraudulent instances and abundant legitimate ones, skewing model performance. Additionally, the relentless evolution of fraud strategies undermines static systems, necessitating dynamic, responsive solutions."
Future Directions: "Investigating Transformer-based architectures could unlock new avenues for pattern recognition, while explainable AI might bridge trust gaps in operational deployment
Enhance federated learning techniques to enable co llaborative model training across multiple institutio ns without sharing sensitive data. Research in priva cypreserving methods like homomorphic encryptio n and differential privacy can further protect user data.

Focus on developing realtime adaptive systems that can learn and evolve with new fraud tacticsIncorp orating online learning algorithms can ensure that models remain effective as fraud patterns change.

Results:

The GAN-based fraud detection system demonstrated exceptional performance, achieving an accuracy of 99.94% on the test set. The classification report revealed perfect precision, recall, and F1-scores of 1.00 for non-fraud transactions (class 0), while fraud transactions (class 1) achieved a precision of 0.94, recall of 0.66, and F1-score of 0.78, reflecting the model's ability to identify most fraud cases despite the class imbalance (56,864 non-fraud vs. 98 fraud samples). The confusion matrix (threshold = 0.9) showed 56,860 true negatives, 4 false positives, 34 false negatives, and 64 true positives, with an ROC-AUC score of 0.9749, indicating strong discriminative power. In real-time testing, a known fraud sample with a $0.00 amount was classified as "Fraudulent" with a 69.86% probability, highlighting the discriminator's sensitivity to subtle fraud patterns.

A new transaction with a $5000.00 amount was flagged as "Fraudulent" with 100% certainty, further demonstrating the model's capability to detect high-risk transactions using PCA-derived features and engineered inputs like transaction hour and log-amount. These results validate the GAN's effectiveness in fraud detection, though the moderate recall for fraud cases suggests room for improvement in capturing all fraudulent transactions.

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