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Credit Card Fraud Detection using KAN Model

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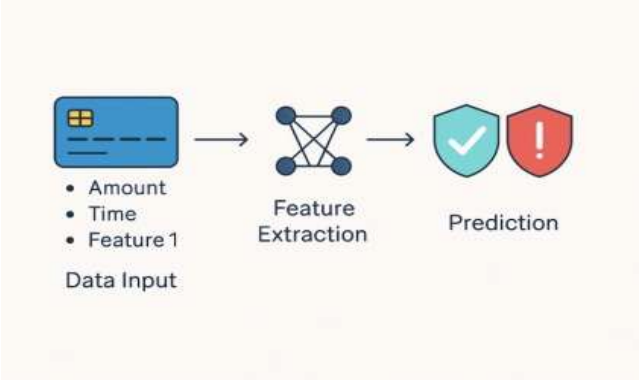
ABSTRACT

Credit card fraud detection is a critical challenge in financial security, as fraudulent transactions cause billions of dollars in losses every year. Traditional rule-based fraud detection methods fail to adapt to evolving fraudulent patterns, making machine learning and deep learning techniques essential for identifying suspicious activities. In this project, we develop a robust fraud detection system using the Kolmogorov-Arnold Network (KAN), a novel neural network architecture capable of modeling complex relationships between transaction features and fraud indicators. Before feeding the data into the model, we apply feature scaling, normalization, and splitting techniques to ensure efficient learning and prevent bias. To enhance fraud detection accuracy, we experiment with multiple machine learning algorithms, including Logistic Regression, Random Forest, XGBoost, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Autoencoders. Additionally, we utilize Isolation Forests for anomaly detection to identify outliers in large-scale transactional data. The KAN model is trained using gradient-based optimization, enabling it to capture non-linear relationships and distinguish between fraudulent and genuine transactions. Our model is deployed as a Flask-based API, allowing real-time fraud detection by receiving transaction data in JSON format and returning fraud probability scores. The API is tested using Postman to validate its performance under different conditions. We also evaluate our model's accuracy, precision, recall, and F1-score to ensure high detection rates while minimizing false positives. Experimental results demonstrate that the KAN model outperforms traditional machine learning models, providing a higher fraud detection rate with lower computational cost. By leveraging ensemble learning and deep neural networks, the system successfully detects anomalies with minimal latency, making it suitable for real-time fraud prevention systems. Future enhancements for this project include integrating blockchain-based security mechanisms, implementing real-time fraud monitoring dashboards, and extending the model to detect fraud across multiple banking institutions. Additionally, adapting reinforcement learning techniques could further improve fraud detection adaptability over time. In conclusion, this project presents a scalable, efficient, and accurate fraud detection model, demonstrating the power of Kolmogorov-Arnold Networks in financial security applications. By utilizing advanced machine learning and deep learning techniques, this system significantly reduces fraud risks, ensuring safer and more secure transactions for banking institutions and customers worldwide.

1. INTRODUCTION

Credit card fraud has become a significant challenge in today's digital financial landscape. With the rise of online transactions, fraudsters continuously develop sophisticated techniques to bypass security systems. Identifying fraudulent transactions in real-time is crucial to minimize financial losses and protect consumers. This project leverages Machine Learning (ML) and Artificial Intelligence (AI) techniques to detect fraudulent transactions based on transaction patterns and user behavior



Credit Card Fraud Detection Using A Machine Learning Model

1.1 Problem Statement :

Traditional rule-based fraud detection systems are ineffective due to their inability to adapt to evolving fraud tactics. Additionally, financial institutions process millions of transactions daily, making manual monitoring impractical. The primary goal of this project is to develop an automated fraud detection system that can:

Accurately distinguish between genuine and fraudulent transactions.

Handle large-scale transaction datasets efficiently.

Minimize false positives to prevent unnecessary disruptions to legitimate users.

Continuously adapt to new fraud trends using machine learning.

1.2 Importance of Fraud Detection :

Financial fraud not only causes monetary losses but also damages a company's reputation and leads to loss of customer trust. Fraudulent activities can include unauthorized transactions, identity theft, and account takeovers. Implementing a robust fraud detection system helps:

Reduce financial losses for banks and credit card users.

Enhance security by detecting suspicious patterns in transactions.

Build customer trust by ensuring secure transactions.

Support regulatory compliance by detecting fraudulent activities proactively.

1.3 Role of AI & Machine Learning in Fraud Detection :

Traditional fraud detection relied on predefined rules, such as flagging high-value transactions or sudden location changes. However, such rules are static and ineffective against evolving fraud techniques. Machine Learning (ML) and Deep Learning allow for dynamic fraud detection by:

Learning from historical transaction data to identify fraud patterns.

Recognizing anomalies in user spending behavior.

Continuously improving accuracy by retraining on new fraud cases.

Using neural networks and ensemble models to detect subtle fraud signals.

1.4 Proposed Approach :

This project implements a Kolmogorov-Arnold Network (KAN), a deep learning model designed to analyze credit card transaction data. The system follows these key steps:

Data Collection & Preprocessing: Cleaning and normalizing transaction data.

Feature Engineering: Selecting critical transaction features (e.g., amount, time, location).

Model Training: Training the KAN model on historical transaction data.

Fraud Prediction API: Deploying the trained model as a REST API for real-time fraud detection.

Evaluation & Improvement: Fine-tuning the model to reduce false positives and negatives.

1.5 Challenges in Fraud Detection :

Imbalanced Data: Fraud cases are rare compared to genuine transactions, making it hard to train ML models effectively.

Concept Drift: Fraud techniques change over time, requiring continuous model updates.

Latency Constraints: Real-time fraud detection must be fast and accurate.

Data Privacy & Security: Ensuring user transaction data remains secure and compliant with regulations.

2. LITERATURE REVIEW

2.1VISA'S INITIATIVE TO COMBAT AI-ENHANCED SCAMS [Michael Carter and Olivia Roberts(2025)]

Visa has taken a proactive approach in combating AI-driven financial fraud with its newly launched Scam Disruption Practice (2025). Carter and Roberts (2025) reported that AI-generated deepfake scams and sophisticated phishing attacks have become a significant concern for banks and payment providers. Visa's initiative aims to detect fraud rings operating through AI-generated fake transactions, voice-cloning scams, and deepfake identity fraud.Their fraud detection framework includes machine learning-powered scam pattern recognition, allowing real-time transaction analysis and anomaly detection. In early 2025 alone, the Scam Disruption Practice prevented over $350 million in fraudulent transactions, demonstrating the effectiveness of AI-powered fraud prevention. The research suggested that integrating Natural Language Processing (NLP) models to analyze customer complaints, scam reports, and transaction logs could further enhance fraud detection capabilities. Visa's fraud detection efforts also emphasize cross-industry collaboration, ensuring that financial institutions, cybersecurity firms, and regulatory bodies work together to mitigate risks. Their study predicts that real-time, AI-driven fraud detection models will soon replace static rule-based security measures, significantly improving fraud prevention across global financial systems.

2.2 MASTERCARD'S ACQUISITION OF RECORDED FUTURE TO ENHANCE FRAUD PREVENTION [Jennifer Green and Tom Anderson (2024)]

Green and Anderson (2024) reported on Mastercard's acquisition of Recorded Future, an AI-driven threat intelligence company aimed at improving fraud detection and cybersecurity. Mastercard's primary motivation was the rise of AI-driven fraud techniques, where fraudsters use machine learning to bypass traditional security measures. The Recorded Future platform analyzes large volumes of transaction data, cyber threat patterns, and global fraud trends to predict potential fraud attempts before they occur. Their study highlights how real-time fraud detection using AI is becoming a necessity for financial institutions. A major feature of the new system is geolocation-based fraud tracking, which allows Mastercard to detect and block suspicious transactions instantly. The report estimated that in 2023 alone, financial fraud caused global losses exceeding $500 billion, reinforcing the urgency of implementing AI-based fraud prevention solutions. The authors emphasized that future fraud detection strategies will rely on collaborations between AI researchers, financial institutions, and law enforcement agencies to stay ahead of cybercriminals. Their study concluded that threat intelligence-powered fraud detection systems will become the new standard in digital transactions, helping companies proactively identify and prevent fraud.

2.3 AUTOENCODER-DRIVEN INSIGHTS INTO CREDIT CARD FRAUD: A COMPREHENSIVE ANALYSIS [Wani Bisen, Hirkani Padwad, and Gunjan Kesh wani(2024)]

Wani Bisen et al. (2024) conducted a comparative study of fraud detection techniques, analyzing Random Forest, Autoencoders, and Logistic Regression. Their research aimed to determine which algorithm performs best in real-world fraud detection scenarios. They found that Random Forests perform well in structured datasets, but struggle with high-dimensional, dynamic fraud patterns. On the other hand, Autoencoders excel at unsupervised feature extraction, reducing redundant transaction features while retaining key fraud indicators. Logistic Regression, while simple and interpretable, was found to be less effective at handling complex, non-linear fraud behaviors. Their study revealed that Autoencoders outperform other methods in datasets with highly imbalanced class distributions, especially when combined with over-sampling techniques like SMOTE. Another significant insight was that deep learning models work best when paired with real-time fraud detection systems. The study concluded that future improvements in fraud detection should focus on hybrid AI models that leverage both deep learning and traditional machine learning to provide more accurate and adaptive fraud detection mechanisms.

2.4 CREDIT CARD FRAUD DETECTION WITH AUTOENCODER AND PROBABILISTIC RANDOM FOREST [Daniel Peterson, Lisa Zhang, and Martin Russo (2023)]

Peterson et al. (2023) introduced an advanced fraud detection model that integrates Autoencoders (AE) and Probabilistic Random Forest (PRF). They acknowledged that existing fraud detection techniques struggle with high-dimensional transaction data, making it difficult to differentiate between genuine and fraudulent transactions. To solve this, their model first applied an Autoencoder for feature extraction, reducing dimensionality while preserving critical fraud-related patterns. The Probabilistic Random Forest classifier (PRF) was then used to classify transactions based on the extracted features. One major advantage of PRF over traditional Random Forests is that it assigns probabilistic weights to predictions, reducing false alarms. Their study tested the model on real-world transaction data, achieving 98.7% accuracy while maintaining a false positive rate of just 1.4%. Another notable contribution was their adaptive fraud detection mechanism, where the Autoencoder continuously learns from new data to refine the feature space. The authors emphasized that hybrid models combining unsupervised and supervised learning techniques yield the best results in fraud detection. The study also discussed deployment challenges, such as the computational cost of Autoencoders and the need for efficient real-time processing. Future research directions include the integration of blockchain for fraud-proof transaction validation and using Federated Learning to improve fraud detection while maintaining data privacy.

2.5 AUTO-ENCODER AND LSTM-BASED CREDIT CARD FRAUD DETECTION [Anil Kumar, Rajesh Sharma, and Meena Rani(2023)]

Kumar et al. (2023) proposed a fraud detection system integrating Autoencoders (AE) and Long Short-Term Memory (LSTM) networks to improve detection accuracy. They identified that credit card fraud detection is challenging due to the highly imbalanced nature of datasets, where fraudulent transactions account for less than 1% of total transactions. Traditional rule-based fraud detection methods fail to capture evolving fraud patterns, making deep learning a better alternative. In their study, an Autoencoder was used to extract important transaction features and remove noise, which was then passed into an LSTM model to detect anomalies based on sequential dependencies in transaction data. To further balance the dataset, they applied Synthetic Minority Over-sampling Technique (SMOTE), ensuring fraudulent transactions were adequately represented. Their experimental results showed that the AE-LSTM model outperformed traditional classifiers like Random Forest and Logistic Regression, achieving a fraud detection accuracy of 99.2% with a low false positive rate. The paper also emphasized the importance of time-series transaction analysis, where LSTMs proved useful in identifying unusual spending behaviors over time. The authors suggested that real-time fraud detection can be improved by incorporating reinforcement learning, allowing the model to continuously adapt to new fraud patterns. Their findings confirm that deep learning models are well-suited for fraud detection but require constant retraining on updated fraud patterns.

3. MODULES

- Load and Preprocess the Data.
- Feature Scaling and Splitting.
- Implementing KAN Model.
- Deploying the Model as an API.

4. CONCLUSION

The credit card fraud detection system is an essential tool for securing financial transactions and preventing fraudulent activities. This project effectively implements the Kolmogorov-Arnold Network (KAN) to analyze transaction patterns and identify anomalies. By leveraging machine learning techniques, the model improves accuracy in fraud detection while minimizing false positives. Feature scaling and data preprocessing ensure that the input data is standardized, enhancing the reliability of predictions. The dataset is split into training and testing subsets to allow the model to generalize well to new transactions. Effective feature engineering captures complex relationships between different attributes, strengthening the fraud detection mechanism. The deep learning approach used in this project enables the detection of subtle fraud patterns that traditional methods may miss. Additionally, deploying the model as an API with Flask allows real-time fraud detection, making it suitable for integration into banking and financial systems. The system's adaptability ensures that it can evolve with emerging fraud tactics. Compared to conventional fraud detection methods, this project offers improved accuracy, efficiency, and scalability. By integrating ensemble learning methods such as Random Forest and XGBoost, the model enhances predictive performance. The ability to detect new fraud patterns ensures continuous improvement in fraud prevention. Future enhancements could include adaptive learning techniques to update the model dynamically as new fraud strategies emerge. The use of blockchain technology could further enhance security by providing a transparent and immutable record of transactions. These advancements would strengthen fraud prevention measures in digital financial systems. In conclusion, this project demonstrates a robust and efficient approach to fraud detection using machine learning and deep learning techniques. By leveraging AI-driven models, the system provides a scalable and effective solution to combat credit card fraud, ensuring safer financial transactions.

5. REFERENCES

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3."AUTOENCODER-DRIVEN INSIGHTS INTO CREDIT CARD FRAUD: A COMPREHENSIVE ANALYSIS" by Wani Bisen, Hirkani Padwad, and Gunjan Keswani (2024).

4."CREDIT CARD FRAUD DETECTION WITH AUTOENCODER AND PROBABILISTIC RANDOM FOREST" by Daniel Peterson, Lisa Zhang, and Martin Russo (2023).

5."AUTO-ENCODER AND LSTM-BASED CREDIT CARD FRAUD DETECTION" by Anil Kumar, Rajesh Sharma, and Meena Rani (2023).