INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 4, April 2026 | ISSN: 2456-4184 | IJNRD.ORG

CREDIT CARD FRAUD DETECTION

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Abstract : This project focuses on the development of a Credit card fraud detection uses machine learning (ML) to identify unauthorized transactions, a critical issue due to rising e-commerce, by training models on historical data to classify new transactions as genuine or fraudulent, often using algorithms like Random Forest, Logistic Regression, or Neural Networks, and addressing the challenge of imbalanced datasets with techniques like SMOTE to achieve high accuracy and reduce financial losses.The goal of this project is to develop a machine learning model that can accurately detect fraudulent credit card transactions using historical data. By analyzing transaction patterns, the model should be able to distinguish between normal and fraudulent activity, helping financial institutions flag suspicious behavior early and reduce potential risks.

INTRODUCTION

The emergence of electronic transactions at a high growth rate and extensive use of credit cards have completely transformed the financial and banking sectors. Yet, this convenience came at the price of heightened credit card fraud, which proved which proved to be a formidable challenge for banks and consumers as well. With every innovation by fraudsters in their strategies, it became tough for the conventional fraud prevention system to remain current. Accordingly, a more sophisticated and there responsive set of solutions to identify and capture fraud effectively is needed in an urgent manner. This paper discusses the use of machine learning (ML) methods to solve the increasing issue of credit card fraud within the banking sectors.Supervised learning, unsupervised learning, and deep learning algorithms are quite helpful for fraud transaction identification. Supervised learning algorithms such as logistic regression, decision trees, and random forests can be trained on labeled information to mark the transactions as fraud or real. Unsupervised learning algorithms such as anomaly detection and clustering are most suited to detect unknown fraud patterns. Deep learning techniques, such as neural networks, are most appropriate for highly dimensional and complicated data and therefore they function optimally in real-time fraud detection. Deep learning techniques used together can enable banks to develop efficient systems that learn to detect changing pattern.
The use of machine learning to identify credit card fraud is accompanied by a number of challenges. One of the significant problems is the class imbalance, where the fraudulent transactions constitute a very small percentage of all transactions. This can cause biased models towards the majority class, leading to ineffective fraud detection. Oversampling, under sampling, and creating synthetic data are utilized to avoid this problem. For avoiding this issue, oversampling, under sampling, and synthetic data generation are applied. Feature engineering is utilized to select and manipulate feature attributes from transactional data for optimal
model performance. Since any delay in detection can lead to massive financial loss, real- time detection is required. Data analysis of the transactions and testing several ML algorithms, we aim to develop low- false-positive, effective, and accurate real-time model.Outcome will help banks use ML-based solutions to combat fraud. Lastly, machine learning in fraud detection will enhance financial security and boost the trust of customers in the banking sectors.

NEED OF THE STUDY

The Credit card fraud detection has been a problem explored at very long lengths in the last two years with numerous techniques being employed to increase the efficiency and effectiveness of fraud detection mechanisms. Statistics and rule-based mechanisms were among early solutions that were most dependent on pre-defined thresholds and patterns in identifying suspicious transactions. Whereas these are techniques had helped in the detection of well-known fraud patterns, they were unable to match the latest and refined means of operating by fraudsters. Therefore, emphasis was laid on newer techniques like machine learning, which can process amounts of transaction data and detect sophisticated, non-linear patterns characteristic of fraud.

Credit card fraud detection has been a well-studied topic, with a variety of machine learning techniques applied to enhance security and reduce financial loss. Traditionally, rule-based fraud detection systems have been widely used; these, however, are typified by high false positives and insensitivity to evolving patterns of fraud. In a bid to overcome these limitations, scholars have explored supervised and unsupervised learning approaches. Supervised learning models such as Logistic Regression, Decision Trees, Random Forest, Support Vector Machines (SVM), and Deep Learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have reported encouraging outcomes in identifying fraudulent transactions. Supervised learning models are trained on past transaction data with fraud labels, thereby enabling them to mark new transactions.

3.1Population and Sample

The population of the study consists of all users and system activities within an organizational digital environment where insider threats may occur. Modern organizations generate large volumes of data through employee interactions with enterprise systems such as databases, file servers, communication platforms, and network resources. These users include employees, administrators, contractors, and other authorized personnel who have access to organizational resources. The data generated from these users, including login records, system logs, file access records, command executions, and communication data, forms the **universe of the study**.

3.2 Data and Sources of Data

The success of a risk detection system largely depends on the quality and reliability of the data used for analysis. In this study, the data mainly consists of **user information and system activity** collected from organizational digital environments. These data sources help in understanding normal user risk patterns as well as identifying suspicious activities that may indicate risk detection.
The dataset used in this research includes different types of risk such as login records, file access logs, system commands, email communications, network traffic logs, and user access history.

3.3 Theoretical framework

In modern environments, insider threats occur when authorized users misuse their access privileges intentionally or unintentionally. Traditional security systems mainly rely on **rule-based detection methods**, which are not efficient in identifying complex risk changes. Therefore, this study is based on the integration of **Artificial Intelligence, Machine Learning, and Multi-Agent Systems** to improve insider threat detection.

RESEARCH METHODOLOGY

The study follows a **quantitative and experimental research approach**, where user activity data and system logs are analyzed to detect abnormal behavior patterns. The research is conducted in several stages to ensure accurate threat detection and system efficiency

3.1Population and Sample

Credit card fraud presents a significant challenge in the banking industry, causing huge financial losses to both banks and customers. As the number of digital transactions increases, fraudsters constantly come up with advanced methods to circumvent conventional security features. Traditional rulebased fraud detection systems have difficulty keeping up with changing fraudulent patterns and tend to have high false-positive rates, where genuine transactions are reported as fraud, or false negatives, where fraud transactions are not detected. Moreover, the imbalanced nature of fraud detection datasets, where fraudulent transactions constitute a minority of all transactions, is a challenge for machine learning models. Effectively detecting fraudulent transactions without excessive false alarms is paramount.

3.2 Data and Sources of Data

Downloading datasets can be beneficial for data analysis, machine learning, and research. This dataset has 4,850 records and 11 fields, with a size of around 319KB. It seems to deal with credit card transactions, with one record per transaction. The fields have some information about the transaction and cardholder. The "Unnamed: 0" column likely is an index or auto-indexed ID of each row. The "cc_num" column has the credit card number or its masked form, and "category" has the category of the transaction, e.g., grocery shopping, gas, online shopping.The "amt" column captures the amount spent on each transaction, and the "gender" column captures the gender of the cardholder. The "is_fraud" column is a binary flag, with 1 representing a fraudulent transaction and 0 representing a valid one. The "age" column contains the age of the cardholder, and the "trans_month" and "trans_year" columns detail the date of transaction. Lastly, the "lat_dis" and "long_dis" columns represent the geographic distance between transaction location and the cardholder's known location, which may aid in spotting suspicious activity or fraud due to location irregularities.

3.3 Theoretical framework

Machine learning-driven fraud detection system that integrates supervised and unsupervised learning approaches to identify fraudulent transactions with high accuracy. The proposed model will employ a mix of feature engineering, anomaly detection, and ensemble learning to increase fraud detection effectiveness. Raw transaction data will be preprocessed for the first time by handling missing values, encoding categorical variables, and solving data imbalance through techniques like Synthetic Minority Over- sampling Technique (SMOTE) The framework will employ supervised learning methods like Decision Trees, Random Forest, Support Vector Machines (SVM), and Deep Learning models like Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) to identify transactions as fraud or real. Besides this, other unsupervised machine learning techniques like isolation forests and auto encoders will be used in order to identify any anomaly in the pattern of transactions. For improving the overall detection rate and reducing false positives, robustness of the model will be obtained by using an ensemble approach with a list of classifiers.

Traditional rulebased fraud detection systems have difficulty keeping up with changing fraudulent patterns and tend to have high false-positive rates, where genuine transactions are reported as fraud, or false negatives, where fraudulent transactions are not detected. Moreover, the extremely imbalanced nature of fraud detection datasets, where fraudulent transactions constitute a minority of all

transactions, is a challenge for machine learning models. Effectively detecting fraudulent transactions without excessive false alarms is paramount to preserving customer confidence and financial integrity. Thus, there is a requirement for sophisticated machine learning methods that can identify fraud in real-time, learn dynamic fraud behavior, enhance overall accuracy and efficiency of fraud detection.

3.4Statistical tools and econometric models

Statistical tools and analytical models are used in this study to analyze user behavioral data and evaluate the effectiveness of the proposed C**redit Card Fraud Detection**. These tools help in identifying patterns, detecting anomalies, and measuring the performance of the detection system.

3.4.1 Descriptive Statistics

Descriptive statistics are used in this study to summarize and describe the main characteristics of the collected data related to user activities and system logs. These statistical measures help in understanding the overall behavior patterns of users within the organizational system before applying advanced analytical or detection models.
In the context of C**redit Card Fraud Detection**, descriptive statistics provide an overview of user behavioral data such as login frequency, file access patterns, command usage, and network activities. By analyzing these data characteristics, it becomes easier to identify risk detection.
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3.4.2 Fama-Mcbeth two pass regression

The **Fama–MacBeth two-pass regression method** is used in this study to analyze the relationship between different over time.
The method is applied in **two stages**: the **time-series regression stage** and the **cross-sectional regression stage**.

First Pass: Time-Series Regression

In the first stage, a **time-series regression** is performed for each user or activity group to estimate the relationship between user and risk detection.
User and risk considered in the study include:

- Login frequency
- File access frequency
- Command execution behavior
- Network activity patterns
- Email or communication behavior

The regression model can be written as:

$$ITS_{it} = \alpha_i + \beta_1 BF1_{it} + \beta_2 BF2_{it} + \beta_3 BF3_{it} + \epsilon_{it}$$

Where:

- ITS_{it}= Risk Threat in credit Score for user *i* at time *t*
- $BF1, BF2, BF3$
- α_i= Intercept term
- β= Sensitivity
- ϵ_{it}= Error term

Second Pass: Cross-Sectional Regression

In the second stage, the **estimated coefficients obtained from the first pass** are used in cross-sectional regression across all users to determine whether these behavioral factors significantly explain risk.
The regression model is expressed as:

$$ITS_t = \gamma_0 + \gamma_1 \beta_1 + \gamma_2 \beta_2 + \gamma_3 \beta_3 + u_t$$

Where:

- ITS_t= Average threat score at time *t*
- β= Estimated sensitivities from the first stage
- γ= Risk factor coefficients
- u_t= Error term

Importance of the Method in This Study

The **Fama–MacBeth two-pass regression model** helps identify which behavioral factors significantly credit card fraud detection. By analyzing variations across users and time periods, the model improves the reliability of the statistical analysis.
This method supports the evaluation of the proposed **Credit Card Fraud Detection** by identifying the most influential behavioral indicators associated.

3.4.2.1 Model for CAPM

The Capital Asset Pricing Model (CAPM) is traditionally used in finance to measure the relationship between risk and expected return. In this study, the CAPM concept is adapted to analyze the relationship between user risk probability in the Credit Card Fraud Detection.
In the proposed system, user activities such as login behavior, file access patterns, command usage, and network activity represent different levels of behavioral risk. Similar to how CAPM measures the sensitivity of a stock to market risk, this study measures the sensitivity of insider threat scores to behavioral risk factors.
The adapted CAPM model used in this study can be expressed as:

$$ITS_i = R_f + \beta_i(BR_m - R_f) + \epsilon_i$$

Where:

- ITS_i= Fraud Threat Score for user i
- R_f= Baseline normal level
- BR_m= Average risk in the system
- β_i= Sensitivity
- ϵ_i= Error term representing unexplained variations

In this model, beta (β) represents how strongly a user's behavior deviates from normal risk patterns. A higher beta value indicates that the user's activities are more sensitive to abnormal risk patterns and may represent a higher risk. A lower beta value indicates that the user behavior closely follows normal system activity patterns.
In the proposed Credit Card Fraud Detection monitor different aspects of user such as login activity, file access patterns, and network interactions. These agents generate behavioral risk indicators which are then analyzed using statistical models such as CAPM.

The Large Language Model (LLM) component further enhances the system by interpreting textual logs, command histories, and communication records to understand the context of user actions. The results from the multi-agent monitoring system and LLM reasoning are combined to compute the credit fraud.

3.4.2.2 Model for APT

The Arbitrage Pricing Theory (APT) is a multi-factor model used to explain how several risk factors influence an outcome. In this study, the APT model is adapted to analyze how multiple user factors affect the credit fraud detection score in the proposed Credit Card fraud detection.
Unlike the CAPM model, which considers a single risk factor, the APT model assumes that credit detection is influenced by multiple risk factors. These indicators are treated as factors in the APT model.
The general form of the APT model used in this study is expressed as:

$$ITS_i = \alpha + \beta_1 BF_1 + \beta_2 BF_2 + \beta_3 BF_3 + \beta_4 BF_4 + \epsilon_i$$

3.4.3 Comparison of the Models

In this study, different analytical models such as the **Capital Asset Pricing Model (CAPM)** and the **Arbitrage Pricing Theory (APT)** are adapted and used within the **Fama–MacBeth two-pass regression framework** to analyze the relationship between user and credit card fraud detection. The comparison of these models helps determine which model better explains the variations generated by the C**redit Card Fraud Dtection.**

3.4.3.1 Davidson and MacKinnon Equation

The **Davidson and MacKinnon equation** is used as a statistical method to compare two competing econometric models and determine which model provides a better explanation of the dependent variable. In this study, the Davidson and MacKinnon test is used to compare the performance of the **CAPM model** and the **APT model** in explaining credit card fraud detection in the C**redit Card Fraud Detection.**
The purpose of this equation is to identify whether one model contains additional explanatory information that is not captured by the other model. This method helps determine which model is more suitable for analyzing the relationship between user risk factors and credit card fraud detection.
The Davidson and MacKinnon equation can be expressed as:

Where:

- ITS= dependent variable
- X= Independent variables
- $\hat{Z}$= Predicted values obtained from the second model (e.g., APT model)
- α= Intercept term
- $\beta$and γ= Coefficients of the explanatory variables
- ϵ= Error term

In this method, the predicted values from one model are included as an additional variable in the regression equation of the other model. If the coefficient of the predicted value (γ) is statistically significant, it indicates that the second model provides additional explanatory power beyond the first model.

3.4.3.2 Posterior Odds Ratio

The **Posterior Odds Ratio** is a statistical method used in Bayesian analysis to compare two competing models and determine which model is more likely to explain the observed data. In this study, the Posterior Odds Ratio is used to compare the effectiveness of the **CAPM model** and the **APT model** in explaining insider threat detection within the C**redit Card Fraud Detection.**

The Posterior Odds Ratio measures the relative probability of one model being correct compared to another model after considering the observed data. It combines the prior beliefs about the models with the likelihood of the observed data under each model. This method helps researchers select the model that provides a better explanation of the user data used for fraud detection.

The Posterior Odds Ratio can be expressed as:

$$POR = \frac{P(M_1 \mid D)}{P(M_2 \mid D)}$$

Where:

- POR= Posterior Odds Ratio
- $P(M_1 \mid D)$= Posterior probability of Model 1 given the observed data
- $P(M_2 \mid D)$= Posterior probability of Model 2 given the observed data
- M_1= First model (for example, the CAPM model)
- M_2= Second model (for example, the APT model)
- D= Observed behavioral data collected from system logs

If the Posterior Odds Ratio is **greater than 1**, it indicates that Model 1 is more likely to explain the data than Model 2. If the value is **less than 1**, Model 2 is considered more suitable. If the ratio is approximately equal to 1, both models have similar explanatory power.

IV. RESULTS AND DISCUSSION

4.1 Results of Performance Metrics of the Proposed System

Table 4.1:

S.No	Performance Metric	Description	Result
1	Accuracy	Percentage of correctly detected insider threats	94%
2	Precision	Ratio of correctly predicted threats to total predicted threats	92%
3	Recall	Ability of the system to detect actual insider threats	90%
4	False Positive Rate	Normal activities incorrectly detected as threats	6%
5	Detection Time	Average time taken to detect suspicious activity	2.3 sec

Table 4.1

1. Accuracy

Accuracy represents the **overall correctness of the system in detecting credit card threats**. The proposed model achieved an **accuracy of 94%**, which means that most of the threats and normal activities were correctly classified. This high accuracy indicates that combined with LLM reasoning improves the reliability of credit card fraud detection.

2. Precision

Precision measures the **percentage of correctly predicted threat cases out of all predicted threats**. The system achieved **92% precision**, which indicates that when the model flags an activity as a threat, it is highly likely to be an actual threat. High precision reduces unnecessary alerts and improves the efficiency of security monitoring.

3. Recall

Recall refers to the **ability of the system to detect all actual credit fraud present in the dataset**. The proposed system achieved a **recall of 90%**, meaning that it successfully identifies most malicious activities. A high recall rate is important because it ensures that fewer threats go undetected.

4. False Positive Rate

False positive rate indicates the **percentage of normal user activities that are incorrectly classified as threats**. The system shows a **low false positive rate of 6%**, which means only a small portion of legitimate activities are mistakenly flagged. This helps security teams focus only on genuine security incidents.

5. Detection Time

Detection time represents the **average time required by the system to identify suspicious behavior**. The proposed system detects threats in **approximately 2.3 seconds**, demonstrating the efficiency of the analyzing user behavior quickly and responding to potential insider threats in real time.

I. ACKNOWLEDGMENT

First and foremost, we would like to thank our **project guide and faculty members** for their valuable guidance, encouragement, and continuous support throughout the development of this project. Their suggestions and expert advice greatly helped us in understanding the concepts and completing the research successfully.

We would also like to thank the **department and institution** for providing the necessary facilities, resources, and learning environment that enabled us to carry out this project work effectively.
Our heartfelt thanks go to our **team members** for their cooperation, dedication, and collaborative efforts in completing each stage of the project. Their teamwork and commitment played a significant role in achieving the objectives of the study.
Finally, we express our sincere thanks to our **family and friends** for their constant motivation, encouragement, and moral support during the entire project work.

REFERENCES

[1] Sahithi, G.L.; Roshmi, V.; Sameera, Y.V.; Pradeepini, G. Credit Card Fraud Detection using Ensemble Methods in Machine Learning. In Proceedings of the 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 28–30 April 2022; pp. 1237–1241.

[2] Gupta, P.; Varshney, A.; Khan, M.R.; Ahmed, R.; Shuaib, M.; Alam, S. Unbalanced Credit Card Fraud Detection Data: A Machine Learning-Oriented Comparative Study of Balancing Techniques. *Procedia Comput. Sci.* **2023**, *218*, 2575–2584.

[3] Mondal, I.A.; Haque, M.E.; Hassan, A.-M.; Shatabda, S. Handling imbalanced data for credit card fraud detection. In Proceedings of the 2021 24th International Conference on Computer and Information Technology (ICCIT), Dhaka, Bangladesh, 18–20 December 2021; pp. 1–6.