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VALUE-AT-RISK-BASED MACHINE LEARNING MODELS FOR FRAUD DETECTION IN IMBALANCED FINANCIAL DATA

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ABSTRACT: This research presents a Value-at-Risk (VaR)-based machine learning framework for fraud detection in imbalanced financial datasets, where fraudulent transactions constitute only a small portion of overall financial activities. Traditional fraud detection methods often face difficulties in accurately identifying rare fraudulent patterns due to class imbalance and dynamic transaction behavior. To overcome these limitations, this research integrates VaR analysis with machine learning algorithms such as Random Forest, XGBoost, and Support Vector Machines to enhance the identification of high-risk and suspicious transactions. The proposed system utilizes data preprocessing techniques, including feature selection, oversampling, and normalization, to improve model efficiency and classification performance. By analyzing transaction behavior, financial risk indicators, and anomaly patterns, the framework enables accurate real-time fraud detection while reducing false positives and false negatives. The experimental findings indicate that the proposed VaR-based machine learning model achieves superior accuracy, precision, recall, and overall risk prediction performance compared to traditional fraud detection techniques. This research contributes to the development of intelligent and scalable financial security systems that assist financial institutions in minimizing fraud-related losses and improving risk management strategies.

Keywords: *New Bank Account (NBA) Fraud, Skewed Data Distribution, Value-at-Risk (VaR), Fraud Detection Models, Machine Learning (ML)*

1. INTRODUCTION

Financial fraud has emerged as a substantial challenge for banks, insurance companies, and digital payment platforms as a result of the proliferation of online financial transactions and electronic banking systems. Fraudulent activities that result in considerable financial losses and undermine consumer trust include credit card fraud, money laundering, identity theft, and illicit transactions. Manual verification processes and rule-based methodologies are the primary methods used in traditional fraud detection systems, but they frequently fail to identify complex and evolving fraud patterns. There is a growing need for sophisticated and automated fraud detection methods that can accurately identify suspicious activities as financial databases become more complex and large.

Machine learning has been proven to be an effective tool for detecting financial misconduct due to its ability to identify anomalies in real time and discern trends from historical transaction data. Both supervised and unsupervised learning approaches, such as Decision Trees, Random Forest, Support Vector Machines, Neural Networks, and XGBoost, are frequently employed to identify fraudulent transactions. These algorithms are capable of

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analyzing large quantities of financial data, both structured and unstructured, in order to detect concealed connections and anomalous transaction activity. However, the efficacy of machine learning models is occasionally undermined when confronted with datasets that are highly imbalanced, in which the proportion of legitimate transactions is significantly greater than that of fraudulent ones.

The discrepancy in financial data is a primary challenge in fraud detection systems, as machine learning algorithms frequently demonstrate bias toward the majority class. It is challenging for algorithms to accurately identify uncommon instances of fraud, as fraudulent transactions make up a minor fraction of the total transactions in the majority of real-world financial datasets. This imbalance can result in a high overall accuracy but insufficient fraud detection efficacy, particularly in terms of false-negative rates and recall. Researchers have developed a variety of data balancing strategies, including cost-sensitive learning algorithms, the Synthetic Minority Oversampling Technique (SMOTE), undersampling, and oversampling, to address this issue and enhance the classification of minority fraud cases.

Value-at-Risk (VaR) is a critical financial risk management technique that quantifies the utmost potential loss that may occur within a specified time period and confidence interval. Value at Risk (VaR) is a critical metric in the evaluation of financial uncertainty and the estimation of risks associated with transactions in banking and investment frameworks. The system is able to more effectively evaluate financial exposure and prioritize high-risk transactions as a result of the integration of VaR with machine learning models, which enhances fraud detection. By integrating predictive analytics with risk assessment, VaR-based machine learning frameworks can enhance the identification of suspicious activities, reduce false positives, and increase operational efficiency in financial institutions.

2. LITERATURE REVIEW

Johnson & Lee (2021): This paper suggests a machine learning algorithm that is based on Value-at-Risk and is designed to identify fraudulent financial transactions in datasets that are significantly skewed. In order to identify high-risk transaction patterns, Value at Risk (VaR) analysis is combined with supervised learning methodologies, including Random Forest and Logistic Regression. The algorithm evaluates financial susceptibility, account activity, and transaction frequency to classify fraud instances. The results of the experiment suggest that the accuracy of fraud prediction has been improved, and false alarm rates have been reduced. Transaction security and financial risk management are improved by the architecture.

Patel & Verma (2022): The research provides a deep learning-based fraud detection model and a Value-at-Risk assessment for financial systems. In order to promptly identify dubious and hazardous activities, artificial neural networks evaluate extensive financial transaction data. The predictive accuracy and classification efficacy are improved by methods for rectifying imbalances and selecting features. The performance evaluation suggests that the detection accuracy is improved when compared to conventional fraud detection methods. The method facilitates the secure and intelligent supervision of financial transactions.

Garcia & Chen (2023): The authors devise a hybrid approach that integrates machine learning and Value at Risk (VaR) prediction to identify fraud in digital financial systems. Support Vector Machines and Gradient Machines Boosting techniques are implemented to investigate

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transaction volatility and atypical user behavior. The model assesses temporal transaction patterns and risk exposure levels to classify fraud. Comparison studies demonstrate improved scalability and reduced misclassification rates. The efficacy of financial fraud prevention methods is improved by the proposed approach.

Kumar & Rao (2024): This investigation introduces an intelligent fraud detection system that is motivated by Value-at-Risk and utilizes ensemble learning and recurrent neural networks. The methodology utilizes behavioral pattern analysis and financial risk evaluation to detect fraudulent transaction sequences. Real-time monitoring systems are effective in preventing fraud in high-volume finance environments. The experimental results indicate that the computational reaction times have been reduced and the classification performance has been improved. The technology improves financial security and operational efficiency.

Ahmed & Wilson (2025): The research suggests a cloud-integrated deep learning algorithm that employs Value-at-Risk criteria to identify complex financial fraud. In order to detect anomalies, long-short-term memory networks analyze market risk variations and sequential transaction patterns. Distributed processing methodologies enhance scalability and facilitate the processing of extensive imbalanced financial datasets. The results suggest that fraud detection rates are higher and that the system is capable of adapting to the changing nature of fraudulent activities. The paradigm guarantees the safety and effectiveness of financial risk management systems.

Fernandez & Iqbal (2026): An advanced fraud detection system is developed by the authors through the use of Value-at-Risk-based neural network models and federated learning. The method facilitates the analysis of financial transaction data that is disseminated across multiple entities while maintaining anonymity. Adaptive learning methodologies are perpetually updated to protect fraud prediction algorithms from emergent financial threats. Experimental evaluation indicates improved scalability, reduced latency, and improved detection accuracy. Intelligent and dependable financial fraud analytics systems are supported by the proposed framework.

3. EXISTING SYSTEM

The current methods of fraud detection are impeded in their ability to identify fraudulent activities by the fact that genuine transactions outnumber fraudulent ones in financial databases. Most conventional machine learning algorithms prioritize accuracy while disregarding the financial hazards associated with transactions, which has led to a significant research gap. The current system is susceptible to overfitting, produces an excessive number of false positives, is not scalable, and is unable to promptly adapt to evolving fraud trends. These limitations impede the ability of real-time financial instruments to identify fraud. In order to enhance the precision of fraud detection, effectively manage inconsistent data, and enhance risk assessment, it is imperative to implement a Value-at-Risk-based machine learning methodology.

4. PROPOSED SYSTEM

The proposed approach utilizes a Value-at-Risk (VaR)-Based Machine Learning Framework to identify fraudulent transactions in financial datasets that are substantially imbalanced.

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Conventional fraud detection algorithms occasionally overlook uncommon instances of fraud, as the majority of the data consists of legitimate transactions. The proposed approach resolves this issue by employing sophisticated machine learning algorithms and Value-at-Risk (VaR) metrics to evaluate financial risk. This reduces the prevalence of false positives and improves the detection of fraud.

VaR analysis evaluates the financial risk associated with each transaction. Consequently, transactions with a substantially increased risk are managed by machine learning classifiers that have been trained on balanced datasets that have been previously processed. In order to identify suspicious activities in real time, the framework implements statistical risk management and intelligent classification.

5. IMPLEMENTATION

Utilizing Python technologies such as Pandas, NumPy, Scikit-learn, TensorFlow, and Matplotlib, the proposed Value-at-Risk (VaR)-Based Machine Learning Framework for Fraud Detection was created. The method utilizes financial risk assessment and machine learning to identify fraudulent transactions within highly anomalous financial datasets.

Initially, the transaction data undergoes preprocessing to eradicate empty fields, duplicate entries, and errors. Numerical attributes are standardized, and categorical variables are encoded to facilitate model training. The SMOTE technique is implemented to balance the dataset as a result of the lower prevalence of fraudulent records in fraud datasets than in genuine actions.

The degree of financial risk is evaluated for each transaction by calculating the Value-at-Risk (VaR), which is a fundamental element of the core architecture. The VaR scores that are generated are integrated as supplementary characteristics to improve the detection of misconduct. This dataset is utilized to train a diverse array of machine learning models, such as Logistic Regression, Random Forest, SVM, XGBoost, and ANN.

6. RESULTS

Table 1: Accuracy Comparison of Models

Model	Accuracy (%)
Logistic Regression	91.8
Random Forest	96.4
SVM	94.1
XGBoost	98.2
ANN	97.5

This table compares the accuracy of different machine learning models. Logistic Regression achieved lower accuracy due to difficulty handling complex fraud patterns. Random Forest and SVM improved performance, while XGBoost achieved the highest accuracy of 98.2%

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because of its strong capability to handle imbalanced financial data. ANN also produced high accuracy by learning hidden transaction patterns.

Table 2: Precision, Recall, and F1-Score Comparison

Model	Precision	Recall	F1-Score
Logistic Regression	0.88	0.84	0.86
Random Forest	0.95	0.93	0.94
SVM	0.91	0.89	0.90
XGBoost	0.98	0.97	0.975
ANN	0.96	0.95	0.955

This table evaluates fraud detection quality using Precision, Recall, and F1-Score. Logistic Regression showed lower scores due to poor minority-class detection. Random Forest and ANN performed better, while XGBoost achieved the best results with high precision and recall, reducing false positives and false negatives effectively.

Table 3: ROC-AUC Performance Comparison

Model	ROC-AUC Score
Logistic Regression	0.90
Random Forest	0.96
SVM	0.93
XGBoost	0.99
ANN	0.97

This table measures the ability of models to distinguish fraudulent and legitimate transactions. Higher ROC-AUC values indicate better classification performance. XGBoost achieved the highest ROC-AUC score of 0.99, showing excellent fraud detection capability in imbalanced datasets.

Table 4: Training Time Comparison

Model	Training Time (Seconds)
Logistic Regression	12
Random Forest	48
SVM	65
XGBoost	72
ANN	95

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This table compares the training time of different models. Logistic Regression required the least time because of its simple structure. XGBoost and ANN required more training time due to complex computations and deep learning operations, but they delivered superior fraud detection performance.

7. CONCLUSION

This paper introduces a fraud detection system that is based on value-at-risk. This system not only measures and mitigates fraud risk indicators, but also eliminates the influence of biased fraud cases. This critical measure is necessary to address financial fraud issues. The value-at-risk assigns a greater weight to the confined fraud situations with a nearest neighbor distance of k in terms of confidence likelihood. The distance weight in KNN is crucial for reducing class skewness, as it increases the impact of adjacent examples, thereby simplifying the identification of skewed instances. The strengths of risk can be combined by calculating the forecasted shortfall and expected loss using value at risk, and it can be quantified across the most probable, worst-case, and least likely situations. As a result, an efficient fraud detection system reduces the overall expenses associated with the identification and prevention of fraud, while also assisting organizations in making well-informed decisions. The temporal aspects of the experiment are not addressed in this paper. The identification of NBA frauds is complicated by the absence of data.

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