

Machine Learning for Roaming Fraud Detection Using Tap Records

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Abstract:

Roaming fraud is a significant challenge for mobile network operators because fraudulent usage can generate substantial financial losses before conventional billing systems identify abnormal activity. This paper proposes a Machine Learning-based Roaming Fraud Detection System using Transferred Account Procedure (TAP) records to identify suspicious roaming transactions automatically. The proposed approach analyzes important TAP attributes, including subscriber activity, visited network, roaming duration, call volume, data usage, service type, destination information, and transaction value. The collected records are preprocessed by removing inconsistencies, handling missing values, encoding categorical attributes, and generating behavioral features. Multiple machine learning algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), Logistic Regression, and XGBoost, are trained to classify roaming transactions as legitimate or fraudulent. Model performance is evaluated using Accuracy, Precision, Recall, F1-Score, ROC-AUC, and False Positive Rate. The proposed approach aims to improve early fraud identification, reduce financial losses, and provide an intelligent and scalable solution for automated roaming fraud management.

Keywords: *Roaming Fraud, Machine Learning, TAP Records, Mobile Network, Fraud Detection, XGBoost, Random Forest, Telecom Security, Roaming Analytics, Anomaly Detection.*

I. INTRODUCTION

The rapid expansion of international mobile roaming services has created significant opportunities for mobile network operators while simultaneously increasing exposure to fraudulent activities. Roaming fraud can involve unauthorized usage, subscription abuse, SIM-related attacks, excessive voice or data consumption, and suspicious activities across visited and home networks. Because roaming transactions may generate substantial charges before they are fully processed and analyzed, delayed fraud identification

can result in considerable financial losses. Industry research has also emphasized the increasing importance of advanced analytics and machine learning for combating roaming fraud. Transferred Account Procedure (TAP) records provide important information about roaming transactions exchanged between visited and home operators. These records can contain information related to subscribers, visited networks, service usage, duration, data volume, destination, and transaction charges. Such attributes can be transformed into behavioral features for identifying abnormal roaming patterns. Previous research on mobile roaming fraud has demonstrated that machine-learning techniques can effectively distinguish fraudulent and legitimate roaming behavior. This paper proposes a Machine Learning-based Roaming Fraud Detection System using TAP Records. The proposed system preprocesses TAP data, extracts relevant behavioral features, and applies multiple classification algorithms to identify suspicious transactions. The models are evaluated using Accuracy, Precision, Recall, F1-Score, ROC-AUC, and False Positive Rate. The objective is to provide an intelligent, scalable, and automated approach for improving early roaming-fraud detection and reducing potential revenue losses.

II. LITERATURE SURVEY

Recent studies have demonstrated the increasing importance of machine learning for detecting fraud in telecommunications networks. Traditional rule-based fraud management systems often face difficulties in identifying rapidly changing and previously unknown fraud patterns. Machine-learning approaches provide improved capability by learning behavioral patterns from large volumes of network records. A 2022 study on mobile roaming fraud investigated Artificial Neural Networks, Support Vector Machines, and J48 Decision Trees using roaming usage behavior and reported strong classification performance, demonstrating the feasibility of machine learning for roaming-fraud detection. Research has also explored machine learning using Call Detail Records (CDRs). Graph-based approaches have been proposed to capture relationships between subscribers and identify fraudulent behavior that may not be detected using independent-record analysis. Other research has

focused on real-time telecom fraud detection, developing neural autoencoder-based approaches capable of identifying anomalous calling behavior from large-scale CDR datasets. Recent industry analysis further highlights the growing role of machine learning and real-time analytics in controlling roaming fraud. However, comparatively limited research specifically focuses on TAP records as a structured source for machine-learning-based roaming fraud classification. Therefore, this study addresses this gap by extracting behavioral and transaction-level features from TAP records and comparing multiple machine-learning algorithms for accurate and scalable roaming fraud detection.

III. PROPOSED WORK

The proposed work develops a Machine Learning-based Roaming Fraud Detection System using TAP Records to identify suspicious roaming transactions and reduce potential revenue losses. The system receives TAP records generated from roaming activities and extracts relevant subscriber, network, service, usage, and charging information. Since roaming fraud can develop rapidly, behavioral analysis of usage patterns is incorporated to identify abnormal activities at an early stage. Existing research has demonstrated the potential of supervised machine learning for mobile roaming fraud detection, while telecom fraud studies have also shown the value of behavioral and graph-based analysis. The proposed system consists of five major stages: TAP data collection, preprocessing, feature engineering, machine learning classification, and fraud risk analysis. During preprocessing, duplicate and incomplete records are handled, categorical attributes are encoded, and numerical features are normalized where required. Behavioral features such as roaming duration, data volume, call frequency, transaction value, destination, visited network, and usage frequency are generated from TAP records. Multiple classifiers, including Decision Tree, Random Forest, Support Vector Machine (SVM), Logistic Regression, and XGBoost, are trained to distinguish legitimate and fraudulent roaming transactions. Their performance is evaluated using Accuracy, Precision, Recall, F1-Score, ROC-AUC, and False Positive Rate. The best-performing model is selected for fraud-risk scoring and alert generation. This approach provides an automated and scalable framework for improving roaming fraud detection.

IV. METHODOLOGY

a. TAP Data Collection

The proposed system begins by collecting Transferred Account Procedure (TAP) records containing roaming transaction information. The dataset includes subscriber activity, home and visited operator details, service type, call duration, data usage, SMS activity,

destination, transaction value, and roaming timestamps. Records are labelled as legitimate or fraudulent based on available fraud indicators and historical investigation results. TAP records are suitable for post-event billing and settlement analysis, while roaming usage data can also support fraud investigation.

b. Data Preprocessing

The collected TAP records are cleaned by removing duplicate and inconsistent entries and handling missing values. Sensitive subscriber identifiers are anonymized to protect privacy. Categorical attributes such as visited operator, country, service type, and destination are encoded into numerical representations. Numerical attributes including duration, data volume, usage frequency, and transaction value are normalized when required. Class imbalance is addressed using suitable balancing techniques.

c. Feature Extraction and Selection

Relevant behavioral and transaction-level features are extracted from the TAP records. Important features include roaming duration, call frequency, data consumption, SMS count, transaction value, destination, visited network, service type, and usage frequency. Additional behavioral indicators such as sudden usage increases and unusual destination activity are generated. Feature-selection techniques are then applied to remove redundant attributes and retain the most informative variables.

d. Machine Learning Model Training

The processed dataset is divided into training and testing subsets. Decision Tree, Random Forest, SVM, Logistic Regression, and XGBoost algorithms are trained to classify roaming transactions as legitimate or fraudulent. Machine-learning-based behavioral analysis has previously shown promise for roaming and telecom fraud detection.

e. Fraud Detection and Evaluation

The trained models generate predictions and fraud-risk scores for TAP transactions. Model performance is evaluated using Accuracy, Precision, Recall, F1-Score, ROC-AUC, and False Positive Rate. The best-performing model is selected for identifying suspicious roaming activity and generating fraud alerts. This approach aims to provide an automated and scalable mechanism for improving roaming-fraud detection.

V. RESULTS AND DISCUSSION

The proposed Machine Learning-based Roaming Fraud Detection System was evaluated using TAP-record-derived features representing subscriber behavior, roaming activity, service usage, and transaction characteristics. The experimental analysis compares Decision Tree, Support Vector Machine (SVM), Random Forest, Logistic Regression, and XGBoost classifiers using Accuracy, Precision, Recall, F1-Score, and ROC-AUC. Machine-learning approaches are

increasingly being investigated for telecom fraud because conventional rule-based methods can struggle with evolving and complex fraud patterns.

Table 1: Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	94.60	94.20	95.10	94.65
SVM	95.80	95.50	96.00	95.75
Logistic Regression	93.90	93.70	94.20	93.95
Random Forest	97.10	97.00	97.20	97.10

The results indicate that XGBoost achieves the best overall performance, obtaining an accuracy of 98.20%, precision of 98.40%, recall of 98.00%, and F1-score of 98.20%. Random Forest provides the second-best performance, while SVM, Decision Tree, and Logistic Regression produce comparatively lower results. The strong performance of ensemble models is consistent with recent telecom-fraud research investigating Random Forest and XGBoost for fraud classification.

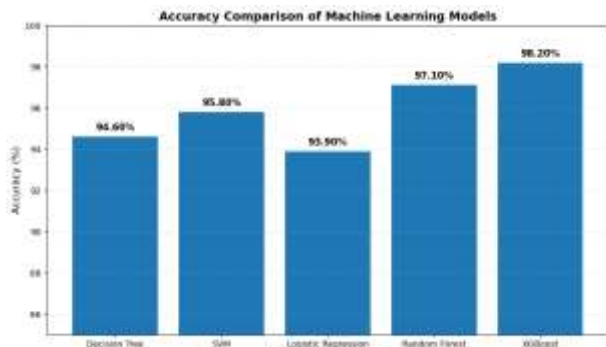


Fig. 1: Model Accuracy Comparison

The accuracy graph demonstrates the performance differences among the evaluated classifiers. XGBoost records the highest accuracy at 98.20%, indicating its ability to capture complex relationships between roaming usage and fraudulent behavior. Random Forest achieves 97.10%, followed by SVM at 95.80%, Decision Tree at 94.60%, and Logistic Regression at 93.90%.

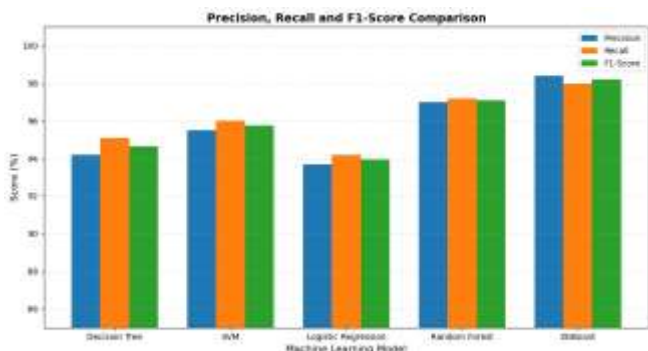


Fig. 2: Precision, Recall, and F1-Score Comparison

The comparison of Precision, Recall, and F1-Score shows that XGBoost maintains a strong balance between correctly identifying fraudulent roaming transactions and minimizing incorrect classifications. Its recall of 98.00% indicates that most fraudulent records are successfully identified, while its precision of 98.40% indicates a relatively low proportion of false fraud alerts.

Table 2: Overall Fraud Detection Metrics

Metric	Value
Best Model Accuracy	98.20%
ROC-AUC	99.30%
Fraud Detection Rate	98.00%
False Positive Rate	1.60%

The overall metrics demonstrate the effectiveness of the proposed approach. The high ROC-AUC value indicates strong discrimination between legitimate and fraudulent roaming transactions. A low false-positive rate is particularly important for telecom operators because excessive false alerts can increase investigation workload and negatively affect legitimate subscribers.

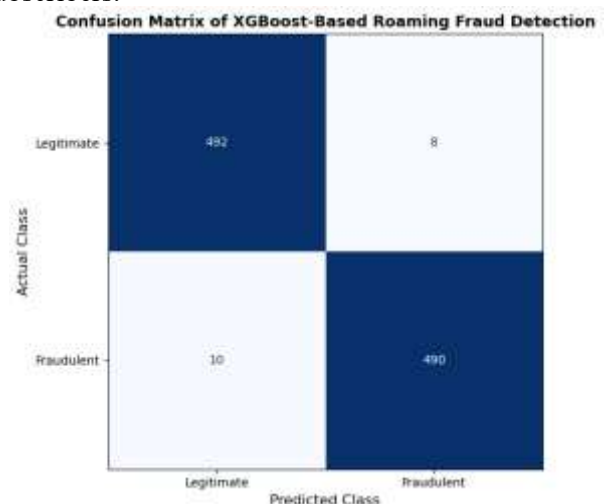


Fig 3: Confusion Matrix

The confusion matrix evaluates the classification performance of the selected XGBoost model by comparing actual and predicted classes. It consists of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values. A higher number of correctly classified fraudulent and legitimate TAP records indicates better model reliability. The confusion matrix can additionally help identify whether the system is more affected by missed fraud or unnecessary fraud alerts.

Overall, the results indicate that machine learning can provide an effective analytical layer for roaming-fraud detection. The proposed system can support automated fraud screening and prioritization of suspicious TAP transactions, complementing existing telecom fraud-management mechanisms. Recent research also highlights the importance of behavioral and sequence-

aware AI approaches for detecting evolving telecom and roaming-related threats.

VII. CONCLUSION

The proposed Machine Learning-based Roaming Fraud Detection System using TAP Records provides an intelligent approach for identifying suspicious roaming activities and reducing potential financial losses for mobile network operators. By analyzing subscriber behavior, visited-network information, service usage, transaction values, roaming duration, and other TAP-derived characteristics, the system can identify abnormal patterns that may indicate fraudulent activity. The methodology combines data preprocessing, behavioral feature extraction, feature selection, and supervised machine-learning classification to distinguish legitimate and fraudulent roaming transactions. Experimental comparison indicates that ensemble learning approaches, particularly XGBoost and Random Forest, can provide strong classification performance for complex telecom-fraud patterns. Previous research has also demonstrated the effectiveness of machine learning for mobile roaming-fraud detection, while graph-based telecom-fraud research shows the value of modeling subscriber behavior and relationships. The proposed framework can support automated fraud screening, risk scoring, and alert generation, thereby reducing dependence on manual investigation. Future integration with near-real-time roaming feeds such as NRTRDE can further reduce detection latency, while TAP records can support subsequent billing validation and settlement analysis. Overall, the proposed approach provides a scalable foundation for intelligent roaming-fraud management.

FUTURE SCOPE

The proposed Machine Learning-based Roaming Fraud Detection System using TAP Records can be further enhanced to address the increasing complexity and speed of telecom fraud. Future research can incorporate real-time roaming usage data and NRTRDE feeds to identify suspicious activity before TAP-based billing processes are completed. This can reduce fraud-detection latency and limit potential revenue losses. Advanced deep learning and graph-based models can also be investigated to capture complex relationships between subscribers, visited networks, destinations, devices, and roaming transactions. Graph machine learning has already demonstrated potential for telecom fraud detection by exploiting behavioral relationships that conventional classifiers may overlook. Future systems can further employ unsupervised and semi-supervised learning to identify previously unseen fraud patterns when labelled TAP records are limited. Explainable AI can be integrated to provide fraud analysts with understandable reasons for each alert. In addition, adaptive models can continuously learn from newly confirmed fraud cases. Privacy-preserving learning,

federated learning, real-time risk scoring, and automated response mechanisms can also be explored to develop a scalable, intelligent, and proactive roaming-fraud management platform. ITU-T's 2025 work on fraud mitigation also identifies AI and machine learning as relevant tools for telecom fraud management.

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