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Full Length Article

Fraud Detection In Fastag Payments

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Abstract
The widespread deployment of FASTag for electronic toll collection across India has significantly improved traffic efficiency and reduced manual intervention. However, this rapid digitization has also introduced new vulnerabilities, including unauthorized transactions, duplicate tag usage, and GPS spoofing attacks. Conventional rule-based fraud detection systems are increasingly ineffective in identifying such evolving and sophisticated fraud patterns. To overcome these limitations, this study proposes a machine learning-driven fraud detection framework that utilizes historical transaction data, behavioral analytics, and anomaly detection techniques to identify fraudulent FASTag activities in real time.The proposed system integrates supervised learning models, particularly Random Forest, for accurate fraud classification, alongside unsupervised methods such as Isolation Forest and Autoencoders to detect anomalous transaction patterns. Key attributes considered in the analysis include transaction timestamp, vehicle classification, toll plaza location, and user behavior trends. Furthermore, the framework incorporates real-time data processing through streaming analytics to enable immediate detection and response to suspicious activities.Experimental evaluation indicates that the proposed approach significantly enhances detection accuracy while reducing false positives compared to traditional rule-based methods. By continuously adapting to emerging fraud patterns, the system ensures scalability, robustness, and improved financial security. This research contributes to the development of a secure, intelligent, and efficient digital toll collection ecosystem, making it highly suitable for large-scale deployment in modern transportation infrastructures.

Keywords: *FASTag fraud detection, machine learning, anomaly detection, Random Forest, Isolation Forest, Autoencoder, real-time analytics, intelligent transportation systems*

INTRODUCTION

The adoption of FASTag technology has transformed toll collection systems in India by enabling seamless, cashless transactions through Radio Frequency Identification (RFID). This system allows vehicles to pass through toll plazas without stopping, thereby reducing congestion, fuel consumption, and travel delays. Despite these advantages, the increasing reliance on digital tolling has introduced new security challenges. Fraudulent activities such as tag cloning, unauthorized usage, and incorrect toll deductions have raised serious concerns regarding system integrity and user trust. Traditional rule-based fraud detection mechanisms are often insufficient to address these evolving threats, as they lack adaptability and fail to detect complex behavioral anomalies.To overcome these limitations, this study proposes a machine learning-based fraud detection framework designed to enhance the reliability and security of FASTag transactions. The system leverages historical data, behavioral analytics, and real-time monitoring to identify suspicious activities and prevent financial losses. By learning patterns of legitimate user behavior, the proposed model can effectively detect anomalies such as geographically inconsistent transactions, abnormal usage frequency, and mismatches in vehicle classification.

Overview of FASTag and Highway Infrastructure

Fig 1 FASTag af fixed to the car's windshield

FASTag is an electronic toll collection system implemented by the National Highways Authority of India (NHAI) to modernize toll operations across national highways. It consists of an RFID-enabled tag affixed to the vehicle's windshield, which enables automatic deduction of toll charges from a linked prepaid or bank account. Vehicles equipped with FASTag can use dedicated lanes at toll plazas, ensuring faster and more efficient transit.The collected toll revenue plays a critical role in maintaining and developing road infrastructure. With widespread adoption across hundreds of toll plazas, FASTag has significantly improved operational efficiency and transparency. However, as the system scales, ensuring secure and fraud-resistant transactions becomes increasingly important.

Limitations of Conventional Tolling Systems

Conventional toll collection systems have historically faced multiple operational challenges, including long waiting times, traffic congestion, and increased fuel consumption. Delays at toll plazas negatively impact both individual commuters and the broader economy. Studies have indicated that transportation inefficiencies result in substantial financial losses annually due to wasted time and fuel. Additionally, abrupt lane changes at toll booths increase the risk of accidents, further highlighting the need for automated and efficient tolling solutions.

Evolution of FASTag in India

FASTag was initially introduced as a pilot project and gradually expanded across the country to become a mandatory system for all vehicles. Over time, the number of FASTag-enabled toll plazas and transactions has increased significantly, reflecting widespread adoption. Government initiatives and regulatory policies have played a key role in accelerating this transition toward digital toll collection. Today, FASTag is integrated into a large network of toll plazas, supporting millions of transactions daily.

FASTag System Functionality

FASTag operates as a prepaid system in which users recharge their accounts to enable toll payments. When a vehicle passes through a toll plaza, RFID readers scan the tag and automatically deduct the applicable fee. The system sends instant notifications to users, ensuring transparency in transactions. This automation eliminates the need for manual intervention and significantly enhances user convenience.

RFID Technology in FASTag

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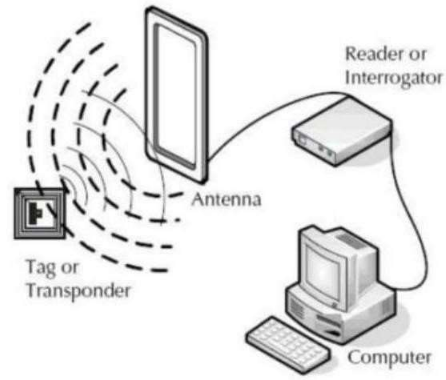

Fig 2 RFID System

RFID technology forms the backbone of the FASTag system by enabling wireless communication between tags and readers. Each RFID tag contains a unique identification number that is linked to a vehicle and its associated account. The reader captures this information and transmits it to a centralized database for processing. While this technology improves efficiency, it also introduces vulnerabilities, such as tag duplication and misuse, especially when tag identity is not adequately linked with vehicle verification mechanisms.

Methodological Approach

Machine learning provides a robust framework for analyzing large volumes of transactional data and identifying patterns indicative of fraud. Unlike traditional approaches, ML models can adapt to evolving fraud techniques and improve performance over time. The proposed methodology involves data collection from multiple sources, preprocessing and feature engineering, model selection, training, and validation. Both supervised models (such as Random Forest and Logistic Regression) and unsupervised techniques (such as Isolation Forest and Autoencoders) are utilized to enhance detection accuracy.

The system is designed to operate in real time, continuously monitoring transactions and flagging anomalies. A feedback mechanism allows the model to learn from newly identified fraud cases, ensuring continuous improvement and adaptability.

Roles and Responsibilities

The development of the system involves multiple roles, including data engineering for data preparation, machine learning engineering for model development and optimization, and interface development for creating a monitoring dashboard. This collaborative approach ensures efficient system design and implementation.

SYSTEM STUDY

Existing System Analysis

The FASTag system, implemented by the National Highways Authority of India (NHAI), represents a significant advancement in electronic toll collection through the use of RFID technology. This system enables automatic toll deduction as vehicles pass through toll plazas, thereby reducing waiting time, minimizing fuel consumption, and promoting digital transactions. By linking FASTag accounts with banking systems, the framework ensures seamless and cashless payments, contributing to improved operational efficiency across highway networks.Despite these advantages, the current system exhibits several limitations that expose it to fraudulent exploitation. One of the primary concerns is the absence of dynamic vehicle verification mechanisms. FASTags are issued based on a declared vehicle category, such as light or heavy vehicles, without continuous validation at toll points. This creates opportunities for misuse, where users may intentionally register vehicles under incorrect categories to reduce toll charges. Additionally, the system lacks real-time validation capabilities to ensure that the vehicle passing through the toll plaza corresponds to the assigned FASTag classification.Another critical limitation lies in the static configuration of FASTags, which does not adapt to changes in vehicle characteristics over time. The lack of integrated monitoring systems further prevents the detection of anomalies such as duplicate tag usage or mismatched vehicle identities. As a result, while the existing FASTag system improves efficiency, it does not adequately address evolving fraud scenarios, leading to revenue losses and reduced system reliability.

Proposed System

To overcome the identified limitations, this study proposes an enhanced fraud detection framework that integrates machine learning, Internet of Things (IoT), and computer vision techniques into the FASTag ecosystem. The primary objective of the proposed system is to ensure accurate vehicle classification and detect fraudulent activities in real time by comparing declared and observed vehicle characteristics.The system utilizes advanced deep learning models, such as Mask R-CNN, to perform automated vehicle classification based on physical attributes including size, shape, and structural features. IoT-enabled devices, such as cameras and sensors installed at toll plazas, capture real-time images and measurements of vehicles as they approach the toll gate. These inputs are processed by the classification model to determine the actual vehicle category.The detected vehicle type is then compared with the category associated with the FASTag in the backend database. Any discrepancy between the two is flagged as a potential fraud case, triggering alerts for further investigation. This real-time fraud detection mechanism enhances the accuracy of toll collection and prevents revenue leakage.The proposed system offers several advantages, including improved financial accuracy, adaptive learning capabilities, and scalability across multiple toll locations. By continuously learning from new data, the system becomes more effective in identifying emerging fraud patterns. However, the implementation of such a system also introduces challenges, including increased technical complexity, higher deployment costs, and the need to address data privacy concerns related to image and user data collection. Despite these challenges, the proposed approach provides a robust and future-ready solution for secure toll management.

REQUIREMENT ENGINEERING

Functional Requirements

The functional requirements of the proposed fraud detection system define the core operations necessary to identify and manage fraudulent FASTag transactions. The system begins with an image acquisition module that captures real-time visual data of vehicles using cameras or IoT-enabled sensors at toll plazas. This data is then processed through an input interface, which may be implemented as a graphical user interface or command-line system, allowing operators to interact with the application.Once the data is captured, it is passed to the vehicle classification module, where deep learning algorithms analyze the image to determine the vehicle category. The output of this module is forwarded to the fraud detection engine, which compares the predicted vehicle class with the registered FASTag category stored in the database. If a mismatch is identified, the system flags the transaction as suspicious and generates alerts for further verification.The system also includes an output interface that displays classification results and fraud alerts to operators. Additionally, all transactions and flagged cases are stored in a centralized database for auditing, reporting, and model retraining purposes. This end-to-end functionality ensures continuous monitoring and effective fraud detection.

Non-Functional Requirements

In addition to functional capabilities, the system must satisfy several non-functional requirements to ensure reliability and efficiency. Accuracy is a critical factor, as the system must achieve high classification performance, ideally exceeding 90%, to minimize false detections. The system should also provide real-time or near-real-time processing, ensuring that vehicle classification and fraud detection occur within a minimal delay.

Usability is another important consideration, requiring the development of an intuitive interface that enables operators to easily monitor transactions and respond to alerts. The system must be highly available, operating continuously without interruption to support toll plaza operations. Reliability is essential to ensure consistent performance under varying environmental conditions, including changes in lighting and weather.Scalability is required to handle increasing volumes of transaction data across multiple toll plazas, while maintainability ensures that the system can be updated and enhanced with minimal effort. Finally, strong security and privacy measures must be implemented to protect sensitive user and vehicle data, ensuring compliance with relevant data protection regulations.

ANALYSIS AND DESIGN

The use case diagram represents the interaction between system actors and the functionalities of the fraud detection system. The primary actors include toll operators, system administrators, and the automated detection system. These actors interact with various system functions such as data capture, vehicle classification, fraud detection, and alert management. The diagram illustrates how each actor contributes to the overall workflow and ensures efficient system operation.The sequence diagram describes the chronological flow of interactions between system components during a transaction. It illustrates how data is captured from sensors, processed by the classification module, evaluated by the fraud detection engine, and finally presented to the user interface. This step-by-step representation highlights the communication between different

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modules and ensures clarity in system behavior during real-time operations.The activity diagram provides a visual representation of the workflow within the system. It outlines the sequence of activities, starting from vehicle detection at the toll plaza to the final decision-making process regarding fraud identification. The diagram helps in understanding the logical flow of operations, including decision points, parallel processes, and system responses to different scenarios.

System Architecture

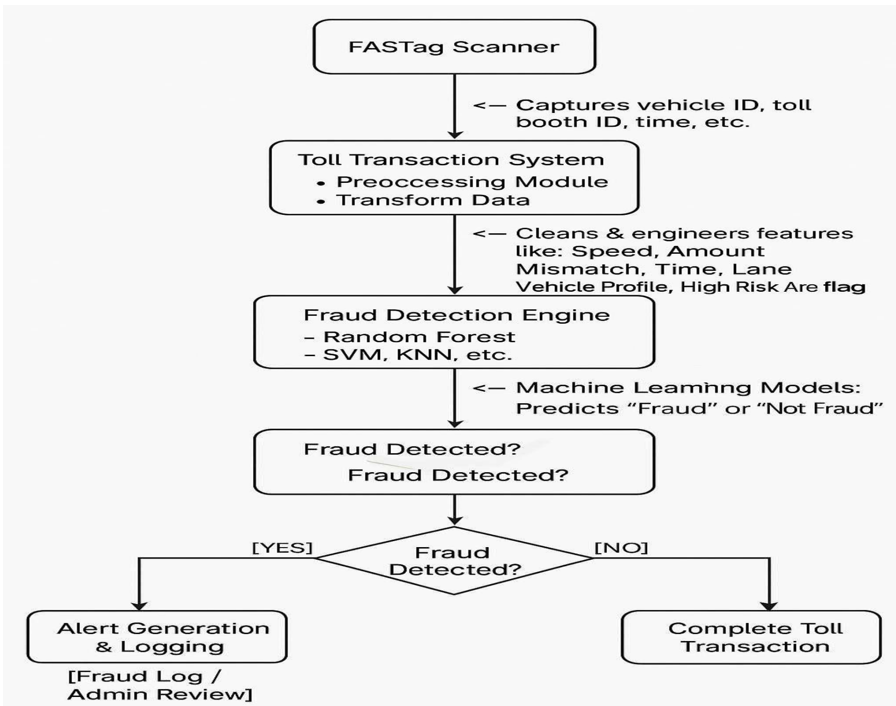

Fig 3 Systemarchitecture

The system architecture defines the overall structure of the proposed fraud detection framework, including its subsystems and their interactions. It consists of multiple layers, including data acquisition, processing, analysis, and presentation. The data acquisition layer collects input from cameras and sensors, while the processing layer performs preprocessing and feature extraction. The analysis layer applies machine learning models to classify vehicles and detect anomalies, and the presentation layer provides dashboards and alerts for users.This modular architecture ensures flexibility, scalability, and efficient communication between components. It also allows for future enhancements, such as integration with additional technologies like GPS tracking or license plate recognition, further strengthening the system's capabilities.

SYSTEM CONSTRUCTION

System Requirements

Software Requirements

The development of the proposed fraud detection system relies on a set of modern software tools and libraries that support machine learning, data processing, and visualization. The primary development environment is Visual Studio Code, which provides flexibility and integration with Python-based workflows. Python (version 3.0 or above) is used as the core programming language due to its extensive ecosystem for data science and machine learning applications.Key libraries include Scikit-learn for implementing classification algorithms, Pandas and NumPy for data manipulation and numerical computations, and Matplotlib and Seaborn for data visualization. Additionally, Streamlit is used to develop an interactive web-based interface that allows users to perform real-time fraud detection and visualize results effectively.

Hardware Requirements

The system is designed to operate on standard computing infrastructure, ensuring accessibility and ease of deployment. A machine running Windows 10 or later with a 64-bit architecture is recommended for optimal performance. The minimum hardware configuration includes an Intel Core processor (or equivalent), 2 GB of RAM (with 4 GB or more recommended), and at least 500 MB of available storage. Internet connectivity is optional but beneficial for cloud-based model updates and integration with external data sources.

IMPLEMENTATION

System Modules and Development

The implementation of the proposed system follows a modular approach, where each component is responsible for a specific function within the fraud detection pipeline. The process begins with the importation of essential libraries required for data preprocessing, model training, evaluation, and visualization. These libraries provide the computational foundation for building and deploying machine learning models.The dataset used in this study consists of FASTag transaction records, including features such as vehicle type, toll booth identifier, transaction amount, vehicle speed, lane type, and regional codes. A target variable indicating fraudulent or legitimate transactions is also included. Before model training, the dataset undergoes preprocessing steps such as handling missing values, removing inconsistencies, and encoding categorical variables into numerical representations. Feature engineering techniques are applied to enhance the predictive power of the models.Multiple machine learning algorithms are implemented to evaluate their effectiveness in detecting fraudulent transactions. These include Random Forest, Decision Tree, Support Vector Machine, Logistic Regression, and K-Nearest Neighbors. Each model is trained on a portion of the dataset and evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Among these, ensemble-based approaches such as Random Forest demonstrate strong performance due to their ability to capture complex patterns in the data.

Web Application Development

To enable real-time interaction and usability, the trained models are integrated into a web-based application developed using Streamlit. The application allows users to input transaction data either manually or by uploading a dataset in CSV format. Once the data is processed, the system applies the trained model to generate fraud predictions.The application provides a comprehensive dashboard that displays prediction results, performance metrics, and visualization tools such as confusion matrices and comparative graphs. Additionally, the system supports data export functionality, enabling users to download prediction results for further analysis. This interactive interface enhances accessibility and facilitates practical deployment in real-world scenarios.

Testing and Validation

A comprehensive testing strategy is employed to ensure the reliability and robustness of the system. Unit testing is conducted to validate individual components, such as data preprocessing functions and model training routines. Integration testing ensures that all modules work cohesively, enabling seamless data flow from input to prediction output.Performance testing evaluates system efficiency, including model training time, prediction latency, and resource utilization. Validation testing focuses on verifying that the system meets predefined performance criteria and business requirements. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess the effectiveness of fraud detection. The results indicate that the system performs reliably under various conditions and maintains consistent accuracy.

EXPERIMENTS AND RESULTS

Experimental Analysis

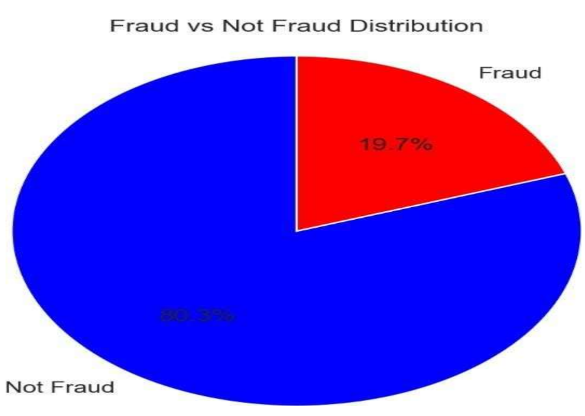

Fig 4 Percentage of Fraud vs Not Fraud

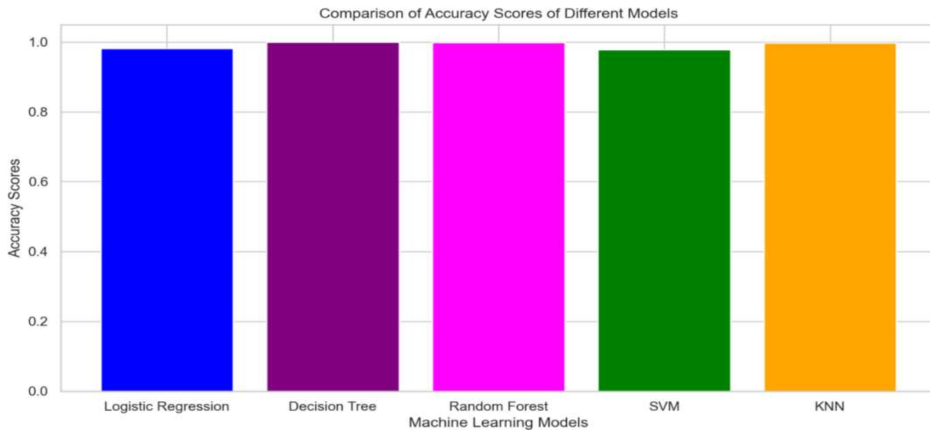

Fig 5 Comparison of Accuracy scores

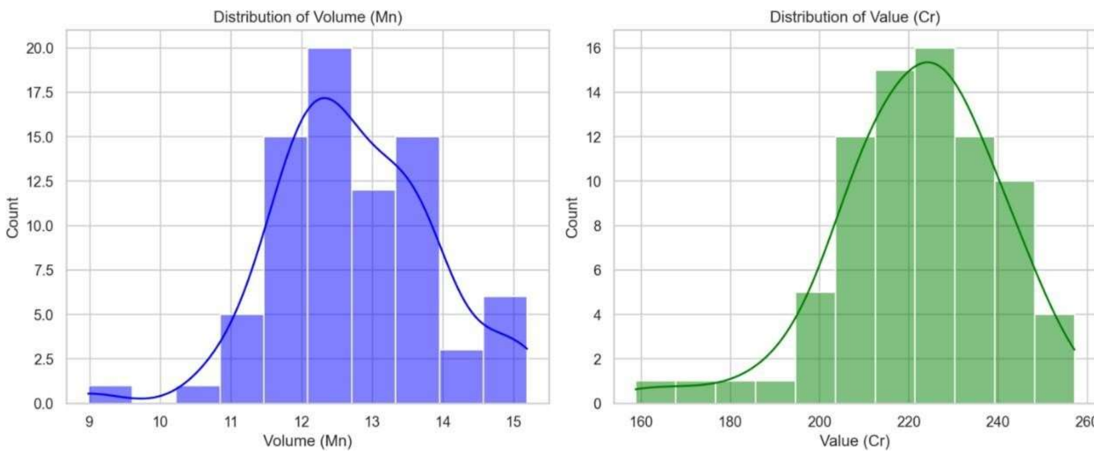

Fig 6 Statistics of Real-Time data

The experimental evaluation focuses on comparing the performance of different machine learning models for FASTag fraud detection. The dataset is divided into training and testing subsets, and each model is evaluated using standard classification metrics.The results indicate that ensemble and tree-based models outperform simpler algorithms in capturing fraud patterns. Random Forest achieves high accuracy and balanced performance across precision and recall, making it suitable for real-world deployment. Decision Tree models also demonstrate strong performance but may exhibit overfitting when trained on limited data. Support Vector Machines and Logistic Regression provide consistent results but require careful parameter tuning. K-Nearest Neighbors shows comparatively lower performance due to sensitivity to high-dimensional data.The analysis also highlights key fraud trends, including geographic regions with higher fraud occurrences and temporal patterns indicating peak fraud periods. Visualization techniques such as confusion matrices and performance comparison graphs are used to illustrate these findings effectively.

Conclusion

The integration of machine learning techniques into FASTag-based toll collection systems significantly enhances fraud detection capabilities and overall system reliability. The proposed framework demonstrates the ability to accurately identify fraudulent transactions by leveraging data-driven insights and real-time analytics. Compared to traditional rule-based approaches, the system offers improved adaptability, scalability, and detection accuracy.The results confirm that ensemble models, particularly Random Forest, provide the best balance between accuracy and generalization. The implementation of an interactive web application further enhances usability, enabling efficient monitoring and decision-making. Despite challenges such as data imbalance and feature selection, the system successfully addresses key fraud detection requirements.Future enhancements may include the incorporation of deep learning models, real-time data streaming, and advanced technologies such as blockchain for secure transaction tracking. These advancements will further strengthen the robustness and transparency of digital toll collection systems, contributing to the development of intelligent transportation infrastructure.

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