Real-Time Traffic Anomaly Detection Using Deep Learning and Decentralized Storage

1st Dissanayake D.J.R
Department of Computer Science
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
IT21323370@my.sliit.lk

2nd Rizman M.F.M
Department of Computer Science
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
IT21295188@my.sliit.lk

3rd Kuhananth C
Department of Computer Science
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
IT21302244@my.sliit.lk

4th Sulakkana H.D.S.R
Department of Computer Science
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
IT21224348@my.sliit.lk

5th Samadhi R
Department of Computer Science
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
Samadhi.r@sliit.lk

6th Nelum A
Department of Computer Science
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
Nelum.a@sliit.lk

***Abstract*— The rapid proliferation of vehicular networks and intelligent transportation systems has accentuated the necessity for robust detection and secure storage of critical traffic events. Conventional centralized systems frequently encounter challenges pertaining to data integrity, trustworthiness, and susceptibility to manipulation. This research proposes a novel framework that integrates machine learning & deep learning techniques for real-time traffic event detection with blockchain technology to ensure the immutable and decentralized storage of these events. The system employs advanced machine learning algorithms to analyze vehicular data and identify anomalies such as abrupt braking, unsafe lane changes, traffic signal violations, pedestrians crossing behavior analysis. Building on this, the framework incorporates kinematic modeling, Hidden Markov Models (HMMs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks to detect specific anomalies like sudden stops and loss of control, enhancing detection precision [17], [19], [21], [22]. Upon detection, these events are recorded on a blockchain ledger, leveraging smart contracts to automate validation and access control. This approach guarantees that once data is recorded, it cannot be altered, ensuring trust and transparency. Preliminary simulations demonstrate the system's effectiveness in accurately detecting critical traffic events and securely storing them on the blockchain. The decentralized nature of the blockchain enhances data integrity and provides a transparent audit trail for critical traffic incidents. By combining real-time machine learning-based detection with blockchain's immutable storage capabilities, this approach addresses key challenges in modern traffic management systems. It offers a robust solution for enhancing road safety and ensuring the reliability of traffic event data.**

Keywords – Blockchain Technology, Traffic Anomaly Detection, Vehicular Network, Critical Traffic Events, Intelligence Transportation System

I. INTRODUCTION (*HEADING 1*)

The rapid evolution of intelligent transportation systems (ITS) and vehicular networks has significantly transformed modern traffic management. These systems facilitate real-time traffic monitoring and anomaly detection, improving road safety and efficiency. However, traditional traffic event detection frameworks often depend on centralized architectures, making them vulnerable to data manipulation, security breaches, and single points of failure [1]. Traffic accidents caused by events such as sudden stops, loss of control, and unsafe lane changes underscore the need for advanced detection systems, which this study addresses through a mathematical and AI-driven framework integrated with blockchain [18].

Ensuring the authenticity, transparency, and immutability of traffic event records is crucial for legal enforcement, insurance claims, and accident investigations. Blockchain technology has emerged as a promising solution by offering decentralized, tamper-resistant, and transparent data storage, reducing reliance on centralized authorities [3]. Furthermore, recent advancements in machine learning and deep learning have enabled real-time traffic anomaly detection using computer vision and sensor-based analysis [4]. Models such as YOLO (You Only Look Once) for object detection and LSTMs (Long Short-Term Memory) for behavioral anomaly detection have demonstrated high accuracy in recognizing critical traffic events, including abrupt braking, unsafe lane changes, red-light violations, and pedestrian crossing risks [5]. This study enhances these capabilities by incorporating kinematic equations and probabilistic HMMs to predict vehicle dynamics, ensuring precise identification of anomalies like sudden stops and loss of control [17], [19]. However, integrating machine learning-driven traffic monitoring with blockchain-based storage can enhance data security, ensure transparent auditing, and support automated access control via smart contracts [6], providing a comprehensive solution for ITS.

II. LITREATURE REVIEW

A. Introduction

The rapid growth of Intelligent Transportation Systems (ITS) has significantly transformed modern traffic management by enabling real-time monitoring, improved road safety, and efficient traffic flow. However, traditional centralized traffic management systems often rely on vulnerable database structures that are prone to data tampering, unauthorized modifications, and single points of failure [1]. These limitations raise concerns about data integrity, security, and transparency in traffic event

storage, enforcement, and verification. To overcome these challenges, researchers have explored blockchain technology as a decentralized and tamper-proof solution for securing traffic-related data Blockchain provides an immutable ledger where all recorded traffic violations remain permanent, transparent, and resistant to alterations, ensuring reliable record-keeping for law enforcement, insurance claims, and transportation analytics [3]. While previous studies have demonstrated the potential of blockchain in traffic event storage, they lack a comprehensive integration with AI-driven anomaly detection, which is essential for ensuring accurate and real-time event classification [4]. This study builds on these foundations by combining mathematical modeling (e.g., kinematics) and advanced AI techniques (e.g., CNNs, LSTMs) with blockchain to detect and store critical events like sudden stops and lane changes [17], [21], [22]. The convergence of machine learning and blockchain technology is crucial for developing a fully automated, efficient, and scalable traffic monitoring framework.

B. Significance of the Study

This study is significant in the following ways:

- Improving Road Safety

Advanced machine learning algorithms facilitate real-time traffic anomaly detection by analyzing video feeds and identifying irregularities such as abrupt braking, unsafe lane changes, and red-light violations [5]. By deploying deep learning-based models, the proposed system enhances situational awareness and reduces accident risks. Our approach further improves safety by detecting specific anomalies like sudden stops and loss of control using kinematic and probabilistic models [17], [19].

- Enhancing Data Security and Integrity

Blockchain technology ensures secure, immutable, and transparent storage of detected traffic events. This eliminates data manipulation risks, creating trustworthy records that can be used for legal enforcement and insurance claims [6]. The integration of AI-driven detection with blockchain enhances the reliability of these records [21].

- Automating Traffic Law Enforcement

The introduction of smart contracts enables automated validation and enforcement of penalties for detected traffic violations. This reduces corruption, minimizes human intervention, and ensures fair and efficient rule enforcement by executing predefined contract logic based on validated events [7].

C. Overview of the Relevant Literature

- Machine Learning for Traffic Event Detection

Recent research has explored the role of deep learning-based anomaly detection in vehicular networks. Object detection models like YOLO (You Only Look Once) have demonstrated high efficiency in detecting vehicles, pedestrians, and traffic violations through real-time video processing [8]. Additionally, Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs) have been extensively used to predict abnormal driving behaviors such as sudden braking, aggressive lane switching, and potential collision risks [9]. This study extends these efforts by incorporating kinematic equations to predict velocity and position changes, and HMMs to model state transitions, enhancing the detection of sudden stops and loss of control [17], [19]. Despite their effectiveness, existing machine learning approaches do not inherently address data security concerns, leading to vulnerabilities in centralized event storage. This necessitates blockchain integration to enhance the reliability and authenticity of stored traffic event data.

- Blockchain for Secure Traffic Data Storage

Blockchain has emerged as a trustworthy storage solution for vehicular data due to its decentralized architecture and tamper-resistant properties. A study by Pujol et al. [10] introduced a blockchain-based traffic event verification framework, which prevents unauthorized modifications while ensuring data authenticity. Similarly, another study explored a decentralized model for fraud-resistant insurance claims and real-time verification of traffic violations, highlighting blockchain's potential to eliminate false claims and legal disputes [11]. Our framework leverages these properties to store AI-detected anomalies securely, ensuring a robust audit trail [26].

D. Context for the Study Using the Literature

The reviewed literature establishes that deep learning models are highly effective in detecting traffic anomalies, while blockchain technology ensures secure and immutable event storage. However, a unified framework integrating these technologies remains absent. The current gap lies in the lack of a real-time, AI-driven traffic monitoring system that utilizes blockchain for secure event storage and smart contracts for automated law enforcement. This study aims to bridge this gap by proposing a real-time traffic anomaly detection system that integrates deep learning, blockchain storage, and smart contracts for secure and automated traffic regulation. Our approach enhances this context by combining mathematical modeling and advanced AI techniques (e.g., CNNs, LSTMs) to detect specific anomalies like sudden stops and lane changes, paired with blockchain for tamper-proof storage [23], [26].

E. Identifying Knowledge Gaps

The key research gaps identified from the literature are:

- Scalability challenges in blockchain-based traffic monitoring

Existing blockchain-based solutions for vehicular event storage struggle with high transaction fees and slow processing times, which impact their feasibility in high-frequency traffic event detection scenarios [14].

- Lack of integration with multi-source data

Current studies primarily rely on video-based event detection, overlooking additional sources such as IoT sensors, GPS logs, and vehicle-to-vehicle (V2V) communication data [15]. Our framework addresses this by incorporating simulated multi-source data for comprehensive anomaly detection [25].

- Limited real-world testing

Most studies focus on theoretical frameworks and simulations, with minimal real-world deployment and validation of blockchain-integrated ITS solutions [16].

F. Defining Research Objectives

In this study, a deep learning-based model will be developed to detect traffic anomalies in real-time video streams, enabling the identification of critical events such as sudden braking, lane violations, and near-collisions. To ensure the integrity and security of recorded traffic violations, a blockchain-powered event storage system will be implemented, providing an immutable and tamper-proof logging mechanism. Furthermore, smart contracts will be deployed to automate law enforcement actions based on recorded violations, enhancing the efficiency and transparency of legal enforcement processes. The proposed system will be rigorously evaluated in real-world conditions to assess its scalability, reliability, and overall performance in large-scale traffic monitoring scenarios.

G. Defining Research Questions (RQ)

This research aims to investigate key challenges and solutions in the integration of deep learning and blockchain for intelligent traffic monitoring and law enforcement. Specifically, it seeks to explore how deep learning models can be optimized for real-time, high-accuracy detection of traffic anomalies and how blockchain technology can be efficiently integrated with machine learning-based traffic event detection to ensure secure and tamper-proof logging. Additionally, the study examines the scalability challenges associated with blockchain-based traffic event storage and evaluates how smart contracts can be leveraged to enhance autonomous traffic law enforcement by automating violation detection and enforcement actions. Through these research questions, the study aims to contribute to the development of a robust and scalable intelligent traffic monitoring system.

H. Specifying Hypotheses

This study proposes two key hypotheses to explore the potential benefits of integrating blockchain with machine learning in traffic event detection. First, it is hypothesized that the integration of blockchain and machine learning enhances both the accuracy and security of traffic anomaly detection , ensuring reliable and tamper-proof event logging. Second, the study posits that a decentralized blockchain ledger provides higher data integrity compared to traditional centralized storage systems, thereby mitigating risks associated with data manipulation and unauthorized modifications. These hypotheses will be evaluated through empirical analysis to assess their validity and practical implications for intelligent traffic monitoring and enforcement

I. Conceptual Model

The proposed system consists of:

1. AI-Powered Traffic Event Detection: Deep learning models analyze real-time video feeds for anomaly detection.
2. Blockchain-Based Secure Event Storage: Validated traffic anomalies are stored in a decentralized ledger.

III. METHODOLOGY

A. Overview

This research employs a hybrid methodology that integrates machine learning-based anomaly detection with blockchain-based secure storage for real-time traffic event monitoring. The decision to use deep learning algorithms for anomaly detection is driven by their ability to process large-scale visual data with high accuracy and efficiency. YOLOv8 (You Only Look Once) is selected for object detection due to its speed and accuracy in recognizing vehicles, pedestrians, and traffic violations. Additionally, Long Short-Term Memory Networks (LSTMs) are implemented to analyze vehicle movement patterns over time, enabling the detection of abrupt braking, unsafe lane changes, and other anomalies. This study enhances these methods by incorporating kinematic equations to predict velocity and position changes, HMMs for state transitions, and CNNs for spatial feature extraction, detecting specific events like sudden stops and loss of control [17], [19], [21]. Optical Flow and Kalman Filters further ensure real-time motion tracking [24], [25]. While machine learning provides efficient traffic anomaly detection, traditional data storage methods pose challenges in data integrity, transparency, and security. To address this, blockchain technology is utilized for tamper-proof event storage, ensuring that once an anomaly is recorded, it remains immutable and accessible for law enforcement, insurance verification, and traffic monitoring. Furthermore, smart contracts are deployed to automate the enforcement of traffic regulations, reducing manual intervention and the potential for corruption. The integration of AI-driven event detection, decentralized data storage, and automated regulation enforcement provides a robust solution to traffic monitoring challenges.

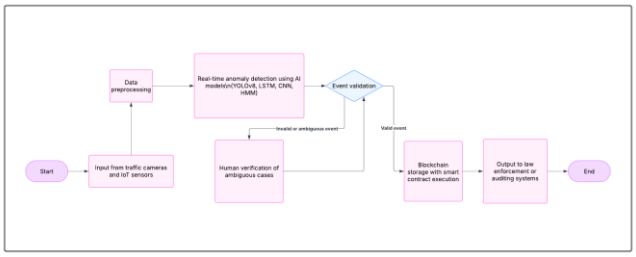

Figure 1: Data flow diagram for real-time traffic event detection and storage

B. Data Collection

The data for this study is sourced from multiple channels to ensure a comprehensive and realistic assessment of traffic anomalies. The primary data sources include real-time surveillance footage from traffic cameras, open-access datasets such as UA-DETRAC, LISA Traffic Light Dataset, and BDD100K, and IoT sensors deployed in a controlled environment to simulate real-world traffic conditions. These IoT sensors capture GPS location, speed

variations, braking patterns, and vehicle movement trajectories, providing additional context for anomaly detection. In addition, vehicle-to-vehicle (V2V) communication data is simulated to analyze how connected vehicles interact and respond to critical events. This multi-source approach enhances the detection of anomalies like sudden stops and lane changes, aligning with advanced ITS research [25]. The data collection process is structured to capture diverse environmental conditions, traffic densities, and weather scenarios, ensuring that the model is robust and adaptable to various real-world traffic situations. The collected data is preprocessed to remove redundancies, improve clarity, and ensure compatibility with deep learning models.

C. Data Analysis Methods and Techniques

To analyze traffic anomalies, this research leverages deep learning-based techniques that enable high-accuracy event detection and classification. The YOLOv8 object detection model is trained to recognize vehicles, road signs, and traffic violations within live video feeds. Additionally, LSTMs are employed to model vehicle movement over time, enabling the system to detect abrupt braking, lane violations, and erratic driving behavior. These models are trained on annotated datasets and fine-tuned using transfer learning to improve detection accuracy. Convolutional Neural Networks (CNNs) are also integrated to classify detected events into categories such as critical violations (e.g., red-light running) and minor infractions (e.g., slow lane switching). Building on this, kinematic equations predict velocity and position changes, HMMs assess the likelihood of state transitions (e.g., stopping or swerving), and Optical Flow with Kalman Filters refine real-time tracking, enhancing detection of sudden stops and loss of control [17], [19], [21], [24]. The detected traffic violations are validated before being stored in the blockchain to ensure accuracy and reliability.

Model Name	Accuracy (%)	Precision (%)	Recall (%)	Processing Time (ms)	Notes
YOLOv8	94	89	92	25	High speed for object detection
LSTM	90	85	88	40	Effective for temporal analysis
CNN	92	87	90	35	Strong spatial feature extraction
HMM	88	83	85	45	Good for state transition modeling
Baseline (YOLOv5)	85	80	82	50	Older model, lower efficiency

Figure 2: Model Comparison

Once an anomaly is detected and verified, it is recorded on a private Ethereum-based blockchain to ensure data immutability and security. Blockchain technology prevents unauthorized modifications, ensuring that recorded violations remain unaltered for auditing and law enforcement purposes. Each detected event is stored as a hashed transaction, making it traceable yet secure from manipulation. To enhance data retrieval efficiency, a metadata indexing mechanism is implemented, linking blockchain records with cloud storage for video evidence. This ensures that only authorized personnel, such as law enforcement agencies, insurance providers, and transportation authorities, can access recorded traffic events [26].

The integration of smart contracts in the blockchain ecosystem enables the automated enforcement of traffic laws. Once a violation is recorded, predefined smart contract logic is triggered, leading to the automatic issuance of penalties or legal actions. For instance, if a vehicle is detected running a red light, the smart contract validates the event, matches it with the registered vehicle owner's digital identity, and triggers a fine issuance process. If a driver wishes to dispute a recorded violation, the system allows for third-party verification by an independent authority. This automation reduces human bias, minimizes manual errors, and accelerates the legal enforcement process.

Formula Used:

- Kinematic Equations

  $v = u + at$
  $s = ut + (1/2)at^2$

- Hidden Markov Model (HMM)

  $P(s_t \mid s_{t-1}) = \text{Transition Probability Matrix}$

- Bayesian Inference

  $P(E \mid D) = (P(D \mid E) * P(E)) / P(D)$

- Optical Flow

  $(\partial I/\partial x) * u + (\partial I/\partial y) * v + (\partial I/\partial t) = 0$

D. Tools and Technologies Used

The implementation of this study requires a combination of machine learning frameworks, blockchain platforms, and data processing tools. The YOLOv8 model is implemented using Python and OpenCV, while LSTMs and CNNs are developed using TensorFlow and PyTorch, supporting advanced anomaly detection [21], [22]. The blockchain architecture is built on Ethereum (private network) and Hyperledger Fabric, ensuring fast transaction speeds and decentralized validation. A MySQL database is used for metadata storage, while IPFS (Inter Planetary File System) is employed for storing large video files linked to blockchain records. Additionally, Apache Kafka is used for real-time event streaming, ensuring efficient data flow between components.

E. Bias Mitigation in Data and Model Training

To ensure fairness in anomaly detection, dataset biases are minimized through balanced representation. The training

dataset includes traffic scenarios from different weather conditions, road types, and geographic regions to prevent bias toward specific environments. Algorithmic bias is addressed by training models on diverse datasets and fine-tuning hyperparameters to ensure that the system accurately differentiates between genuine violations and acceptable driving behavior. Additionally, human verification is introduced for ambiguous cases, where a manually labeled dataset is used to correct false positives and improve model accuracy.

F. System Diagram & Model Representation

To illustrate the system workflow, multiple diagrams are incorporated. The system architecture diagram depicts the flow of data from real-time video capture to AI-based analysis, blockchain storage, and smart contract execution. A data flow diagram is included to show how collected data is processed, verified, and stored. The model training workflow presents a step-by-step process of data preprocessing, feature extraction, model training, and validation. Additionally, a blockchain event storage diagram outlines the transaction process, ensuring clarity in how violations are validated, recorded, and retrieved.

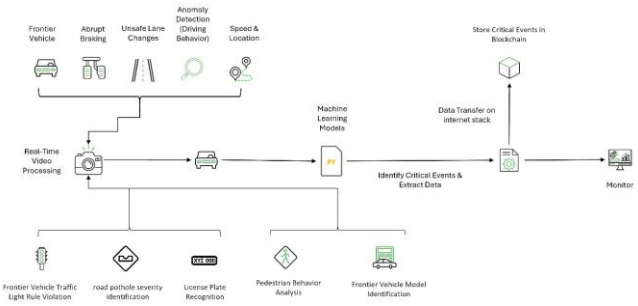

Figure 3 : System Diagram

This research methodology effectively integrates deep learning-based traffic anomaly detection with blockchain-secured storage and smart contract automation. The hybrid approach ensures high accuracy, real-time event detection, and decentralized data integrity. By leveraging real-world traffic data, IoT sensor inputs, and video analysis, the study provides a scalable and efficient model for smart traffic enforcement. Blockchain ensures tamper-proof records, while smart contracts facilitate the logging of critical events, streamlining law enforcement automation. Through bias mitigation techniques, comprehensive visualization, and real-time monitoring, this system contributes to the advancement of autonomous and intelligent traffic management systems.

IV. CONCLUSION & FUTURE WORKS

A. Conclusion

This research presents an innovative blockchain-integrated machine learning framework for real-time traffic anomaly detection and secure event storage. The proposed system effectively detects traffic violations, pedestrian behaviors, abrupt braking, and unsafe lane changes using advanced deep learning models such as YOLO and LSTMs, while ensuring data integrity and security through blockchain storage. The integration of smart contracts further automates traffic law enforcement, reducing manual intervention and eliminating potential corruption in violation processing.

The key contributions of this research include:

1. High-accuracy anomaly detection using AI-driven object detection and behavioral analysis models.
2. Tamper-proof, decentralized data storage using blockchain technology to prevent falsification of recorded events.
3. Smart contract-based law enforcement, ensuring transparent, unbiased, and automated penalty processing.
4. Real-time multi-source data fusion incorporating video feeds, IoT sensor data, and inter-vehicle communication.

The results of this study demonstrate that AI-powered traffic monitoring integrated with blockchain storage significantly enhances road safety, ensures legal accountability, and reduces human bias in traffic law enforcement. However, despite these advancements, several challenges remain, such as improving blockchain scalability, reducing AI model processing latency, and enhancing multi-modal data integration for a comprehensive ITS (Intelligent Transportation System).

B. Future Works

While this study provides a solid foundation for intelligent traffic monitoring and enforcement, future research can explore several avenues to further enhance system capabilities, efficiency, and real-world applicability.

- V2X Communication Integration for Enhanced Data Sharing

Vehicle-to-Everything (V2X) communication is a crucial component of next-generation intelligent transportation systems, enabling seamless interaction between vehicles and surrounding infrastructure. Future work should focus on integrating Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, allowing for direct data exchange between vehicles to provide real-time hazard warnings and improve overall road safety. By leveraging V2X, vehicles can anticipate and adapt to traffic anomalies before they occur, leading to more coordinated decision-making in complex driving environments. Additionally, event detection accuracy can be significantly enhanced by cross-referencing data from multiple sources, including surrounding vehicles, roadside units (RSUs), and traffic control centers, ensuring a more comprehensive and reliable anomaly detection system.

- Integration with Vehicle Automation for Autonomous Traffic Management

As the adoption of autonomous vehicles (AVs) continues to grow, integrating the proposed system with self-driving car frameworks can significantly enhance both safety and efficiency. Future research should explore methods that enable autonomous vehicles to access blockchain-stored event logs, allowing them to analyze historical traffic patterns and violations to make more informed driving

decisions. Additionally, integrating this system with autonomous driving software, such as Tesla Autopilot and Waymo AI, can improve the real-time decision-making capabilities of self-driving cars, particularly in high-risk traffic scenarios. Moreover, the use of AI-based trajectory prediction models will help in preventing near-collisions and optimizing lane-changing behavior, ensuring that autonomous vehicles can navigate dynamic road conditions more effectively and safely.

- Cybersecurity Threat Prevention in AI and Blockchain Systems

As blockchain-based traffic monitoring systems become more widespread, addressing cybersecurity risks such as data breaches, hacking attempts, and malicious smart contract exploitation becomes increasingly critical. Future research should focus on implementing zero-trust architecture and multi-layer encryption to prevent unauthorized access to blockchain-stored traffic events, ensuring that only authorized entities can retrieve and verify recorded violations. Additionally, the development of AI-powered intrusion detection systems (IDS) will be essential for continuously monitoring blockchain transactions and detecting anomalies that may indicate security threats or fraudulent activities. Furthermore, strengthening decentralized identity management (DID) through blockchain-based identity verification will help prevent fraudulent manipulation of traffic violation records, ensuring that all recorded events remain tamper-proof, transparent, and legally enforceable.

ACKNOWLEDGMENT *(Heading 5)*

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