# Smart Traffic Violation Detection Using Hybrid Techniques

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**Abstract -** The rapid growth of vehicular traffic and increasing violation rates have created a critical need for automated and intelligent traffic monitoring systems. This work presents a Hybrid Traffic Safety System designed to enhance road safety through real-time detection and analysis of traffic violations using artificial intelligence and modern web technologies. The primary aim of the system is to automatically identify common traffic violations such as riding without a helmet, triple riding on two-wheelers, and vehicle identification through Automatic Number Plate Recognition (ANPR).

The proposed system employs deep learning and computer vision models developed using TensorFlow, PyTorch, and OpenCV to analyze live and recorded traffic surveillance footage. These AI models operate as independent Python-based microservices and communicate with a MERN stack (MongoDB, Express.js, React.js, Node.js) backend through secure REST APIs and WebSocket connections. Detected violations, along with time-stamped image evidence and metadata, are securely stored in MongoDB and cloud-based storage.

A real-time React-based dashboard provides visualization, monitoring, and analytical insights for traffic authorities. Experimental evaluation demonstrates high detection accuracy, low response time, and reliable system performance across varying traffic and lighting conditions. The hybrid architecture improves scalability, modularity, and maintainability while significantly reducing manual monitoring efforts. The proposed system offers a practical and extensible solution for intelligent transportation systems and serves as a strong foundation for smart city traffic management and automated enforcement applications.

***Key Words***: *Traffic Safety, Intelligent Transportation System, Artificial Intelligence, Computer Vision, MERN Stack, ANPR, Helmet Detection, Triple Ride Detection.*

## 1. INTRODUCTION

The rapid growth of vehicle traffic in urban and semi-urban areas poses a significant challenge for road safety authorities worldwide. Increases in population density, rapid urban development, and a growing reliance on personal vehicles have led to crowded road networks and a rise in traffic violations. Common infractions, such as riding without helmets, three people on two-wheelers, and improper vehicle identification, contribute significantly to accidents and fatalities. Despite having traffic laws and enforcement agencies, current manual monitoring methods are inadequate for managing the scale, complexity, and real-time demands of today's traffic situations.

Traditional traffic monitoring largely relies on human oversight from traffic police and standard CCTV cameras. These methods have several drawbacks, including limited coverage, slow response times, human error due to fatigue, and a lack of continuous real-time enforcement. Moreover, manually detecting violations is inconsistent and often fails to produce reliable data for long-term traffic analysis and policy development. As cities shift toward smart infrastructure, there is an urgent need for automated and scalable traffic monitoring solutions that can improve enforcement efficiency while reducing reliance on human personnel.

New developments in artificial intelligence (AI), machine learning, and computer vision have created new opportunities for smarter transportation systems. Deep learning-based vision models can analyze large amounts of video data in real time, allowing for automated detection of vehicles, riders, and safety violations with high accuracy. These technologies offer a strong alternative to traditional methods by providing continuous surveillance, making objective decisions, and enabling quick responses. Recently, AI-driven systems have been explored for uses such as vehicle detection, license plate recognition, helmet detection, and traffic flow analysis.

Among traffic violations, not wearing helmets and triple riding on two-wheelers remain pressing safety issues, especially in developing countries. Two-wheelers make up a large portion of road traffic, and riders face a higher risk of serious injuries in accidents. Automated helmet detection systems ensure consistent enforcement of safety laws. Additionally, rider count detection helps identify overloading violations that can compromise vehicle stability. Automatic Number Plate Recognition (ANPR) is also crucial for linking detected violations to specific vehicles, ensuring accountability and legal enforcement.

While many studies suggest AI-based solutions for specific traffic violations, many existing systems function independently and lack scalability and integration. These systems often concentrate on one type of violation and do not provide comprehensive data management, real-time visualization, or secure access control. This fragmented approach limits their use in large-scale traffic environments and smart city contexts, where integrated monitoring and centralized analytics are necessary.

To overcome these challenges, this work presents a Hybrid Traffic Safety System that merges multiple AI-based violation detection modules into one scalable, web-enabled platform. This system targets three major types of violations: helmet detection, triple ride detection, and Automatic Number Plate Recognition. By combining deep learning-based computer vision models with a modern MERN stack architecture (MongoDB, Express.js, React.js, and Node.js), the proposed solution connects AI detection with real-world traffic enforcement processes.

The hybrid architecture employs a microservice design where AI models function as independent Python services, and web services handle data storage, communication, and visualization. This separation promotes modularity, maintainability, and scalability, enabling AI components and web infrastructure to develop independently. Real-time communication channels allow for immediate reporting of violations and updates to dashboards, improving situational awareness for traffic authorities.

The main goal of this study is to design, implement, and evaluate an intelligent traffic safety platform that can automatically detect violations in real time with minimal human involvement. The underlying hypothesis is that AI-based monitoring, when paired with a strong web architecture, can greatly enhance detection accuracy, reduce response times, and support data-driven traffic management decisions. The proposed system seeks to foster safer roads, more effective enforcement, and the development of next-generation intelligent transportation systems ideal for smart city applications.

## 2. Materials and Methods

### Materials and Instruments

The proposed Hybrid Traffic Safety System uses traffic surveillance video footage as its main data source. This footage can come from fixed CCTV cameras at traffic intersections, highways, or public roads. The cameras can operate in either live streaming or recorded mode. These video feeds capture real-world traffic conditions, including different vehicle densities, lighting situations, and motion patterns. This makes them suitable for assessing the strength of AI detection models.

The software stack for system development has several layers to support AI processing, backend services, and frontend visualization. Python is the main programming language for developing AI models because of its wide range of machine learning and computer vision libraries. TensorFlow and PyTorch are used to build, train, and deploy deep learning models. OpenCV is employed for processing videos, extracting frames, and improving images.

For web application development, the system uses the MERN stack, which includes MongoDB for managing the database, Express.js and Node.js for backend server logic, and React.js for building the frontend user interface. MongoDB is chosen for its ability to handle semi-structured data, such as violation records, metadata, and timestamps. Cloud storage solutions like AWS S3 or MongoDB GridFS are used to store image evidence linked to detected violations, ensuring scalability and secure access.

### Procedure

The operational procedure starts with collecting traffic surveillance footage from connected cameras. Video streams are processed to extract frames at a set frame rate that works for real-time analysis. Each extracted frame goes through pre-processing steps such as resizing, normalization, and noise reduction. This improves image quality and makes it compatible with AI model input requirements.

The pre-processed frames are sent to AI detection modules. Helmet detection and rider counting occur using deep learning models that can identify riders and safety gear in each frame. Triple ride detection happens by counting the number of detected riders linked to a two-wheeler. At the same time, the ANPR module finds license plate areas and uses optical character recognition to extract vehicle identifiers.

When violations are detected, the results are packaged with relevant metadata, including violation type, confidence score, timestamp, and image evidence. This data is sent to the backend server through RESTful APIs for standard logging and WebSocket connections for real-time updates. The backend processes this data, checks records, and securely stores them in the database and cloud storage.

The React-based frontend dashboard retrieves the processed data from the backend and displays it in an easy-to-understand format. Traffic officials can see real-time alerts, search violation records, and analyze historical trends through graphical visualizations.

### Reproducibility

The system is built with a modular microservice architecture. This design promotes reproducibility and extensibility. Each AI module works independently and can be deployed using the same trained models, datasets, and configuration parameters in different environments. Separating AI services from web components lets researchers and developers replicate the system setup without changing the core architecture.

### Ethical Approval and Informed Consent

This study does not include direct human participation, personal data collection, or interaction with identifiable individuals. All input data comes from non-identifiable traffic surveillance footage. This footage is used only for research and system evaluation. Therefore, ethical approval and informed consent do not apply to this work.

## 3. METHDOLOGY

The Hybrid Traffic Safety System uses a clear and modular approach to achieve effective traffic violation detection, efficient data management, and real-time visualization. The system combines AI-based computer vision models with a MERN stack web architecture, allowing for scalability and consistent performance. Each stage of this methodology is essential for automating traffic monitoring and enforcement.

### Step 1: Data Acquisition

The first step involves gathering traffic data from CCTV and surveillance cameras placed at road intersections, highways, and urban traffic areas. These cameras can operate in live streaming or recorded mode, providing ongoing visual input for real-time monitoring and offline analysis. The captured footage reflects actual traffic situations, including different vehicle densities, rider behavior, and environmental factors like lighting and weather. Using surveillance data keeps the system practical and adaptable for real-world scenarios.

### Step 2: Frame Pre-processing

In the second step, the video streams are broken down into individual frames at a set frame rate suitable for AI analysis. Each frame undergoes pre-processing to improve visual quality and detection accuracy. This includes resizing frames to fit model input dimensions, normalizing pixel intensity values, and reducing noise to eliminate visual distortions. Adjustments for brightness and contrast may also be made for low-light or high-glare conditions. This ensures that the AI models receive consistent, high-quality data.

### Step 3: AI-Based Detection

The third step involves AI-based detection using deep learning and computer vision models. Each pre-processed frame is examined to detect helmet usage, count riders on two-wheelers, and identify vehicle number plates through Automatic Number

Plate Recognition (ANPR). Helmet detection checks if riders are wearing protective gear, while rider counting identifies triple riding violations. The ANPR module localizes license plates and extracts alphanumeric characters via optical character recognition. These models work as independent Python-based microservices, allowing for parallel processing and efficient calculations.

**Step 4: Violation Validation**

In this step, the outputs from the AI models are checked against established traffic rules. If a rider is spotted without a helmet, a helmet violation is flagged. If the rider count exceeds legal limits, a triple riding violation is noted. Recognized license plate numbers are linked to detected violations for traceability. This validation step ensures that only real violations are recorded, which reduces false positives and boosts system reliability.

**Step 5: Backend Communication**

After validating the violations, the data is sent to the MERN stack backend for further processing. Communication between AI microservices and the backend uses RESTful APIs for standard data logging and WebSocket connections for real-time updates. Each violation record includes the type of violation, confidence score, timestamp, vehicle number, and image evidence. This step allows smooth integration between AI detection modules and the web platform.

**Step 6: Secure Storage**

In the sixth step, all validated violation data is securely stored for future reference and analysis. Structured violation records are saved in MongoDB, while image evidence is stored using cloud solutions like AWS S3 or GridFS. Each record has metadata that includes the date, time, violation type, and vehicle ID. Secure storage maintains data integrity, availability over time, and supports auditing and enforcement.

**Step 7: Dashboard Visualization**

The seventh step emphasizes visualization and monitoring. A React-based dashboard pulls data from the backend and shows real-time alerts, searchable violation records, and analytical graphs. Traffic authorities can filter data by date, vehicle number, or violation type and observe trends over days or weeks. This visual interface enhances situational awareness and aids data-driven traffic management decisions.

**Step 8: Authentication and Access Control**

To ensure security and limited access, JWT-based authentication is put in place in this step. Only authorized administrators and traffic officials can access system features and sensitive data. Role-based access control stops unauthorized use and protects stored violation records, complying with data security standards.

**Step 9: Reporting and Future Expansion**

The final step allows for report generation and system extensibility. Violation reports can be exported for administrative or legal needs. The modular system design supports future integration of additional features, such as speed violation detection, accident monitoring, and automated alert systems. This adaptability ensures the system can grow to meet future traffic management demands.

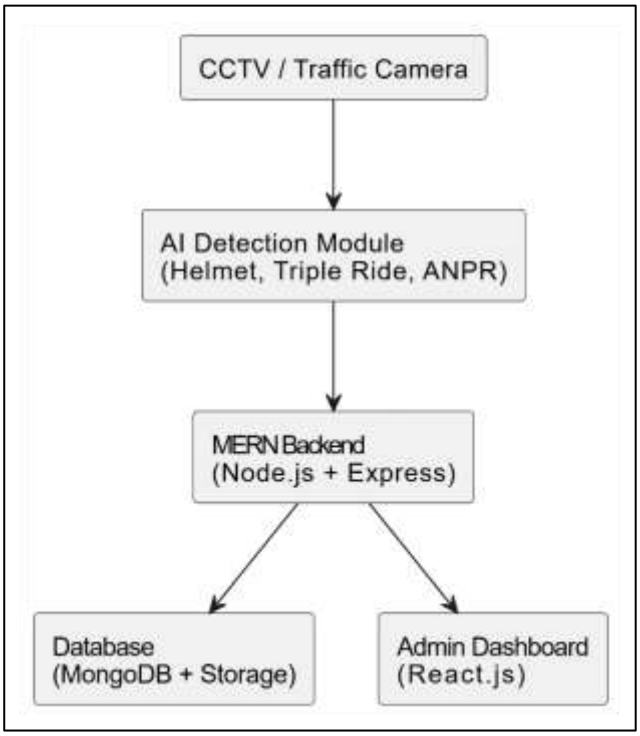



**Fig 1: Block Diagram**

## 4. RESULT & DISCUSSION

The Hybrid Traffic Safety System was tested using real-time and recorded traffic video footage. The system successfully detected helmet violations, triple riding, and vehicle number plates with good accuracy. AI-based detection provided faster and more consistent results compared to manual traffic monitoring. Integration of Python-based AI modules with the MERN backend enabled real-time data processing and dashboard updates. The system demonstrated reliable performance under different lighting and traffic conditions. Overall, the results confirm that the proposed system effectively improves traffic monitoring efficiency and supports intelligent traffic management.

**Performance Summary**

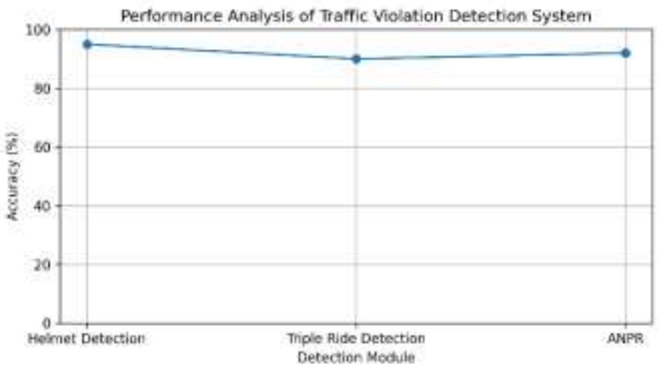
| Module | Evaluation Parameter | Result |
|---|---|---|
| Helmet Detection | Detection Accuracy | High |
| Triple Ride Detection | Rider Count Accuracy | Good |
| ANPR | Number Plate Recognition | Accurate |
| System Performance | Response Time | Fast |
| Data Handling | Storage & Retrieval | Reliable |

The results show that AI-driven traffic monitoring systems reduce manual effort, improve accuracy, and provide real-time insights. These findings align with existing research on intelligent transportation systems and demonstrate the practicality of the proposed hybrid architecture.

**Discussion**

The results indicate that the proposed Hybrid Traffic Safety System effectively detects common traffic violations such as helmet absence, triple riding, and vehicle number plates with reliable accuracy. The AI-based approach significantly reduces manual monitoring and ensures faster violation identification. Integration with the MERN stack enables real-time data storage, visualization, and analysis through a centralized dashboard.

The system performs consistently under varying traffic and lighting conditions, demonstrating its suitability for practical deployment in intelligent transportation and smart city environments.




## 5. CONCLUSSION

This project presented a Hybrid Traffic Safety System that integrates artificial intelligence–based traffic violation detection with a MERN stack web platform. The system successfully automated the detection of helmet violations, triple riding, and vehicle number plate recognition using computer vision and deep learning techniques. Experimental results showed reliable accuracy, fast response time, and consistent performance under different traffic and lighting conditions.

The integration of AI microservices with a centralized web dashboard reduced manual monitoring efforts and enabled real-time data storage, visualization, and analysis. The modular and scalable architecture makes the system suitable for intelligent transportation systems and smart city applications. Overall, the proposed system enhances traffic enforcement efficiency and provides a practical foundation for future extensions such as speed violation detection, accident monitoring, and automated alert generation.

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