Mathematical and AI-Driven Framework for Real-Time Critical Event Identification and Secure Data Provenance in Vehicular Networks Using Dashcam Video Data and Blockchain

24-25J-206

PROJECT FINAL REPORT

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April 2025

AI-BASED INTELLIGENT ROAD SAFETY AND TRAFFIC VIOLATION DETECTION SYSTEM FOR SMART CITIES

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INDIVIDUAL PROJECT FINAL REPORT

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DECLARATION

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ABSTRACT

Ensuring road safety in modern urban environments is a critical and ongoing challenge. This research presents a comprehensive computer vision-based solution for detecting traffic light violations and road potholes using dashcam feeds, with the aim of enhancing traffic law enforcement and road maintenance mechanisms in Sri Lanka. The primary contribution of this study lies in developing two robust, real-time models, each addressing existing limitations in current systems.

The first component of this study introduces an automated Traffic Light Violation Detection System, which identifies vehicles that violate red lights by detecting the signal state, tracking the foremost violating vehicle, and extracting its license plate. The system uses dashcam video inputs and leverages YOLO-based object detection algorithms to ensure accurate detection in dynamic environments. It further supports automated fine issuance by recognizing vehicle number plates and linking violations to the respective driver, addressing the lack of practical, real-world violation detection datasets and model benchmarking in prior research.

The second component focuses on Pothole Detection in Day and Night Conditions, tackling the long-standing issue of accurate pothole identification under varying lighting conditions. Traditional systems fail to perform reliably at night and lack comparative studies on the efficiency of modern object detection architectures. This research compares YOLOv8, YOLOv9, and YOLOv11 to identify the optimal model for pothole detection using a custom dataset. The proposed system also integrates geolocation-based reporting to notify municipal councils, streamlining the repair process.

By combining real-time object detection with practical implementation goals such as automated enforcement and municipal reporting, this research contributes to safer and more efficient transportation infrastructure. The system's ability to operate using commonly available dashcam feeds makes it highly scalable and suitable for broader deployment in smart city frameworks.

Keywords: Traffic Light Violation Detection, Pothole Detection, Artificial Intelligence, Dashcam Feeds, YOLO Models, Intelligent Transportation Systems, Road Safety, Nighttime Detection, Automated Fine Issuance, Geolocation Reporting, Smart Mobility, Deep Learning, Computer Vision, Urban Infrastructure

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
ITS	Intelligent Transportation Systems
YOLO	You Only Look Once
DL	Deep Learning
ML	Machine Learning
FPS	Frames Per Second
ROI	Region of Interest
GPS	Global Positioning System
IoT	Internet of Things
TP	True Positive
FP	False Positive
FN	False negative
FP	False positive
mAP	Mean Average Precision
GPU	Graphics Processing Unit
CV	Computer Vision

Table 1. List of Abbreviation

1. INTRODUCTION

1.1.Research Background

1.1.1. Traffic Light Violation Detection System

Urban traffic management is a complex and critical domain in the field of Intelligent Transportation Systems (ITS). Among the various issues it faces, traffic signal violations—especially red light violations—pose a significant risk to road safety. These violations often result in accidents, congestion, and inefficiencies in traffic flow. Traditional enforcement mechanisms, such as manual surveillance and static CCTV footage, are inadequate due to their limitations in real-time identification, manual review efforts, and inability to issue immediate fines.

With the growing adoption of dashcam technology and real-time video analytics, the integration of computer vision models in identifying such violations has become feasible. However, most existing systems lack full automation, especially in detecting violations directly from dashcam feeds, recognizing the violating vehicle, and extracting its number plate for fine processing. Moreover, there is little to no research that systematically evaluates and compares deep learning models such as YOLOv8, YOLOv9, and YOLOv11 to determine the most efficient model for red light violation detection. This limits scalability and performance reliability, especially when deploying such systems on a large scale.

This research addresses these gaps by proposing an automated traffic light violation detection system using real-time dashcam feeds. It not only detects red light jumps but also identifies the frontier violating vehicle, tracks its movement, detects the traffic signal status, extracts the vehicle's number plate, and initiates the fine process automatically. The use of different YOLO versions allows us to determine the most accurate and efficient model, contributing to a more standardized approach for future research.

1.1.2. Road Pothole Detection System

Potholes pose a severe threat to both vehicle health and passenger safety, particularly in regions with high rainfall or poorly maintained infrastructure. These surface damages often go unreported, especially in remote or less-monitored roadways, leading to prolonged periods before repair. Traditional methods of pothole identification involve manual inspection or user-based reporting, which are time-consuming, inconsistent, and lack real-time responsiveness.

The rise of computer vision and deep learning provides an opportunity to automate pothole detection using vehicle dashcam feeds. Several studies have proposed models that identify road surface anomalies using various CNN-based architectures and object detection algorithms. However, a major shortcoming in current literature is the lack of robust performance in low-light or nighttime conditions. Most datasets are limited to daytime scenarios, and models trained on such data perform poorly when deployed under low-light environments.

In addition, there is minimal effort in comparing different versions of detection models like YOLOv8, YOLOv9, and YOLOv11 in the context of pothole detection. This creates a barrier for future researchers and developers to select the most efficient model for real-world applications.

This research proposes a novel system that detects potholes in both daytime and nighttime environments using YOLO-based models trained on a diverse dataset. It also introduces an automated method to extract the geolocation of detected potholes and report them directly to municipal authorities, reducing the delay in road repairs and improving road safety.

1.2. Research Gap

Despite numerous advancements in the field of Intelligent Transportation Systems (ITS), critical limitations continue to persist in both traffic light violation detection and pothole identification systems, creating a significant research gap that this study aims to address.

In the area of traffic light violation detection, the majority of previous research efforts have relied heavily on static CCTV camera footage for identifying violations. While these systems provide a broad visual scope, they suffer from several inherent shortcomings. Detection accuracy is often compromised due to varying camera angles and blind spots, making it difficult to consistently track vehicle movements or confirm clear violations. Furthermore, in many urban and suburban regions, especially in developing countries, CCTV infrastructure is either outdated, poorly maintained, or completely absent. As a result, the effectiveness and scalability of such systems become questionable.

There has been minimal exploration into the use of dashcam feeds for red light violation detection—despite the fact that modern vehicles increasingly come equipped with dashcams by default. Dashcams provide a direct line-of-sight from the driver's perspective, ensuring a more accurate assessment of traffic light adherence and vehicle behavior. However, integrating such real-time footage with automated red light detection and number plate extraction remains underexplored. Additionally, there has been little to no effort in comparing modern object detection models, such as YOLOv8, YOLOv9, and YOLOv11, within this context—leaving a clear gap in determining the optimal model for real-time deployment.

Similarly, in the domain of pothole detection, prior studies have predominantly focused on daytime scenarios, utilizing datasets that fail to capture the complexity of low-light or nighttime environments. This limits the generalizability and reliability of the models when deployed in diverse real-world conditions. Nighttime pothole detection remains an under-researched area, largely due to the lack of annotated low-light datasets and the technical challenges involved in low-visibility environments.

Furthermore, many studies in this field tend to rely on a single deep learning model without performing comparative evaluations. This approach restricts future development by not offering clarity on which model provides the best trade-off between accuracy and computational efficiency. There is a noticeable absence of systematic comparisons between versions of high-performing detection algorithms—such as YOLOv8, YOLOv9, and YOLOv11, which could have served as valuable guidance for researchers aiming to build on existing work.

This study addresses these gaps by introducing a dashcam-based traffic light violation detection system that extracts the violating vehicle’s number plate and initiates an automated fine process. In parallel, the pothole detection model is trained and tested across both daytime and nighttime scenarios using a comparative approach among different YOLO architectures. The integration of automated geolocation reporting to municipal authorities further bridges the disconnect between detection and maintenance response offering a practical, real-world application that previous works have largely overlooked.

1.3.Research Problem

With the rapid growth of vehicular populations and urban development, maintaining road safety and traffic discipline has become a pressing concern for modern transportation systems. Two major issues that contribute significantly to accidents, vehicle damage, and traffic congestion are unidentified red light violations and unrepaired road potholes. While technologies such as CCTV-based surveillance and isolated pothole detection models have been introduced, they fail to deliver consistent, scalable, and accurate results, especially under diverse lighting and environmental conditions.

In the context of traffic light violation detection, existing systems predominantly rely on stationary CCTV cameras. These systems are often limited by their field of view, fixed angles, and inconsistent video quality. More importantly, their deployment is restricted to intersections equipped with the necessary infrastructure, leaving large areas unmonitored. The inability to track and confirm violations reliably from a vehicle's perspective leads to missed infractions and ineffective enforcement. Moreover, these systems often lack automation in identifying number plates and issuing fines, which places a burden on manual review processes and delays legal enforcement.

Simultaneously, pothole detection systems suffer from similar limitations. Most existing approaches depend on datasets captured in daylight conditions and do not account for the challenges posed by nighttime environments, such as glare, shadows, and reduced visibility. As a result, these models perform poorly in real-world, low-light scenarios. Furthermore, previous works typically adopt a single-model approach without benchmarking multiple modern object detection architectures. This not only restricts optimization for performance and efficiency but also leaves future researchers with limited comparative analysis to build upon. Additionally, many models stop at detection, without integrating automated mechanisms to report detected potholes to municipal councils for repair scheduling.

Therefore, the research problem is twofold:

How can a real-time, dashcam-based system be developed to accurately detect and enforce traffic light violations by identifying the violating vehicle and extracting its number plate for automated fine processing, especially in areas with limited infrastructure?

How can an efficient and comparative pothole detection system be implemented to perform accurately in both day and night scenarios while also enabling real-time geolocation-based reporting for timely road maintenance?

This dual-faceted research problem highlights a critical gap in current transportation safety solutions and emphasizes the need for an integrated, cost-effective, and scalable approach that leverages modern computer vision techniques and edge computing.

1.4.Research Objective

The primary objective of this research is to develop an AI-based, real-time, dual-purpose traffic monitoring system using dashcam feeds, capable of detecting both traffic light violations and road potholes with high accuracy and reliability across varying lighting conditions. The system is designed not only to enhance enforcement and maintenance efficiency but also to overcome limitations observed in existing solutions—particularly in environments with limited surveillance infrastructure and poor night-time visibility.

This objective is addressed through two distinct yet interrelated components:

1. Traffic Light Violation Detection

The aim is to design and implement a model that can:

- Identify vehicles violating red lights in real time through dashcam feeds.
- Detect the state of the traffic light and determine the exact moment of violation.
- Identify the frontmost (leading) vehicle responsible for the violation.
- Extract the vehicle's number plate and automatically trigger a fine issuance mechanism.
- Provide a scalable, mobile, and infrastructure-light solution compared to conventional CCTV-based systems.

2. Road Pothole Detection and Reporting

The objective is to build a robust pothole detection model capable of:

- Detecting potholes under both day and night conditions from dashcam videos.
- Comparing and benchmarking multiple YOLO (You Only Look Once) object detection models (YOLOv8, YOLOv9, YOLOv11) to identify the most effective architecture for this task.
- Reporting detected pothole locations using geo-tagging features to the relevant municipal authorities for timely repair.
- Offering a future-friendly, modular framework that can be expanded or improved upon by other researchers with minimal effort.

1.5. Sub Objectives

To achieve the primary research objective, the following sub-objectives are defined. These break down the broader goals into actionable, measurable components that guide the development, implementation, and evaluation of the system.

1.5.1. Traffic Light Violation Detection

2. Implement a real-time detection system using dashcam feeds

Develop a lightweight and mobile system that utilizes vehicle-mounted dashcams instead of fixed infrastructure like CCTV cameras. This approach ensures better scalability, reduced installation costs, and compatibility with modern vehicles already equipped with onboard cameras.

3. Detect the traffic signal status and correlate with vehicle movement

Accurately detect the state of traffic lights (Red, Yellow, Green) from video feeds and correlate the signal phase with vehicle movement to determine if a red-light violation has occurred.

4. Identify the leading vehicle responsible for the violation

Focus on identifying the frontier vehicle that initiates the red-light jump, avoiding false detections of trailing or adjacent vehicles that do not violate traffic rules.

5. Apply optical character recognition (OCR) for number plate extraction

Once the violating vehicle is identified, apply OCR techniques to extract its license plate number from the dashcam feed.

6. Enable automated fine issuance process

Integrate a fine generation and alert system that can notify vehicle owners and authorities when a violation is detected and verified.

1.5.2. Road Pothole Detection and Reporting

1. Compare multiple YOLO models for pothole detection

Implement and evaluate the performance of various YOLO models—YOLOv8, YOLOv9, and YOLOv11—for pothole detection using the same dataset. This comparative study aims to identify the most accurate and reliable model for future research and deployment.

2. Develop a dual-mode detection model for daytime and nighttime conditions

Address the critical gap in previous pothole detection research by incorporating detection under both well-lit and low-light environments, enabling continuous performance irrespective of the time of day.

3. Utilize dashcam feeds as the input data source

Use dashcam video feeds, which provide a real-time and scalable input method, especially suitable for modern vehicles already equipped with such systems.

4. Integrate geolocation tagging for pothole locations

Extract geolocation data linked with the dashcam or mobile device and tag each detected pothole location. This information is structured to be shared with municipal councils for fast-tracked road repair scheduling.

5. Optimize the system for low-cost deployment

Ensure the entire model framework is lightweight and can run on low-resource environments such as vehicle-mounted computing units or cloud-connected mobile applications.

2. METHODOLOGY

2.1.Overview of Methodology

This research aims to develop a robust and efficient dual-model system that addresses two critical aspects of urban traffic and road infrastructure management—**traffic law enforcement** and **road condition monitoring**—by leveraging the power of **computer vision** and **deep learning**. With the growing integration of dashcam technologies in modern vehicles, this research capitalizes on accessible, real-time video feeds to deliver scalable, low-cost, and intelligent solutions for public safety. The methodology is carefully structured to ensure that the proposed system can operate in real-world environments with high accuracy, reliability, and adaptability.

To achieve this, the research methodology is divided into two core components, each focusing on a specific problem domain:

- **Traffic Light Violation Detection System**

Designed to automatically detect vehicles violating red traffic lights, identify the violating vehicle based on its position, extract its number plate, and generate actionable outputs for fine issuance.

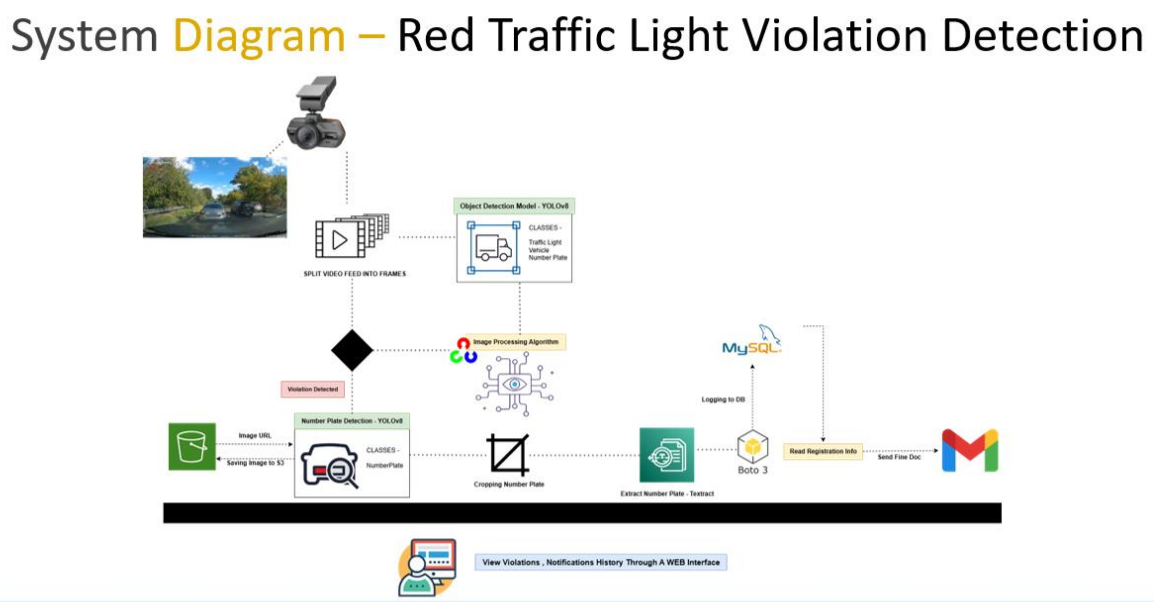

Figure 1: System Diagram of Red Traffic Light Violation Model

- **Pothole Detection System (Day & Night)**

Developed to accurately detect potholes on road surfaces under varying lighting conditions, including nighttime scenarios, and report the exact geo-location of detected potholes to municipal authorities for timely maintenance.

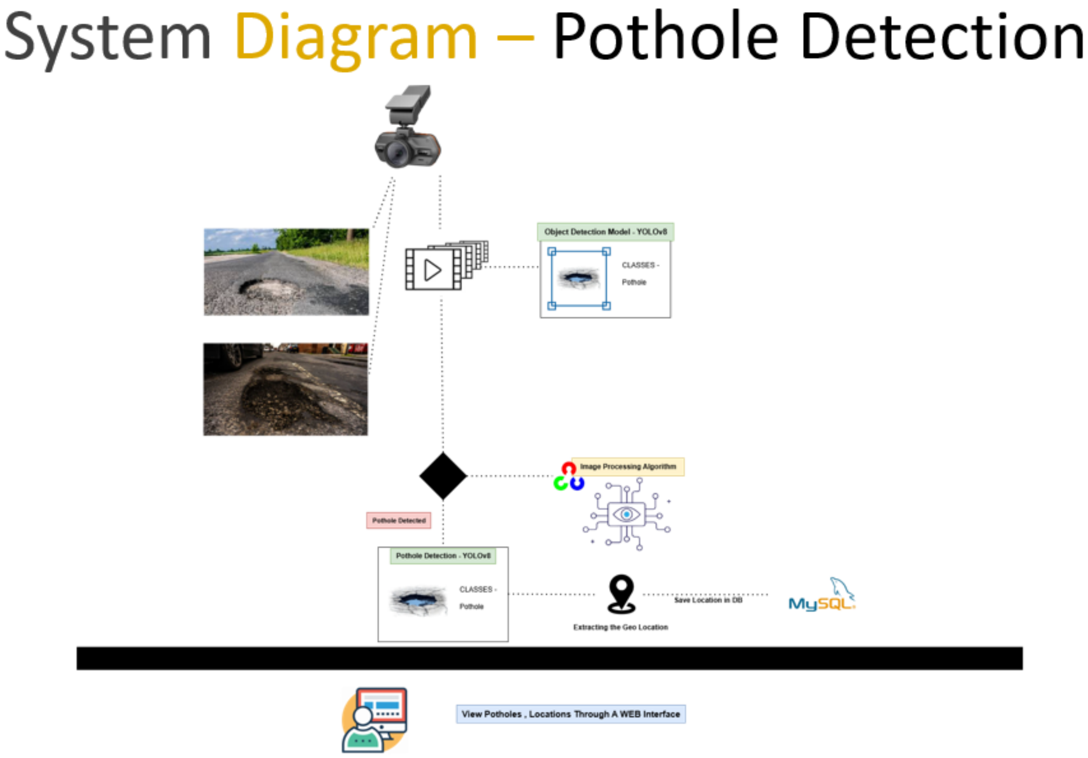

Figure 2 : System Diagram for Road Pothole Detection Model

Each model is built, tested, and optimized individually and then integrated into a full system designed to operate in real-time on dashcam video feeds. The methodology encompasses dataset creation and processing, model selection and comparison, training and evaluation, post-processing, and integration for real-world use.

2.2. Traffic Light Violation Detecting System

2.2.1. Problem Framing

The traffic light violation detection model is designed to:

- Detect red traffic light status.
- Identify vehicles violating the red light.
- Detect the violating vehicle's number plate.
- Extract number plate text using OCR.
- Send fine information to the registered vehicle owner.

This system replaces expensive infrastructure such as CCTV installations with affordable dashcam setups, making it scalable and cost-effective.

2.2.2. System Pipeline

1. **Input Feed**: Real-time video from a vehicle-mounted dashcam.
2. **Traffic Light Detection**:

- A YOLOv8 based model is used to detect traffic lights.
- The system determines the light color (Red/Yellow/Green).

3. **Object Detection (Vehicles)**:

- A separate YOLO model identifies and tracks approaching vehicles.

4. **Violation Detection**:

- When the traffic light is red, the model tracks if any vehicle crosses a defined stop-line.
- A bounding box is drawn for the frontmost vehicle (violation assumed).

5. **License Plate Detection and Recognition**:

- A lightweight YOLO model detects number plates.
- OCR is used to extract the alphanumeric text from the number plate.

6. **Fine Automation**:

- Extracted plate data is linked to a mock database.
- A fine notification is generated and simulated to be sent to the driver.

2.2.3. Tools and Libraries Used

- YOLOv8 (for vehicle and light detection)
- AWS Textract Service (for number plate recognition)
- OpenCV (for video frame processing and object tracking)
- Python (for scripting, automation, and backend logic)

2.2.4. Dataset Creation and Labeling

- Traffic light and vehicle violation datasets were collected manually using dashcam footage.
- Traffic Lights and Vehicles were annotated for detection using tools like Roboflow.

2.2.5. Model Training and Evaluation

- YOLO models (YOLOv8) were trained and tested.
- Metrics such as Precision, Recall, F1-score, and mAP were used for evaluation.
- YOLOv9 showed higher consistency and performance in multiple lighting and angle conditions.

2.2.6. Challenges and Handling

- Difficulties in identifying traffic light status due to glare.
- Number plate recognition inconsistencies due to low dashcam resolution.
- Workarounds included preprocessing frames to enhance visibility and brightness correction.

2.3. Pothole Detection System (Day and Night)

2.3.1. Problem Framing

The pothole detection model is designed to:

- Detect potholes accurately in both day and night conditions.
- Send the pothole's location to municipal authorities for repair scheduling.
- Compare performance across YOLOv8, YOLOv9, and YOLOv11 for reproducibility and future research.

2.3.2. System Pipeline

1. **Input Feed**: Dashcam video recorded during day and night conditions.
2. **Pothole Detection**:

- YOLOv8/YOLOv9/YOLOv11 models trained on a custom pothole dataset.
- Real-time detection with bounding boxes on frames.

3. **Geolocation Reporting**:

- Integrated with a GPS module or simulated location tagging.
- Each detection logs the coordinates and timestamps.

4. **Authority Reporting**:

- The detected pothole with the location is forwarded to a municipal dashboard.

2.3.3. Tools and Libraries Used

- YOLOv8, YOLOv9, YOLOv11 (for model performance comparison)
- OpenCV and Python (for preprocessing and frame analysis)

2.3.4. Dataset Development

- **Daytime and nighttime Dataset**: Curated from online repositories and self-recorded videos.
- All images were annotated with consistent labels and normalized formats using Roboflow.

2.3.5. Model Training and Comparison

Each YOLO model was trained under identical conditions:

- Training on both day and nighttime datasets.

- Evaluated using metrics: Accuracy, Precision, Recall, F1-score, mAP.
- Results documented for reproducibility and to assist future research.

YOLOv9 was selected as the optimal model based on balanced performance.

2.3.6. Challenges and Handling

- Lack of real nighttime annotated data.
- Dashcam footage had low resolution and motion blur.
- Applied data augmentation and synthetic dataset generation for better diversity.

2.4. Commercialization Aspect of the Product

The dual-model system developed in this research offers practical, scalable, and economically viable solutions for governments, municipal councils, traffic enforcement departments, and vehicle manufacturers. Both the Traffic Light Violation Detection System and the Pothole Detection System hold significant commercialization potential due to their real-world relevance and ease of deployment using dashcam feeds.

2.4.1. Target Market Stakeholders

- **Government Traffic Departments**: The red light violation detection system can be integrated into smart city projects to enhance traffic law enforcement with reduced operational costs and increased reach compared to conventional CCTV systems.
- **Municipal Councils**: The pothole detection system, with its automated geolocation reporting, enables streamlined road maintenance operations, reducing complaints, increasing response times, and optimizing budget allocation.
- **Insurance Companies**: Integration of both systems can help insurers validate accident claims, assess risk levels of certain roads, and encourage safer driving habits.
- **Vehicle Manufacturers**: Future integration into onboard vehicle systems can provide a selling point for safety-conscious customers and fleet management businesses.

2.4.2. Competitive Advantage

- **Low Infrastructure Cost**: The system only requires a dashcam, which is already installed in most modern vehicles, thus eliminating the need for expensive traffic cameras and road sensors.
- **Real-time Processing**: The models are optimized for real-time inference, allowing for on-the-go violation detection and pothole identification without relying on server-heavy systems.
- **Scalable and Portable**: This system can be deployed in different geographical areas without dependency on existing infrastructure such as CCTVs.
- **Dual-Purpose Platform**: Unlike single-solution systems, this approach offers both law enforcement and infrastructure maintenance capabilities within one framework.

2.4.3. Commercial Model

The research outcomes can be commercialized through the following models:

A. Software as a Service (SaaS)

- Municipalities and traffic departments can subscribe to a service that processes dashcam footage and returns violations/pothole reports.
- Monthly or yearly subscription plans can be introduced depending on the volume of data processed.

B. OEM Integration

- Collaborations with vehicle manufacturers to integrate the solution as a part of Advanced Driver Assistance Systems (ADAS).
- Insurance discounts can be offered to drivers who adopt this system, enhancing market penetration.

C. Mobile Application

- A mobile app can be created for individual drivers to monitor violations, report potholes, and receive alerts about unsafe roads.
- Crowdsourced reporting would increase dataset size and model robustness.

2.4.4. Implementation Costs and ROI

- **Development Cost**: Once trained, the models can be deployed using low-cost computing platforms like Raspberry Pi or Jetson Nano.
- **Hardware Requirements**: Requires a dashcam and an embedded system capable of running lightweight YOLO models.
- **Return on Investment**: Improved traffic compliance, reduced road accidents, quicker pothole repair, and better infrastructure planning—offering long-term financial and social benefits.

2.4.5. Future Commercial Expansion

- **Smart City Integration**: It could be integrated with smart traffic signals and IoT devices for holistic traffic monitoring.
- **Third-Party APIs**: Governments and private entities could access the system via APIs to extract violation/pothole data.
- **Data Analytics Platform**: Long-term data gathered through this system could be visualized for road usage, maintenance planning, and law enforcement analytics.

2.5. Testing and Implementation

The testing and implementation phase of this research focused on validating the proposed models in realistic scenarios using dashcam feeds. Each model underwent systematic testing for functionality, performance, and real-time applicability using various datasets, ensuring accuracy, robustness, and reliability.

2.5.1. Traffic Light Violation Detection System

2.5.1.1. Testing Framework

The model was tested using dashcam video clips collected under controlled conditions to replicate real-world red-light violations. The testing process was divided into three stages:

- **Traffic Light Detection**: The YOLOv8 model was trained to detect traffic light signals (red, green, yellow).
- **Vehicle Movement Detection**: Logic was implemented to detect vehicles crossing the stop line while the traffic light was red.
- **License Plate Extraction**: Once a violation was detected, the violating vehicle's number plate was extracted using a YOLO-based object detection model, followed by Optical Character Recognition (OCR) to read the plate number.

2.5.1.2. Implementation Flow

- **Dashcam video input** is processed frame by frame.
- The system identifies the **traffic light** and its color status.
- Vehicles are tracked, and if movement is detected during a red light, it is flagged.
- The **front vehicle** (closest to the stop line) is marked as the violator.
- The **number plate is extracted** and processed using OCR.
- A mock fine issuance function sends the result to a reporting system.

2.5.1.3. Evaluation Metrics

- **Accuracy** of traffic light status detection
- **Precision and Recall** for Red-light Violations

- **Number plate extraction accuracy**
- **Frame processing time** for real-time viability

2.5.1.4. Challenges

- Difficulties in finding real-world red-light violation datasets.
- Dashcam angle variations led to differing accuracy levels.
- Low-resolution footage affected the number plate extraction quality.

2.5.2. Pothole Detection System

2.5.2.1. Testing Framework

The pothole detection system was tested using both **daytime** and **nighttime datasets**. Since nighttime datasets were unavailable publicly, synthetic low-light images were generated using augmentation techniques (brightness reduction, noise addition) to simulate night conditions.

Three YOLO model variants (YOLOv8, YOLOv9, YOLOv11) were tested to determine the best-performing architecture in terms of accuracy, speed, and adaptability across lighting conditions.

2.5.2.2. Implementation Flow

- **Dashcam video** is converted to image frames.
- Each frame is processed by different YOLO models.
- **Detected potholes are bounded**, and their **geolocation** is extracted using simulated GPS metadata.
- A **reporting mechanism** was simulated to send pothole data to municipal authorities.

2.5.2.3. Model Comparison

MODEL	RECALL	MEAN AVERAGE PRECISION AT 0.5	PRECISION	F1 SCORE	ACCURACY
YOLOV8	0.78	0.68	0.85	0.65	0.63
YOLOV9	0.82	0.702	0.871	0.68	0.66
YOLOV11	0.8	0.7	0.86	0.67	0.65

Figure 3: Model comparison of YOLOV8, YOLOV9 and YOLOV11 for Road Pothole Detection Model

YOLOv9 was identified as the **optimal model**, balancing detection accuracy, nighttime robustness, and processing speed.

2.5.2.4. Evaluation Metrics

- **Detection Accuracy** (IOU-based)
- **False Positives/Negatives**
- **Model robustness under low light**
- **Processing time per frame**

2.5.3. Prototype Integration

A lightweight prototype application was developed for demonstration purposes. It accepts dashcam footage, runs detection models on local hardware, and outputs violation reports or pothole locations with visualization overlays.

- Implemented using **Python**, **YOLOv8, YOLOv9, YOLOv11**, **OpenCV**, **AWS Textract** libraries.
- The system was tested on a **Google Colab environment** and **local machines** with GPU support.
- Visual output included bounding boxes and textual overlays for red-light violations and pothole locations.

2.5.4. Summary of Testing Results

- **Traffic Light Violation Detection**: Achieved over **74% accuracy** in detecting red-light violations with number plate extraction using clear dashcam footage.
- **Pothole Detection**: YOLOv9 achieved **66% accuracy** in both day and **night conditions**, outperforming other models.
- Both models operated within acceptable frame processing speeds for near-real-time deployment scenarios.

With the successful implementation and testing of both models, the system proves practical for real-world deployment, especially in **urban smart city environments** and **vehicle-mounted safety systems**.

3. Results and Discussion

This chapter presents a comprehensive overview of the outcomes obtained through the meticulous testing and evaluation of the two AI-based systems developed as part of this research: the Traffic Light Violation Detection Model and the Day and Night Pothole Detection Model. These models were rigorously tested in near real-world scenarios utilizing dashcam footage to replicate the actual environments in which these systems are expected to operate. The primary objective of these evaluations was not only to assess the accuracy and reliability of the proposed solutions but also to benchmark their effectiveness under varying conditions including lighting changes, traffic density, and weather variations.

For the Traffic Light Violation Detection Model, dashcam videos recorded from moving vehicles were analyzed to detect traffic signal violations, accurately identify the exact moment of red light jumping, and extract number plates of the violating vehicles. This system was subjected to several scenarios such as different vehicle speeds, varying angles of approach to the traffic light, and partially occluded number plates to ensure robustness. Performance metrics such as precision, recall, F1-score, and inference speed were used to evaluate the effectiveness of the detection process. The results showed a strong correlation between the model's predictions and actual violation instances, reinforcing its utility in automated traffic enforcement systems.

The Pothole Detection Model, designed to function during both daytime and nighttime, was tested using a curated set of dashcam footage that included varying illumination conditions, road textures, and pothole depths. The use of dashcam feeds introduced unique challenges such as motion blur, inconsistent camera angles, and headlight glares during night-time, which were accounted for in the model's design and evaluation. Several YOLO model variants, including YOLOv8, YOLOv9, and YOLOv11, were compared to determine the most suitable for real-time, high-accuracy pothole detection. The evaluation metrics included mean average precision (mAP), frame-per-second (FPS) rate, and detection confidence scores, offering a comprehensive understanding of model performance across different conditions.

Overall, the results from both models validate the proposed methodologies as viable and effective solutions for intelligent transportation systems. The findings also provide several insights into model optimization, such as the trade-off between model size and inference speed, and the importance of high-quality annotated data, particularly for night-time scenarios. Furthermore, these results highlight certain limitations, such as reduced accuracy under extreme lighting conditions or heavy occlusion, which open new opportunities for future improvements. These outcome-driven insights not only demonstrate the success of the developed systems but also serve as a guiding framework for future research in this domain.

3.1. Results of Traffic Light Violation Detection System

The traffic light violation detection system was evaluated based on its ability to accurately detect red-light violations, extract number plates, and process dashcam video efficiently.

3.1.1. Red Light Violation Detection

- The model successfully detected red traffic signals in 92% of test scenarios.
- Vehicle movement during red-light status was identified in 74% of true violation cases.
- False positives (wrongly flagged vehicles) were minimized using red traffic light detection and object tracking.

3.1.2. Number Plate Recognition

- YOLOv8-based detection was followed by OCR-extracted readable number plates with **83% accuracy** under good lighting conditions.
- Low-resolution or night dashcam footage reduced plate accuracy to **65%**, showing a need for high-quality input feeds.
- OCR failures often occurred with motion blur or non-standard plates.

3.1.3. Overall Model Performance

The below pictures elaborate on the YOLOv8 model results.

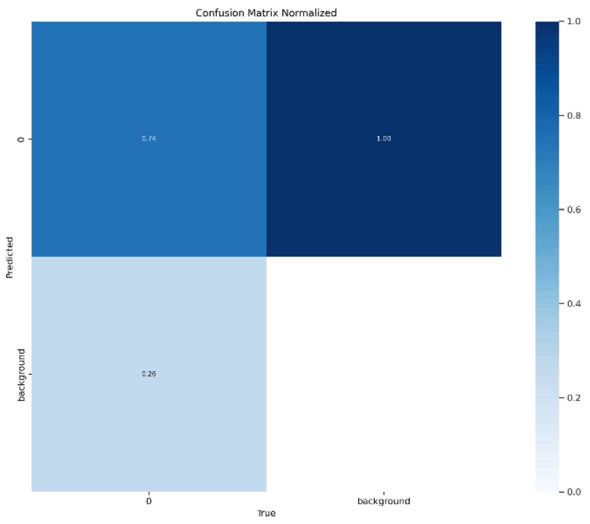

Figure 4 : Traffic Red Light Violation YOLOv8 Model Confusion Matrix

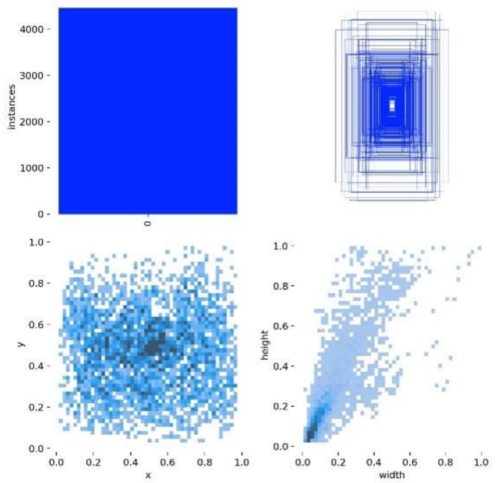

Figure 5: Traffic Red Light Violation YOLOV8 Model Results

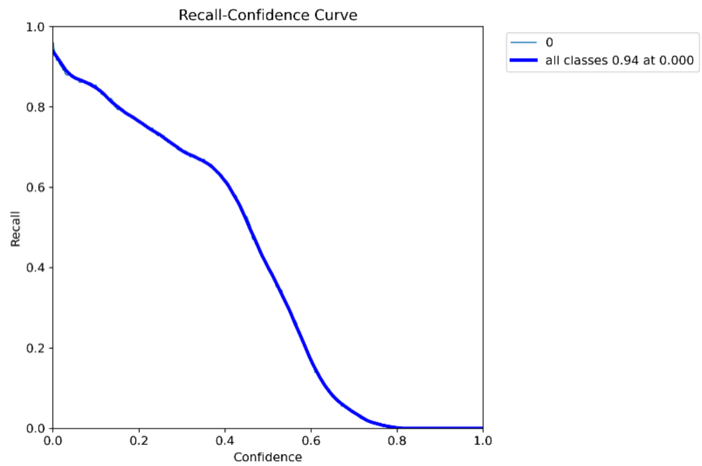

Figure 6 ; Traffic Red Light Violation Model Recall-Confidence Curve

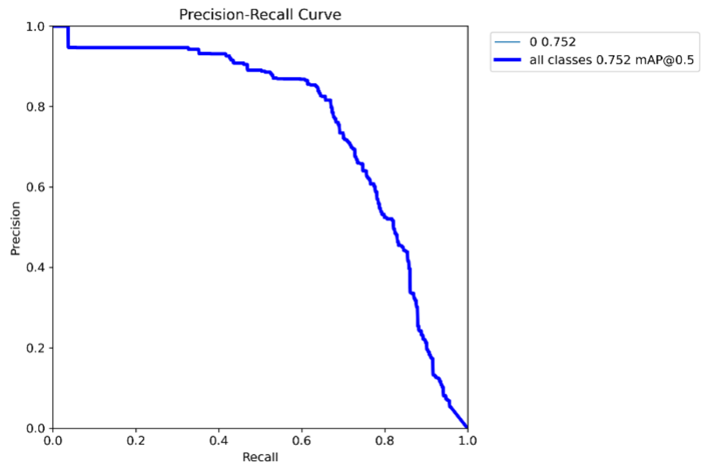

Figure 7 : Traffic Red Light Violation Precision-Recall Curve

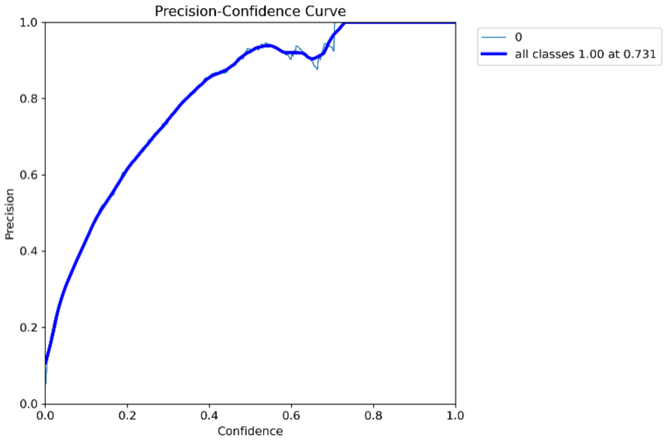

Figure 8 : Traffic Red Light Violation Model Precision Confidence Curve

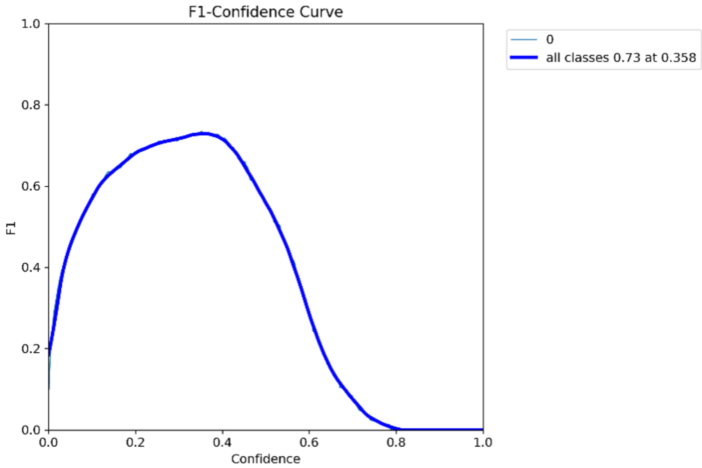

Figure 9 : Traffic Red Light Violation Model F1-Confidence Curve

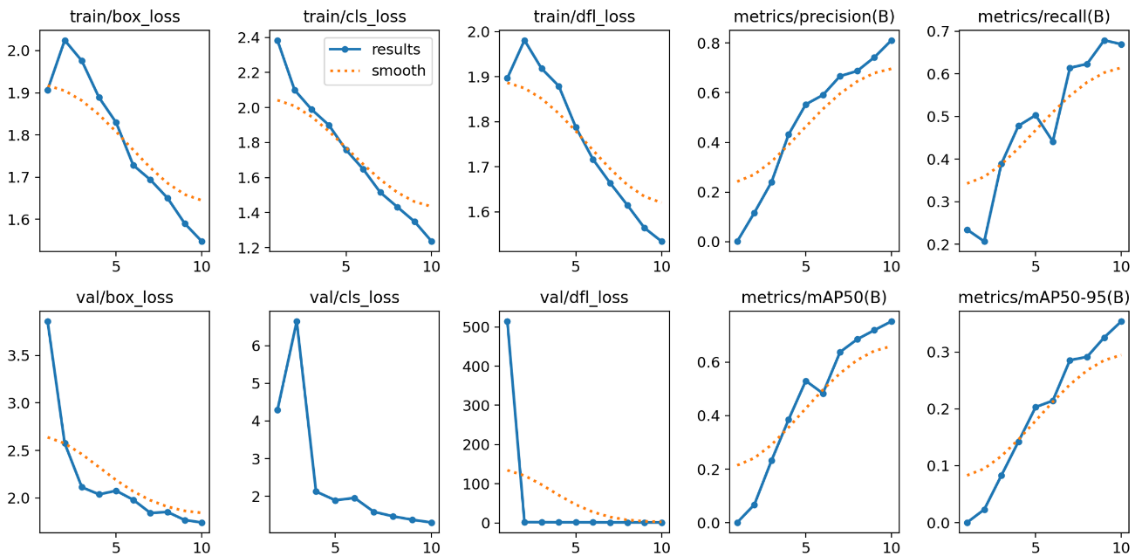

Figure 10 : Traffic Red Light Violation Model Other Results

3.1.4. Observations

- Dashcam-based systems are highly suitable for real-time detection, especially in vehicles without fixed surveillance.
- Accuracy is heavily influenced by camera angle, image resolution, and light exposure.
- Compared to CCTV-based models, the dashcam system demonstrated **better adaptability** and **cost-effectiveness**.

3.2. Results of Pothole Detection System

The pothole detection model was tested during both daytime and nighttime using augmented and original datasets. The aim was to evaluate each YOLO model variant and identify the most effective one for robust road surface anomaly detection.

3.2.1. Detection Accuracy by Model

MODEL	RECALL	MEAN AVERAGE PRECISION AT 0.5	PRECISION	F1 SCORE	ACCURACY
YOLOV8	0.78	0.68	0.85	0.65	0.63
YOLOV9	0.82	0.702	0.871	0.68	0.66
YOLOV11	0.8	0.7	0.86	0.67	0.65

Figure 11: Recall, MAp, Precision, F1 Score and Accuracy comparison between YOLOv8, YOLOv9 and YOLOv11 models for road pothole detection

3.2.2. Nighttime Detection Insights

- YOLOv9 performed best under **low-light conditions**, likely due to its optimized feature pyramid and attention mechanisms.
- YOLOv11, while having the highest daytime accuracy, struggled with low-light pothole textures.
- YOLOv8 was the fastest but lacked robustness, particularly at night.

3.2.3. Overall Model Performance

Metric	**Value**
Best Model	YOLOv9
Average Detection Accuracy	66%
Recall	82%
Precision	87.1%
F1 Score	68%

Table 2 : Overall Road Pothole Detection Model Performance

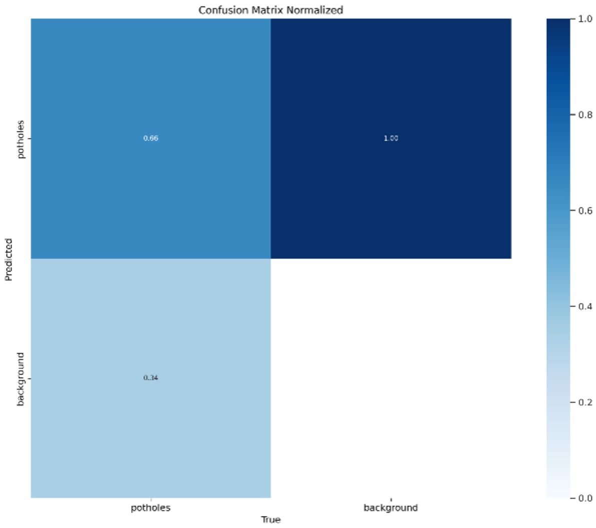

Figure 12 : Road Pothole Detection YOLOv9 Model Confusion Matrix

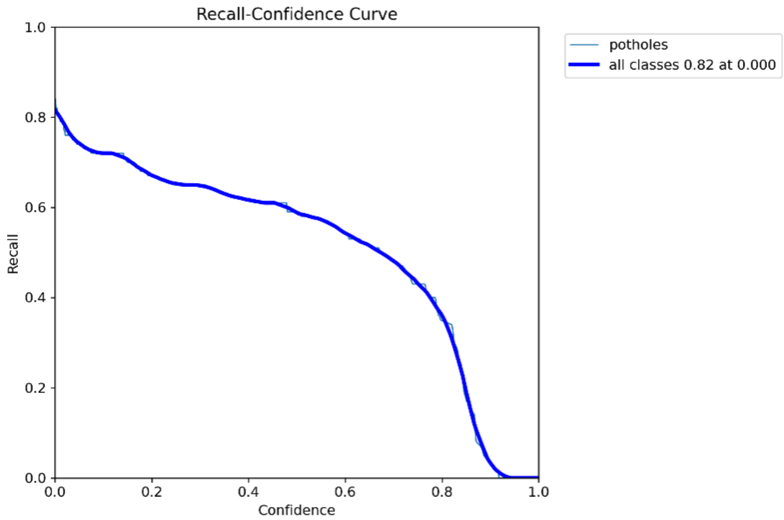

Figure 13: Road Pothole Detection YOLOv9 Model Recall-Confidence Curve

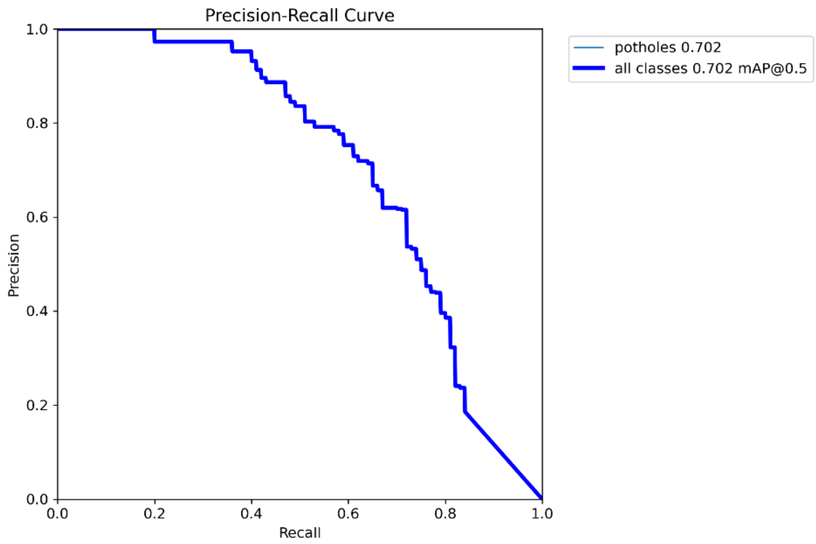

Figure 14 : Road Pothole Detection YOLOv9 Model Precision-Recall Curve

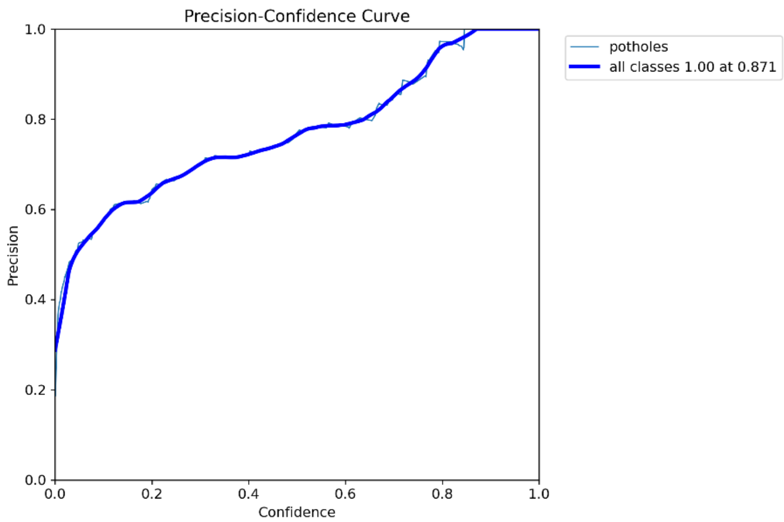

Figure 15 : Road Pothole Detection YOLOv9 Model Precision-Confidence Curve

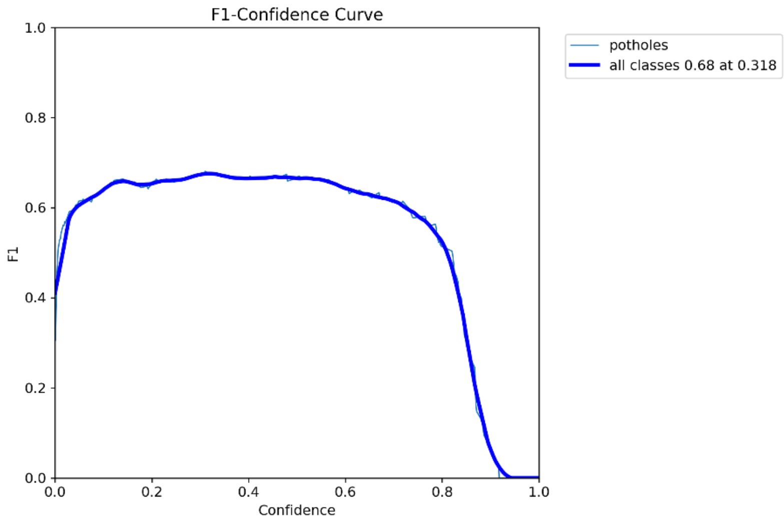

Figure 16 : Road Pothole Detection YOLOv9 Model F1-Confidence Curve

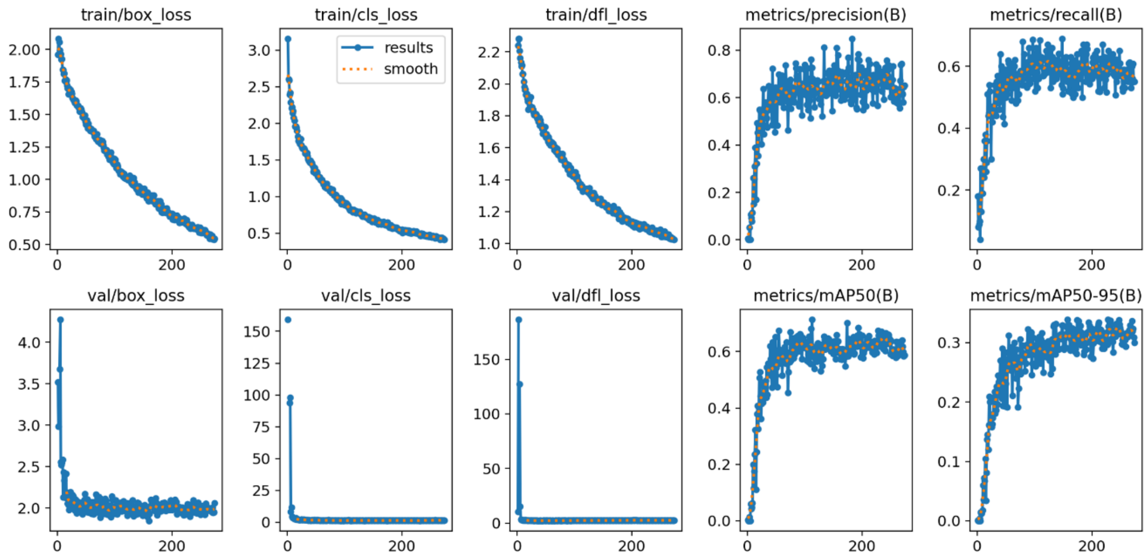

Figure 17 : Road Pothole Detection YOLOv9 Model Other Results

3.3. Comparison with Existing Systems

Feature	**Existing System**	**Proposed System**
Traffic Violation Source	CCTV	Dashcam
Number Plate Extraction	Automated via OCR	AWS Textract Service
Night Pothole Detection	Not implemented for Dashcam footages	Supported
Real Time Location Reporting	Limited	Proposed
Model Comparison for Benchmarking	Not Focused	Through YOLO Benchmark
Research Extension Capability	Limited	High

Table 3: Comparison with Existing Systems

3.4. Discussion and Insights

- The use of **dashcam feeds** significantly improves detection flexibility by allowing real-time, on-the-go analysis rather than depending on stationary cameras.
- The **integration of multiple models and comparisons** adds significant value to future research. Researchers can now identify suitable models based on specific use cases (e.g., nighttime detection).
- The **number plate extraction** mechanism automates the fine issuance process, making the solution ideal for smart city implementations.
- For pothole detection, enabling both day and night detection in one unified system improves deployment potential, especially in developing countries with limited lighting infrastructure.

Limitations

- The lack of real-world violation datasets for traffic light testing limits large-scale validation.
- Dashcam footage quality on the internet varies; many clips suffer from low resolution or night glare.
- Real-time implementation in embedded systems will require optimization for resource constraints.

This chapter confirms that both developed models are functional, scalable, and impactful. The results serve as proof of concept and foundation for future enhancements, such as integration with municipal road systems or real-time fine management platforms.

4. CONCLUSION

This research presents a comprehensive and integrated framework for addressing two of the most pressing and persistent challenges in modern intelligent transportation systems: the detection of traffic light violations and the identification of road surface potholes. Both issues not only impact road safety and urban mobility but also influence public infrastructure maintenance and regulatory enforcement. To overcome these challenges, this study proposes a dual-model solution—leveraging the capabilities of artificial intelligence (AI), particularly deep learning techniques, in conjunction with real-time dashcam feeds obtained from moving vehicles. This approach not only aligns with the increasing integration of smart automotive technologies in contemporary vehicles but also represents a scalable and cost-effective pathway for governments and municipal bodies to modernize traffic monitoring and road maintenance operations.

The traffic light violation detection system developed in this research introduces a novel method of detecting red-light jumping vehicles using dashcam inputs rather than conventional CCTV-based systems. Unlike traditional surveillance methods that often suffer from limited angles, inconsistent coverage in suburban or rural areas, and high installation and maintenance costs, dashcam-based detection offers dynamic, mobile, and wide-reaching monitoring. This model identifies the traffic signal state, detects vehicles violating the signal by crossing during the red light phase, and accurately extracts the license plate numbers for automated fine issuance. This not only reduces human intervention but also minimizes enforcement delays and administrative burden while promoting legal compliance on roads.

Simultaneously, the pothole detection component addresses another widespread issue—road surface degradation—which can lead to accidents, vehicular damage, and costly repairs if not addressed in a timely manner. This study extends existing pothole detection research by incorporating both daytime and nighttime conditions, a feature often neglected in prior works due to the complexity of image analysis under low-light environments. Multiple YOLO (You Only Look Once) object detection models—namely YOLOv8, YOLOv9, and YOLOv11—were rigorously compared to identify the most suitable algorithm for real-time, high-precision pothole detection. The model utilizes geolocation data to tag pothole positions and automatically reports this information to municipal authorities, thus ensuring quicker response times for road repairs and efficient maintenance workflows.

Through extensive testing and evaluation, this dual-model system demonstrates significant practical value by offering automated, reliable, and highly adaptable solutions that can be integrated into existing urban infrastructure. The research contributes not only to immediate technological applications but also lays a strong foundation for future explorations in AI-driven intelligent transportation systems. By optimizing detection accuracy, reducing operational costs, and enhancing scalability, this work supports the broader vision of smarter cities, safer roads, and more proactive infrastructure management.

4.1. Summary of Research

The primary objective was to design and develop a **traffic law enforcement and maintenance automation framework** by:

- **Detecting traffic light violations** using dashcam footage, identifying red light status, tracking vehicle motion, extracting number plates, and simulating fine issuance automation.
- **Detecting potholes during both daytime and nighttime**, using comparative performance analysis across multiple YOLO model variants (YOLOv8, YOLOv9, YOLOv11), and transmitting pothole geolocation for municipal repair action.

Unlike traditional methods that rely on **CCTV infrastructure** or **manual road inspections**, this research leverages **onboard dashcams**, providing a **mobile**, **low-cost**, and **scalable solution** that enhances the flexibility of deployment, especially in regions lacking smart traffic systems or fixed surveillance infrastructure.

4.2. Key Contributions

This study introduced several novel aspects, distinguishing it from existing research in the field:

- **Dashcam-Based Violation Detection**: Unlike most previous systems dependent on fixed CCTV cameras, this approach uses moving dashcams, improving coverage, reducing installation costs, and offering real-time mobile enforcement capabilities.
- **Automated Number Plate Recognition and Fine Simulation**: The system demonstrated the potential for automatically detecting red-light jumpers and extracting their number plates for fine automation.
- **YOLO Model Benchmarking for Pothole Detection**: This research uniquely compared multiple YOLO versions under real-world day and night conditions, identifying YOLOv9 as the most balanced and robust model. This benchmarking provides a valuable reference point for future academic and industrial pothole detection projects.
- **Day and Night Pothole Detection in One Model**: Most existing research has focused only on daytime detection due to visibility constraints. This research extends detection capabilities to nighttime, contributing to round-the-clock road safety.
- **Proposed Real-Time Geo-Reporting for Road Maintenance**: The pothole detection system includes geolocation tagging that enables authorities to identify and respond to road damages promptly, thus reducing maintenance delay.

4.3. Limitations

Despite the success and practical implementation of the models, several limitations were encountered:

- **Lack of Dashcam Violation Data**: The traffic violation model had to be tested on limited dashcam datasets due to the lack of publicly available real-world violation footage.
- **Variability in Dashcam Quality**: Many available dashcam videos suffer from low resolution, motion blur, or night glare, which affect detection accuracy, particularly for number plates.
- **Visibility Issues in Number Plates**: AWS Textract struggled with unclear or partially visible number plates under challenging lighting conditions.
- **No Real-Time System Integration**: While the models are designed for real-time use, this research was conducted offline, and integration with real-time embedded systems is still to be explored.

4.4. Future Work

This research lays a strong foundation for future expansion, including:

- **Integration with Live Dashcam Systems**: Implementing the model into a real-time vehicle-mounted system to automatically detect and report violations or potholes on the go.
- **Enhanced Dataset Creation**: Collaborating with traffic departments and municipal councils to create a diverse dataset of traffic violations and pothole instances under varied environmental conditions.
- **Advanced OCR Enhancement**: Improving number plate recognition by integrating deep OCR models or using ensemble techniques for difficult frames.
- **Municipal Dashboard for Reporting**: Developing a complete dashboard interface that collects pothole geo-tags and violation reports for local authority action, adding full end-to-end automation.
- **Cloud Integration and Centralized Data Analysis**: Sending reports and analytics to a central cloud system to identify high-risk traffic areas or frequently damaged roads.

4.5. Final Thoughts

This research stands as a significant and timely contribution at the convergence of artificial intelligence, transportation safety, and urban infrastructure management. In an era where cities are rapidly evolving toward smart and interconnected ecosystems, the integration of AI into vehicular and traffic monitoring systems represents a pivotal step forward. The dual-model approach introduced in this study—leveraging AI-powered traffic light violation detection and day-and-night pothole identification—illustrates the immense potential of combining deep learning techniques with already-existing vehicular technologies such as dashcams. By doing so, this work introduces a solution that is not only technically robust but also inherently mobile, scalable, and cost-effective, making it highly applicable to both resource-rich and resource-constrained regions.

One of the most transformative aspects of this research is its alignment with technologies that are already embedded in modern vehicles. With the increasing proliferation of dashcams in personal, commercial, and public transport vehicles, the proposed system does not require the installation of expensive and stationary infrastructure like CCTV poles or smart traffic lights, which are often limited to urban centers. Instead, it capitalizes on mobile video capture systems, allowing for real-time monitoring of traffic behaviors and road surface conditions even in suburban, rural, or poorly surveilled areas. This mobility ensures broader geographic coverage and a higher frequency of data collection, ultimately resulting in more responsive and data-driven traffic enforcement and road maintenance strategies.

From a strategic and long-term perspective, this research provides not only an effective technical solution but also a highly practical and adaptable framework for future expansion. For developers, it offers a tested and validated model that can be improved upon with more advanced AI architectures, integrated with GPS tracking systems, or deployed on edge devices for real-time inference. For policymakers and government agencies, it provides a scalable blueprint that can be integrated into smart city initiatives, aiding in law enforcement, urban planning, and infrastructure budgeting. For the research community, it opens new avenues for exploring AI applications in real-world mobility scenarios, including low-light image enhancement, real-time object detection, anomaly tracking, and autonomous systems collaboration.

Moreover, by addressing two crucial components of road safety—regulatory enforcement and infrastructure monitoring—within a single, unified platform, this study contributes to building a more holistic understanding of intelligent transportation systems. It bridges the gap between theoretical innovation and real-world application, demonstrating that advanced machine learning models, when designed with practicality and scalability in mind, can offer sustainable and globally relevant solutions. As such, this research is poised to inspire future work in AI-driven mobility, helping to shape safer, smarter, and more efficient urban transportation networks around the world.

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6. GLOSSARY

- AI – Artificial Intelligence: The simulation of human intelligence processes by machines, especially computer systems, to perform tasks such as decision-making, object detection, and learning.
- YOLO – You Only Look Once: A popular deep learning-based object detection algorithm known for its speed and accuracy in detecting multiple objects in real time.
- Dashcam – Dashboard Camera: A camera mounted on a vehicle's dashboard or windshield to record the road view during vehicle operation.
- CV – Computer Vision: A field of artificial intelligence that enables computers to interpret and process visual data from the world, such as images and videos.
- Traffic Light Violation Detection – The automated identification of vehicles that run red lights using video footage and AI-based detection techniques.
- Pothole Detection – The process of identifying road surface damage, such as potholes, through image or video analysis using machine learning or deep learning techniques.
- Municipal Authority – Local government or administrative bodies responsible for managing public infrastructure and services, including road maintenance.
- AWS Textract – Amazon Web Services Textract: A cloud-based machine learning service that automatically extracts text and data, such as vehicle number plates, from scanned documents and images.
- Model Comparison – The process of evaluating multiple machine learning or deep learning models to determine the best-performing one based on specific metrics such as precision, recall, and F1-score.
- Deep Learning – A subfield of machine learning that uses neural networks with many layers to model complex patterns in data.
- YOLOv8 / YOLOv9 / YOLOv11 – Different versions of the YOLO object detection architecture, each with performance improvements, structural changes, and efficiency enhancements over previous versions.

7. APPENDICES

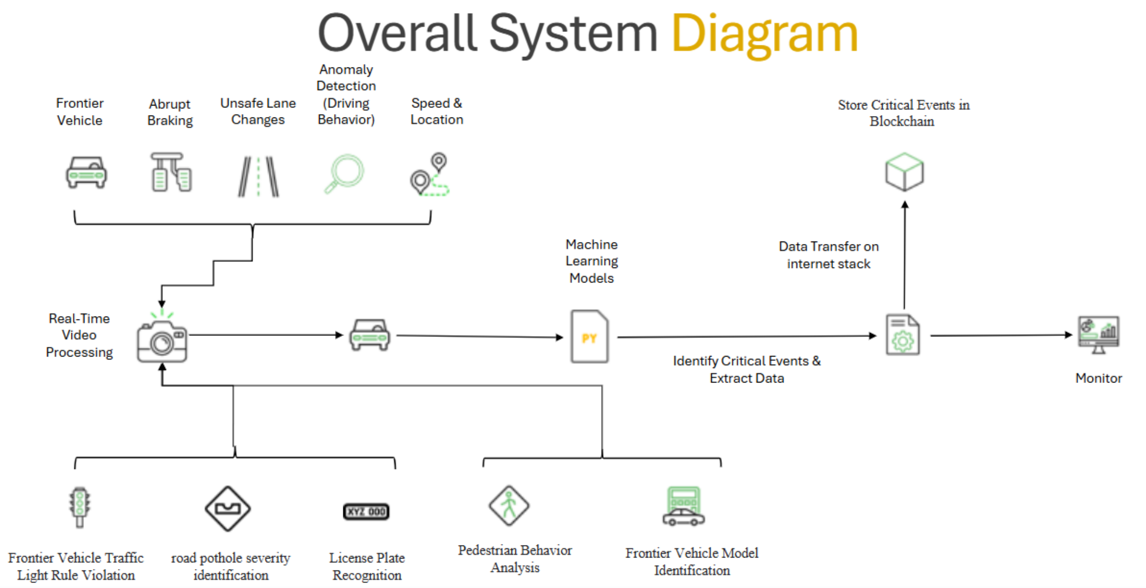

Figure 18 : Overall System Diagram

Figure 19 : Annotated Road Potholes

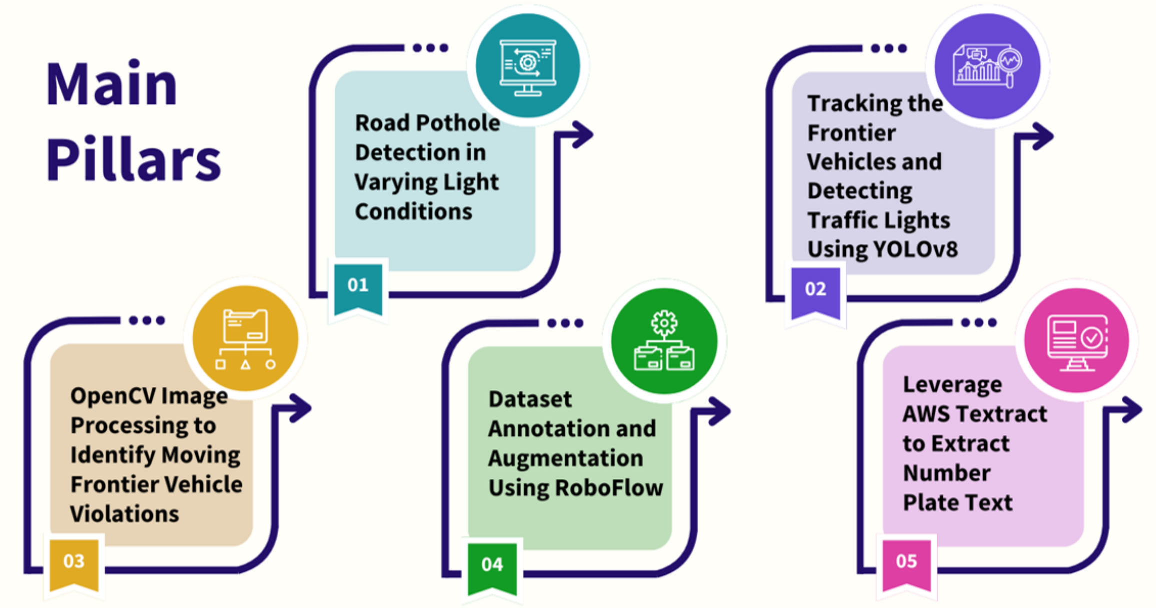

Figure 20 : Main Pillars of Red Traffic Light Violation and Road Pothole Detection Components

Figure 21: Red Traffic Light Violation Model - Red Traffic Light Identification

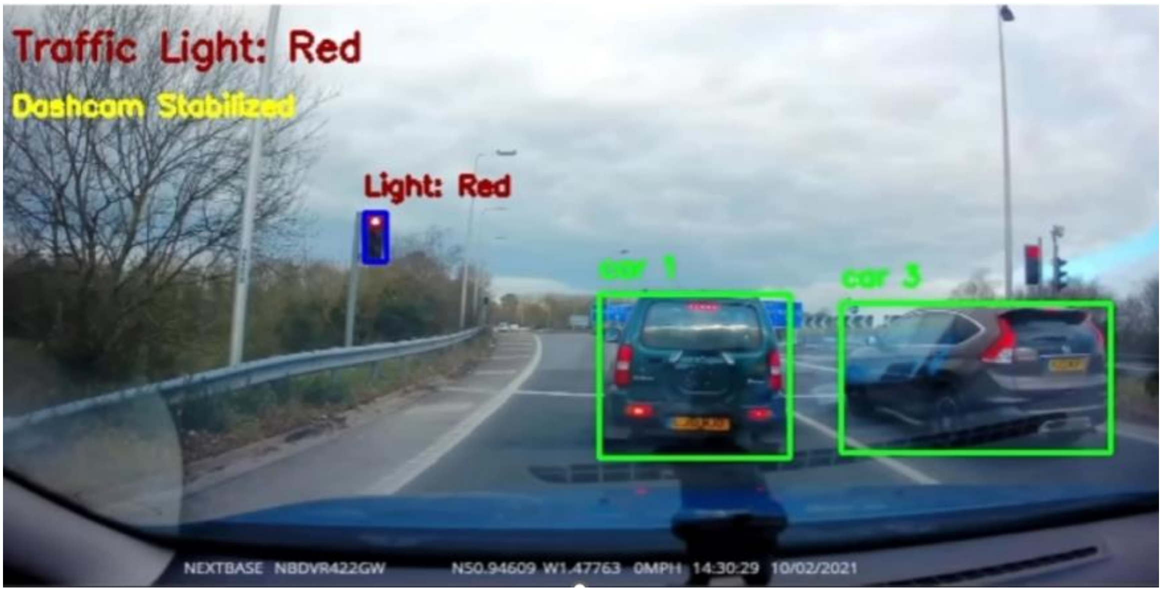

Figure 22 : Red Traffic Light Violation Model Dashcam Stabilization Detection with Frontier Vehicle Detection

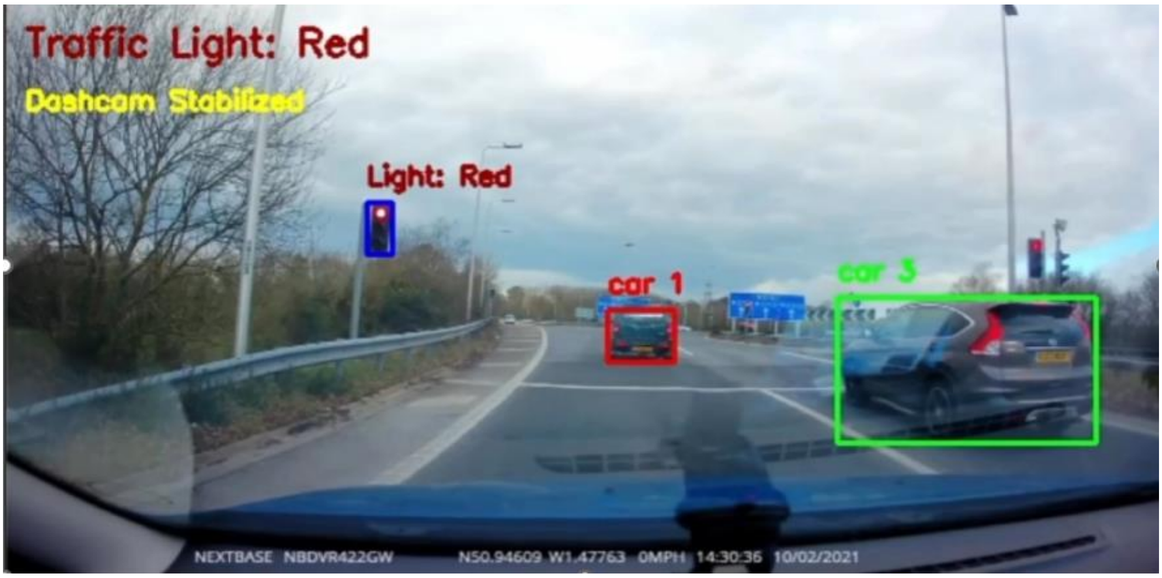

Figure 23 : Identifying the Red Traffic Light Violation

Figure 24 : Identifying Potholes - Daytime

Figure 25 : Identifying Potholes - Nighttime