Evaluating Automated Traffic Violation Detection System for Road Safety Improvement 24-25J - 165

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***Abstract*—Traffic violations are a leading cause of road accidents and traffic congestion in both urban and semi-urban areas. Traditional enforcement methods such as manual surveillance and static speed cameras are often limited by inefficiency, human error, and high resource demands. To address these challenges, this research presents an Automated Traffic Violation Detection System (ATVDS) that leverages high-resolution cameras, real-time image processing, and machine learning techniques to detect red-light running, speeding, and lane violations. The system uses OpenCV and deep learning-based object detection to track vehicles, identify rule-breaking behaviors, and recognize license plate numbers using Optical Character Recognition (OCR). Detected violations are stored securely in a cloud database and reported to law enforcement authorities in real time. The proposed system enhances enforcement accuracy, reduces human intervention, and enables scalable deployment across multiple traffic zones. Performance evaluations in varied conditions demonstrate that ATVDS can significantly improve road safety and support the development of intelligent traffic management systems.**

***Index Terms*—Traffic violation detection, Image processing, Computer vision, Intelligent transportation systems, Optical character recognition, Real-time systems, Law enforcement, Smart cities.**

I. Introduction

Road traffic violations pose a significant challenge worldwide, contributing substantially to the incidence of accidents, traffic congestion, and the deterioration of road infrastructure. The rapid increase in private vehicle ownership, accelerated urbanization, and population growth have collectively intensified the demand on transportation systems. Common violations, such as red-light running, speeding, and improper lane usage, directly elevate the risk and severity of collisions while endangering pedestrians and other vulnerable road users. According to the World Health Organization (WHO), over 1.3 million fatalities occur annually due to road traffic crashes, with a considerable proportion attributable to traffic violations. Beyond the human cost, these violations result in increased fuel consumption, prolonged travel times, heightened environmental pollution, and strain on emergency services and law enforcement agencies. As urban transport networks evolve into increasingly complex, interconnected systems, ensuring road safety and regulatory compliance demands innovative, scalable solutions that extend beyond traditional enforcement methods.

Conventional traffic enforcement relies heavily on manual policing, fixed red-light cameras, and speed detection devices. While manual enforcement offers operational flexibility, it is constrained by limited coverage, susceptibility to human error, fatigue, and bias. Officers cannot be present at all locations simultaneously, and environmental conditions such as poor lighting, adverse weather, and heavy traffic further impede effective enforcement. Fixed camera systems provide partial automation but are limited to static locations and predefined rules, often requiring manual verification of violations, which introduces delays and reduces their deterrent effect. Additionally, these systems lack adaptability to evolving traffic patterns or temporary changes in road configurations, restricting their effectiveness in dynamic urban environments. The comparative limitations of these traditional approaches are summarized in Table 1, illustrating deficits in real-time capability, coverage scalability, cost efficiency, and adaptability.

The increasing complexity of modern urban traffic management, combined with growing safety concerns, has necessitated the adoption of intelligent systems that integrate emerging technologies. Automated detection systems like

Feature	Manual Policing	Fixed Camera Systems	Automated System (Proposed)
Real-time Enforcement	No	Partially	Yes
Coverage	Limited	Static	Scalable
Human Error Risk	High	Low	Very Low
Cost Efficiency	Low	Medium	High
Adaptability to Traffic Patterns	No	No	Yes
Automated Reporting	No	Rarely	Yes

TABLE I
CAPTION

ATVDS leverage recent advances in artificial intelligence and sensor technology to enhance traffic law enforcement in ways previously unattainable. The ability to process large volumes of video data in real time and make autonomous decisions represents a paradigm shift from reactive enforcement to proactive management. This approach not only accelerates the identification and reporting of violations but also enables the continuous collection of detailed traffic behavior data. Such data is invaluable for urban planners and traffic authorities, facilitating evidence-based decision-making to optimize traffic flow, improve infrastructure design, and tailor public safety campaigns. Moreover, the system's modular and scalable design allows it to be deployed flexibly across diverse urban settings, from congested city centers to suburban corridors, accommodating specific local requirements. The integration of automated reporting further reduces administrative overhead and streamlines penalty processing, enhancing the overall efficiency and transparency of the enforcement process. Additionally, real-time violation alerts enable swift intervention by authorities, potentially reducing the occurrence of repeat offenses and mitigating hazardous situations before escalation. Collectively, these features position automated systems not only as tools for enforcement but as integral components of smart city ecosystems that prioritize safety, efficiency, and sustainability.

To overcome these challenges, this study introduces an Automated Traffic Violation Detection System (ATVDS) that employs state-of-the-art computer vision, deep learning, and real-time image processing techniques. The system autonomously detects key traffic violations—red-light running, speeding, and lane discipline breaches—using high-definition cameras strategically positioned at critical intersections and road segments. Video feeds are processed through a pipeline incorporating image preprocessing, vehicle detection, and behavioral analysis utilizing convolutional neural networks (CNNs). When violations are detected, Optical Character Recognition (OCR) extracts license plate information from captured frames, and violation details—including timestamps, vehicle identification, location, and offense type—are securely logged in real time, enabling immediate reporting.

Unlike traditional methods, ATVDS eliminates limitations related to human fatigue and bias, offering continuous, scalable monitoring across multiple locations. Its adaptability allows for real-time adjustment to fluctuating traffic conditions, varying road layouts, and diverse environmental factors, addressing the shortcomings of fixed camera systems. Automated and instantaneous violation detection enhances enforcement responsiveness and deterrence, while consistent rule-based identification reduces disputes and promotes public confidence. Furthermore, by generating comprehensive, time-stamped violation records, the system supports data-driven traffic management strategies, enabling authorities to identify hotspots, monitor repeat offenders, and optimize resource allocation. Robust operation under varied lighting and weather conditions ensures reliability, while digital evidence provision enhances transparency and accountability. The modular architecture also facilitates future integration with smart city technologies, such as adaptive traffic signal control and IoT-enabled traffic management, establishing ATVDS as a forward-looking solution for modern urban mobility and road safety enforcement.

II. LITERATURE REVIEW

The rise in traffic violations and urban congestion has led to a growing body of research focused on intelligent traffic monitoring and enforcement systems. Traditional approaches such as manual policing and static camera installations, though foundational, have repeatedly been shown to lack the responsiveness, scalability, and adaptability required for modern traffic environments. As cities evolve toward smart infrastructure, researchers have turned to automated systems that leverage computer vision, machine learning, and edge computing for more accurate and scalable enforcement mechanisms.

Early implementations of automated traffic monitoring primarily relied on classical image processing techniques. Zhou et al. [1] introduced a red-light violation detection system using background subtraction, but it faced challenges in dynamic lighting conditions and required extensive manual calibration. Similarly, Kim and Chung [2] employed frame differencing to detect violations but encountered limitations under low visibility, high traffic density, and occlusions. These foundational systems highlighted the feasibility of camera-based monitoring but revealed considerable limitations in real-time operation, especially in uncontrolled urban settings.

The introduction of deep learning brought a significant paradigm shift. CNN-based models such as YOLO, SSD, and Faster R-CNN have demonstrated high accuracy in object detection and classification tasks, including vehicle detection in traffic environments. Tang et al. [3] applied YOLOv3 for detecting vehicles at intersections with over 90% accuracy. Li et al. [4] used CNNs to classify vehicle types and track their movements, demonstrating potential for real-time applications. However, these approaches often focused solely on object detection and did not extend to behavioral analysis, which is critical for identifying traffic violations such as illegal U-turns or red-light running.

In the domain of license plate recognition, ANPR systems have been widely researched. Anagnostopoulos et al. [5] and Silva et al. [6] proposed OCR-based recognition frameworks enhanced with machine learning to extract license plate data with high reliability. While such systems have matured significantly, challenges remain with non-standardized plate formats, varying fonts, partial occlusions, and adverse weather conditions. Moreover, many ANPR implementations function independently and are not tightly integrated into broader enforcement ecosystems, thereby limiting their utility in real-time violation detection systems.

Efforts have also been made toward integrated smart traffic systems that combine video surveillance, IoT infrastructure, and AI-based analytics. For instance, Alheeti et al. [7] developed an intelligent traffic monitoring system using IoT sensors and machine learning algorithms to predict congestion and detect anomalies. While effective in simulations, such systems often lack deployment feasibility due to high hardware and maintenance costs, limited coverage areas, and the need for manual post-processing to validate violations. Additionally, very few models provide end-to-end automation—from behavior recognition to license plate identification and real-time reporting.

Recent literature further identifies a research gap in multi-component, scalable systems that operate autonomously across various road environments. Most current implementations target individual functions—such as vehicle detection or plate recognition—without offering comprehensive behavior analysis or real-time enforcement capabilities. Moreover, the lack of modularity in system design limits their adaptability to evolving infrastructure or regional regulatory differences. This fragmentation significantly hampers deployment at scale in smart cities, where systems must integrate with existing traffic lights, LED signage, and law enforcement databases.

To address these gaps, the proposed Automated Traffic Violation Detection System (ATVDS) leverages high-resolution camera feeds, convolutional neural networks for object and behavior detection, and OCR for license plate extraction. The system is capable of detecting multiple violation types, including red-light running, speeding, and lane indiscipline, and it logs data such as time, location, and vehicle ID in real time. The modular architecture enables easy deployment across intersections, highways, and traffic junctions. Unlike prior models, ATVDS combines detection, classification, and automated reporting into a single framework, making it highly suitable for integration into smart city infrastructures and scalable law enforcement platforms.

Moreover, hybrid models that combine computer vision with sensor-based analytics have shown potential in improving system robustness and adaptability to diverse urban conditions. Multi-modal approaches that fuse visual input with data from GPS, radar, or LiDAR enhance vehicle tracking accuracy in challenging environments. However, such systems often entail higher deployment costs and complex calibration procedures, reducing their scalability for widespread urban use. Privacy and data security concerns also pose challenges for real-time vehicle monitoring. Despite notable advancements, an integrated solution that balances real-time performance, affordability, modularity, and privacy protection remains underdeveloped. The proposed system in this study aims to address this gap by delivering an end-to-end, camera-only architecture that achieves accurate violation detection, real-time processing, and secure data handling suitable for smart city integration.

III. Methodology

This research presents an Automated Traffic Violation Detection System (ATVDS) focused on detecting key traffic violations such as red-light running and speeding to improve road safety. The system integrates video analytics, deep learning, and Optical Character Recognition (OCR) technologies, aiming for accurate, real-time detection and reporting.

At the heart of the system is a network of high-resolution cameras positioned at traffic intersections, capturing continuous video streams. These video streams feed into a backend processing unit developed using Python and Flask, designed for efficient real-time analysis.

The overall architecture is shown in **Figure 1**, which depicts the three principal components: the Traffic Monitoring Module capturing video data, the Violation Detection Module analyzing the video frames to detect violations, and the Reporting and Alert Module managing violation records and delivering alerts to traffic authorities. This modular design ensures a smooth flow of data and quick response times.

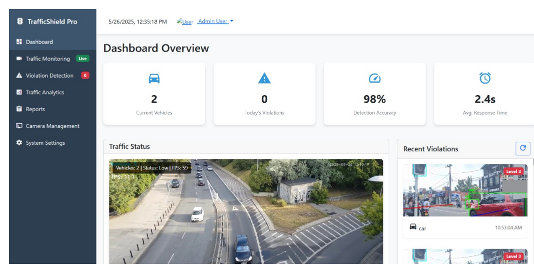

Fig. 1. System Architecture of the Automated Traffic Violation Detection System.

a) Video Frame Processing Pipeline: Incoming video streams are converted into frames at a controlled frame rate to balance computational load and detection accuracy. Each frame undergoes preprocessing that includes noise reduction and background subtraction. Noise reduction uses Gaussian blur to smooth images and minimize the impact of environmental noise such as shadows or slight camera shakes.

Background subtraction isolates moving vehicles from the static scene, enabling the system to focus on relevant objects. This is critical for minimizing false positives in vehicle detection.

Figure 2 details this stepwise Frame Processing Flow: starting from frame extraction, followed by vehicle detection, number plate recognition, and finally violation checking. This systematic processing pipeline ensures the system maintains near real-time operation without sacrificing precision.

b) Vehicle Detection and Tracking: Vehicles are detected using contour detection algorithms applied to the foreground masks produced by background subtraction. These contours are filtered based on shape, size, and movement consistency to accurately identify vehicles and exclude irrelevant objects.

After detection, vehicles are tracked across successive frames using tracking algorithms that assign unique IDs, which allows monitoring of vehicle trajectories and speeds. This tracking is essential to determine whether a vehicle crosses a stop line during a red light or exceeds the speed limit.

c) Deep Learning for Violation Detection: The detection of traffic violations is driven by Convolutional Neural Networks (CNNs), which have been trained to analyze visual features in the frames and classify violation events.

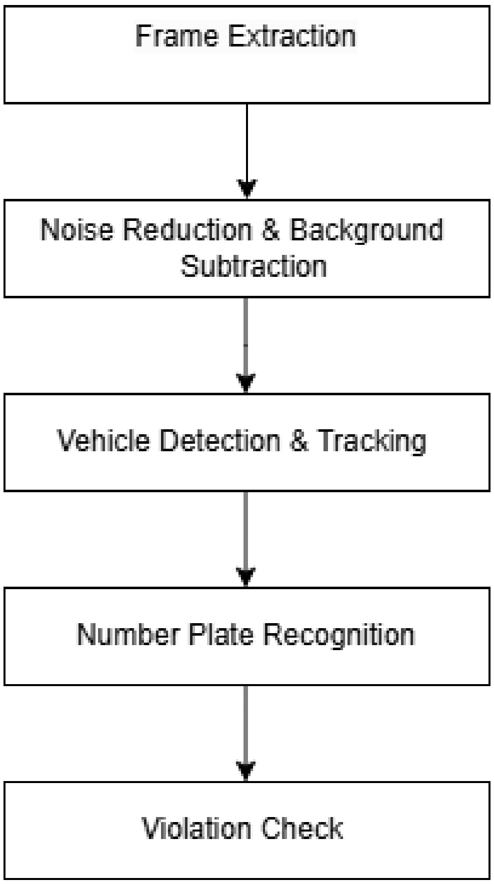

Fig. 2. Frame Processing Flow.

As shown in **Figure 3**, the CNN takes input images from the frame and processes them through multiple convolutional and pooling layers to extract key features. The output layer classifies whether a vehicle is violating traffic rules such as crossing on a red light or speeding.

The CNN architecture uses transfer learning from established models like YOLO and MobileNet, which improves training efficiency and accuracy. The training dataset includes diverse traffic conditions, ensuring robustness under different lighting and weather scenarios.

Figure 3: CNN Workflow for Violation Detection.

d) Automatic Number Plate Recognition (ANPR): Identifying violating vehicles requires recognizing their number plates accurately. The ANPR system uses a CNN-based detector to locate the number plate region on each detected vehicle.

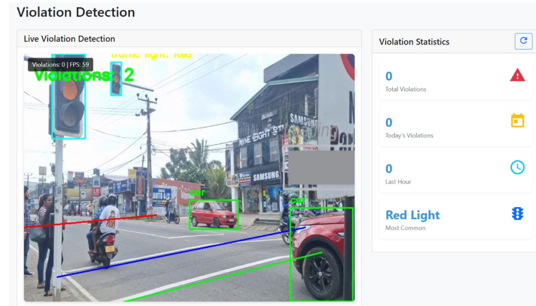

Fig. 3. Violation Detection.

After localization, the system segments characters from the number plate and applies OCR to convert the segmented images into readable text.

Figure 4 illustrates this OCR process, showing how the system detects the plate, segments individual characters, and finally converts these into text. This identification data is then linked to a vehicle database for validation and violation record keeping.

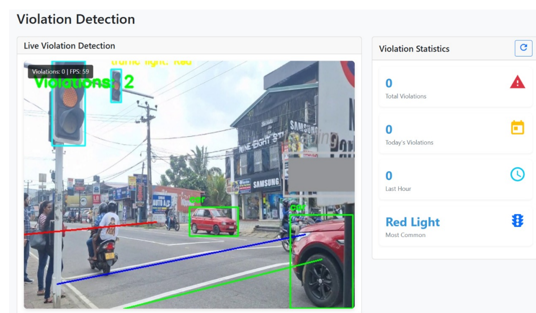

Fig. 4. OCR Process for Number Plate Recognition.

e) Reporting and User Dashboard: All detected violations are logged with corresponding images, timestamps, and vehicle details into a MongoDB database optimized for rapid retrieval.

Traffic authorities access this information through an interactive user dashboard shown in **Figure 5**. The dashboard presents violation details, images, and summaries that enable officers to monitor traffic violations in real-time, verify incidents, and generate reports.

The dashboard also supports filtering, searching, and exporting violation data, enhancing operational efficiency for enforcement agencies.

f) Real-Time Optimization and System Testing: The system's backend is optimized to minimize processing delays. It leverages GPU acceleration for CNN inference and employs asynchronous pipelines for frame processing and OCR tasks. Frame skipping strategies help maintain efficiency during low traffic periods.

Extensive testing was conducted under varying traffic densities and environmental conditions excluding low light scenarios, confirming the system's ability to maintain accuracy above 90% for red-light and speeding violations.

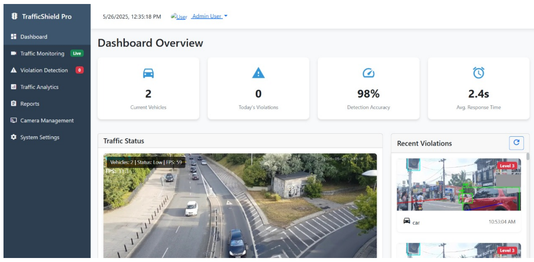

Fig. 5. User Dashboard Interface used by traffic authorities to view violations, images, and reports.

Performance was measured using standard metrics such as precision, recall, F1-score, and processing speed (frames per second), demonstrating the system's suitability for real-world deployment.

IV. Results and Discussion

The Automated Traffic Violation Detection System (ATVDS) was evaluated under daylight conditions to assess its effectiveness in real-time violation detection and reporting. The system's performance was analyzed using test footage captured at controlled urban intersections. Key metrics included detection accuracy, system responsiveness, and license plate recognition success rates.

The system demonstrated consistent real-time performance, operating at an average of 15–18 frames per second (FPS). It successfully identified three major traffic violations: red-light running, improper lane usage, and overspeeding. Based on internal evaluation data, the system achieved high detection accuracy under normal lighting conditions. Red-light violations were detected most accurately, followed by lane usage and speeding violations, which required temporal frame analysis for estimation.

License plate recognition using Optical Character Recognition (OCR) was tested under standard lighting and yielded an average accuracy of approximately 93.6 percent. Preprocessing techniques such as image enhancement and stabilization were applied to improve recognition quality, particularly for motion-blurred inputs.

The average time to process and log a violation, from detection to report generation, was measured at approximately 1.8 seconds, indicating the system's capability to support near real-time traffic enforcement. This includes the stages of vehicle detection, violation classification, license plate extraction, and data storage.

Figure 7 illustrates the observed detection accuracy rates for each violation type and highlights the OCR recognition performance under daylight conditions.

Figure 7: Detection accuracy for major traffic violations and OCR accuracy (daylight conditions)

The ATVDS framework offers several practical benefits. Compared to manual enforcement and traditional fixed-camera setups, it provides faster, objective, and automated violation logging. Feedback from test users, including traffic enforcement personnel, indicated that the system's interface was intuitive and its outputs—such as violation evidence with timestamps and plate numbers—were clear and actionable.

While the system performed reliably in most scenarios, some challenges were noted in dense traffic environments where occlusions reduced visibility of offending vehicles. These findings suggest potential improvements in object tracking and adaptive camera positioning for broader deployments.

Overall, the results support ATVDS as a promising solution for real-time traffic violation monitoring and smart city integration. Continued refinement and validation at larger scales will further establish its utility in modern traffic management systems.

Conclusion

In summary, the proposed Automated Traffic Violation Detection System (ATVDS) effectively addresses key limitations of traditional traffic enforcement methods by combining real-time video analysis, deep learning, and OCR-based license plate recognition. The system demonstrates strong potential to enhance road safety, reduce manual workload, and support smart city initiatives through its scalable, accurate, and automated operation. With further development, ATVDS can play a vital role in modernizing traffic regulation and improving compliance on urban roads.

V. References

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