

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Two-Wheeler Traffic Violations Detection and Automated Penalty Issuance System

Mahesh Datta Pendyala¹ and Rishitha Naik Pipavath²

¹Department of Information Technology, Mahatma Gandhi Institute of Technology(A), Gandipet, Hyderabad, 500075, Telangana, India. ²Department of Information Technology, Mahatma Gandhi Institute of Technology(A), Gandipet, Hyderabad, 500075, Telangana, India. * E-mail(s): pmahesh <u>csb213250@mgit.ac.in</u>; prishithacsb213250@mgit.ac.in

ABSTRACT

Road safety is among the utmost importance, as road accidents rank among the leading causes of death in India. Road Accidents are majorly due to violators and lawbreakers of road safety rules like not wearing helmets, triple riding etc. Although there are numerous smart systems to monitor these violations, efficiently tracking and accessing the data remains a challenge. Also, the tickets are generated manually and this manual process often leads to delays and errors. To address these issues, we are proposing an integrated system that automates the detection of violations, streamlines the tracking of offenders, and ensures timely issuance and collection of penalties. Such a system would enhance enforcement efficiency, improve road safety, and reduce the incidence of accidents caused by non-compliance with traffic rules. The proposed system can detect whether the rider is wearing a helmet or not, detects the number of pillion riders (not more than 2 persons including rider and pillion), and even if they cross the specified speed limit, under any violation of the above-mentioned rules the system is capable of automatically issuing tickets on the corresponding vehicles using its registration number (i.e., License plate). Though the ticket is issued, most of them won't pay the challan on time, hence we introduce the concept of penalty points for every vehicle. If the penalty points exceed a certain barrier, then we restrict the vehicle owner from further renewal of the vehicle insurance and even he/she will be unable to claim the insurance amount if required.

Keywords: Triple Riding Detection, Helmet Detection, Over Speeding Detection, Automated Ticket Generation, License Plate Recognition.

1. Introduction

1.1 Importance of Road Safety

It's of high importance on the international level because, on a yearly basis, roadrelated incidents cause a lot of death; most of them take place in developing and middle-income countries. Among those, India has been highlighted to possess one of the highest rates of road-related fatalities, where two-wheelers also have a leading part in this matter [1], [2]. Motorcycles and scooters are categorized as two-wheelers. These are the most popularly preferred vehicles in India due to their lower cost, fuel efficiency, and agility in maneuvering through highly populated cities. However, these are dangerous vehicles for the user as these have a relatively weaker protective structure. Therefore, the accidents occurring with two-wheelers frequently result in grievous injury or even death. Compliancy of the most basic traffic laws such as the wearing of helmets, speeding limits and restriction of three riding also exposes dangers. Failure to obey the law concerning helmets has been shown to be one of the biggest contributors to the casualties at road tolls. In addition, the majority of fatalities can be avoided if motorcycle users don their helmets. The behavior of two-wheeler operators, such as driving at high speed and refusing to wear helmets, was found to be uniquely linked to increasing accident rates [5]. This is evident from the work of Chouhan et al. where it is presented that the behavior of riders, which forms habitual violations of traffic codes, is highly responsible for the alarming number of injuries [6]. In addition to direct health impacts, road accidents are a significant source of economic burden on society. Demands related to health care, law enforcement, and insurance place huge strains on public resources, especially in developing countries. Traffic crashes adversely affect families by creating long-term socioeconomic burdens characterized by diminished incomes and elevated dependency ratios [7]. These burdens highlight the necessity for more robust enforcement of traffic regulations. Emerging automated systems that monitor and enforce traffic regulations are increasingly seen as the best solution to the problems. Such systems have the capability to significantly reduce accident rates as a result of compliance with helmet regulation, speed limit, and other important safety measures. Besides saving lives, stronger enforcement breeds social responsibility and restraint toward the use of roads and therefore to the benefit of society in general [8], [9]. This implies that road safety is of great importance and advanced technological interventions should be part of it. Automated detection systems for two-wheeler violations are a significant development in the reduction of road accidents and the mitigation of the significant social and economic consequences accompanying traffic violations.

1.2 Challenges in Monitoring Two-Wheeler Traffic Violations

1. Limitations of Manual Enforcement:

Traditional traffic rule enforcement practices are based largely on manual intervention by traffic police. The whole process is often plagued with human error, inefficiency, and inconsistency, particularly in densely populated urban areas where two-wheeler traffic volume is high. Law enforcement personnel are sometimes overwhelmed to monitor violations of helmet non-compliance, triple riding, or over-speeding in real time, which creates a wide gap in enforcement [1], [2].

2. Scalability and Coverage:

This process also raises immense logistical challenges since the whole areas could not be reached in the giant cities and rural regions. It necessitates immense resources, usually scarce, for the comprehensive monitoring across the long varying different geographical regions including the risky ones such as inter-sections and highways [3],[4].

- Helmet Detection: Variations in helmet designs, colors, and rider postures can confuse detection systems.
- License Plate Recognition: Inconsistent license plate designs, fonts, and potential obstructions make accurate recognition difficult.
- **Triple Riding Detection:** Differentiating between permissible and nonpermissible rider configurations requires advanced image processing techniques [7], [8].

3. Real-Time Detection and Processing:

Monitoring violations in real-time, such as detecting non-helmeted riders or identifying over-speeding vehicles, requires high computational power and efficient algorithms. Many existing systems face delays in processing data, which hinders their ability to respond promptly. Integrating systems capable of handling large volumes of video feeds and real-time analytics remains a persistent issue [5], [6].

4. Technological Barriers:

Two-wheeler violations detection have various technological challenges. For example:

5. Integration of Systems:

Many cities have different systems to identify specific infractions. However, these systems are rarely connected into a whole system that can process detection, tracking of offenders, and the issuance of penalties. Lack of interoperability between traffic monitoring tools and administrative systems results in inefficiency [9].

6. Public Awareness and Compliance:

Even when offenders are caught and fined, most of them do not pay their fines. The public awareness of the penalty points or insurance implications for example is very low thus reducing the effectiveness of the monitoring systems [10].

7. **Privacy and Ethical Considerations:**

With automation comes the fear of violation of personal data privacy and misuse of information. One of the significant challenges is ensuring observance of data protection rules in conjunction with maintaining openness and accountability of the systems [11]. Above, these can be seen as the basis for how traffic enforcement bodies can engineer more robust, scalable monitoring systems of the two-wheelers' contravention. These modern technologies-including artificial intelligence, machine learning, and edge computing-will overcome them, and safer roads emerge.

1.3 OBJECTIVES OF THE SURVEY

The main objective of this review is to provide an appropriate and detailed assessment of the latest techniques and systems developed toward identifying two-wheeler road violations and automating penalty issuance mechanisms. Holding a review of new techniques alongside the weakness of previously used methodologies has been enough for improving betterment of road safety and betterment of the traffic management system.

1. Criticize the current traffic violation detection systems:

The survey aims to explore the techniques that have been developed for detecting prevalent traffic violations, including helmet non-compliance, triple riding, and over-speeding. It reveals the practical effectiveness of such systems and the technological progress that makes their development possible.

2. Review of Key Technologies and Methodologies:

This paper discusses the technologies, especially deep learning, machine learning, OCR, and computer vision, which present an analysis of the recent advancements in these technologies. This work focuses on how much these approaches contribute towards achieving reliable detection, scalability, and real-time processing in incidents of violations involving two-wheelers.

3. Research Automated Penalty Issuance Systems:

The survey examines the mechanisms used for the automated generation of challans and their enforcement, including the use of penalty points systems and their integration with vehicle registration and insurance databases. In addition, it underlines the importance of these systems in streamlining traffic law enforcement and enhancing compliance.

Mitigating the Potential for Manipulation: In centralized systems, a singular authority or organization exerts control over the voting process, presenting opportunities for bias, fraud, or coercion. Distributed systems eliminate this risk by distributing control across multiple nodes, ensuring that no single entity can influence the outcome [5].

4. Identify the challenges and limitations:

Amplifying Electoral Mechanisms These have implications regarding security, transparency, and decentralization and alter the electoral system fundamentally. electoral process in the following ways:

Through these objectives, the survey aims to provide a structured framework by which researchers, policymakers, and technologists can cultivate safer and more efficient systems for traffic monitoring and management.

2. Overview of Traffic Violations

2.1 Common Violations: Helmet Non-Compliance, Triple Riding, Over-Speeding

Traffic violations involving two-wheelers are one of the major issues in managing road safety, mainly for their large impact on the accelerating rates of accidents and death. Violations are most often attributed to negligence and ignorance coupled with blatant disregard for established rules of traffic [1, 2].

• Helmet Use: The most common violation recorded against two-wheelers remains the failure to wear helmets. Helmets are manufactured as a means of protection for rider heads during accidents and are even mandatory in many countries. Nonetheless, people still do not follow the helmet rule and follow it only partially, mainly because of the semi-urban and rural regions. The significant reasons behind this include being uncomfortable, an assumed annoyance for short distances, and unenforceable measures. Helmets not only mitigate the severity of injuries but also significantly enhance a rider's chances of survival in the event of an accident. Tackling this concern is a primary emphasis of contemporary traffic management systems[4].

• **Triple Riding:** The two-wheelers are designed for a maximum of two people, which include the rider and one pillion passenger. Triple riding considerably compromises the stability of the vehicle, leading to significant difficulties in manoeuvrability and increasing the risk of loss of control, especially at higher speeds or abrupt stops. It is especially common in urban centers, where people often pick such unsafe practices for their ease but remain ignorant of the threat it poses [5]. Not only does triple riding expose lives to danger, but the consequences put other road users at greater risk [6].

• **Over-Speeding:**Over speeding is one of the major causes of two-wheeler accidents. Most of the drivers surpass the set speed limit for highways and open roads. It is often a case of over-estimating the risk increase of losing control or crashing into another vehicle. The braking system is made ineffective and increases the impact of collision by a percentage; therefore, it is one of the major killers [7]. This behaviour, coupled with the inherent vulnerabilities of two -wheelers, points to an urgent need for speed monitoring and enforcement mechanisms [8].

2.2 Impact on Road Safety and Accident Rates

The cumulative impact of these breaches on road safety is significant, as they are directly linked to an increased risk of accidents [9].

• **Fatality Rates:**Not wearing helmet has been identified as one of the major contributors to fatalities in two-wheeler accidents. Persons riding without helmets are substantially more likely to suffer from severe head injuries, often leading to death. Similarly, the practice of triple riding leads to multiple casualties in a single accident, thereby aggravating the aftermath of any given accident [10].

• Economic and Social Costs: Traffic violations and their consequential accidents incur much economic losses for families, healthcare, and the governmental institution. Accident victims pay the prices for a lifetime to rehabilitate, in addition to foregone earnings; while the families incur both financial and psychological loss. The same easily collapses the limited public services of such underdeveloped economies [11].

• **Cultural Impact on Compliance:** The culture of frequent violations also has a very significant impact in terms of undermining the effect of traffic regulations. Repeated violators often spur others to ignore the rules, further weakening traffic discipline [12]. This indiscipline cycle emphasizes that stringent enforcement measures and education programs for the public, to make them responsible towards the road, are urgently needed [13].

These violations can be addressed only by an integrated approach that encompasses technological advancements, such as real-time detection systems, public awareness, and strict law enforcement. Concentrating on these common violations will help authorities significantly enhance road safety and reduce the social cost of traffic accidents.

3. Technologies for Violation Detection

3.1 Helmet Detection Systems

Helmet detection systems are one of the highest technologies in traffic monitoring, combining computer vision, machine learning, and deep learning techniques to enable full automation and real-time identification in traffic. These systems are continuously evolving to address multiple challenges that come with distinct traffic environments, types of helmets, and light conditions change. The basic helmet detection systems developed earlier used the traditional techniques of image processing. These rely more on edge detection methods, shape analysis, and color segmentation. These systems relied on the shapes or colour patterns associated with the head of the rider to detect helmets. However, under challenging conditions such as low illumination, occlusion, and variability in helmet design, these systems were inefficient. The methods had a high false-positive rate and showed low robustness, which made them unsuitable for practical use [3], [4].

• Machine Learning Approaches: With the advent of machine learning, SVMs and Random Forests came into existence, improving the accuracy of detection using manually derived features, including texture, gradients, and object boundaries. Although these techniques showed impressive performance, they still called for extensive manual feature engineering and were highly computationally intensive when used with high-dimensional data. In addition, adaptation to diverse traffic situations was not very effective since they struggled to generalize proficiently in different contexts [5].

• Deep Learning-Based Detection: The most important change has occurred in helmet detection, along with the basic framework of system architecture based on Convolutional Neural Network (CNN). Models through deep learning like YOLO, Faster R-CNN, and MobileNet led to feature extraction in quite a simple way followed by classification without any manual need for feature engineering. Besides static images, subsequent models can process live video streams with high efficiency and accuracy in the situations dominated by highly congested roads, different helmet colors, or various designs. Recent progress has added attention mechanisms, multiscale feature fusion, and transformer-based architectures for detection precision and robustness in real-world applications [6], [7].

• Edge computing: It is a crucial technology in dealing with latency issues and providing real-time capabilities. Currently, edge computing devices are coupled with AI algorithms in the systems to meet this end. These systems limit their usage of cloud servers since the processing of data occurs locally on the device like a traffic camera or IoT-enabled edge processor. This architecture ensures zero delay and thus best fits high-traffic regions that require swift decisions. It is both cost-effective and scalable, thus making it highly deployable in smart city infrastructures [8].

• Multimodal Hybrid Approaches Using Multimodal Input Data: Modern helmet detectors are increasingly using more and more multimodal input data, which comprises visual data combined with sensor information such as LIDAR data or thermal imaging [9]. A multimodal hybrid approach, applied to further enhance detection, reduces the adverse effects of rain, heavy shadows, and glares.

Helmet detection systems have been found used in different parts and lands all across to prove the effectiveness which contributes to increasing compliance besides driving safe roads [10]. Few of the implementations are discussed below,

• Smart City Deployments: In metropolitan areas, artificial intelligence-enabled helmet detection systems have been incorporated with traffic surveillance cameras to monitor real-time violations. For instance, the systems that have been implemented in cities such as Bengaluru and Hyderabad utilize YOLO-based frameworks in conjunction with license plate recognition to autonomously identify non-compliant riders and issue e-challans without necessitating manual intervention. These systems have attained detection accuracies exceeding 95

• **LPR Integration:** This technology is commonly used in conjunction with advanced OCR for license plate recognition purposes. It is a practical process that enables a seamless transition from identifying violators to gathering information on the vehicle details and automation of fine issuance. Studies in integrated systems show significant decreases in manual workloads along with a great improvement in the effectiveness of enforcement [12].

• **Low-Light and Extreme Condition:** The most critical usage was the "Loltv" dataset, which was very carefully curated to handle helmets in low-light conditions. While using advanced anomaly detection methods, along with improved preprocessing schemes, the system showed reliable performance that was considered challenging for many AI models in extreme cases [13].

• **AI-Based Enforcement in High Density Traffic Areas:** In scenarios where there is a significant density of traffic, camera-based helmet detection is installed covering wide-angle views. The images are captured over some time interval through multi-frame analysis so that when there is a violator with part of his face or his

Table 1 Comparison of Different Technologies for Traffic Monitoring

Aspect	Machine Learning	Deep Learning-	Edge Computing	Multimodal Hybrid
	Approaches	Based Detection		Approaches

Key Features	Relies on manually derived features (e.g., texture, gradients, object boundaries). Models include Support Vector Machines (SVMs) and Random Forests.	Utilizes end-to-end learning with CNNs. Models like YOLO, Faster R-CNN, and MobileNet automatically extract and classify features.	Processes data locally on devices (e.g., IoTenabled cameras, edge processors). Reduces dependence on cloud servers.	Combines multiple data inputs (e.g., visual, LIDAR, thermal imaging). Mitigates environmental issues like rain, shadows, and glare.
Strengths	Performs well on structured datasets with well-defined features. Relatively lightweight and faster for smallscale, low- complexity tasks.	Capable of real-time processing with high accuracy. Eliminates the need for manual feature extraction. Handles complex traffic scenarios effectively.	Ensures low-latency, real- time performance. Cost- effective and scalable for large deployments. Minimizes data transmission overhead.	Enhances detection robustness in challenging environmental conditions. Reduces false positives/negatives caused by single data modality.
Limitations	Requires extensive manual feature engineering. Struggles with high-dimensional and diverse traffic scenarios. Poor adaptability to varying conditions.	High computational requirements. Requires large labeled datasets for training. Performance may degrade in low- resource environments.	Limited by the computational power of edge devices. Initial deployment costs for hardware can be high.	Requires integration of multiple hardware components. Higher setup costs and complexity in deployment.
Cost and Scalability	Low cost; suitable for small-scale systems.	High cost; scalable for large urban deployments.	Moderate cost; scalable with additional edge devices.	High setup costs; best suited for specialized systems.
Best Use Cases	Basic helmet detection in low-density traffic environments. Early implementations for feature-driven tasks.	Real-time helmet detection in highdensity traffic. Smart city applications with dynamic, large-scale data.	Real-time traffic violation detection in highdensity zones. Helmet detection at busy intersections.	Helmet detection in adverse conditions (e.g., poor lighting, weather). Specialized systems for all-weather monitoring.

helmet not appearing, chances of identifying the person increase. It is really useful for places of risk like highways and zones of crossing intersections [14].

Although helmet detection systems have been proven to be effective, scalability and deployment issues remain. This is because helmets come in different types, the rider's posture, and environmental factors such as glare or rainfall. Therefore, model retraining with diverse datasets and dynamic algorithms is continuously required to ensure reliable performance in different locales [15].

3.2 Triple Riding Detection

Triple riding on two-wheelers is referred to as the capability of some advanced computer vision techniques that try to count the number of riders on a single two-wheeler.

This activity is full of challenges: dynamic motion of traffic, varying posture of riders, and ambient conditions [1], [2].

• **Traditional Image Processing Methods:** Basic image processing techniques such as edge detection and contour analysis were used in early attempts at triple riding detection. The methods tried to identify more heads or bodies on a twowheeler based on static thresholds of size, spacing, or shape. These proved to be ineffective in actual environments such as crowded traffic scenes or complicated backgrounds because they are not adaptive [3].

• **Deep Learning-Based Approaches:** Most of today's systems depend on CNNs and other architectures, such as YOLO or Faster R-CNN, for determining the number of people present on a vehicle. It considers the spatial arrangement of the riders and correctly detects more than one person riding on the two-wheeler. The state-ofthe-art techniques make multi-frame analysis to trace the existence of an individual from a video frame to another, therefore enhancing robustness against the occlusion of objects or overlapping objects [4], [5].

• **Computer vision:** Computer vision has important research areas on pose estimation and human keypoint detection. Among the most common algorithms used for detecting keypoints in human bodies are OpenPose and HRNet. With these keypoints, using precise identification of their locations and orientations, the systems can be used to count the number of riders on a two-wheeler. This approach is particularly useful when partial occlusion of riders is involved, such as when the rear passenger is partially covered by the front riders [6].

3.2.1 Challenges in Real-World Scenarios

• Occlusions happen when riders partially obscure one another, making algorithms that detect people have challenging times distinguishing between two or three individuals.

- Diverse Postures: In dense traffic, side sitters or forward leaners might not be caught right.
- Low light, glare conditions, and adverse weather conditions such as rain or fog affect the performance of detection.

• Diversity in datasets poses a problem, specifically, lack of different, annotated datasets designed especially for triple riding detection holds the development of robust models able to properly generalize to various regions and scenarios across [7].

3.2.2 Remarkable implementations

• Urban Traffic Monitoring Systems: In Pune and Chennai, pilot deployments of AI-based systems, where triple riding detection has been integrated with LPR to enforce automatic penalties have been started. Overhead cameras fitted with deep learning models track busy junctions. For example, a pilot in Chennai scored above 90

• **Integrated within Smart City Frameworks:** There is integration of a triple riding detection with overarching traffic management in smart city schemes. For example, Hyderabad had developed an overlay system that integrates triple riding identification with the helmet identification and monitoring of speed. It links all the violations and generates an offender profile by auto flagging it, which issues penalty against them [9].

• Edge Computing for Real-time Detection: Real-time detection systems used at busy junctions have used edge computing in order to process video feed in realtime locally, thereby reducing latency dramatically. These are using lightweight deep learning models that are specifically optimized for working on edge devices. In an experiment held at Bengaluru, delays in detection in seconds as compared to less than one second when processed with an edge device [10].

• **Triple Riding Dataset Development:** To counter this problem of limited diverse datasets, recently, researchers have even developed a labeled dataset for triple riding. The dataset consists of different riding configurations, including sideways passengers or children sitting between adults. The dataset has been used to train the hybrid detection model, a combination of CNNs and pose estimation, which worked more accurately under diverse traffic conditions [11].

• **AI-Driven Enforcement Systems:** Automated enforcement systems link triple riding detection with e-challan generation, ensuring seamless violation processing. In Delhi, a pilot project combined detection with penalty points systems, where repeated violations result in suspension of vehicle registration or the rider's driving license. Such initiatives prove that AI-driven solutions could help foster compliance and promote road safety [12].

3.3 Over-Speeding Detection

Over-speeding detection systems use a combination of hardware and software technologies to accurately measure the speed of vehicles and identify violations in real-time. These systems are important in enforcing speed limits and mitigating accidents caused by excessive speed.

• **Radar-Based Systems:** The radar technology-based speed guns may be one of the most common speed-measuring devices for vehicle speeds. This transmits radio waves which reflect back from moving vehicles and may measure the Doppler effect due to the resulting frequency shift to calculate the speed. Radar systems have been found to be very effective for monitoring single-lane or low-density traffic conditions. However, these systems require human intervention and are prone to errors due to overlapping signals in multi-lane conditions [1], [2].

• LIDAR: This term refers to the technology or equipment known as Light Detection and Ranging. A LIDAR device measures distance and speed by utilizing laser beams. Given that its operation relies on recording the time taken for the laser to return after striking a vehicle, the systems are capable of providing precise speed measurements. Regarding traffic patterns, LIDAR equipment may also concentrate on individual vehicles located in specific lanes within multi-lane traffic situations. This characteristic makes LIDAR devices particularly suitable for application in urban environments with complex traffic conditions. Nevertheless, LIDAR systems are costly, operate under only a line-of-sight paradigm, and are sensitive to environmental conditions, like rain or fog [3], [4].

• Video-Based Speed Estimation: Video analytics systems make use of cameras in combination with computer vision algorithms to calculate vehicle speeds. These systems calculate the distance covered by a vehicle within a given time frame by computing successive video frames. Moreover, sophisticated models make use of object detection algorithms such as YOLO or Faster R-CNN to track individual vehicles in complex traffic scenarios. Video-based systems are scalable and can easily be integrated with other violation detection systems, such as license plate recognition, but have high computation power requirements and are adversely affected by adverse weather conditions and low light levels [5], [6].

• **ANPR-Integrated Systems:** These ANPR systems are usually integrated with a speed detection feature with the use of time-distance approximation methods. For the procedure, cameras are mounted on a roadway at two different points. The measurement of the time taken by any vehicle to traverse the distance between these two camera points enables the calculation of its speed. In addition, ANPR integrated systems are relatively inexpensive and most commonly used in highway speeding or open-road speedings. However, their accuracy can only be ensured with precise setting and unobstructed view of the license plates [7].

• **IoT and GPS-Based Solutions:** Devices enabled by the Internet of Things (IoT), such as GPS tracking systems integrated within vehicles or roadside units, possess the capability to monitor speed in real-time and transmit data to central traffic management systems. These solutions have been increasingly adopted within the realms of fleet management and public transportation systems to ensure compliance with established speed limits. Although this technology is precise and offers realtime readings, its implementation necessitates widespread adoption and is presently confined to applications such as logistics and ride-hailing services [8].

The effectiveness of speed monitoring technologies.

• Accident Prevention: Studies find that persistent monitoring and enforceable speed limits reduce the actual occurrences of accidents, highly at the risk-prone locations including school zones and highway lanes. LIDAR, along with radar technologies, has been found to be so efficient at detecting violations in near-real-time, thus saving time to intervene by respective traffic authorities.

• Integration with Automated Penalty Systems: Technologies like ANPR and video-based analytics reduce manual enforcement by automatically generating challans for offenders. Such interference, naturally tends to reduce human intervention leading to higher compliance.

• Scalability: Video-based and IoT solutions can be scaled up or spread over large urban environments as they integrate well within a Smart city structure. They provide only speeding measurement but also valuable data of the traffic for analysis as well as planning.

Limitations:

• Environmental Sensitivity: Most of the LIDAR and video-based devices will be very sensitive in different environmental conditions such as rain, fogging or low lighting, which consequently tends to degrade the accuracy at specific points. Radar sensors generally are less sensitive to certain elements of weather conditions except during multi-lane detection incidences where signal overlapp occurs.

• **Cost:** LIDAR and IoT-enabled systems require large investments in hardware, installation, and maintenance, thus becoming a barrier to their use in resource-poor regions.

• **Data Processing and Latency:** The processing of data and latency in video-based systems requires significant processing power to process real-time data. Increased traffic levels will result in delays, thus reducing the efficiency of the system in detecting infractions during peak hours.

3.4 License Plate Recognition

License Plate Recognition systems also have an important role in traffic management because it can automatically identify any vehicle that is registered or associated with a violation through the use of optical character recognition combined with more refined deep learning techniques in its extraction and recognition processes for license plates and characters.

• OCR-Based Methods: Traditional LPR employs OCR to extract text-based information from images of plates. The procedure involves three major stages:

1. **Image Preprocessing:**This step uses preprocessing techniques that include denoising, contrast adjustment, and edge detection. These are the techniques applied to define the license plate region from the background.

2. Segmentation: License plate is segmented into individual characters for recognition. At this stage, the most common technique used is either connected component analysis or region-based segmentation.

3. Character Recognition: Tesseract employs OCR algorithms that recognize and then convert the segmented characters into an alphanumeric text. While traditional Optical Character Recognition (OCR) works well for static images, it fails when it comes to low-quality images, motion blur, and license plate format variations. This limitation prevents its use in dynamic traffic situations [1], [2].

• **A Deep Learning Approach:** The most recent modern LPR system implements deep learning algorithms, specifically CNN. This results in higher accuracy along with more superior adaptability against challenging conditions.

• License Plate Detection: Using real-time object detection structures such as YOLO (You Only Look Once) along with Faster R-CNN, region detection of the license plate is very commonly used. These models are thus robust against size and orientation variations caused by the plates even resulting from glare or shadowy effects in the environment surrounding the plate.

• **Character Recognition using Deep Learning:**RNNs and LSTM networks are often combined with CNNs for end-to-end character recognition. These models can handle sequential data, thereby improving the accuracy of recognition for distorted or partially visible plates.

• **Transformers and Attention Mechanisms:** In recent advancements, the latest breakthroughs regarding transformers and attention mechanisms include the application of transformer-based architectures that apply self-attention to focus on relevant information regarding the image. One finds remarkable efficiency in dealing with complex backgrounds and different font styles. Deep learning outperforms traditional optical character recognition (OCR) methods; it is scalable for high-traffic environments and has flexibility, especially regarding different forms of license plates [3,4].

Table 2	Comparison	of License	Plate	Recognition
---------	------------	------------	-------	-------------

Aspect	OCR-Based Methods	Deep Learning Methods
Accuracy	Moderate; works well with static, highquality images but fails in dynamic scenarios.	High; robust in dynamic traffic, poor lighting, and non-standard plates [3],[4].
Adaptability	Limited; struggles with motion blur, glare, and plate variations [1], [2].	Highly adaptable to diverse and complex environments [3], [4].
Performance	Effective in controlled, low-traffic environments.	Excels in high-density, real-time traffic[3].
Cost and Scalability	Low cost, ideal for small-scale systems [1].	High cost but scalable for large urban deployments [3].
Use Cases	Parking lots, toll booths, and gated premises [1].	Smart city systems, over-speeding detection, and integrated traffic control [4].

3.5 Integration with Violation Detection Systems

LPR systems are equipped with mechanisms meant for traffic violation detection and therefore help in the automation of enforcement processes.

• Helmet and Triple Riding Detection: The technologies related with License Plate Recognition (LPR) are often converged with systems for helmet and triple riding detection. LPR captures the license number of the violating vehicle whilst the system concurrently detects an infringement of the helmet and upon triple riding violation, instantly. The improved deep algorithms enable high definition plate identification even under different dynamic states of traffic and thus also enable automatic issuance of challan without human intervention [5].

• **Over-Speeding Detection:**LPR systems commonly are integrated with ANPRs in speed enforcement structures. Taking cameras at two fixed positions on a road, they capture the time taken by a vehicle to travel between such points and hence, its speed can be determined. If its captured speed exceeds the permissible limit then the license plate of a vehicle is captured to pose fines. This is very effective over highways and high-speed roads [6].

• **Real-Time E-Challan Systems:**LPR is implemented in real-time e-challan generation in high-end traffic monitoring systems. Immediately after the system captures the license plate of the vehicle for the detected violation (such as over-speeding or jumping of signals), it will be matched with the central registration database. Echallans are issued automatically to offenders, thereby eradicating manual processes and enhancing enforcement efficiency [7].

• Integration of the License Plate Recognition Technology in Smart City Framework. This kind of technology plays an essential role in the smart city framework in allowing systems to communicate with one another freely, thereby creating room for coordination especially during the implementation of centralised traffic management systems. Therefore, this could make it possible trace habitual offenders, correlate penalty fees with renewals, or even analyze flows when giving traffic suggestions in urban planning. The integration system profoundly reinforces traffic enforcement and leads towards an improvement in general public safety [8].

4. Automated Penalty Issuance System

It helps in automating challan generations in updating traffic law and highway code through automated violations and penalties issue in a much more fast-time mechanism. Instead of the traditional old system, which was only relying on paper, this will combine IoT-based equipment and cameras, along with machine learning technology, for efficiency in capturing violators correctly and timely. It increases the effectiveness of enforcing traffic laws in cities as well as in areas recognized for high traffic volumes [3]. In general, the above operation covers three basic levels: Firstly, infractions are detected through advanced computer vision models and analytics powered by artificial intelligence in the detection of incidents of not wearing helmets; tripling; speeding to uncontrolled speed; and failure to comply with red traffic signal commands, among others, through detection [4]. The license plate recognition is further processed so that the vehicle registration information becomes available through the use of OCR models and deep learning-based object detection [5]. Further, after ascertaining the violation against the central database of vehicle registration, the e-challan is issued to the offender [6].

Generally, notices delivered by SMS, email, or even custom traffic management applications are more effective in improving the effectiveness of enforcement procedures and reducing delay [7]. Maximum benefits can be achieved from these systems by the integration of multiple technologies used for traffic violation detection. As seen earlier, helmet or triple riding violations detected by the AI-based system automatically connect with LPR; hence, the vehicle owned by the offender is captured, and penalties are issued directly. The over-speeding event occurs through detection using a radar, LIDAR, or video speed estimator, where distance-over-time calculations further collaborate with LPR for non-interruptive enforcement. Such systems can be used to integrate with central platforms in smart cities for large-scale violations management, and therefore, contribute to regulating traffic ecosystems [10]. Although the automated challan systems look effective, their implementation would require due diligence in legal and administrative factors. For instance, artificial intelligence and surveillance technology would only be used when proper regulations are put in place in support of fines and the mechanism by which such fines might be contested [11]. Additionally, strong data privacy and security concerns call for the necessity of encryption and controlled access measures to ensure information confidentiality [12].

Furthermore, such systems must also facilitate openerror management and mechanisms for dispute resolution as well as accessible appeal mechanisms in case of false positives or mistaken identification [13]. Public awareness and cooperation are essential to the efficacy of automated penalty issuance systems. Effective and transparent communication concerning their function in improving road safety and minimizing human errors can foster trust and acceptance [14]. The provision of timestamped evidence to violators, in conjunction with avenues for grievance redressal, ensures that the system is perceived as fair and impartial [15]. Taking into account these factors, automated challan systems are a great leap forward in the development of safer and more orderly roadways while also enhancing the efficiency of traffic enforcement activities.

4.1 Integration with Traffic Violation Detection

Automated penalty issuing systems show high adaptability as they can be integrated with various detection mechanisms of traffic violations in establishing a complete solution [1], [2].

Helmet Violation And Riding Triple:

AI-powered detection systems monitor helmet usage and detect triple riding on two-wheelers. Deep learning models like YOLO or Faster R-CNN are used for realtime detection of non-compliance [3]. For instance, a camera at an intersection can capture a rider without a helmet or a two-wheeler with three passengers. Simultaneously, the License Plate Recognition (LPR) systems extract the number plate of the vehicle and automatically generate an electronic challan. This process has been effectively carried out in cities like Bengaluru and Hyderabad where, it has reduced helmet violations significantly by the automation [4], [5].

Over-Speeding Violation:

Over-speeding violations are managed through an automated penalty system and speed monitoring systems, including radar guns, LIDAR devices, and video-based speed estimation. A radar system measures the speed of a vehicle in real-time; if the speed limit is exceeded, the LPR system captures the number of the license plate number of the vehicle [6]. Time-distance-based estimation methods for speed are significantly effective for highways, based on automatic number plate recognition (ANPR) systems. Such approaches measure the time a vehicle requires to cover a distance from one fixed point to the next point and automatically identify violators. Integration ensures that penalties are levied immediately without the necessity of manual intervention [7].

• Smart City Integration:

Automated penalty issuing systems are the center piece of the smart city concept. It aggregates data coming from surveillance cameras, IoT sensors, and other sources that include centralised traffic management systems and thereby constitutes an integrated enforcement framework [8]. Smart city integrated systems allow authorities to more efficiently manage extensive networks because of the real-time provision for violation detection and immediate issuance of penalties. For instance, in Delhi, a system has been developed that integrates helmet detection, triple riding detection, over-speeding detection, and red-light violations into a singular platform. This integration ensures seamless enforcement and offers valuable data for urban planning

[9], [10].

4.2 Legal and Administrative Considerations

In order to make automated penalty issuance systems run, several legal and administrative structures need to be set into place to ensure transparency, justice, and public confidence.

• Legal Validity: Sanctions by automatic systems should be recognized as legal. This should cover whether AI-determined offenses can be used as proof in court [3]. Enough proof of the offense must be provided to the offending party, such as images or videos with time-stamped precisely what was infringed. How to dispute penalties should also be defined along with easy-to-access appeal processes [4].

• **Data Privacy and Security:** With the reliance of automated systems on surveillance and data collection, there come questions on personal information protection [5]. Therefore, measures like encryption, access control, and safe data storage should be put into place to protect the sensitive information. Data retention policies should also be well stated to ensure that the data collected is only used in enforcement and not for mischief [6].

5. Challenges and Limitations

Automated systems for violation detection and issuance of penalties have improved the effectiveness of enforcement of traffic law. However, these systems have challenges and weaknesses that detract from overall performance. Some examples of such problems are related to data fundamentals in handling said data, real-time processing, adaptability to environment and contextual factors, which are critical for their mass adaptation and scalability.

5.1 Real-Time Processing and Scalability

One of the critical problems of automated systems is that they cannot rectify real-time violations and provide functionality over vast urban terrain.

- Heavy Computational Demands: It requires AI models such as YOLO or Faster R-CNN to capture real-time violations such as helmet noncompliance, triple riding, and over-speeding. The processing of these high-resolution video feeds of complex traffic scenarios causes lags in densely populated cities.
- Scalability Issues: The deployment of these systems throughout a city or region requires significant investments in infrastructure, including high-performance edge computing devices, cloud servers, and network bandwidth. Financial constraints in developing regions make the scaling of such systems difficult.
- **Complexity:**High-density traffic environment. Multi-lane roads combined with dynamic violations such as abrupt lane changing or overlapping, are generally complex and are difficult in real-time and, consequently, tend to cause false positives or late penalty decisions.

5.2 Environmental and Contextual Factors

These will have a direct impact on the accuracy and reliability of violation detection and penalty issuance systems.

- Adverse weather conditions: pose significant challenges to the ability of systems to maintain accuracy, especially in cases of heavy rain, fog, or glare. These factors degrade the quality of video feeds and disrupt detection processes. For example, the reliability of license plate recognition or helmet detection diminishes under poor lighting conditions or during nighttime operations.
- **Different designs of Vehicles and Plates:** Non-uniform formats, styles, and placements of the license plates, and different types of helmets are challenging for OCR and AI-based models. At times, weird head gear or objects that may conceal the plates might lead to false negatives or positives.
- **Highly congested traffic condition:**detection becomes very hard with fastmoving vehicles and with congested roadways becoming a hurdle, lane change becomes too frequent, thereby complicating the detection. Systems do not work perfectly for violations to be tracked right in populous cities or highways.

5.3 Systemic and Operational Challenges

Apart from technological problems on violation detection and penalty issuances systems, there also are operational problems that challenge the functionality of such systems.

- **Public Acceptance:**The public will react against automated systems, especially when they are deemed too severe or intrusive. Without clarification, offenders will be skeptical about the reasonableness of the penalties, especially in case of false positives.
- **Disputes and Appeals:**Automated penalties should have explicit legal frameworks in support of them so that they are enforceable. In addition, provisions for appeal against fines should be made to give the wrongdoer a chance to make their case in case of mistaken or incorrect detection.
- Integration with existing infrastructure: This has not been possible in many areas because most areas don't have the infrastructure support which includes stable supply of electricity and stable internet, and especially on centralized databases for vehicles that cause their installation to be expensive as well as labour-intensive.
- Some of the key challenges should be addressed for the high adoption and effectiveness of automated violation detection and penalty issuance systems [1], [2]. For instance, strengthening the data privacy framework by guaranteeing secure storage, encrypting data transfer, and ensuring compliance with privacy laws can help instill trust in the public [3], [4]. Scaling can be enhanced through using cost-effective edge computing devices as well as optimizing AI models for resource-constrained environments [5], [6]. Furthermore, environmental adaptability can be enhanced with model training on other datasets

and hybrid detection systems that can cope up with challenges arising from unfavourable weather and difficult traffic conditions [7],[8]. Yet another very vital aspect is public involvement and transparency; awareness programs along with transparent procedures in disbursing penalties enhance the acceptability and cooperation level of the citizens [9], [10]. With such challenges overcome, such systems can thus be more robust, reliable, and widely accepted in paving for safer and more disciplined road networks [11].

6. Conclusion

The survey points out that automation of violation detection and penalty issuance systems has a transformative impact on modernizing traffic law enforcement [1], [2]. Computer vision, deep learning, license plate recognition (LPR), and IoT sensors are used for the detection of violations such as helmet non-wearing, triple riding, and over-speeding [3], [4]. With less dependency on manual processes, the effectiveness and accuracy in enforcement is significantly improved. The real-time processing done through edge computing, integrated with smart city infrastructures, allows for efficient scalability of the systems, particularly in high-density traffic areas of cities [5], [6]. Several challenges make these systems less popular; they include data privacy issues, scalability limitations, and the degradation of performance in adverse environmental conditions [7]. These issues need to be addressed to ensure that these systems maintain their reliability, thus being adopted by the public [8], [9]. In order to fully exploit these technologies, several areas need more research and development. Improving the environmental robustness of artificial intelligence models for handling challenges such as poor illumination, adverse weather, and complex traffic conditions should be priority work in future endeavors [10], [11]. Hybrid approaches that integrate data from a variety of sensors, such as LIDAR, cameras, and infrared imaging, along with the use of diverse, real-world datasets, are expected to enhance the accuracy and adaptability of systems [12]. Cost-effective scalability is another critical domain where optimized lightweight AI models for edge computing can help in the reduction of deployment costs and computational overhead, thus making such systems more viable for developing regions [6], [13]. Equally important is data privacy and security; proper encryption protocols, safe storage of data, and following the law of privacy will ensure information security, while developing public trust [8], [14]. Public cooperation will further be encouraged through clear policies and awareness campaigns about data [9]. Further, there is a rising need for the standardization of inputs including the license plate format and the enforcement protocols of the LPR systems across regions so that they could recognize in a proper way and are interoperable [5], [12]. The helmet detection systems must also be trained in greater varieties of helmet designs, which are culturally-specific headgears [15]. The integration of violation detection systems with centralized platforms can allow for seamless e-challan generation, penalty tracking, and real-time monitoring [6], [10]. Linking the system with the penalty point system and insurance databases will further encourage people to abide by traffic rules [7], [13]. Public involvement is the key to successful implementation; the government must make public awareness programs so that people are able to know the benefits of these systems for road safety and grievances redressal process should be transparent so that disputes can be solved fairly [14], [15]. The implementation of automated traffic violation detection systems along with penalty issuance systems, is a giant leap within the realms of road safety as well as enforcement [1], [4]. As these implement proper frameworks and garner enough public cooperation, it's poised to reduce traffic violations significantly, improve compliance and promote disciplined road behavior in the country [3], [10]. To address the identified challenges and provide long-term success and sustainability, the safer and smarter road networks will be generated across the world [6], [15].

References

- Charran, R. Shree, & Dubey, R. K. (2022). Two-wheeler vehicle traffic violations detection and automated ticketing for Indian road scenario. IEEE Transactions on Intelligent Transportation Systems, 23(11), 22002–22007.
- 2. Muneer, V. K., & Azil, A. Study of An AI-Powered Vehicle Monitoring System: An Ensembled Approach for Intelligent Surveillance.
- Ren, Y. (2024). Intelligent Vehicle Violation Detection System Under Human– Computer Interaction and Computer Vision. International Journal of Computational Intelligence Systems, 17(1), 40.
- 4. Sangsuwan, K., & Ekpanyapong, M. (2024). Video-based vehicle speed estimation using speed measurement metrics. IEEE Access.
- 5. Bose, S., Kolekar, M. H., Nawale, S., & Khut, D. (2023). Loltv: A low light two-wheeler violation dataset with anomaly detection technique. *IEEE Access*.
- Li, C. H., Huang, D., Zhang, G. Y., & Cui, J. (2024). Motorcyclist helmet detection in single images: a dual-detection framework with multihead self-attention. Soft Computing, 28(5), 4321–4333.
- Tripathi, P., Singh, P., Bano, M., Sharma, K., & Shahi, A. A Review on Helmet and Number Plate Detection. *Journal homepage: www.ijrpr.com ISSN*, 2582, 7421.
- 8. Lai, Y. L. (2022). Car over-speeding detection using time-distance approximation. PhD Thesis, UTAR.
- Chandravanshi, S. K., Bhagat, H., Darji, M., & Trivedi, H. (2021). Automated Generation of Challan on Violation of Traffic Rules using Machine Learning. *International Journal of Science and Research (IJSR)*, 10(3), 1157–1162.
- Pandiaraja, P., Abisheck, S., Mohan, A., & Ramanikanth, M. (2024). Survey on Traffic Violation Prediction using Deep Learning Based on Helmets with Number Plate Recognition. 2024 5th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), 234–239.

- 11. Sindhu, V. (2020). A Novel Approach to Automated Centralized e-Challan System for Traffic Management. CGC Int. J. Contemp. Technol. Res., 2(2), 131–133.
- Jichkar, N., Deulkar, A., Thakare, A., Bolakhe, S., & Vaidya, S. (2019). A Novel Approach for Automated E-challan Generation using QR Code and OCR. International Journal of Research in Engineering, Science and Management (IJRESM), 2(3), 167–171.
- 13. Jayasree, M. (2021). Traffic Violation Proctoring System: Helmet and Triple Riding Detection.
- 14. Deep, D. P., Ramya, C. G., Veni, M. K., Divya, B., & Alekhya, J. L. Automatic Challan Generation.
- Malik, S. M., Iqbal, M. A., Hassan, Z., Tauqeer, T., Hafiz, R., & Nasir, U. (2014). Automated over speeding detection and reporting system. 2014 16th International Power Electronics and Motion Control Conference and Exposition, 1104–1109.
- 16. Rani, M., Kulshrestha, A., Saini, B., Vijay, D., & Upreti, D. (2024). Velocity Violation Monitoring and Charge System. PRATIBODH, RACON.
- 17. Adi, K., Widodo, C. E., Widodo, A. P., & Masykur, F. (2024). Traffic Violation Detection System on Two-Wheel Vehicles Using Convolutional Neural Network Method. *TEM Journal*, *13*(1).
- Nagaonkar, J., Lobo, N., Varghese, J., Fernandes, N., & D'souza, D. (2023). Third Eye: A Comprehensive Solution for Road Safety. SAMRIDDHI: A Journal of Physical Sciences, Engineering and Technology, 15(03), 337–340.
- Saravanan, M., & Rajini, G. K. (2024). Comprehensive study on the development of an automatic helmet violator detection system (AHVDS) using advanced machine learning techniques. *Computers and Electrical Engineering*, 118, 109289.
- Tyagi, A., Kumar, A., Goel, M., & Sambhyal, R. (2024). Traffic Detection Using Computational Approach. *Educational Administration: Theory* and Practice, 30(5), 11091–11098.
- 21. Rajabhushanam, C., Kumar, P. K., Sai, P. S., Ajay, P., & Jayaprada, P. S. (2024). Helmet Detection and Number Plate Recognition Using Deep Learning.
- Prakash-Borah, J., Devnani, P., Kumar-Das, S., Vetagiri, A., & Pakray, P. (2024). Real-Time Helmet Detection and Number Plate Extraction Using Computer Vision. *Computaci'on y Sistemas*, 28(1), 41–53.
- 23. Akhtar, A., Ahmed, R., Yousaf, M. H., & Velastin, S. A. (2024). Real-time motorbike detection: AI on the edge perspective. *Mathematics*, *12*(7), 1103.
- 24. Tripathi, P., Singh, P., Bano, M., Sharma, K., & Shahi, A. (2024). A Review on Helmet and Number Plate Detection. *Journal homepage:* www.ijrpr.com ISSN, 2582, 7421.
- 25. Tripathy, P. C. An Automated System for Number Plate Recognition Employing OCR and Deep Learning Techniques. ISSN: 2347-7180.