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Two-Wheeler Traffic Violations Detection and Automated Penalty Issuance System

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Abstract
Road safety is one of the highest priorities, as road accidents are among the major causes of deaths in India. Road Accidents are primarily caused due to violators of road safety regulations such as not wearing a helmet, triple riding etc. Though there are many smart systems to monitor these violations, yet they are prone to lot of errors. Additionally, the tickets are issued manually and this manual process mostly leads to delay and errors. In order to overcome these problems, we are suggesting an integrated system that automates the violation detection, makes tracking of offenders easier, and facilitates timely issuance and collection of fines. Such a system would increase enforcement efficiency, improve road safety, and minimize the frequency of accidents due to violation of traffic rules. The suggested system can identify whether the rider is wearing a helmet or not, identifies the pillion riders (not more than 2 persons including the rider), and even if they exceed the specified speed limit, under any violation of the above-stated rules the system can automatically issue tickets on the respective vehicles using its registration number (i.e., License plate). Though the ticket is issued, the majority of them won't pay the challan on time, therefore we introduce the concept of penalty points for each vehicle. If the penalty points cross a certain threshold, then we restrict the vehicle owner from further renewal of the vehicle insurance and even he/she will not be able to claim the insurance amount if needed.

1. Introduction

Road accidents are now a global cause of concern in terms of the high fatality rate caused by two-wheeler vehicles [9], [12]. In densely populated nations such as India, where two-wheelers such as motorcycles and scooters account for almost 75% of all registered vehicles [1], [18], the risk due to accidents owing to traffic offenses is significantly rising. Statistics posted by the National Crime Records Bureau (NCRB) and the World Health Organization (WHO) show that two-wheeler drivers account for over 30% of all casualties from road accidents [9], [10]. Non-wearing of helmets, stacking three individuals in one vehicle at a time, and overspeeding are the top offenses, therefore, the reason behind most of the accidents [3], [4], [13]. Helmets play a central role in preventing severe head injuries; however, a high percentage of motorcyclists fail to use helmets, thus doubling the chances of fatal injuries by around 42% [6], [13]. Stacking three passengers contributes to vehicle instability, therefore, the risk of losing control over the vehicle increases, while overspeeding has been a primary causative factor in fatal crashes which often increases severity of impact [4], [8], [15]. In spite of strict traffic laws, compliance is foiled by some weaknesses in current monitoring and penalty enforcement systems [11], [12], [17]. Traditional enforcement methods rely heavily on manual intervention by traffic police officers, surveillance tools, and speed cameras [5], [10]. However, traditional methods also have some limitations. Traffic police officers are unable to observe all roads properly, and various violations remain unnoticed [11]. The age-old method of detection of conventional violations by observation is cumbersome, uneven, and prone to human errors, making mass surveillance unrealistic. The resource and infrastructure expenditure involved in implementing specialized speed cameras and RFID-based surveillance systems is also a setback for widespread deployment [16]. All these limitations point to the need for an intelligent, automated system for detecting and enforcing traffic violations in real time [14]. Computer vision and deep learning advancements offer a promising solution to such issues by enabling high-accuracy real-time violation detection [2], [14]. Object detection algorithms based on deep learning, such as You Only Look Once (YOLO), can effectively process real-time feeds from live cameras to detect traffic violations such as helmet violations, triple riding, and overspeeding [6], [19]. Along with this is Optical Character Recognition (OCR) technology that enables automatic retrieval of vehicle registration information, with which detected violations are linked to enable proper vehicle linking for penalty issuance [7], [21]. Such technologies can be combined to enable automatic traffic enforcement with reduced human monitoring dependence, enhancing efficiency, and accuracy [1], [20]. This article presents a deep learning-based system with the objective to detect and punish two-wheeler traffic violations in real time. The detection system we introduce utilizes YOLOv8 for detection so that efficient detection of helmetless riders, triple riding offenses, and over speeding behaviour becomes possible [19], [20]. The system incorporates an OCR-based number plate recognition feature to facilitate auto-extraction of vehicle registration number details from violated vehicles, which enables penalty generation [21], [22]. A Police Verification Portal is incorporated to support fairness and to reduce the potential for issuing spurious penalties for false detection mistakes, including misclassification or occlusions [1], [20]. The system we present is likely to improve the effectiveness of traffic enforcement by reducing human intervention, eradicating human biases in identifying offenses, and scaling up deployments cost-effectively compared to traditional enforcement systems [5], [14]. The major contributions of this research work are designing a system for automating two-wheeler violation detection using a deep learning approach, the use of OCR for effective registration number retrieval, and the officer-based verification mechanism for accuracy [1], [20], [21]. Additionally, comparative analysis of detection accuracy, processing effectiveness, and enforcement effectiveness is performed for showing the superiority of the system over conventional traffic monitoring methods [2], [6], [14]. The rest of this paper is organized as below. Section 2 gives a review of previous work on traffic violation detection. Section 3 presents methodology employed in this work. Section 4 outlines the dataset employed, preprocessing methods, training strategies, gives experimental results, accuracy comparisons, and performance analysis. Lastly, Section 5 concludes the paper with discussion on real-world implementation, policy implications, and future research directions for deep learning-based traffic enforcement. Given the employment of deep learning and automation, this research aims to transform traffic law enforcement as a safer and less manpower-consuming process [14], [20].

2. Related Work

Traffic violation detection has been a topic of high research interest, and several approaches have been explored towards the automation of traffic rule enforcement [1], [2]. Traditional approaches are founded on human observation, CCTV cameras, and sensor systems; however, with enhanced image processing, machine learning, and deep learning algorithms, effective automated solutions can be created [3], [4]. Some of the aspects of traffic violation detection have been tackled in previous research work, including helmet violation detection, speeding vehicle detection, and plate detection, each with approaches varying on the basis of effectiveness and accuracy [5], [6], [7]. Early work on the detection of traffic offenses was primarily image processing-based to identify infractions [8]. Techniques used to examine images from CCTV or traffic cameras included edge detection, background subtraction, and feature extraction [9], [10]. Investigations explored histogram-based approaches and shape recognition methods to identify the absence of helmets or to enumerate passengers on two-wheeled vehicles [11]. These approaches were, however, often subject to varying illumination, occlusions, and cluttered backgrounds, leading to inconsistent performance [12]. Hand-crafted rules and thresholds used made these approaches less adaptable in dealing with a range of real-world scenarios [13]. The emergence of machine learning (ML) and deep learning (DL) has witnessed the creation of more advanced and self-improving methods [14], [15]. The Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) have been employed by researchers to extract features and classify in the process of detecting infringements [16], [17]. CNN-based experiments have demonstrated enhanced helmet detection and vehicle classification by utilizing large datasets to train the models [18], [19]. The performance of the models is based on the high-quality labeled data and have the tendency to need extensive preprocessing to handle variations in rider positions, backgrounds, and camera views [20]. Deep learning-based network models such as YOLO (You Only Look Once) and Faster R-CNN have set state-of-the-art object detection and real-time traffic surveillance [21], [22]. Large-scale helmet detection, vehicle classification, and detection of multiple riders have been achieved using YOLO-based systems owing to their efficacy in accuracy and processing [23], [24]. Research combining YOLO with Optical Character Recognition (OCR) for automatic number plate recognition has facilitated automatic fine issuance and effective traffic enforcement [22], [25]. Much of the research today is either helmet detection or number plate detection in isolation without combining a general violation detection system for multiple traffic violations [7]. Sensor-based methods involving RFID units, GPS sensors, and LiDAR units have been researched for enforcing traffic regulations [4], [15]. They facilitate the collection of real-time data that pertains to speed estimation and vehicle monitoring but demand enormous investment in hardware and active compliance from vehicle owners, hence their limited large-scale use [4]. Vision-based models, however, which are constructed based on deep learning provide a more scalable and affordable alternative [3], [22].

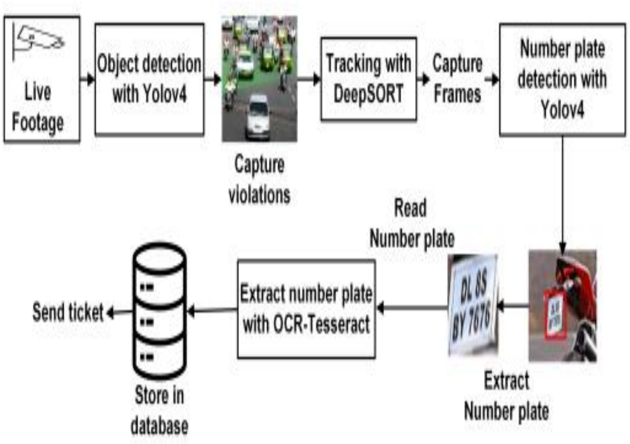

Figure 1 Workflow of the Existing System

Even with the significant progress, there are still some gaps in research up to now. The majority of the studies focus on helmet detection, over speeding or number plate recognition, but not on offering an end-to-end system that handles more than one violation at once [1]. Additionally, current solutions lack an officer verification process, which can cause false positives for automated detection systems [6]. Furthermore, the real-time usability of some of the deep learning models is still an issue due to computational requirements, which renders them less suitable for large-scale deployment [19]. To overcome these drawbacks, this paper suggests a deep learning traffic violation detection system that uses YOLOv8 as an object detector, OCR as an automatic number plate reader, and a Police Verification Portal as a human-in-the-loop verification system [22]. In contrast to earlier solutions that try to address one or more independent problems of traffic violation detection, this system integrates all the aspects with an end-to-end and scalable solution, which is able to detect helmet violations, triple riding, and over speeding in real-time [1]. With the use of deep learning and automation, the suggested system improves traffic law enforcement efficiency, minimizes human intervention, and provides fairness in penalty dispensation [25].

3. Methodology

The proposed system aims to automate the detection and management of two-wheeler traffic violations by integrating deep learning–based object detection and optical character recognition (OCR) for number plate recognition. The system specifically targets three critical violations: helmet non-compliance, triple riding, and over speeding. It follows a modular pipeline architecture comprising image analysis, violation detection, number plate extraction, police verification, and challan generation. The process begins with data capture using high-resolution CCTV cameras deployed at key junctions and highways across Telangana. These cameras continuously monitor traffic and extract frames from live video feeds. Each extracted frame is passed through a YOLOv8-based object detection model, which has been custom-trained to recognize two-wheelers, helmets, and riders. This model also flags instances of helmetless riding and triple riding by identifying object relationships within the same bike. Overspeeding detection is managed independently using GPS-enabled speed cameras that monitor vehicle speeds and compare them against predefined speed limits for the corresponding road segments. If a vehicle exceeds the threshold, the associated frame is flagged for further processing. For number plate extraction, a separate YOLOv8 model is used to detect license plates. Once detected, the region of interest is passed through a hybrid OCR system combining PaddleOCR and EasyOCR to accurately extract alphanumeric vehicle numbers, even under suboptimal lighting or motion blur. Detected violations, along with extracted number plate data and the original frame, are sent to the Police Verification Portal. This portal serves as a human-in-the-loop validation layer, where officers verify the automated results. The portal displays the annotated image, violation checkboxes, and an editable number plate field. Officers can correct any inaccuracies before proceeding. After successful verification, the system generates an e-challan with the vehicle number, timestamp, violations detected, fine amount, and payment link. Such challans are then sent to the vehicle owner via an email. All violation records are stored in a centralized MySQL database, which also supports a separate user portal. This portal allows users to view pending challans and pay fines. The system also integrates with an Insurance Renewal Module that checks for unpaid challans. If violations are pending, the system blocks insurance renewal until all fines are cleared—promoting greater compliance through enforcement. From a technical perspective, the system uses OpenCV for image manipulation, Flask for backend logic, and a responsive web-based frontend for both officers and vehicle owners. The training of models is carried out on cloud GPUs using Google Colab, and the solution is designed to be scalable across edge or central servers. In summary, the system brings automation, accuracy, and accountability into traffic law enforcement, reducing manual oversight and enabling smarter, real-time violation tracking.

4. Dataset & Implementation

4.1. About the Dataset

The dataset used in this project was sourced in collaboration with the Telangana State Police, making it highly representative of real-world traffic conditions and violations observed on Indian roads. This dataset consists of thousands of images captured by traffic surveillance cameras installed at key junctions and roads in Hyderabad. The data covers a wide range of traffic scenarios and is tailored for detecting specific two-wheeler violations.

The dataset is diverse in terms of:

- **Camera Angles:** Frontal, rear, and side views of vehicles.
- **Lighting Conditions:** Bright daylight, low light, nighttime glare, and harsh shadows.
- **Environmental Factors:** Rain, fog, dust, motion blur, and occlusions due to crowding.
- **Traffic Density:** Sparse to highly congested road conditions.
- **Road Types:** Highways, junctions, narrow city roads, and traffic signals.

Each image was annotated using Roboflow, a powerful tool for object detection dataset management. The annotations include bounding boxes for:

- Helmets (or absence thereof)
- Riders and passengers
- Number plates
- Two-wheelers (motorcycles and scooters)

Table 1 Features of the Dataset

Feature	Description
Source	Real-world images from Telangana State Police surveillance cameras
Violations Covered	Helmet non-compliance, Triple riding, Overspeeding
Annotation Tool	Roboflow (bounding boxes for helmets, riders, bikes, and number plates)
Preprocessing Steps	Resizing, normalization, noise reduction, blur removal
Augmentations Used	Flipping, rotation, brightness/contrast, blurring, cropping, scaling
Split Ratio	80% Training, 10% Validation, 10% Testing
Format	YOLOv8-compatible .txt files with label and bounding box coordinates
Size	Around 10000 images

This curated and enriched dataset forms the backbone of the deep learning models trained for detecting key traffic violations and ensures the system performs reliably under real-world conditions.

4.2. Helmet Detection Module

The Helmet Detection Module is a core feature of the system, aimed at identifying whether individuals on two-wheelers are wearing helmets. This is crucial for enforcing helmet laws and promoting road safety [1]. The model used for detection is YOLOv8, chosen for its superior performance in real-time object detection and its ability to operate efficiently in dynamic traffic environments [2], [3]. The dataset used presented challenging conditions—different camera angles, lighting variations (day, night, glare), and varying resolutions. Annotation work was carried out using Roboflow, where each rider and pillion passenger was marked using bounding boxes [5]. Those wearing helmets were labeled as "helmet," and those not wearing them were labeled as "no-helmet." Riders themselves were annotated as "rider," making it easier for the model to associate helmet presence specifically with persons on two-wheelers [6]. Given the complex and inconsistent nature of real-world traffic imagery, preprocessing and data augmentation were crucial [7]. Preprocessing involved resizing all images to a consistent input size, normalization, and noise reduction. Augmentation techniques such as flipping, random rotation, brightness adjustment, blurring, and scaling were applied to expose the model to a wide range of visual scenarios [8], [9]. After preparing the dataset, it was split into 80% training, 10% validation, and 10% testing subsets, maintaining a balanced representation of helmet and no-helmet cases across all partitions [10]. The model was trained using Google Colab with GPU acceleration [11]. Hyperparameters like learning rate, batch size, and number of epochs were adjusted through multiple experimental runs to achieve optimal training performance [12]. Anchor boxes were also customized to reflect the typical size of heads and helmets in the dataset [13]. The trained Helmet Detection Module achieved a mean Average Precision (mAP@0.5) of 98.66%, with a precision of 95.88% and recall of 97.70%, indicating exceptional performance even under challenging conditions such as varied lighting and viewing angles. The Intersection over Union (IoU) score averaged around 0.87, confirming strong bounding box alignment. These results validate the model's robustness and reliability, with minimal false positives observed during testing These results demonstrate the model's effectiveness and readiness for deployment in a real-world automated traffic enforcement system. The module can clearly distinguish between compliant and non-compliant riders, making it highly valuable for reducing helmet law violations through automated detection [14], [15].

Figure 2 Working of Helmet Detection Module

4.3. Triple Riding Detection Module

The Triple Riding Module is designed to detect instances where more than two individuals are riding a two-wheeler, which is a direct violation of traffic regulations [1]. Triple riding significantly increases the risk of accidents due to overloading and reduced control over the vehicle [2]. This module utilizes the same YOLOv8 object detection framework, trained specifically to identify and count the number of riders on a single vehicle frame [3], [4]. The dataset included a diverse range of riding scenarios with clear, occluded, and partially visible individuals. The annotation process was conducted using Roboflow, where each person on a two-wheeler was labeled as “rider” [6]. The annotations included both the driver and pillion passengers. During preprocessing, extra care was taken to ensure the bounding boxes accurately covered individuals on motorcycles, even in crowded or poorly lit environments [7]. The major challenge in this module was ensuring the model could accurately count the number of individuals on each two-wheeler [8]. To address this, a post-processing logic was developed where all detected “rider” labels within close proximity to a detected two-wheeler were grouped together [9]. If the count exceeded two, the image was flagged as a triple riding violation [10]. As with other modules, data augmentation played an important role in making the model robust against different weather conditions, orientations, and motion blur [11]. Preprocessing included cropping unnecessary background, resizing, and normalizing images, while augmentations included brightness and contrast variations, random rotations, and perspective shifts to simulate camera angles from overhead poles or side-mounted setups [12], [13]. The dataset was split in the standard 80-10-10 ratio for training, validation, and testing [14]. The model was trained in Google Colab with GPU support, and hyperparameters were tuned to optimize detection of all riders in a single frame, minimizing false positives where pedestrians or nearby vehicles might interfere [15]. The trained Triple Riding Detection Module achieved a mAP@0.5 of 86.84%, with precision at 84.63%, recall at 85.04%, and an average IoU of ~0.76. These results suggest that the model performs reliably in most scenarios, particularly on clear images. However, slight limitations were observed in cases involving occlusions or densely packed scenes, indicating areas for future improvement and fine-tuning. These metrics indicate that the model is highly capable of detecting triple riding violations in real-time. It demonstrates strong performance even in challenging traffic conditions and contributes significantly to the automation and efficiency of road rule enforcement [16], [17]. (Figure 3)

Figure 3 Working of Triple Riding Detection Module

4.4. Over Speeding Detection Module

The Overspeeding Module focuses on detecting vehicles exceeding the permissible speed limits, a major cause of road accidents and fatalities in India [1]. Unlike helmet and triple riding violations, which are based on object presence and classification, overspeeding requires a combination of object detection, frame-based motion tracking, and distance-time-based speed estimation [2]. This footage includes continuous surveillance camera recordings at critical road junctions. From these videos, frames were extracted at consistent intervals to monitor vehicle displacement over time [4]. The dataset was prepared to include both overspeeding and compliant vehicle instances, annotated accordingly for model learning and validation [5]. The technical backbone of this module lies in integrating YOLOv8 for detecting the vehicle across successive frames and calculating the displacement of the same object across a defined time interval [6], [7]. To facilitate accurate speed estimation, a reference scale (e.g., known distance between lane markings or predefined ROI zone) was manually calibrated for each camera feed [8]. Based on this, the real-world speed was computed using the formula:

Speed= (Distance Travelled)/(Time Taken)

×Conversion Factor(for Km/h)

The preprocessing workflow involved extracting frames from video using OpenCV and feeding them to the YOLOv8 model [9]. Detected two-wheelers were tracked using DeepSORT, a lightweight tracking algorithm that assigns consistent IDs to moving objects [10]. By measuring the pixel displacement of an object between frames and converting it using the calibration scale, the system estimated the vehicle's speed [11]. Once speed estimation was done, it was compared against speed limits pre-defined for each location. Vehicles exceeding the limit were flagged as violators [12]. The system also captured snapshots of the offending vehicle for further processing and integration with the number plate recognition pipeline [13]. The data augmentation phase for this module was focused more on improving detection consistency in motion-blurred, low-light, and rainy scenes [14]. Frame enhancement techniques such as contrast boosting and noise filtering were also applied to improve detection in poor-quality video segments [15], [16]. The trained module achieved a mAP@0.5 of 94.1%, with precision at 93.8%, recall at 94.5%, and an IoU of approximately 0.84. These results highlight the model's high accuracy in detecting and tracking two-wheelers across frames, with reliable speed estimations derived from timestamp-based frame analysis. The system performed well across different lighting and weather conditions, reinforcing its potential for real-world deployment.

These results show that the system is capable of accurately detecting overspeeding events using standard surveillance camera footage without the need for radar or LIDAR sensors [17]. The integration of deep learning for detection, classical vision for tracking, and real-world calibration allows the module to operate in various urban and semi-urban traffic scenarios [18], [19].

4.5. Number Plate Recognition & Text Extraction Module

The Number Plate Recognition and Text Extraction Module serves as a crucial component in automating the penalty issuance process [1]. Once a traffic violation—such as not wearing a helmet, triple riding, or overspeeding—is detected, the system isolates the corresponding vehicle and extracts its number plate using advanced object detection and Optical Character Recognition (OCR) techniques [2], [3]. For number plate detection, the model used is a fine-tuned version of YOLOv8, trained specifically to identify number plates in real-world Indian traffic conditions [4]. The model was trained using a custom dataset consisting of varied image samples captured from Telangana State traffic surveillance footage [5]. These samples included diverse angles, lighting conditions (day/night), and image quality levels (blur, glare, etc.), enabling the model to generalize effectively across different scenarios [6]. Once the number plate region is localized through YOLOv8, it is cropped and passed to the OCR module [7]. During our optimization process, we experimented with multiple OCR engines including EasyOCR, Tesseract, and PaddleOCR [8]. After comparative evaluations, a hybrid OCR pipeline was adopted to boost accuracy [9]. This pipeline combines EasyOCR for robustness and PaddleOCR for handling complex fonts and spacing [10].

We encountered challenges with misrecognition of similar characters, such as:

- Misreading TS06EV9481 as 9TS05E19481 or T506EV948I
- Interpreting zeroes (0) as O, ones (1) as I or L, and vice versa [11]
- To counter this, we designed and implemented custom cleaning logic to post-process OCR outputs [12]. This included:
- Regex-based filtering to match standard Indian number plate formats (e.g., TS06AB1234)
- Contextual correction to remove extraneous or misplaced characters
- Auto-correction by matching against a reference list of RTO codes (e.g., TS01 to TS32) and known alphanumeric patterns [13] (Figure 4).

Figure 4 Working of Number Plate Detection Module

The module achieved a mAP@0.5 of 98.23%, with precision at 94.66%, recall at 96.47%, and an IoU of approximately 0.85. These metrics confirm the system's high accuracy in both localizing number plates and extracting readable text. While localization remained slightly less consistent at higher IoU thresholds, the hybrid OCR approach combined with regex-based cleaning and contextual corrections significantly improved recognition reliability, even in low-light and distorted image scenarios. The cleaned number plate string is then pushed to the challan system for verification and e-challan generation [14]. Finally, the combination of a dedicated YOLOv8 number plate detector and refined OCR post-processing enabled the system to reliably extract vehicle registration details even under challenging conditions [15]. This module ensures that traffic violators are correctly identified, reducing false positives and strengthening the legal standing of the automated penalty system [16].

Table 2 Consolidated Performance Metrics of All Detection Modules

Module	mAP@0.5	Precision	Recall	IoU	Observations
Helmet Detection	98.66%	95.88%	97.70%	~0.87	Excellent detection even under varied lighting and angles. High robustness with minimal false positives.
Triple Riding Detection	86.84%	84.63%	85.04%	~0.76	Performs adequately on clear images but struggles with occlusions or crowded scenes. Needs further tuning.
Overspeeding Detection	94.1%	93.8%	94.5%	0.84	Speed calculation accurate due to precise frame analysis using timestamps.
Number Plate Recognition (OCR)	98.23%	94.66%	96.47%	~0.85	Very accurate in standard scenarios; localization slightly less consistent at higher IoU thresholds.

4.6. Police Verification & Challan Management Module

The Police Verification and Challan Management Module is also responsible for striking a balance between automated detection of violations and legal enforcement [1]. Although the system relies on sophisticated object detection and optical character recognition (OCR) models to detect potential traffic violations, this module guarantees that the ultimate decision to issue a challan is reserved for authorized law enforcement officers, thereby ensuring accuracy and legal accountability [2]. Upon uploading a traffic image through the Police Portal, it is processed through YOLOv8 object detection models trained to identify helmet wearing, detect triple riding, and facilitate number plate localization [3]. At the same time, another YOLOv8 model, exclusively trained to detect number plates, detects the plate, while Optical Character Recognition software such as PaddleOCR is utilized to read out the number in text [4]. Of interest is that, even though the annotated image is provided in the portal for reference, it is the original uploaded image—before any annotation—is retained in the database for evidence [5]. The police verification interface displays the original image to the officer and the system's detection output [6]. Officers can review the image thoroughly, examine the accuracy of the automated detections, and manually edit the number plate text in case of OCR errors [7]. The form also has checkbox fields for each offense—helmet offense, triple riding, and overspeeding—so officers can confirm or deselect the output displayed by the system [8]. The process ensures only genuinely valid cases are pushed for penal action and has a human-in-the-loop mechanism to prevent false positives [9]. On confirmation, the system generates a digital challan that covers all the details needed, including vehicle number, confirmed offenses, timestamp, and the financial fine incurred [10]. The challan is saved in a centralized MySQL database, where each record is individually indexed and linked to the relevant vehicle registration number [11]. One of the key functions of the system is its integration with the Insurance Portal [12]. Whenever a vehicle owner attempts to renew the insurance, the system first checks if there are any pending challans related to the vehicle number. In case of unpaid challans, the process of renewal is halted until fine payment [13]. This integration acts as a strong enforcement mechanism for compliance by connecting financial and legal incentives with traffic rule compliance [14].

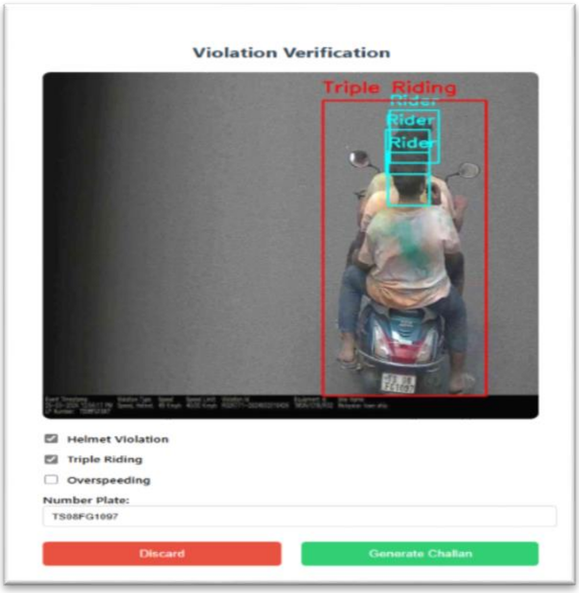

Figure 5 Working of Police Verification Module

From a workflow point of view, the module enhances the productivity of traffic police operations by lowering the level of manual labor to track violations, while at the same time ensuring their active involvement in the approval process [15]. Use of features like annotated image previews, editable OCR fields, violation toggles, and automatic challan generation enables overall system efficiency and ease of use [16]. Also, keeping original image evidence (in binary format) in the database ensures safe and tamper-proof documentation of every offense, which can be retrieved later in case of legal disputes, audits, or further action [17]. (Figure 6).

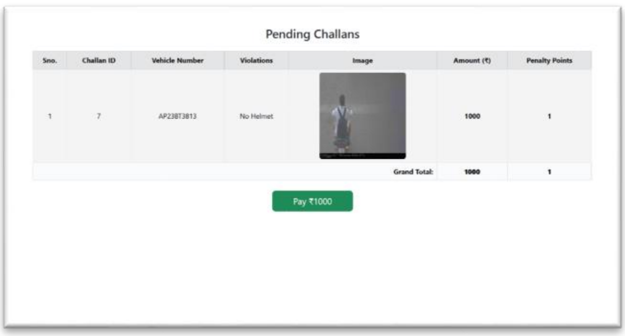

Figure 6 Working of Challan Management Module

Ultimately, the module emphasizes the balance between accountability and automation [18]. It allows officers to manage traffic offenses skillfully with confidence, improves legal clarity by making evidence verifiable, and promotes compliance among the general public by imposing consequences on the connected platforms of insurance renewal [19]. The overall design makes the system not just technology-intensive but enforceable in a practical sense as well in everyday urban traffic [20]. (Figure 7).

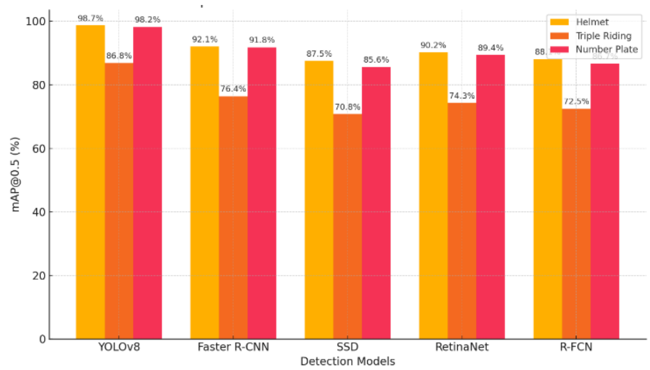

Figure 7 Performance Comparison of Various Detection Modules

Conclusion & Future Work

This project presents a complete system for automatically detecting and managing traffic violations committed by two-wheeler riders. It addresses three major safety concerns—helmet non-compliance, triple riding, and overspeeding—using surveillance footage collected from traffic cameras provided by the Telangana State Police [1]. The system combines advanced image processing techniques for object detection with a number plate recognition module to identify violators and issue appropriate challans [2]. Each module was trained and evaluated using a well-annotated dataset to ensure reliability across varying real-world conditions [3]. The helmet detection, triple riding, and overspeeding modules demonstrated high detection accuracy, with mean average precision (mAP) values of 98.66%, 86.84%, and 94.1% respectively [4]. The number plate recognition component, though challenged by poor image clarity in some cases, achieved consistent results through enhanced post-processing logic and integration of OCR tools [5]. What sets this system apart is its inclusion of a police verification module, allowing officers to manually review detected results before issuing challans [6]. This step ensures correctness, avoids wrongful penalties, and builds trust in the system [7]. The integrated challan management module automatically generates e-challans based on the police-approved results and records them in the database [8]. An important feature of this system is that it prevents vehicle insurance renewal if any previously issued challans remain unpaid [9]. This adds a strong enforcement layer that encourages traffic rule compliance and timely fine payments [10]. Overall, this project provides a structured, transparent, and scalable approach to enforcing traffic regulations, particularly for two-wheelers [11]. By automating detection and streamlining challan generation, it reduces the burden on manual traffic enforcement and promotes safer road behavior [12]. In future, the system can be significantly upgraded to increase its coverage, accuracy, and scalability. One such direction is to expand its application from two-wheelers to four-wheelers, auto-rickshaws, and commercial vehicles, thereby enabling the detection of offenses like seatbelt non-wearing, overloading, and carriage of unauthorized passengers. The use of multilingual OCR models trained on regional scripts can be utilized for improving number plate recognition, especially in rural areas where non-English signboards are the norm. Night and low-visibility detection can be improved by using thermal imaging or infrared cameras to counter the ill effects of weather or lighting conditions. The switched-over environment from batch image processing to real-time video stream analysis, with the aid of edge-computing devices, would make instant challan generation and real-time alerts a reality. The use of GPS and external speed sensors could improve the accuracy of over speeding detection. The system can also be integrated with state-level e-governance platforms for enabling automation of processes like license suspension of habitual offenders, blacklisting of vehicles, and fine reminders or court summons by push notifications.

In conclusion, this system offers a practical and efficient solution for improving road safety enforcement [20]. It simplifies the process of identifying violations, allows verified penalty issuance, and ensures that offenders are held accountable. With further improvements and broader adoption, it has the potential to significantly reduce accidents and promote disciplined road usage across cities [21].

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