SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V13I6P101

Volume 13 Issue 6, 1-11, June 2026

Original Article

Wrong Side Vehicle Detection and Illegal Parking Detection using the Centroid Method and YOLOv8

Palakkumar B. Bhatt[1,3], Dipesh Kamdar[2]

[1]*Department of Electronics and Communication, Gujarat Technological University, Gujarat, India.*
[2]*Department of Electronics and Communication, V.V.P. Engineering College, Gujarat, India.*
[3]*Department of Electronics and Communication, Government Polytechnic, Gandhinagar, Gujarat, India.*

[1]*Corresponding Author : connectpalakbhatt@gmail.com*

Received: 04 March 2026 Revised: 03 April 2026 Accepted: 02 May 2026 Published: 27 June 2026

***Abstract** - Traffic violations such as illegal parking and wrong-side vehicle driving significantly contribute to traffic congestion and road accidents in urban environments. According to recent reports, India records nearly five lakh road accidents annually, resulting in approximately 1.8 lakh fatalities. Continuous monitoring of traffic using conventional manual surveillance is inefficient and requires automated intelligent systems. This paper proposes a computer vision-based framework for detecting illegal parking and wrong-side vehicle movement using traffic surveillance videos. The proposed system integrates deep learning-based vehicle detection with motion analysis and centroid-based tracking to identify traffic violations in real time. Initially, a Region of Interest (ROI) and a reference direction line are defined during scene initialization. Vehicles are detected in each frame using the YOLOv8 object detection model, and centroid positions of detected bounding boxes are calculated for tracking vehicle movement across frames. Displacement analysis of centroid positions is used to determine vehicle motion and direction. Wrong-side driving is detected by evaluating vehicle movement against the predefined traffic direction, while illegal parking is identified using ROI-based spatial validation combined with temporal duration analysis. The proposed system was evaluated using CCTV traffic videos from different locations in Ahmedabad. Experimental results show that the system successfully detected illegal parking with 90% accuracy and wrong-side driving with 83.33% accuracy. The results demonstrate the effectiveness of the proposed approach for automated traffic violation monitoring in real-world surveillance environments.*

***Keywords** - Traffic violation detection, Illegal parking detection, Wrong-side vehicle detection, YOLOv8, Traffic surveillance.*

1. Introduction

Due to the high growth of road accidents and other road violations, road safety has become a significant issue worldwide. According to the latest reports, road accidents are recorded as the number one cause of deaths in India, as evidenced by the statistics; almost five lakh road accidents are reported in the country every year, with the number of deaths also being about 1.8 lakh every year [1]. The most significant causes are traffic violations like speeding, improper U-turns, driving on the wrong lane, and illegal (wrong) parking. These offenses interrupt the traffic, create traffic jams, and pose a high probability of accidents.

A common violation of traffic in the urban environment is illegal parking. Had individuals parked their vehicles in these restricted areas, such as sidewalks, crossroads, and identified no-parking places, it would lead to the hindrance of the movement of traffic and evidently decrease the road capacity. In the case of Intelligent Transportation Systems (ITS), traffic surveillance systems' automated detection of illegally parked vehicles has been one of the significant trends of research. The first research in the area of illegal parking detection relies on conventional computer vision methods like background subtraction and motion tracking to identify stationary vehicles in surveillance videos [2, 6]. This was done by having an analysis of pixel-level changes between successive frames to determine whether the vehicles had been stationary during a period of time.

More experiments added foreground modeling and vehicle motion tracking to enhance the level of detection. Multi-object tracking methods examine and compute the trajectories of vehicles across frames and decide whether they are stationary in specific regions over extended periods of time [4, 10].

To overcome the difficulty associated with overlapping vehicles and traffic jams, researchers also invented occlusion-tolerant detection techniques [5]. Also, background modeling methods known as adaptive (Gaussian Mixture Models (GMM), dual background models, and so on) were presented to enhance the resilience of dynamic settings [9, 12]. These methods examine the temporal changes of video frames to distinguish between separated vehicles that are temporally stopped and vehicles that are parked unlawfully.

Wrong-side driving is another severe violation of traffic that often leads to serious accidents, especially on highways and one-way roads. Traffic that moves contrary to the allowed direction of traffic considerably exposes the potential of head-on crashes and congestion of traffic. Initial investigations on the wrong-way vehicle tracking were based on motion-based methods like optical flow to determine the direction of vehicle movement according to surveillance videos [22, 23]. These methods determine motion vectors to detect vehicles that are moving against the designated traffic direction.

As computer vision and machine learning continued to develop, more advanced ways of detecting wrong-side vehicles were created. The method of lane detection and trajectory analysis was presented to predict the direction of traffic and find vehicles that break the traffic rules [24]. Object detectors built with deep learning, as well as tracking algorithms, have now been used extensively to detect wrong-directional vehicle movement in real-time [25, 27, 28]. These systems detect vehicles on the initial frame through models based on a convolutional neural network and track the vehicle on a series of successive frames to estimate its direction. The advancement of deep learning has been rapid, and the smart traffic monitoring systems have largely been enhanced. The contemporary methods combine object detection, motion analysis, and trajectory tracking techniques to identify traffic offenses automatically. Specifically, the object detection models based on YOLO support real-time processing and high accuracy of detection, which is why they can be used in the application of traffic surveillance [32, 36, 39].

Driven by these advances, this paper presents a computer vision model for identifying illegal parking and wrong-side movement of vehicles through traffic surveillance video taken at urban traffic cameras. The system suggested adheres to a systematic processing cycle. At the first stage, scene initialization is carried out in which the Region of Interest (ROI) and a reference direction line are identified according to the traffic movement within the monitored region. The input video is then pre-processed, and a vehicle detection model based on YOLOv8 is used to identify vehicles in every frame of the input video. The identified vehicles are represented with the help of bounding boxes, and centroid positions are derived. The tracking mechanism is centroid-based, and it uses successive frames to track vehicles and determine their movement direction and displacement. The system carries out parallel violation analysis based on the pattern of the tracked motions. Directional constraint evaluation is applied to identify vehicles that are moving in the opposite direction of the anticipated traffic movement, which shows wrong-side driving. At the same time, illegally parked vehicles are identified with the help of ROI based evaluation and verification of the time period, which helps to determine whether a vehicle is parked at a particular place, within a limited area, for a long period. In case of a violation, the system identifies and marks the relevant video frame and keeps the evidence that can be monitored and enforced. The processed frames are then repeated until the video stream is terminated, and the resources are then freed by the system.

In spite of such developments, the current methods have drawbacks in real-life usage because most of the research is done on one type of violation and not on a combined multi-violation framework. Also, the illumination variations, occlusions, and dynamic traffic environments tend to influence performance. This is where a powerful and scalable solution featuring object recognition, trustworthy tracking, and motion detection is required. Thus, to detect violations of the traffic, it is necessary to have a single framework that will be based on ROI-based assessment, temporal validation, and directional constraint analysis.

2. Literature Review

The literature review of this study is organized into three subsections to provide a clear overview of existing research. The first subsection discusses studies related to illegal parking detection, while the second subsection reviews methods for wrong-side vehicle detection. The third subsection highlights the research gap identified from the reviewed literature.

2.1. Illegal Parking Detection

The problem of illegal parking has been given a lot of research interest because of the effects it has on traffic jams and road safety in urban areas. Older methods were mainly based on the conventional image processing methods like background subtraction and motion detection to extract stationary cars in surveillance video footage [2, 6]. The techniques identify vehicles that spend long periods in motion through the difference between successive frames. To enhance the detection process, researchers proposed scene modeling and image transformation mechanisms in the identification of parked cars in an outdoor surveillance setup [3]. Multi-object tracking systems were also created to operate on the path of vehicles in the frames of the video and to identify whether vehicles are stagnant in the limited zones [4]. Nevertheless, the issue of tracking vehicles in a highly congested road scene is a challenge because of vehicle occlusion and overlaps. To solve these problems, occlusion-tolerant detectors were suggested to enhance the detection of parked vehicles [5].

Some of the works used motion analysis in order to identify unusual vehicle activity at traffic sites. The optical flow techniques are used to identify motion vectors to identify abnormal vehicle behaviour in surveillance footage [8]. Moreover, adaptive background modeling methods, including Gaussian Mixture Models (GMM), have been employed to accommodate the changes in illumination and dynamic background in real-world setups [9]. They were further introduced as dual background models and cumulative foreground difference models in order to differentiate between temporarily stopped and illegally parked vehicles based on the temporal variation of video frames [10, 12]. Other methods that have been investigated in order to enhance the detection performance include machine learning and hybrid feature-based methods. These techniques merge the spatial level, the shape properties of the objects, and the movement patterns in order to identify parking offenders more efficiently [7, 11].

As deep learning is evolving, object detection systems like YOLO are increasingly popular in vehicle detection and traffic monitoring systems since they have high accuracy and can perform real-time processing [13]. A number of papers can combine deep learning-based vehicle detection and tracking algorithms to understand the pattern of vehicle movements and identify parking offenses automatically [14], [15]. Newer studies also examine the use of the spatiotemporal analysis method to identify cases of illegal parking through the analysis of vehicle tracks and movement trends with time [17], [18]. According to survey studies, intelligent video analytics with deep learning can enhance the efficiency of traffic violation detection systems to a great extent in a smart city setting [19, 21].

All in all, the state of the art concerning illegal parking detection indicates a shift towards less traditional image processing methods like background subtraction and motion detection, to more modern tracking algorithms and the implementation of deep learning. The early techniques worked well in controlled conditions, but were limited in uncontrolled conditions due to changing illumination, occlusion, and moving traffic conditions. Multi-object tracking and adaptive background modeling were introduced to enhance the reliability of detection, but they are still ineffective in high-congestion urban situations. More recent deep learning-based solutions, especially based on YOLO frameworks, are more accurate and can perform in real-time. However, the majority of available research is centered on the detection tasks in isolation and is not combined with the temporal and spatial validation, which implies that more powerful and intelligent solutions to the real-life traffic surveillance systems are required.

2.2. Wrong Side Vehicle Detection

Wrong-side driving is a serious road offense that has brought terrible accidents, especially on the highways and one-way roads. The initial studies were mostly based on motion-based detection. Surveillance videos were estimated through optical flow to determine the vectors of the vehicle motion and identify vehicles that moved in the opposite direction of the anticipated traffic flow [22, 23]. As computer vision developed, it introduced the method of lane detection and trajectory analysis to identify the normal direction of the traffic and the violation of the traffic law [24].

Moreover, there is the use of anomaly detection methods to identify abnormal traffic flow patterns of vehicles at the scenes of traffic congestion [26]. Object detection models based on deep learning have greatly enhanced wrong-side vehicle detection. Various researchers used the YOLO-related frameworks in conjunction with tracking algorithms to identify vehicles and determine their motion direction in video surveillance [25, 27, 28].

In this type of system, vehicles are identified with the help of deep neural networks and followed over frames in order to estimate their displacement and identify the direction of movement. Abnormal vehicle behaviour has also been detected using the methods of trajectory-based analysis. Unsupervised trajectory clustering techniques can be used to identify vehicles that travel in a direction contrary to the overall traffic without having to use large sets of labelled data [29].

In other methods, road boundary detection and vehicle detection algorithms are used to identify the anticipated direction of traffic, and the violations are detected [31]. Current studies emphasize the accuracy of detecting improvement and computational efficiency with high-quality deep learning structures. Smart traffic monitoring applications usually combine YOLO-based detection networks with tracking algorithms to resolve various traffic offences in real time [32-36]. The current object detection models, including YOLOv8 and YOLOv9, offer greater accuracy of detection and can run much faster inference in the context of surveillance of real-time traffic [39, 40]. Other systems also have automated alerts that alert authorities in cases of violations [41]. Most recently, research has been conducted on hybrid deep learning methods combining object detection with more sophisticated tracking and behavior detection methods to further the functionality and correctness of wrong-side vehicle detection systems [42].

In general, the research on the problem of wrong-side vehicle detection shows a definite progression of the motion-based methods, like optical flow and trajectory estimation, to the sophisticated deep learning-based architectures. Although pioneering techniques gave crude directional analysis, they were prone to environmental changes, and they failed to hold up in intricate road traffic situations. Object detection models like YOLO, combined with tracking algorithms, have greatly enhanced the accuracy of detection and real-time performance. Nevertheless, the vast majority of the current strategies are devoted to the detection of a single violation and use controlled data sets, which restricts their use in dynamic real-world settings.

This shows that more elaborate and combined structures are required that can accommodate various traffic offenses with enhanced capacity and scalability.

2.3. Research Gap

Through the literature provided above, it can be seen that despite the great progress that has been achieved, there are still a number of significant challenges.

Even though a considerable amount of significant progress has been achieved in detecting traffic violations, there are still a number of limitations to the existing research. Most studies are aimed at identifying illegal parking or wrong-side driving, and not both.

Conventional image processing algorithms are also illumination variant, occlusion, and dynamic background aware, which constrains their functionality in real-life surveillance situations [2, 9]. Thus, the necessity of an efficient and scalable structure that will be able to detect various violations of traffic in real-time with the help of traffic surveillance videos is identified.

To overcome the findings of the existing studies, the present study proposes a computer vision-based method of detecting illegal parking and unlawful movement of vehicles on the road by monitoring the traffic surveillance video. The given system is a combination of vehicle detection with the help of YOLOv8 and centroid tracking and motion analysis to identify traffic violations on the basis of directional constraint analysis and Region-Of-Interest (ROI) based validation.

As observed in the comparative analysis in Table 1, the majority of the current approaches are restricted to single-violation detection and are not robust enough to be validated in real-life scenarios. Conversely, the suggested solution presents a single framework that integrates detection, tracking, and spatial-temporal validation to make it possible to monitor traffic in a multi-violation manner. This combined design is the main innovation of the given work and contributes to its relevance in real-life intelligent traffic surveillance systems.

Table 1. Comparison of my work with existing work

Method	Violation Type	Technique	Processing Type	Key Limitation	Proposed Advantage
Optical Flow	Wrong-side	Motion vectors	Offline	Noise sensitive	Improved robustness
YOLO + Tracking	Single	Detection + tracking	Real-time	Single violation	Multi-violation
YOLO + DeepSORT	Single	Detection + tracking	Real-time	High complexity	Lightweight tracking
Lane-based Methods	Wrong-side	Lane + trajectory	Semi real-time	Structured roads needed	Works in complex scenes
Multi-violation (existing)	Multiple	YOLO + tracking	Real-time	Limited validation	Better validation logic
Proposed Work	Multiple	YOLOv8 + centroid + ROI + direction + temporal	Near real-time (video-based)	--	Evidence generation + robust detection

3. Methodology

The project will come up with a computer vision-based model to detect illegal parking and the wrong-side movement of vehicles based on videos taken by the traffic surveillance. The suggested system combines deep learning-based vehicle detection, centroid-based tracking, and motion analysis in order to detect traffic violations in real-time. The general tasks of the proposed system can be shown in the system flowchart, which is made of various consecutive stages such as the system initialization, frame pre-processing, vehicle detection, centroid-based tracking, and violation analysis.

3.1. Scene Configuration and System Initialization

Initialization and configuration of the scene start the system. The surveillance environment in this stage is prepared by setting up important parameters needed in the analysis of traffic violations. A Region of Interest (ROI) is indicated to show the place where violations of parking occur may take place. Also, a direction reference line is established to indicate the expected flow of the vehicles in the monitored road segment. After the scene configuration has been finalized, the input traffic video stream is opened, and the system reads out the frames one after another. The frame pre-processing stage is done to resize and prepare each frame with a uniform input resolution to the detection model.

3.2. Vehicle Detection with YOLOv8

Vehicle detection is done after pre-processing with the help of the YOLOv8 object detection model. YOLOv8 is a real-time object detection framework that uses deep learning, thus able to identify multiple objects on a single image with a high degree of accuracy and speed. Each frame, once processed by the YOLOv8, is detected with vehicles and bounding boxes around detected objects of the vehicle types cars, buses, trucks, and motorcycles.

A bounding box is used to represent each identified vehicle with the coordinates of the top-left and bottom-right corners. Relevant vehicle classes are only saved in the vehicle class filtering process, and the bounding box data is processed out to be processed further.

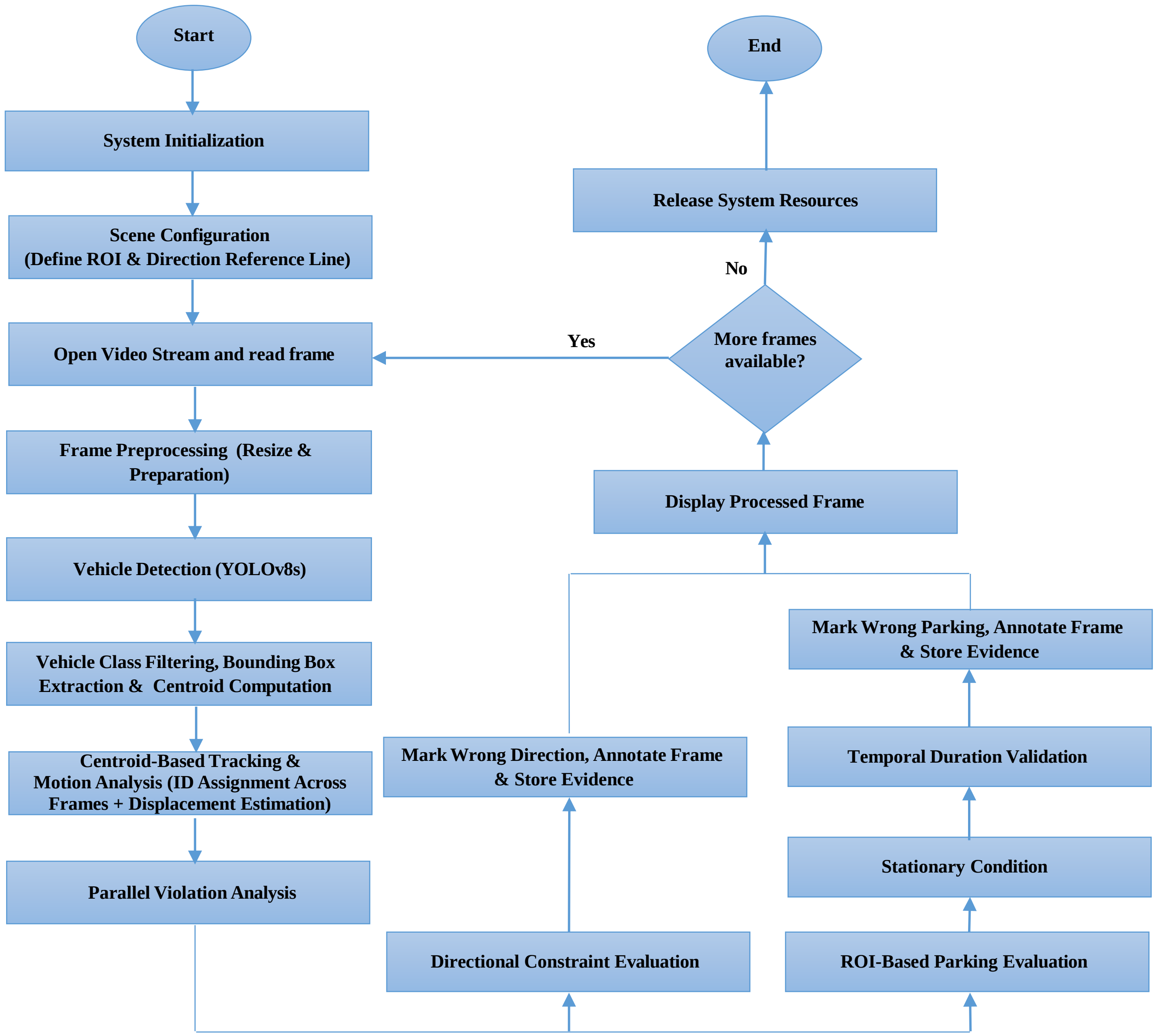

Fig. 1 Proposed methodology

The system adopts the YOLOv8s (small) model for a trade-off between detection performance and speed. The system uses a pretrained YOLOv8s (yolov8s.pt) model trained on the COCO dataset for vehicle detection. No additional training or fine-tuning is performed in this study. The model is directly applied to recorded CCTV video frames for real-time detection. Furthermore, the image size is set to 640×640 pixels to ensure uniformity in detection. Detection confidence and IoU thresholds are set to 0.5 to filter relevant bounding boxes.

3.3. Vehicle Localization by Centroid Computation.

Following the process of object detection, each of the detected vehicles is modeled as a bounding box with the coordinates of the top-left corner and the bottom-right corner:

$$B = (x_1, y_1, x_2, y_2)$$

where:

- $x_1, y_1 \rightarrow$ coordinates of the top-left corner
- $x_2, y_2 \rightarrow$ coordinates of the bottom-right corner

In order to determine the movement of the vehicle frame by frame, the centroid (midpoint) of each bounding box is calculated. The centroid coordinates (C_x, C_y) are calculated as:

$$C_x = \frac{x_1 + x_2}{2}$$

$$C_y = \frac{y_1 + y_2}{2}$$

Centroid is the geometrical center of the detached vehicle region. Thus, the centroid point can be expressed as:

$$C = (C_x, C_y)$$

In the system used, integer division is used to scale the centroid position to pixel coordinates:

$$C_x = \left\lfloor \frac{x_{1+}x_2}{2} \right\rfloor$$

$$C_y = \left\lfloor \frac{y_{1+}y_2}{2} \right\rfloor$$

The centroid is used as a reference to track and perform motion analysis of the vehicle. The system is capable of estimating the patterns of vehicle movement by comparing centroid positions in each consecutive frame.

3.4. Centroid-based Vehicle Tracking and Motion Analysis

The system uses a based tracking mechanism in order to analyse vehicle behaviour with time. A tracking ID is allocated to each identified vehicle that enables the system to retain its identity in the successive frames. The tracking algorithm produces a comparison of centroid positions of identified vehicles in the present frame with those in the previous frame.

Cars whose centroid position is similar are said to be the same object, and the motion trajectories are updated in this case. Frame tracking of the vehicles also allows the system to track the change in position and direction of movement of the vehicle, which are critical in the detection of traffic offenders.

3.5. Movement Detection Displacement Calculation

Vehicle motion is determined by calculating the displacement between centroid positions in consecutive frames. If

$$C_t = (C_{xt}, C_{yt})$$

represents the centroid in the current frame, and

$$C_{t-1} = (C_{x(t-1)}, C_{y(t-1)})$$

represents the centroid in the previous frame, the displacement D that is obtained as:

$$D = \left|C_{xt} - C_{x(t-1)}\right| + \left|C_{yt} - C_{y(t-1)}\right|$$

To effectively detect violations of diverse traffic conditions, a threshold-based decision rule is used on centroid displacement and temporal consistency to differentiate between moving and stationary vehicles. The displacement value is the difference between the position of a vehicle in two frames. When the movement goes beyond a predetermined limit, the car is considered to be in motion. On the other hand, when the displacement is less than the threshold in several successive frames, then the vehicle is said to be stationary. These movement properties are also applied in detecting traffic offenses like overstepping on the wrong side and unlawful parking. Parallel violations are discussed in the next section.

3.6. Parallel Violation Analysis

After the motion analysis is done, the system also conducts parallel violation detection to detect various kinds of traffic violations.

The violation detection logic is parallel on tracked vehicles with designated IDs and centroid-based tracking and can detect multiple violations in the same frame sequence.

3.6.1. Detection of Wrong-Side Driving

To identify wrong-side driving, however, the system assesses the direction the vehicle is moving as compared to the direction of the reference line set. When the direction of movement of a given tracked vehicle is estimated opposite to the direction of the traffic flow, the system determines it as a wrong-side vehicle. After being identified, the violation is indicated in the frame, and the evidence is registered in a folder to be monitored and enforced.

3.6.2. Illegal Parking Detection

A mixture of ROI-based evaluation and temporal duration validation is used to achieve illegal parking detection. To begin with, the system checks the position of the vehicle centroid to be within the predefined parking-restricted area (ROI). A vehicle that stays within this area and its movement is less than the movement limit over a specified time is considered to be parking illegally. This system then annotates the frame and stores the related violation evidence in a folder.

3.7. Visualization and System Termination

The annotated violation frames, which are processed, are presented continuously as the system is running. Processing of the frames goes on until the video stream is finished. Lastly, every resource that has been allocated, including video streams and memory buffers, is freed.

3.8. Experimental Design and Testing Process.

The system was proposed in Python and tested on CCTV traffic videos of various road intersections in Ahmedabad. The experiments were conducted on a laptop having the Intel Core i5 processor (1.7 GHz) and 16 GB RAM. Vehicle detection was done with the YOLOv8 model, and all frames were preprocessed by being resized to a set resolution.

The dataset comprises surveillance videos from CCTV cameras procured from the Ahmedabad Traffic Department covering several locations such as Rakhiyal, Danilimda, Bahucharaji Mata, and Football Ground intersections. Given that the proposed system integrates a pretrained YOLOv8s model with rule-based centroid tracking, there is no independent train-test split carried out, since the research aims at applying a trained model to recorded CCTV video sequences in order to evaluate events.

The dataset will be made up of four CCTV video clips of varying traffic density, camera angles, and environmental conditions. Illegal parking and wrong-side violations ground truth were annotated manually. A direction reference line and a Region of Interest (ROI) were defined at the road layout according to each video.

The system is fed by the frames in order, and violations are detected by centroid displacement and temporal thresholds. The illegally parked vehicle is defined as one that is parked in the ROI during a specific period, whereas the wrong-side movement is defined by centroid movement with respect to the reference direction.

Identified violations are saved in separate folders of each type of anomaly (illegal parking and wrong-side driving), and annotated image frames are used to provide visual confirmation. The evaluation of performance was based on the comparison of the number of violations detected with ground truth annotations, and the detection accuracy was determined on all test videos in a realistic traffic situation.

4. Results and Discussion

The traffic violator detection system had been evaluated on a number of CCTV traffic videos recorded at different road crossings in the city of Ahmedabad. The videos depict different traffic situations, angles, and traffic congestion. The cameras that were placed were each equipped with a manually determined Region of Interest (ROI) that restricted the surveillance area to the area of interest on the road.

Figure (2)-(5) demonstrates that the green border is the boundary of ROI, i.e., the area in which the behaviour of the vehicles is analysed. It is also assisted by a yellow reference line to determine the direction of traffic that is supposed to be observed in order to determine the wrong side.

This is done using real-time CCTV video sequences recorded at various sites in Ahmedabad, such as Rakhiyal, Danilimda, Bahchoraji Mata, and Football Ground crossings, to ensure a variety in the traffic conditions. The system performance is tested in these diverse real-life scenarios instead of a traditional train-test split to test robustness and generalizability.

Fig. 2 CCTV video 1 ROI and wrong side detection line

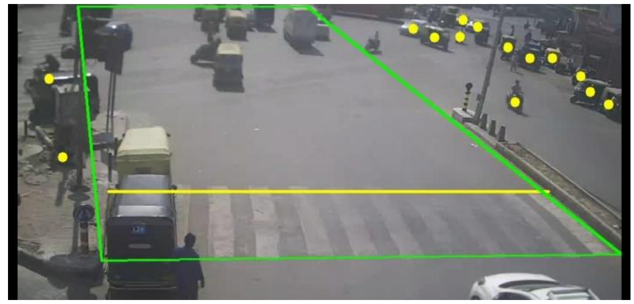

Fig. 3 CCTV video 2 ROI and wrong side detection line

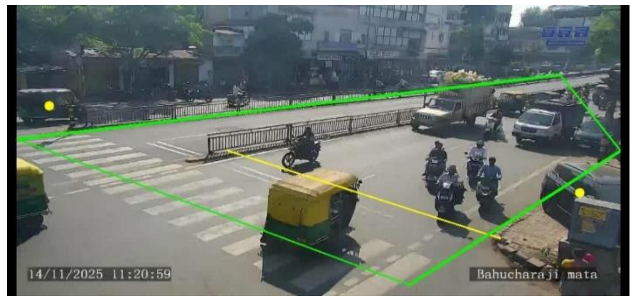

Fig. 4 CCTV video 3 ROI and wrong side detection line

Fig. 5 CCTV video 4 ROI and wrong side detection line

Every frame is input into the system, which processes the frame with the help of Python using the YOLOv8 object detector model in order to recognize vehicles such as cars, motorcycles, auto-rickshaws, buses, and trucks. The centroid of the bounding box of the identified vehicles is calculated, and the bounding box of each vehicle is generated. All the vehicles are assigned IDs that allow the system to recognize the vehicles sequentially on a frame. The vehicle motion is analysed using the centroid displacement, which identifies the vehicle position that is either moving or stationary. The given boundary of the ROI will enable the process of monitoring the vehicles within restricted areas to identify illegal parking, and the yellow line will be used to identify the vehicles moving in the opposite direction of the expected traffic flow. When a car has been parked for over a specific duration in the ROI, then the car is regarded as illegal parking. In the same manner, when the centroid path crosses the reference line in an opposite direction to the direction established, the system regards it as a wrong-side vehicle. The experimental assessment aimed at carrying out an evaluation of four CCTV traffic videos at different locations in Ahmedabad.

Table 2. Violation detection accuracy table

CCTV Video	Illegal Parking (Actual)	Illegal Parking (Detected)	Wrong-side vehicle (Actual)	Wrong-side vehicle (Detected)
Video 1	3	2	0	0
Video 2	3	3	2	2
Video 3	3	3	4	3
Video 4	1	1	0	0
Accuracy	90%		83.33%	

The results of the experiment also reflect these improvements as the proposed system attains 90% accuracy in detecting illegal parking and 83.33 percent accuracy in detecting wrong-side vehicles, as represented in Table 2. Compared to existing methods summarized in Table 1, the proposed approach provides more reliable detection under actual traffic conditions due to its integrated validation mechanism. The integrated multi-stage validation approach in the proposed system leads to better performance than the current methods. Table 1 demonstrates that the conventional approaches, e.g., optical flow, are noisy and ineffective in dynamic traffic, whereas the approaches built on the basis of the YOLO system in combination with tracking can often detect only one violation. By contrast, the suggested approach involves the combination of YOLOv8-driven detection and centroid tracking, ROI-driven filtering, and directional and temporal validation. This integration minimizes false detection and makes it stronger in a real-world situation. Moreover, centroid tracking is used, which guarantees almost real-time performance at reduced computational complexity compared to other algorithms like DeepSORT. The proposed system is more appropriate in a real-life traffic surveillance system, unlike the current methods, which can identify various violations (illegal parking and wrong-side driving) in a single system. The same improvements are applied in the outcomes of the experiment, as the proposed system has 90% accuracy in detecting illegal parking and 83.33% in detecting wrong-side vehicles, as demonstrated in Table 2. The proposed approach offers more accurate detection in real traffic conditions than other current methods, as summarized in Table 1, because it has an inbuilt validation mechanism.

Table 2 shows the number of violations and the detections that were made by the proposed system. These results have shown that the proposed framework is useful in detecting illegal parking and wrong-side vehicle detection under different traffic scenarios. The combination of the YOLOv8-based vehicle detection, ROI-based evaluation, centroid tracking, and motion scan can help to monitor vehicle behaviour efficiently in the real-world surveillance setting.

The considered video recordings had 10 cases of illegal parking and 6 cases of wrong-side vehicle movement. The proposed system was able to identify most of these violations. The system demonstrated a 90 per cent detection rate of illegal parking offenses and an 83.33 per cent detection rate of wrong-side vehicle violations in the experimental conditions, as indicated in Table 2. Such findings reveal that the suggested method is useful in determining traffic offences based on the footage of CCTV surveillance. Nevertheless, the analysis was provided on a small collection of capture videos; thus, additional testing on bigger collections and in more different settings is needed to fully test the strength and scalability of the suggested system.

Fig. 6 CCTV (Video 1) Detected output frame

Fig. 7 CCTV (Video 2) Detected output frame

Fig. 8 CCTV (Video 3) Detected output frame

Fig. 9 CCTV (Video 4) Detected output frame

Figure (6)-(9) demonstrates a representative output frame of the videos tested by CCTV cameras, with the violations identified marked by the help of bounding boxes and text markers. These findings validate the potential of the proposed system to correctly identify illegal parking vehicles and wrong-side vehicles within the context of traffic surveillance video data.

5. Conclusion

This paper suggested a computer vision approach to identify illegal parking and wrong-side vehicle movement through traffic surveillance videos. The system is a combination of vehicle detection on the basis of YOLOv8, monitoring on the basis of ROI, centroid tracking, and motion analysis to detect traffic offenders in CCTV images automatically.

The Region of Interest (ROI) limits the monitored space to be used to detect illegal parking, whereas an orientation reference line can be used to detect vehicles moving against the direction of traffic flow, as expected. The system was tested with the help of several CCTV videos that were taken at various road crossings in Ahmedabad city.

The experimental findings demonstrated that the suggested method is quite effective in identifying traffic offenses in traffic surveillance scenarios. Based on the videos analyzed, 10 cases of illegal parking and 6 cases of movement of vehicles on the wrong side were established. The system was able to detect illegal parking with 90% accuracy and wrong-side vehicle detection with 83.33% accuracy, proving that the system can be used to monitor traffic automatically.

It should be noted that the assessment in this work is carried out at the event level based on the video footage of CCTV recordings in the absence of frame-wise annotated ground truth. So, standard performance measures like precision, recall, and F1-score could not be calculated reliably. The accuracy reported indicates the violation detection rate of real versus detected events. Some false negatives (a few missed detections), like a parked car that was parked illegally, but in one position was noticed, which means that it can be improved. Further development will be done by creating annotated datasets to facilitate comprehensive evaluation using metrics.

Future Work

Future directions will include the creation of frame-wise annotated datasets of the recorded CCTV video footage to allow the calculation of standard evaluation measures, including precision, recall, and F1-score. Moreover, the number of missed detections will be minimized, and robustness in such adversarial conditions as occlusions, heavy traffic, and changing illumination will be enhanced. To increase the scalability and applicability of the system to the real world, the system will also be tested on larger and more diverse datasets.

Acknowledgments

The authors would like to acknowledge the Ahmedabad Traffic Police and the CCTV Surveillance Department for allowing them to access traffic surveillance videos that they used in this study. Their assistance and collaboration helped to a great extent in testing the suggested traffic violation detection system using recorded traffic video data.

References

[1] Nitin Gadkari Flags 5 Lakh Road Accidents a Year, Says Behaviour Change Key to Saving Lives, The Economic Times, 2026. [Online]. Available: https://economictimes.indiatimes.com/news/india/nitin-gadkari-flags-5-lakh-road-accidents-a-year-says-behaviour-change-key-to-saving-lives/articleshow/128804544.cms

[2] Sen-ching S. Cheung, and Chandrika Kamath, "Robust Techniques for Background Subtraction in Urban Traffic Video," *Proceedings of SPIE – Visual Communications and Image Processing*, vol. 5308, pp. 881-892, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[3] Jong Taek Lee et al., "Real-Time Illegal Parking Detection in Outdoor Environments Using 1-D Transformation," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 19, no. 7, pp. 1014-1024, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[4] Jian Wang, and Feng Chen, "Multi-Vehicle Tracking Based Traffic Illegal Parking Detection," *Advanced Materials Research*, vol. 532-533, pp. 540-545, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[5] Waqas Hassan et al., "Real-Time Occlusion Tolerant Detection of Illegally Parked Vehicles," *International Journal of Control, Automation and Systems*, vol. 10, pp. 972-981, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[6] Lucia Maddalena, and Alfredo Petrosino, "Stopped Object Detection by Learning Foreground Model in Videos," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 24, no. 5, pp. 723-735, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[7] Santosh G. Kashid, and Sanjay A. Pardeshi, "Detection and Identification of Illegally Parked Vehicles at No Parking Area," *2014 International Conference on Communication and Signal Processing*, Melmaruvathur, India, pp. 1025-1029, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[8] Tian Wang, and Hichem Snoussi, "Detection of Abnormal Visual Events via Global Optical Flow Orientation Histogram," *IEEE Transactions on Information Forensics and Security*, vol. 9, no. 6, pp. 988-998, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[9] Sarker Md. Mostafa Kamal, Weihua Cai, and Song Moon Kyou, "Detection and Recognition of Illegally Parked Vehicles Based on an Adaptive Gaussian Mixture Model and a Seed Fill Algorithm," *Journal of Information and Communication Convergence Engineering*, vol. 13, no. 3, pp. 197-204, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[10] Wahyono, Alexander Filonenko, and Kang-Hyun Jo, "Illegally Parked Vehicle Detection Using Adaptive Dual Background Model," *IECON 2015 - 41st Annual Conference of the IEEE Industrial Electronics Society*, Yokohama, Japan, pp. 2225-2228, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[11] Mu Chunyang, Ma Xing, and Zhang Panpan, "Smart Detection of Vehicle in Illegal Parking Area by Fusing of Multi-Features," *2015 9th International Conference on Next Generation Mobile Applications, Services and Technologies*, Cambridge, UK, pp. 388-392, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[12] Wahyono, Alexander Filonenko, and Kang-Hyun Jo, "Detecting Illegally Parked Vehicle Based on Cumulative Dual Foreground Difference," *2016 IEEE 14th International Conference on Industrial Informatics (INDIN)*, Poitiers, France, pp. 772-775, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[13] Joseph Redmon et al., "You Only Look Once: Unified, Real-Time Object Detection," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, pp. 779-788, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[14] Wahyono, and Kang-Hyun Jo, "Cumulative Dual Foreground Differences for Illegally Parked Vehicles Detection," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 5, pp. 2464-2473, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[15] Rami Akhawaji, Mohamed Sedky, and Abdel-Hamid Soliman, "Illegal Parking Detection Using Gaussian Mixture Model and Kalman Filter," *2017 IEEE/ACS 14th International Conference on Computer Systems and Applications (AICCSA)*, Hammamet, Tunisia, pp. 840-847, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[16] Xuemei Xie et al., "Real-Time Illegal Parking Detection System Based on Deep Learning," *Proceedings of the 2017 International Conference on Deep Learning Technologies*, pp. 23-27, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[17] Milan P. Patel, and Keyur Shah, "Recognition of Illegal Parked Vehicle Using Machine Learning Approach & Hybrid Classification Method," *Journal of Emerging Technologies and Innovative Research*, vol. 6, no. 5, pp. 276-280, 2019. [Publisher Link]

[18] Jiawei Jiang, Yuchen Chen, and Hsun-Ping Hsieh, "Detection of Illegal Parking Events Using Spatial-Temporal Features," *Proceedings of the 28th International Conference on Advances in Geographic Information Systems*, pp. 667-668, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[19] Prachi Sodegaonkar, and R.A. Khan, "A Comprehensive Review on Deep Learning Models for Illegally Parked Vehicle Detection in Smart Cities," *Journal of Emerging Technologies and Innovative Research*, vol. 12, no. 8, pp. 15-23, 2025. [Publisher Link]

[20] Xinggan Peng et al., "Real-Time Illegal Parking Detection Algorithm in Urban Environments," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 11, pp. 20572-20587, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] Rachel George, "Review of the Vehicle Detection System for No Parking," *International Journal of Science and Advanced Technology*, vol. 16, no. 1, pp. 1-6, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[22] Goncalo Monteiro et al., "Wrong-Way Drivers Detection Based on Optical Flow," *2007 IEEE International Conference on Image Processing, San Antonio*, TX, USA, pp. 141-144, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[23] Synh Viet-Uyen Ha et al., "Improved Optical Flow Estimation in Wrong Way Vehicle Detection," *Journal of Information Assurance and Security*, vol. 9, no. 5, pp. 278-287, 2014. [Google Scholar] [Publisher Link]

[24] Qin Zou et al., "Robust Lane Detection From Continuous Driving Scenes Using Deep Neural Networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 1, pp. 41-54, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[25] Zillur Rahman, Amit Mazumder Ami, and Muhammad Ahsan Ullah, "A Real-Time Wrong-Way Vehicle Detection Based on YOLO and Centroid Tracking," *2020 IEEE Region 10 Symposium (TENSYMP), Dhaka, Bangladesh*, pp. 916-920, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[26] Khac Tuan Nguyen et al., "Anomaly Detection in Traffic Surveillance Videos with GAN-Based Future Frame Prediction," *Proceedings of the 2020 International Conference on Multimedia Retrieval*, pp. 457-463, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[27] Saidasul Usmankhujaev, Shokhrukh Baydadaev, and Kwon Jang Woo, "Real-Time, Deep Learning Based Wrong Direction Detection," *Applied Sciences*, vol. 10, no. 7, pp. 1-13, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[28] Pintusorn Suttiponpisarn et al., "Detection of Wrong Direction Vehicles on Two-Way Traffic," *2021 13th International Conference on Knowledge and Systems Engineering (KSE)*, Bangkok, Thailand, pp. 1-6, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[29] Qing Chang et al., "Identifying Wrong-Way Driving Incidents from Regular Traffic Videos Using Unsupervised Trajectory-Based Method," *Transportation Research Record*, vol. 2676, no. 2, pp. 440-450, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[30] Arya Haghighat, and Anuj Sharma, "A Computer Vision-Based Deep Learning Model to Detect Wrong-Way Driving Using Pan–Tilt–Zoom Traffic Cameras," *Computer-Aided Civil and Infrastructure Engineering*, vol. 38, no. 1, pp. 119-132, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[31] Pintusorn Suttiponpisarn et al., "An Enhanced System for Wrong-Way Driving Vehicle Detection with Road Boundary Detection Algorithm," *Procedia Computer Science*, vol. 204, pp. 164-171, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[32] Cheng-Jian Lin, and Jyun-Yu Jhang, "Intelligent Traffic-Monitoring System Based on YOLO and Convolutional Fuzzy Neural Networks," *IEEE Access*, vol. 10, pp. 14120-14133, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[33] Sriram Narayana Cummaragunta, K.S. Srinandan, and Jyoti Shetty, "Wrong Side Driving Detection," *International Journal of Technology and Emerging Sciences*, vol. 2, no. 3, pp. 5-9, 2022. [Google Scholar] [Publisher Link]

[34] Abu Bakar Siddique Mahi, Farhana Sultana Eshita, and Tanjina Helaly, "An Automated System for Wrong-Way Vehicle Detection Using YOLO and DeepSORT," *Proceedings of the IEEE International Conference on Sustainable Technologies for Industry 5.0 (STI)*, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[35] Rakhi Bharadwaj et al., "Wrong Way Vehicle Detection in Single and Double Lane," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, no. 6s, pp. 457-462, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[36] M. Harsha Vardhan et al., "Wrong Route Vehicles Detection Using Deep Learning," *2023 International Conference on Next Generation Electronics (NEleX)*, Vellore, India, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[37] S.M. Renuka Devi et al., "A Real-Time Multiple Traffic Violation Detection System Using DeepSORT," *2024 4th International Conference on Artificial Intelligence and Signal Processing (AISP)*, Vijayawada, India, pp. 1-6, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[38] Ryan Mo Xian Wee, Tee Connie, Michael Kah Ong Goh, "Wrong-Way Driving Detection for Enhanced Road Safety Using Computer Vision and Machine Learning Techniques," *International Journal of Advanced Science, Engineering and Information Technology*, vol. 14, no. 6, pp. 2157-2165, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[39] Aniket Navneet Patil, Vikram Naglot, and Pallavi Thakur, "Wrong Lane Vehicle Detection Using YOLOv8," *International Journal of Innovative Research in Technology*, vol. 11, no. 12, pp. 8175-8181, 2025. [Publisher Link]

[40] Comus Bala, Nishant Gupta, and Saurabh Kumar, "Real-Time Detection and Alert System for Wrong-Side Driving: A Machine Learning Approach," *2025 International Conference on Networks and Cryptology (NETCRYPT)*, New Delhi, India, pp. 541-546, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[41] Kiranmaie, Abhisatwika Reddy Chada, and Ilaiah Kavati, "Wrong-Way Driving Detection with YOLOv9 and Convolutional Neural Networks," *Procedia Computer Science*, vol. 258, pp. 2060-2069, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[42] Alphons Zacharia James, "*Wrong-Way Vehicle Detection Using YOLOv7 for Enhanced Traffic Safety*," Masters Thesis, National College of Ireland, pp. 1-25, 2025. [Google Scholar] [Publisher Link]