IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 6, Issue 11, April 2026

Impact Factor: 8.2

AI-Based Wrong-Side Driving Detection with Real-Time Alert, Email Notification, and Automated Penalty System

Jedgule U B

Department of Computer Engineering

SREIR's Samarth College of Engineering and Management, Belhe

Abstract: *The rapid rise in traffic rule violations, such as wrong-side driving and triple seat riding, has become a major concern for urban safety management. Manual surveillance is inefficient, time-consuming, and prone to human error. To address this challenge, the proposed system, Wrong Side Vehicle and Triple Seat Detection in Traffic and Penalizing System using Deep Learning Model YOLO, leverages the power of computer vision and deep learning to automate the detection and penalization of traffic violators in real time. The system integrates high-definition CCTV or smart camera feeds with the YOLO (You Only Look Once) object detection framework, known for its remarkable accuracy and real-time performance. In the first stage, live traffic footage is captured and pre-processed through frame extraction, noise reduction, and image normalization techniques. These frames are then passed to the YOLO model, which has been trained on a diverse dataset containing multiple traffic scenarios, including two-wheelers, four-wheelers, and pedestrians in varying light and weather conditions. The model identifies vehicle positions and orientations to detect wrong-side movement, based on lane direction and road marking analysis. Simultaneously, it performs person counting on two-wheelers to identify triple seat violations by detecting and classifying human figures. Once a violation is detected, the system automatically captures the vehicle's image, extracts the vehicle number plate using Optical Character Recognition and logs the incident in a centralized database. This approach ensures accuracy, speed, and scalability, reducing dependency on human monitoring while significantly improving road safety. The model can be deployed in smart city infrastructures, integrated with existing traffic management systems, and scaled across multiple intersections. By combining deep learning, computer vision, and automation, this project aims to enhance intelligent traffic regulation, minimize accidents, and encourage responsible driving behaviour. Ultimately, the proposed YOLO-based detection and penalizing system represents a major step toward AI-driven intelligent traffic monitoring and automated law enforcement in modern cities..*

Keywords: Deep Learning, Computer Vision, Traffic Violation Detection, Wrong Side Vehicle Detection, Triple Seat Detection, Object Detection

I. INTRODUCTION

In today's rapidly urbanizing world, the exponential growth in the number of vehicles on roads has led to an alarming rise in traffic congestion, violations, and accidents. Among the most common and dangerous violations observed on city roads are wrong-side driving and triple-seat riding on two-wheelers. These offenses not only disrupt the smooth flow of traffic but also endanger the lives of both the violators and innocent commuters. Traditional methods of traffic monitoring rely heavily on manual surveillance by traffic police, which is often limited by human fatigue, time constraints, and lack of technological support. As a result, many violations go unnoticed or unrecorded, reducing the effectiveness of law enforcement. To overcome these limitations, there is a growing need for automated and intelligent traffic monitoring systems that can detect violations accurately and in real time.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 11, April 2026
Impact Factor: 8.2

The development of Artificial Intelligence (AI) and Deep Learning (DL) has opened new opportunities in the field of traffic management and surveillance. Specifically, computer vision-based detection models have demonstrated high potential in analysing video footage and identifying objects such as vehicles and pedestrians. Among the various deep learning architectures, YOLO (You Only Look Once) has emerged as one of the most efficient models for real-time object detection. Unlike traditional detection methods that rely on region proposals and multi-stage processing, YOLO treats object detection as a single regression problem, enabling it to achieve high-speed performance with minimal computational cost. Its ability to process multiple frames per second makes it ideal for traffic surveillance applications where continuous real-time monitoring is essential.

The proposed system, Wrong Side Vehicle and Triple Seat Detection in Traffic and Penalizing System using Deep Learning Model YOLO, aims to address this critical issue by automating the detection and penalization process of two major traffic violations. The system uses CCTV or smart surveillance cameras installed at various traffic junctions to capture live footage. Each video feed is processed through image pre-processing techniques such as resizing, noise filtering, and normalization to ensure clarity and uniformity. The YOLO model, trained on a comprehensive dataset of vehicles and riders in different orientations and environments, identifies vehicles and counts the number of riders on two- wheelers. By analysing the direction of vehicle motion with respect to lane markings, it can accurately detect wrong-side movement. Similarly, by counting the number of detected persons on a two-wheeler, it can flag triple-seat violations.

From a technological perspective, YOLO's versatility allows it to be retrained or fine-tuned with new datasets, making the system scalable and adaptable for various regions and environments. Its lightweight architecture ensures that it can operate efficiently even on low-cost embedded devices or

edge computing platforms, making large-scale deployment feasible. This approach not only ensures real-time detection but also minimizes latency, which is crucial for timely penalization and feedback.

In essence, this project represents a significant step toward automating traffic enforcement using AI and Deep Learning. It combines the strengths of object detection, image recognition, and data automation to create a holistic system capable of identifying and penalizing rule violators autonomously. The integration of YOLO with OCR and database management makes the entire process — from violation detection to fine generation seamless and efficient. Beyond enforcement, this system encourages responsible driving behaviour by instilling awareness among commuters that violations are being continuously monitored and penalized without bias.

The Wrong Side Vehicle and Triple Seat Detection System thus stands as a scalable, cost-effective, and intelligent solution to modern traffic challenges. By reducing human workload, improving accuracy, and enabling real-time response, it contributes to safer roads and disciplined

II. RELATED WORK

There are many related works done in this field, for varying requirements. Saidasul et al. [5] developed a real-time intelligent transportation system (ITS) to detect vehicles going on the wrong side of the road using the YOLOv3 model. Our work has been inspired by this paper, and the objective is to upgrade the algorithm to YOLOv4, while also using some of our own techniques to reduce computational costs.

Qin Zou et al. [6] propose a model that uses a hybrid deep neural-network. This model is used for lane detection. The system uses continuous frames extracted from a piece of footage taken from a vehicle driving on the road. This model combines DRNN and DCNN models. Later uses a LSTM model for mapping. The results obtained demonstrate the benefits of ConvLSTM compared to FcLSTM w.r.t sequential feature-learning as well as target information prediction with respect to lane detection. Area for research and improvement under the usage of SegNetConv network rather than UNet-Conv network is stated.

Gonçalo Monteiro et al. [7], proposed a system automatically detects drivers travelling in the wrong direction. This sets off a pre configured alarm on various highway-traffic related telematic systems. It also tracks vehicles against crowded events as well as occlusions. The model used is Optical Flow with Gaussian Mixture model and filtering. However, the

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 6, Issue 11, April 2026 Impact Factor: 8.2

authors stated that there is a possibility that a vector/vectors of flow are detected despite the absence of real motion. This is caused by unexpected vibrations or movement of the camera-pole. This could also be caused by noisy or faulty motion-flow estimation.

Zillur Rahman et al. [8] propose a system that can identify vehicles travelling in the wrong direction on a road. This system marks/demarcates them from the on road CCTV footage. YOLO object detector is used since it's highly accurate. It is also quicker compared to any other object detection algorithm. To verify their system, they captured three videos from the roads in Chittagong, Bangladesh. The resolution of the CCTV footage was 1280 x 720 pixels. Every wrong-side car from the three videos were successfully identified and penalised. Thus, accuracy of their system, in practical scenarios, was almost 100%. One of the limitations of their system was the centroid-tracking technique that was used. The object centroids calculated from the bounding boxes must be in close proximity between neighbouring frames. Otherwise the ID number might be interchanged due to overlapping vehicles (objects).

Junli Tao et al. [9] address multi-lane roads. It uses CCTV footage from a camera to identify the currently occupied lane of a vehicle. GPS information is utilised to determine the constraints that should be enforced w.r.t directions travelled for a certain road taken into consideration. The authors adopted a multi-lane detecting monocular camera. It then analyzes the identified lanes in conjunction with GPS data in order to locate the vehicle more precisely at lane level. The system that was developed was fairly accurate for the identification of wrong side driving provided that the road marking was reasonably visible and were not occluded due to other cars present on the road or in the same lane. This system can be tweaked to take care of GPS temporal- occlusion situations. This is because the GPS data is not required for each and every frame.

A. Sentas et al. [10] address the issue of cars using emergency lanes designated for emergency vehicles like ambulances, etc. If any vehicle travels in the wrong lane, a violation is recorded by their system. Violation detection processes were carried out on the basis of various real-time image-processing algorithms. Unlike many papers, background-subtraction is not utilised in vehicle-detection algorithms. To detect a lane violation, two points are taken from the lane and an imaginary line is drawn by the program indicating the emergency lane. This is done by calculating slope and intercept and using elementary geometric techniques. Their program is resistant to conditions such as moving cameras, changing weather conditions, etc. In future the authors plan to create a model in which the user can choose what type of violations to monitor. aspects namely lane-detection techniques, integration, as well as evaluation-methods. Due to limitations inherent in camera based lane identification models, techniques to develop more robust and precise lane detection systems are pondered upon. The authors also propose a new, state of the art "computational experiment based parallel lane detection framework".

V. Nguyen et al. [12] propose an algorithm to yield information related to the lane as well as the vehicle which can be used by the proposed driver-assistance system, referred to by the authors as a "lane change assistant system (LCAS)". Many papers in the past could only detect the vehicles or the lanes separately and independently of each other. The authors, however, assert that the combination of the lane information as well as the vehicle information can be used to aid the LCAS and improve the accuracy and reliability of the proposed system. An LCAS should be able to identify frontal lanes and also discover the vehicles present around any test vehicle. A computer vision based system is proposed consisting of three cameras, two of which are under the wing mirrors, and one on the test vehicle's windscreen. The cameras' video is processed and is utilised to identify three lanes, and also detect the vehicles around it. After this, the Kalman filter is utilised to track and monitor the vehicles that are detected. And finally, the relative speed between the detected vehicle and the test vehicle is computed. Each frame takes roughly 43 ms to process. This system was tested on various Korean highways.

J. C. Nascimento et al. [13] address the issue of tracking and monitoring moving objects by using deformable models. The authors propose a new Kalman-based technique. Abrantes and Marques, in 1996, proposed a category of constrained clustering techniques in the domain of static shape estimation, which inspired the authors' work. Centroids of the moving objects are tracked and monitored by using inter-frame as well as intra-frame recursions. Centroids are calculated by computing the weighted-sums of the edge-points that correspond to the moving object's bounding box.

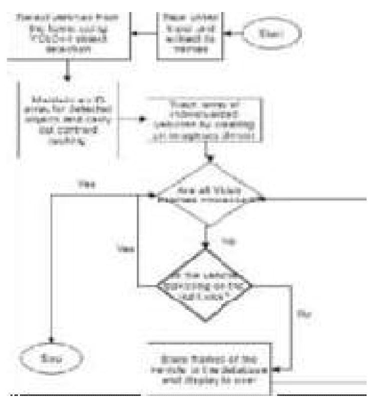
IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 11, April 2026 Impact Factor: 8.2

The authors use various competitive-learning techniques inside the algorithm used for tracking objects. This leads to improved robustness w.r.t. contour sliding as well as occlusion.

J. Jin et al. [14] address the design as well as the implementation of real-time multi-object centroid-tracking for the purpose of gesture recognition. It comprises 4 stages namely “preprocessing, local intensity accumulation, object observation, and particle filter”[14]. They discuss 2 major aspects, which are the trajectory accuracy of moving objects as well as real time processing. With the help of many real world experiments, the performance of the model was evaluated and their processing speed and efficiency were compared to the algorithm itself based on its software simulations. Although their work was focussed on gesture recognition, the very same centroid tracking concepts used in [13] and [14] were taken into consideration for the design of this project’s centroid tracking algorithm.

III. METHODOLOGY

This section discusses the methodology of the proposed work. Figure 1. Flowchart representing the project In Figure 1, one can see the basic architecture of the project. The video input is taken, frames are extracted from them, then the frames are processed on the YOLO model. The model uses object detection to detect vehicles within each frame and form centroids for the objects detected. An imaginary divider is created from the input video file. This divider is necessary as each movement of centroids needs to be categorised using lanes. After all this processing, the output video is returned.



A. Algorithm

1. The program starts by sending an input video frame to the YOLOv4 model that was trained using the OIv6 dataset [15] on a separate Colab notebook as observed in our Git repository. One can download the obtained weights and use that in this system. This is handy to separate the training and prediction processes, since the end user is most likely to be a layperson who wants to use the system for his/her requirements and is only interested with the prediction portion of this project.
2. The program returns us bounding boxes of vehicles, once the frame is processed by the model.
3. To find out the direction of a tracked vehicle, the program computes the difference between a range of frames. It does this by first computing the object centroid from the bounding boxes using elementary geometric techniques. Suppose frame FN has a centroid (xN, yN) then the program computes the pixel difference for varying values of N, during the configuration step as explained below. This step of the algorithm was inspired from [5].
4. In the first few “configuration” seconds, the direction of all vehicles is tracked. The movement of a centroid assigned an ID is tracked using the Euclidean distance algorithm and is used in the next step.
5. To determine whether the car is traveling on the right or wrong side of the road, the program creates an imaginary divider or median in the road based on the average extreme positions of vehicles moving in respective directions. Due to the jittery nature of the initial object detection algorithm, the bounding boxes’ mini oscillations mean that a slope

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 11, April 2026
Impact Factor: 8.2

cannot be calculated easily and therefore the median calculated is assumed to be vertical. In left side driving nations, whatever vehicles moving upwards and to the right of the median are considered as violations.

6. The vehicles moving in the wrong direction are considered as violations and these violations are uploaded to the Firebase database.

7. Finally, using ALPR, the violator's license plate is found and matched with the police database and a challan is generated with the photo evidence.

8. The following dataset is used by the proposed work:

- Object detection image dataset for training : OIv6 [15]

Other CCTV camera videos found on YouTube are used to run validation of wrong side detection.

B. Implementation Details

Language used in the entire project is Python (3.7+). Tools used in this project include:

Darknet : It is an open-source neural network framework. It is simple to setup and install, quick and supports GPU as well as CPU computation.

Google Colab : This is a product from Google Research that provides a Virtual Environment for the execution of Python Code on a reasonably fast GPU to carry out ML- related tasks anywhere on the internet.

Anvil : This is used to convert a Colab’s model into a web application. This was used as the front-end of the project.

Firebase Firestore : The cloud database used to store and send the detections to the front-end of the application.

Anvil and Colab have been used in order to use a moderately powerful GPU along with a functional frontend. This project can be implemented without these tools on a powerful machine, and the above is done for demonstration purposes only.

Although the model does not follow any specific data preprocessing steps, the dataset being used is provided by Open Images v6 (via Google), which provides annotated datasets to the specific classes needed. In this model, a “Cars” dataset was used, which was annotated by OIv6 for object detection. Collecting the dataset from Google's Open Images Dataset and then using the OIDv4 toolkit to generate the required labels is simple, efficient and elementary. The label contains the annotation labels. The labels that the toolkit gives us aren’t in the prescribed YOLOv4 format. Using various helper programs, the labels were successfully converted to the required format. One has to change the label filename to utilise it along with the algorithm during the training process. [15]

The technique chosen to work with on this model is a Validation data split. To avoid re-substitution errors, the data was split into 2 different classes, namely a training dataset as well as a testing dataset. The model is built on a 70/30 split. The technique used here is referred to as the “hold-out validation technique”. There may be a likelihood that a non-uniform distribution of distinct categories of data is found in training and validation dataset. To rectify this issue, the training dataset and the test dataset are created with equally distributed classes of data (referred to as stratification).

IV. RESULTS AND ANALYSIS

For testing purposes, the model was verified with the help of an Anvil Frontend and a Colab backend as mentioned earlier. The input video was fed as a YouTube video link. Vehicles travelling in the wrong direction on the road were edited into the video. On clicking the submit button on the frontend, an output was displayed on the screen. Violating vehicles’ pictures were also stored on the Firebase database for proof. Some of the output obtained is shown below.

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 6, Issue 11, April 2026 Impact Factor: 8.2

Figure 3. Picture of the violation stored in MySQL

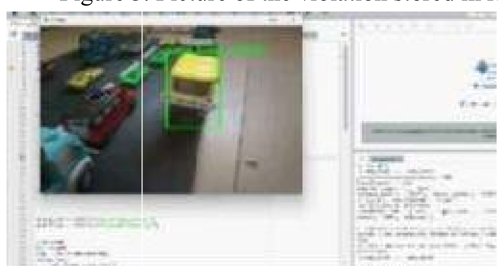


Figure 4. One of the violations detection

Figure 5. Another violation stored in MySQL

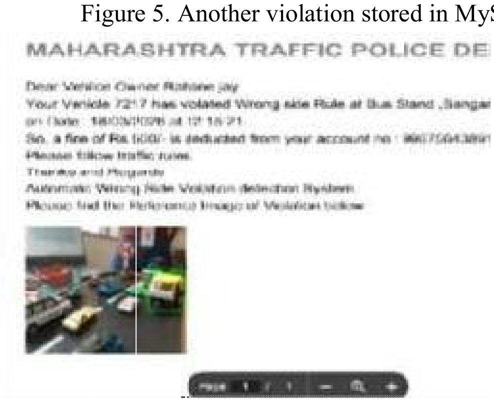


Figure 6. Learning Curve of the YOLOv4 model during the training process

V. LIMITATIONS

The project has met the expectations sought out, but it certainly has faced several limitations along the way:.

1. The sensitivity of the camera input required : The input clipping that the model takes in must be from a fixed and stable CCTV. This rules out Dashboard cameras, rotating surveillance cameras, etc. Or else, the model struggles to find the divider resulting in failure of lane separation.
2. Camera orientation: As discussed in the methodology section, the CCTV camera must be straight and parallel with respect to the road since the imaginary divider does not have any slope.
3. False Positives : The model sometimes results in false positives, due to blurred footage or due to improper detections. Although it isn't very often, it does occur once in a while.
4. Speed of response from Anvil : As the project requirements don't mention a custom made front-end.

DOI: 10.48175/IJARSCT-33673

VI. CONCLUSION AND FUTURE SCOPE

One effective way to improve road safety and enforce traffic regulations is to implement a Wrong Side Vehicle and Triple Seat Detection in Traffic and Penalizing System using computer vision and artificial intelligence. The system can accurately detect traffic violations such as wrong-side driving and triple riding by analyzing real-time video data from surveillance cameras. By utilizing advanced image processing and deep learning techniques, the system minimizes human intervention and reduces errors in monitoring. Automated detection ensures continuous surveillance, even in busy traffic conditions, and enhances the efficiency of traffic law enforcement. The integration of number plate recognition enables quick identification of violators and automatic generation of penalties, thereby improving accountability. In the context of smartpotential of AI-driven solutions in maintaining road discipline and reducing accidents. With proper implementation, the system can be widely adopted in urban and highway traffic management.

In the future, the system can be enhanced by using more advanced deep learning models to improve detection accuracy under challenging conditions such as low light, weather disturbances, and heavy traffic. Integration with edge computing can enable faster real-time processing and quicker response times. Expanding the system with multiple camera networks can provide wider coverage and better monitoring. The inclusion of additional features such as helmet detection, seatbelt detection, and speed monitoring can make the system more comprehensive. Furthermore, improving data privacy, security measures, and compliance with legal standards will ensure ethical and responsible deployment. The system can also be integrated with smart city infrastructure and intelligent transport systems for a more efficient and automated traffic management ecosystem.

REFERENCES

[1] A. M. Ali, A. Al-Qerem, M. R. Hassan, A. Abu-Khadrah and M. Jarrah, "Traffic Monitoring and Control System for Smart City Pollution Regulation Using IoT and Correlated Capsule Networks," in IEEE Access, vol. 13, pp. 46983-47003, 2025, doi: 10.1109/ACCESS.2025.3550966.

[2] V. D. A. Kumar, V. Ramachandran, M. Rashid, A. R. Javed, S. Islam and A. Al Hejaili, "An Intelligent Traffic Monitoring System in Congested Regions with Prioritization for Emergency Vehicle Using UAV Networks," in Tsinghua Science and Technology, vol. 30, no. 4, pp. 1387-1400, August 2025, doi: 10.26599/TST.2023.9010078.

[3] S. Bose, M. H. Kolekar, S. Nawale and D. Khut, "LoLTV: A Low Light Two-Wheeler Violation Dataset With Anomaly Detection Technique," in IEEE Access, vol. 11, pp. 124951- 124961, 2023, doi: 10.1109/ACCESS.2023.3329737.

[4] H. A. Abdelali, H. Derrouz, Y. Zennayi, R. O. H. Thami and F. Bourzeix, "Multiple Hypothesis Detection and Tracking Using Deep Learning for Video Traffic Surveillance," in IEEE Access, vol. 9, pp. 164282-164291, 2021, doi: 10.1109/ACCESS.2021.3133529.

[5] T. Mustafa and M. Karabatak, "Real Time Car Model and Plate Detection System by Using Deep Learning Architectures," in IEEE Access, vol. 12, pp. 107616-107630, 2024, doi: 10.1109/ACCESS.2024.3430857.

[6] N. Htet Htet Aung, P. Sangwongngam, R. Jintamethasawat and L. Wuttisittikulkij, "Fully Synthetic Pedestrian Anomaly Behavior Dataset Generation in Metaverse for Enhancing Autonomous Driving Object Detection," in IEEE Access, vol. 12, pp. 166630-166642,2024, doi:

[7] B. Gao, Z. Li, D. Zhang, Y. Liu, J. Chen and Z. Lv, "Roadside Cross-Camera Vehicle Tracking Combining Visual and Spatial-Temporal Information for a Cloud Control System," in Journal of Intelligent and Connected Vehicles, vol. 7, no. 2, pp. 129-137, June 2024, doi: 10.26599/JICV.2023.9210034.

[8] G. Han, F. Liu, H. Liu, J. Deng, W. Bai and K. Li, "A Dynamic Multitarget Obstacle Tracking and Monitoring Method for Vehicle Routing Based on Multiple Constraint Composite Perception Association Filtering," in IEEE Access, vol. 12, pp. 115151-115170, 2024, doi: 10.1109/ACCESS.2024.3444054.

[9] L. Tang, F. Yan, B. Zou, K. Wang and C. Lv, "An Improved Kinematic Model Predictive Control for High-Speed Path Tracking of Autonomous Vehicles," in IEEE Access, vol. 8, pp. 51400-51413, 2020, doi: 10.1109/ACCESS.2020.2980188.

[10] Z. Sun, R. Wang, Q. Ye, Z. Wei and B. Yan, "Investigation of Intelligent Vehicle Path Tracking Based on Longitudinal and Lateral Coordinated Control," in IEEE Access, vol. 8, pp. 105031-105046, 2020, doi: 10.1109/ACCESS.2020.2994437.