Traffic Violation Detection

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***Abstract*:**
Traffic violations pose significant safety risks and are a growing concern in urban areas. It requires a scalable solution for monitoring and enforcement. There is no alternative for being on the roads but automation may undoubtedly aid the traffic police by reducing the workload associated with booking offenses. Even while this can aid in the recording of violations. The presence of interceptors and police officers on the road tends to serve as a deterrent to traffic violations. This study examines the artificial intelligence role in traffic violation detection. The overall summary of the literature in this field is about classifying different types of detection models over traffic violations and comparative analysis of previous work done in this field.

***Keywords*: Traffic Violation Detection, Computer Vision, Object Detection, YOLO, Machine Learning, Road Safety, Automated Surveillance.**

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I. INTRODUCTION

Traffic violations are one of the major illegal actions committed by drivers. It includes traffic signal violation, not wearing a helmet, not having proper documents, over speeding, improper parking, overloading also driving without a seatbelt, insurance. Most commonly used method of monitoring these violations involve human observation and filing bills/fines. These methods are not very effective as it comprises manual observations which makes it prone to human error and creates scalability issue [1].

In the year 2023, there are a total of 394 million officially registered motor vehicles in India, including 260 million two wheelers, 50 million cars. It is also the country with the second largest road network in the entire world. With the growing number of vehicles plying are roads, there is the increasing demand for traffic violations monitoring. Now that road traffic management problems are prevalent, computer vision and machine learning technology provide new opportunities to overcome these problems [2].

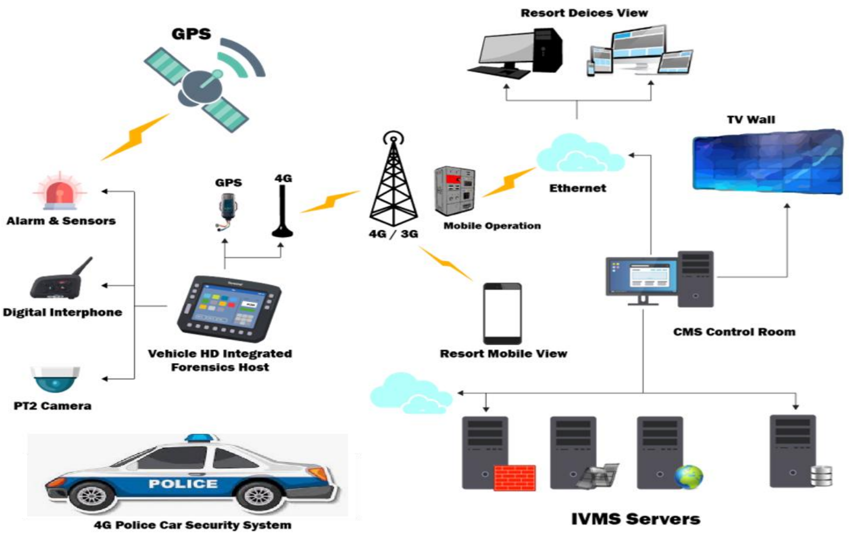

Figure I.1: AI Traffic Violation Detection System

Figure I.1 shows a Traffic violation detection system powered by Artificial Intelligence. Deep learning-based systems for traffic management can analyze video footage to identify and high-speed chase traffic violations.

Traffic violation comes in several types, and all have the biggest effect on road safety. Speeding is one of the most significant types and normally occurs with a delayed reaction, with severe crashes taking place. Another significant issue related to traffic is red-light jumping, especially where the major interchanges of crowded areas exist and leads to various crashes. Also, using mobile phones while driving takes the driver's attention away from the road, making accidents more likely. Wearing helmets for a motorist can reduce injuries; however, wearing helmets has been largely ignored. Other common violation: three or four people are found traveling on two wheelers that distort the vehicle's balance, making more chances for an accident to take place. Other main issues are changing lanes in illegal ways, specially overcrowded area causing traffic disorder with confusion.

For these reasons, systems with YOLO (You Only Look Once) have been found to be suitable within this context because of the speed at which they detect [3]. To achieve automated detection and recording of violations of traffic rules, traffic violation detection models implement some combination of computer vision, deep learning and data processing. These are some of the models and techniques that are often employed in the detection of traffic rule violations:

A. YOLO (You only look once)

It is a very popular and widely used real time object detection model.[4] Because of its versatility and high accuracy it can be used in traffic violation detection. This model can be integrated with hardware to detect violations with video recording.

B. SSD (Single Shot MultiBox Detector)

It is highly accurate real-time object detection and a robust model. It is based on a feedforward convolutional neural network [5].

C. Faster R-CNN (Region Convolutional Neural Network)

Faster R-CNN is yet slower than YOLO but more accurate for object detection. It is useful for applications such as detecting small objects or handling complex scenes in dense traffic [6].

D. Mask R-CNN

Mask R-CNN is an extension of Faster R-CNN includes instance segmentation, which helps to detect and outline specific objects. It's also helped in identifying vehicle positions in congested traffic and with combination with other tools can detect traffic rule violations [7].

E. OpenALPR (Automatic License Plate Recognition)

This model is open-source which specialized in reading and interpreting vehicle license plates in real-time with high accuracy. With its capabilities we can record vehicles violating traffic laws and can also link violations to specific vehicles in real time[8].

F. DeepSORT (Simple Online and Realtime Tracking)

DeepSORT is a computer vision tracking algorithm that helps to detect multiple-objects in a video frame by assigning each of the tracked objects a unique id. It works well with detection models like YOLO which can be used to track vehicles and pedestrians across frames which in turns helps in detecting violations like illegal turns, lane changes, or over takes[9].

G. UNet

UNet is a deep learning model initially designed for biomedical image segmentation but it can also be adapted for traffic applications. These applications can be used to pedestrian crossings, segment lanes, or other road features and detect if vehicles or pedestrians are in unauthorized areas [10].

H. Vision Transformers

Vision transformers are gaining popularity for object detection and segmentation in traffic scenes. They can also be used to analyze complex traffic scenes and provide various applications in real-time analysis of traffic violations [11].

I. LSTM (Long Short-Term Memory)

LSTMs combined with CNNs, excel at analyzing time series data and capturing long-term dependencies, ideal for tracking vehicles and detecting temporal violations like speeding or tailgating [12].

J. Multi-Task Cascaded Convolutional Networks (MTCNN)

MTCNN is commonly used for face and pedestrian detection but can be adapted to traffic scenes for multi-object detection and tracking. It's helpful for detecting pedestrian violations, such as jaywalking or crossing outside designated areas [13].

K. TVDS Mechanisms

We have given a brief overview of the typical workflow of a Traffic Violation Detection System, which includes data acquisition, violation detection using AI models, alert generation, and reporting for enforcement purposes (see figure 1).

L. RFID

We included the use of RFID tags in vehicles for identifying and tracking violations, such as toll evasion or restricted area entry [19][20][21].

M. Artificial Intelligence

We strengthened the discussion on Al by emphasizing its role in real-time detection, classification of objects, and decision-making during traffic violations.

N. VANET

We included a brief description of Vehicular Ad Hoc Networks, highlighting their capability to enhance violation detection by enabling communication between vehicles and infrastructure for real time monitoring[22][23][24].

II. RELATED WORK

With advancements in traffic violation detection like YOLO-based models in combination with other tools has improved accuracy and detection efficiency in various traffic scenarios. In [14], a YOLO model combined with CNN-based classification was applied to detect helmet and seatbelt violations, achieving high accuracy for these specific violations but showing limitations in low-resolution or adverse conditions. Building on this, [15] integrated YOLOv8 with OpenCV DNN for high-speed, real-time detection of speeding and red-light violations, though accuracy was affected in crowded or occluded traffic scenarios. Addressing lighting variability, [16] employed YOLOv8 with AI algorithms for signal-based violations, providing high reliability across different lighting conditions, though it struggled in low-light, high-motion environments. For low-end device applications, [17] utilized YOLOv8-tiny for helmet detection with reduced computational demands, although it faced challenges in high-density or low-resolution settings. Finally, [18] implemented YOLOv8 with Non-Maximum Suppression to lower false positives in dense urban traffic detection, achieving successful outcomes in reducing false detections but requiring substantial computational power, limiting its feasibility for edge deployments. Together, these studies highlight the strengths and limitations of YOLO-based traffic violation detection models in real-world settings.

Table 1: PREVIOUS RESEARCH WORK DONE IN DOMAIN OF TRAFFIC VIOLATION DETECTION

Reference	Method	Advantage	Outcome	Limitation
[14]	YOLO with CNN-based classification	Effective detection of helmet and seatbelt violations	High accuracy in detecting specific violations with CNNs	Limited performance in low-resolution or adverse conditions
[15]	YOLOv8 + OpenCV DNN	Real-time detection with high-speed object tracking	Efficient detection of speeding and red-light violations	Accuracy decreases in occluded, high-density traffic scenes

Reference	Method	Advantage	Outcome	Limitation
[16]	YOLOv8 with AI algorithms	Robust detection across lighting conditions	High reliability for signal-based violations detection	Less effective in low-light and high-motion environments
[17]	YOLOv8-tiny for lightweight processing	Optimized for real-time applications on low-end devices	Effective for helmet detection with reduced computational load	Struggles in high-density or low-resolution environments
[18]	YOLOv8 with Non-Maximum Suppression	Reduces false positives in dense traffic detection	Successful detection in urban settings with reduced false positives	High computational requirements, limiting edge deployment suitability

III. COMPARATIVE ANALYSIS

In the field of traffic violation detection, machine learning models are assessed based on their accuracy [19]. In recent advancements in traffic monitoring and autonomous driving, researchers have developed innovative models to improve detection, tracking, and prediction accuracy across a range of complex scenarios. [20] combined YOLOv8 and Transformer-based CNNs for enhanced vehicle detection, achieving robust performance with accuracy improvements on multiple datasets, specifically in adverse conditions like shadows and occlusions. [21] introduced YOLO-IR, enhancing YOLOv8 with MobileVITv3 and infrared imaging techniques for reliable multi-target detection in dense urban settings, achieving high detection rates and tracking precision. [22] presented a stacking ensemble model using Faster RCNN and YOLOX-Tiny for traffic sign recognition, excelling in complex, shadowed, and motion-blurred environments, with notable gains in mean Average Precision and processing speed. Addressing the detection of variable-sized targets in autonomous driving, [23] utilized a Swin Transformer-based network, effectively enhancing the detection of vehicles and pedestrians in occluded or high-density conditions, with significant accuracy improvements on BDD100K and KITTI datasets. [24] applied a federated learning approach to urban traffic incident prediction, introducing a feature selection-based VFL model that outperformed traditional models in test accuracy, supporting privacy-preserving cross-departmental collaboration. Collectively, these studies underscore the potential of deep learning and federated approaches to advance safety, precision, and resilience in traffic management and autonomous driving systems.

Table 2: COMPARATIVE ANALYSIS PREVIOUS WORK DONE

Reference	Objective	Methodology	Result
[19]	To improve RFID communication using a multi-hop routing protocol for efficient Tag-to-Tag data exchange.	Developed a multi-hop protocol where RFID tags relay data, reducing reliance on direct reader-tag communication.	The proposed protocol improves system accuracy by 15% and boosts precision by 10%, making it more efficient for large-scale traffic violation detection.
[20]	To enhance road safety by accurately detecting and tracking vehicles in autonomous driving, particularly in failure situations.	Combined YOLOv8 with Transformers-based CNNs and integrated a modified pyramid pooling model for real-time vehicle detection, plus kernelized filter-based tracking.	Achieved improved detection accuracy with 4.50%, 4.46%, and 3.59% increases on the DLR3K, VEDAI, and VAID datasets, respectively. Demonstrated robustness in handling shadows and occlusions.
[21]	To improve infrared multi-target detection and tracking in dense urban traffic scenes.	Developed YOLO-IR based on YOLOv8s, integrated infrared image enhancement techniques, and used MobileVITv3 for feature extraction. Incorporated canny edge detection, Gabor filtering, and advanced patch descriptors for tracking.	Achieved 78.6% mAP and 151.1 FPS in detection, and 80.8% accuracy in tracking, with significant robustness in dense urban scenes using FLIR ADAS v2 and InfiRay datasets.
[22]	To improve traffic sign detection and recognition in autonomous driving for enhanced safety.	Integrated Faster RCNN and YOLOX-Tiny models through a stacking ensemble approach, evaluated on NVIDIA GTX 3060 hardware.	Increased mAP by 4.78% over Faster RCNN and improved FPS by 8.1% and mAP by 6.18% over YOLOX-Tiny, achieving high precision in challenging settings like motion blur and diverse sign types.

Reference	Objective	Methodology	Result
[23]	To detect vehicles, bicycles, and pedestrians of varying sizes in complex autonomous driving scenes.	Proposed a hierarchical feature pyramid network with Swin Transformer and CNN-Transformer variant layers using shifted window self-attention.	Improved accuracy by 1.8% and 3.1% on the BDD100K and KITTI datasets, showing effectiveness in dense, occluded settings.
[24]	To enhance accuracy in urban traffic incident prediction using federated learning with privacy protection.	Developed a VFL model with a feature selection strategy (FSVFL-TIP), leveraging cross-departmental data and privacy-preserving techniques.	Outperformed baseline VFL model by 5.7% to 11.6% in test accuracy across datasets, highlighting VFL's potential in accuracy and communication efficiency improvements.

IV. CONLUSION

This paper presents a promising technique for real-time traffic violation detection by leveraging advanced computer vision and machine learning techniques. Violations of traffic laws have increased as the number of cars on the road has grown. ITS is now necessary to obtain traffic data from streets as a result. In order to identify traffic violations, this survey has examined the most contemporary TVDS mechanisms, which include RFID, AI, and VANET. Numerous studies on the identification of traffic violations have been conducted by researchers, which might be significant in the future. YOLO-based models stand out among the techniques discussed due to their ability to quickly and accurately detect violations like speeding, helmet usage, and red-light jumping in real-time scenarios. However, the choice of the best technique often depends on the specific application. For instance, Mask R-CNN performs better in dense traffic conditions that need instance segmentation, while OpenALPR is highly effective for real-time license plate recognition. To tackle the diverse challenges in traffic violation detection, a hybrid approach combining multiple models could provide a more comprehensive and efficient solution. After examining the available data, we deduce that VANET is a promising contemporary technology that still needs a great deal of work and investigation. For automatic rule violation detection and number plate identification, such as motorcyclists without helmets and passenger overloading, AI techniques like ML and DL were integrated with computer vision. The results were good and may be improved.

REFERENCES

[1] Ravish, R., Rangaswamy, S., & Char, K. (2021, October). Intelligent traffic violation detection. In 2021 2nd Global Conference for Advancement in Technology (GCAT) (pp. 1-7). IEEE.

[2] Vijverberg, J. A., de Koning, N. A., Han, J., de With, P. H., & Cornelissen, D. (2007, April). High-level traffic-violation detection for embedded traffic analysis. In 2007 IEEE International Conference on Acoustics, Speech and Signal Processing-ICASSP'07 (Vol. 2, pp. II-793). IEEE.

[3] Wankhede, S. S., & Bajaj, P. (2021, April). Traffic violation detection model using soft computing tools. In 2021 6th International Conference for Convergence in Technology (I2CT) (pp. 1-5). IEEE.

[4] Redmon, J. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition.

[5] Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016). Ssd: Single shot multibox detector. In Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part I 14 (pp. 21-37). Springer International Publishing.

[6] Ren, S., He, K., Girshick, R., & Sun, J. (2016). Faster R-CNN: Towards real-time object detection with region proposal networks. IEEE transactions on pattern analysis and machine intelligence, 39(6), 1137-1149.

[7] Bharati, P., & Pramanik, A. (2020). Deep learning techniques—R-CNN to mask R-CNN: a survey. Computational Intelligence in Pattern Recognition: Proceedings of CIPR 2019, 657-668.

[8] Du, S., Ibrahim, M., Shehata, M., & Badawy, W. (2012). Automatic license plate recognition (ALPR): A state-of-the-art review. IEEE Transactions on circuits and systems for video technology, 23(2), 311-325.

[9] Pereira, R., Carvalho, G., Garrote, L., & Nunes, U. J. (2022). Sort and deep-SORT based multi-object tracking for mobile robotics: Evaluation with new data association metrics. Applied Sciences, 12(3), 1319.

[10] Chen, Y., Wang, K., Liao, X., Qian, Y., Wang, Q., Yuan, Z., & Heng, P. A. (2019). Channel-Unet: a spatial channel-wise convolutional neural network for liver and tumors segmentation. Frontiers in genetics, 10, 1110.

[11] Zhai, X., Kolesnikov, A., Houlsby, N., & Beyer, L. (2022). Scaling vision transformers. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 12104-12113).

[12] Mou, L., Zhao, P., Xie, H., & Chen, Y. (2019). T-LSTM: A long short-term memory neural network enhanced by temporal information for traffic flow prediction. Ieee Access, 7, 98053-98060.

[13] Gradilla, R. (2020). Multi-task cascaded convolutional networks (mtcnn) for face detection and facial landmark alignment. link]. Acessado em, 13.

[14] Tonge, A., Chandak, S., Khiste, R., Khan, U., & Bewoor, L. A. (2020, November). Traffic rules violation detection using deep learning. In 2020 4th international conference on electronics, communication and aerospace technology (ICECA) (pp. 1250-1257). IEEE.

[15] Shubho, F. H., Iftekhar, F., Hossain, E., & Siddique, S. (2021, December). Real-time traffic monitoring and traffic offense detection using YOLOv4 and OpenCV DNN. In TENCON 2021-2021 IEEE Region 10 Conference (TENCON) (pp. 46-51). IEEE.

[16] Asadianfam, S., Shamsi, M., & Kenari, A. R. (2021). TVD-MRDL: traffic violation detection system using MapReduce-based deep learning for large-scale data. Multimedia Tools and Applications, 80(2), 2489-2516.

[17] Elavarasu, M., & Govindaraju, K. (2024). Unveiling the Advancements: YOLOv7 vs YOLOv8 in Pulmonary Carcinoma Detection. Journal of Robotics and Control (JRC), 5(2), 459-470.

[18] Rahman, R., Bin Azad, Z., & Bakhtiar Hasan, M. (2022). Densely-populated traffic detection using YOLOv5 and non-maximum suppression ensembling. In Proceedings of the International Conference on Big Data, IoT, and Machine Learning: BIM 2021 (pp. 567-578). Springer Singapore.

[19] Chang L and Haas Z J, 2017. Multi-hop routing protocol for RFID systems with Tag-toTag communication. 36th IEEE Military Communications Conference, Baltimore, MD, October 23-25.

[20] Ahmed S H, Yaqub M A, Bouk S H and Kim D. 2016. SMARTCOP: ENABLING SMART TRAFFIC VIOLATIONS TICKETING IN VERNACULAR NAMED DATA NETWORKS. Hindawi Publishing Corporation.

[21] Wong S F, Mak H C, Ku C H and Ho W I.2017. Developing advanced traffic violation detection system with RFID technology for smart city. IEEE.

[22]Ardakani S P. 2018. ACR: A cluster-based routing protocol for VANET. International Journal of Wireless & Mobile Networks (IJWMN).

[23]Singh S, Negi S, Verma S K and Panwar N.2017. Comparative study of existing data scheduling approaches and role of cloud in Vanet environment. Elsevier Procedia Computer Science.

[24] Abbas Q.2019. V-ITS: Video-based Intelligent Transportation System for monitoring vehicle illegal activities. (IJACSA) International Journal of Advanced Computer Science and Applications.