TR-TRVD: Triple Riders - Traffic Rule Violation Detection using YOLOv8-BBIA for Intelligent Transportation System

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Abstract: To restraints the rate of fatality due to accident, a powerful and adequate implementation of traffic rules and continuous monitoring is required. Traffic Rule Violation Detection (TRVD) system aims to identify the traffic rule violation – triple riding and ensures that the rule must be followed 24*7 without any human intervention. To detect the traffic rule violation, deep learning based single shot detection algorithm is utilized. YOLO (You Only Look Once) algorithm used for detection of two wheeler and number of persons riding on a motorcycle, the system detect and classify a person is following a traffic rule strictly or not. The suggested method trains a model on a datasets that combines custom images with publicly available datasets. This approach is very effective at accurately detecting traffic rule violations related to triple riding, whether it's a single rider or multiple riders on the bike.Furthermore, to address the issue of class imbalance, data augmentation techniques were utilizedto increase the variation in training data. This strengthen the model's effectiveness in applying to practical scenarios. Different YOLO family algorithm has been utilized for development of detection model. The YOLOv8 model was tested on a total of 80 images and detection accuracy exhibited an F1 score, precision and mAP@50 of 76.4%, 73.5% and 81.6% respectively for all classes. We manually tested triple riding traffic rule violation using our proposed algorithm and found that the system gives 92.7% of accuracy. These findings highlight the potential of proposed model, thus fostering safer motorcycling practices.

Keyword:*Triple riding, Object detection, Traffic Rule Violation, YOLO, Deep learning*

1. Introduction

Over the day, the number of traffic violations on roads is rising quickly because of the Inadequacy of current rules & regulations. Rule violations such as: Over speeding, reckless driving, Alcohol-impaired driving, riding a motorbike without a helmet, triple riding, usage of phone while driving and riding in the opposite lane are some of the infractions that lead to various road accidents. In response to the rapid increase in accidents, the government has implemented necessary measures to prevent them. However, the number of fatalities continues to rise each year due to accidents caused by public negligence. Road traffic accidents are a leading cause of death globally, and traffic-related fatalities have steadily increased over time. 1.35 million in 2019 and slightly fallen to 1.15 million per year in 2021. According to the World Health Organization's (WHO) 2023 road safety report reveals that two and three-wheeler are account for 30% of global road fatalities. The Ministry of Road Transport and Highways also shared information about traffic accidents in India illustrated in Figures 1-4. Figure 1 displays the total number of traffic accidents, fatalities, and injuries from 2018 to 2022. According to the data, the overall number of accidents in India increased by 11.9% in 2022, following the post-pandemic period. There was a 9.4% increase in the number of deaths from road accidents and a 15.3% rise in injuries. Figure 2 shows that overspeeding caused 72.4% of accidents and fatalities due to traffic rule violations on national highways in 2021 and 2022. second largest category 18.5% due to potholes, triple riding and other parameter, 4.8% accidents due to driving wrong side, 2.2% accident due to consumption of alcohol, 1.6% due to usage of mobile phone while driving and 0.5% due to jump signal. Total accidents, fatalities rate 18% and 9% respectively drastically up from 2021 to 2022.In 2022, Figure 3 shows that two-wheelers were involved in the most accidents across all vehicle categories, continuing a trend seen in 2021. This indicates that more efforts are needed to decrease two-wheeler-related accidents on Indian roads. Figure 4 highlights the rising death rate among riders in India each year due to not wearing helmets. Tamil Nadu, Uttar Pradesh, Maharashtra, Madhya Pradesh, and Chhattisgarh together account for 57% of these fatalities[2]. The significant impact of non-usage of helmets, wrong side driving, and triple riding on the safety of two-wheeler riders can be observed from figures. Few nations have employed specialized sensors to identify helmet wearers and triple rid ers, however the cost of such systems are very high compare to vision based detection system.

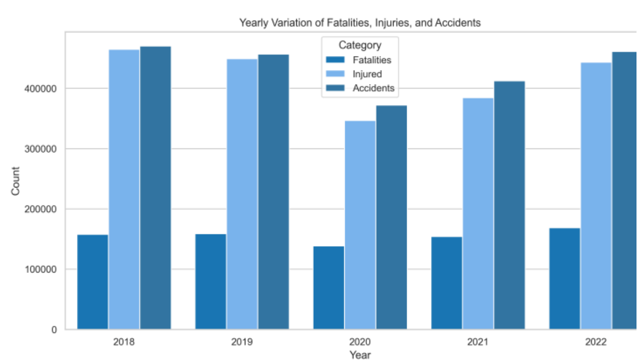

Figure 1. Total number of Accidents, Fatalities and Persons Injured during 2018 to 2022

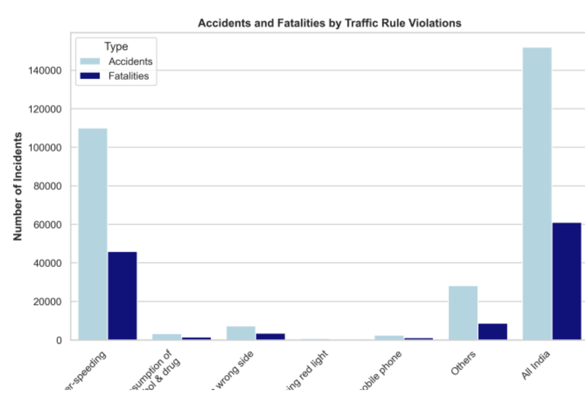

Figure 2. Road Accidents and Fatalities on NH by Traffic Rule Violations

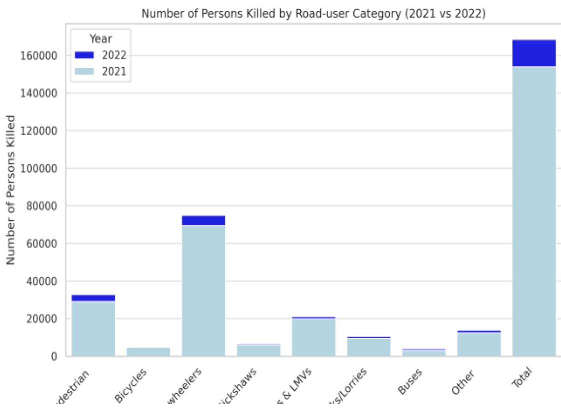

Figure 3. accidents_by_category_2021_vs_2022

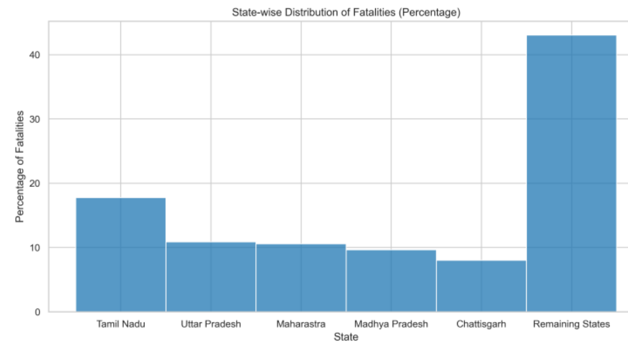

Figure 4. Top 5 state with accident victim due to non helmet

An Intelligent Transportation System (ITS) is a sophisticated network that combines technologies like sensors, cameras, electronics, and communication systems [3]. ITS aims to enhance safety by preventing accidents, saving lives, and offering drivers real-time information on road conditions, such as weather, construction, and emergencies[4-5].

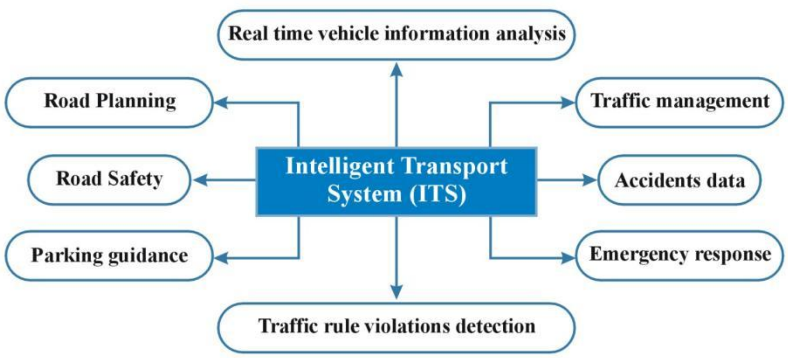

Figure 5. Application area of ITS

By using real-time data processing, ITS supports the creation of a smart and fully functional transportation system.To monitor the violations in Intelligent Transport system (ITS) we use CCTV camera mounted on road side to capture the traffic violations. ITS incorporates several applications varies from basic to advanced., Figure 5 displays some application of ITS i.e. Road Planning, Road Safety, Parking guidance, Traffic management, Traffic rule violations detection, Accidents data, Emergency response, Real time vehicle information analysis etc.

The accident data highlights the necessity of taking decisive action toward reducing violations and minimizing traffic fatalities. The primary goal of the helmet violator detection and triple rider detection system is to enhance accountability and adherence to traffic regulations set by government authorities. Implementing robust enforcement of traffic laws through automatic detection systems can significantly improve outcomes in reducing these critical accidents. The core assumption of proposed model involves creating a rectangular bounding box around the moving vehicle using Roboflow tool and build object detection model based on various techniques. Typically, these models use object localization, neural networks, and deep learning networks to identify and track helmet usage on moving vehicles.The main contributions of our work are as follows:

i. To explore the challenges and limitations of existing systems for managing traffic violations.
ii. To Identify key areas for future research to enhance traffic rule enforcement and reduce road accidents and fatalities.
iii. To Present a Triple Rider framework to automate the detection and enforcement of traffic rule violations.

The remaining of this paper is structured as follows: Section 2 discuss related work, while Section 3 presents the proposed model and provides illustration on datasets creation, YOLO architecture, proposed triple riding detection algorithm and experimental setup. Section 4 includes Result and discussion. Finally, Section 5 concludes this article.

2. Related work

Despite the presence of numerous advanced smart systems designed to monitor traffic violations and tracking remains a complex challenge.Over the past five years, researchers have been looking for new ways to improve traffic rule violation detection systems.i.e. helmet detection and triple riding. A closer examination of recent research papers approaches and solutions that aimed to tackle these persistent challenges are discussed in the following sections.

Traffic rule violation detection system are used for detection of various rule violation such as signal violation, helmet and non-helmet violations, wrong way driving detection and so on. Most of research paper only discussed and implement one or two module for detection of traffic rule violation [6-7]. P. Srinivas Reddy et al., [6] developed a model that detects only signal violation using Support Vector Machine (SVM) & RCNN. Arshad et al., proposed a traffic rule violation detection system to detect rider with helmet and without helmet using YOLOv5 algorithm[8]. The main drawback of system is, not able to detect other traffic rule violation such as triple riding, wrong side driving, driving while using phone. On custom datasets they achieved 92.6% of accuracy. Hu et al. [9] developed a model to classify and detect vehicles in video footage using Histogram of Oriented Gradients (HOG) method. However, their study focused solely on identifying the vehicles and did not address the detection or analysis of the people traveling inside those vehicles.Vaishali et al. [10] proposed machine learning based helmet detection model. The system uses sensors and a machine learning-based cascade classifier with HAAR features to check if a rider is wearing a helmet. If the rider isn’t wearing, they get an immediate alert. If the rider keeps on ignoring multiple warnings, a relay switch and a DC motor controlled by a Raspberry Pi will stop the bike. While this method is highly accurate, it isn’t very cost-effective. R. G. Nandhakumar et al. [11] proposed a method to detect license plate detection of tripe riders based on YOLO and OCR techniques. They collected the data from Kaggle repository and build the model. The system showed 95.5% of accuracy for detection of number plate .Kunal Dahiya et al. [12] proposed a methodology for identifying bike riders in video footage using object segmentation and background subtraction. Their system successfully determines whether the rider is wearing a helmet and achieved a high accuracy of 93.80% in surveillance videos, processing each frame in just 11.58 milliseconds. However, the system is limited to helmet detection and does not address other traffic rule violations. This method detects motorbike riders without helmets in real-time using two steps. First, it identifies the rider in the video and checks for helmet to reduce false predictions. While this approach is more cost-effective than previous methods in terms of accuracy, it runs slower because it relies on basic algorithms like HOG, SIFT, and SVM, along with pre-processing techniques. Saumya et al. [13] developed a DL-based monitoring system to identify bike riders wearing helmets, not wearing helmets, and those involved in triple riding. Initially, they applied YOLOv3 to detect whether a rider was wearing a helmet. Subsequently, they used the vertical projection of a binary image to count the riders and detect instances of triple riding in the images.Q. An et al.,[14], proposed a deep learning based model which is focused on improved YOLOv5s. they developed a model on different deep learning algorithms SSD, Faster R-CNN, YOLOv3, YOLOv4, improved version of YOLOs and compare them. The improved version of YOLOv5s model has significantly improved mAP and FPS compared to other models. H. Lin et al. [15], proposed a CNN based multi-task learning (MTL) method for detection and tracking of different objects presents in an image:motorcycle, motorcyclists with helmet of without helmet. HELMET diverse datasets were created to perform detection and tracking task. The HELMET dataset contains annotated frames of 10,000 motorcycle riders from various regions in Myanmar. A deep learning algorithm identifies the number of riders per motorcycle, their positions, and helmet usage. There are some limitations in this study: trained model detection accuracy compromised while predicting objects on the diverse and dense datasets. Adding uncommon objects to the scene can enhance the model's accuracy. Tasbeeha et al. [16], proposed a detection system based on CNN deep learning approach that helps to detect the traffic rule violators such as rider with helmet or rider without helmet. Mallela et al. [17] proposed a method to detect the vehicle, helmet and triple riders. They utilized YOLOv3 [18]algorithm and trained the model on COCO dataset [19] for detection of vehicle. This system claimed 91.7% of accuracy on real time data. Venkatramulu [21] proposed a method to monitor violations of traffic rules and detection of sign board. In this study, they used synthesis datasets for training. This study used CNN on synthesis datasets to identify the triple rider, helmet and accidents. Most existing methods primarily address single traffic rule violations and do not adequately tackle the issue of triple riding.

Table 1 Summary of related works

Year	Ref	Authors	Algorithms	Datasets	Result	Remarks
2023	[11]	R. G. Nandhakumar et al.	YOLOv3, OCR	Self-generated	95.5%	focused on traffic rule violator's number plate detection. Developed model is unable to detect and extract fancy number plate.
2023	[21]	S. Venkatramulu et al.	CNN	Self-generated	NA	Accuracy of the model is not clearly defined.
2023	[14]	Q. An et al.	YOLOv5s-improved	Safety helmet wearing + SHWD dataset	92.4%	Only focused on a helmet and no helmet detection, other traffic rule violation detection not covered
2022	[16]	Tasbeeha Waris et al.	Faster R-CNN	Self-generated	97.6%	The System is not trained to detect other traffic rule violation such as triple riding, wrong number plate detection
2022	[22]	R. S. Charran et al.	YOLOv4 + DeepSORT / Tesseract	Self-generated +Kaggle (Number Plate)	98.0%	Multiple violation detection system developed but they used separate class label for detection of helmet and Triple riding.
2021	[17]	Mallela et al.	YOLOv3, GSM,	MS COCO datasets	91.7%	The System is not trained to detect other traffic rule violation

			NodeMCU			such as triple riding, wrong number plate detection
2020	[15]	H. Lin et al.	CNN based MTL	HELMET datasets	67.3%	The frame-based motorcycle detection system achieved 95.3% accuracy in identifying motorcycles and a 67.3% score in effectively counting riders and checking helmet usage.
2020	[6]	A. Tonge et al.	CNN, mask RCNN	Self-generated	87%	Accuracy is low that can be improved by including negative data samples.
2016	[12]	K. Dahiya et al.	HOG, SHIFT, LBP	Self-generated	93.8%	Implementation of preprocessing techniques makes the process slow.

Table 1 provides an overview of existing research in the field. This paper focuses on addressing key challenges and limitations found in the reviewed studies. The following sections outline the specific issues we aim to tackle and the approaches we have proposed to resolve them.

- Existing research has focused on detecting helmet usage, counting vehicles in a scene, and identifying license plates. However, violations like triple riding, wrong-way driving, and fancy number plate detection have received little attention, with only limited work done in these areas.
- There is limited literature on combining other violations detection with license plate detection, especially in real-time video. Detecting multiple violations sequentially is computationally expensive.
- Most systems are trained on custom datasets due to the lack of publicly available data for various traffic violation scenarios. Existing models effectively predict only a few traffic rule violations, such as helmet detection and license plate recognition.

3. Proposed model

This research proposed work deals with detection ofmotorcycle, helmet, number of helmet, and triple riding to identify the violators using deep learning based YOLOv8 model. Proposed system detects motorcycle with rider, motorcycle without rider, helmet, non helmet and based on head count in the images, it generate a bounding box with label “Triple Rider”. The process involves creating unique datasets, training algorithms, detecting, and testing to ensure the model achieves high reliability and accuracy. The workflow of proposed model is shown in figure 6.

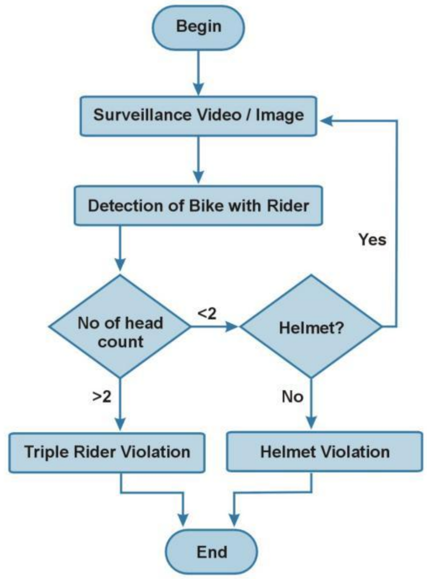

Figure 6. Workflow of Proposed model

3.1. Custom Dataset

We have manually captured the video from the MANUU campus. Datasets were generated from videos by capturing image frames at regular intervals. To avoid duplicate images, we captured images after every 20 seconds. We have added some dense and parsed image data from the internet in order to add diversity to the datasets. Python script were utilized for conversion of video to frames and manual labeling was done. This study utilizes Roboflow for the annotation and pre-processing of image data, streamlining the process of labeling and organizing the datasets required for the Triple Riding Detection System. It has 3 class label : Helmet, Non-Helmet and Bike with rider. Figure 7 below shows the tagging of labels to bounding boxes. A total of 582 images were taken for helmet / non-helmet and triple rider detection. Out of 582, 421 images were consider for training and remaining 161 images for testing & validation.

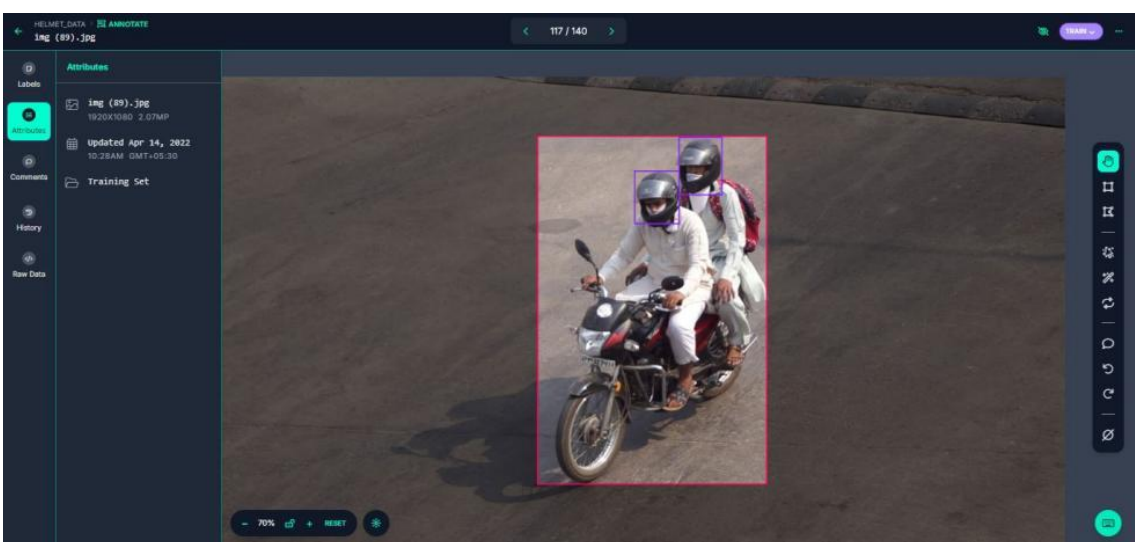

Figure 7. tagging of labels to bounding box (Sample Annotated Images)

3.2 YOLO (You Only Look Once)

The YOLO family employs a single-stage detection mechanism that predicts class labels and bounding boxes from an image in one pass. The backbone, neck, and head are the main components of YOLOv5 [23] architecture. In the backbone, CSPDarknet53 (Cross Stage Partial Darknet) divides the base layer's feature map into two sections, which are then combined through a cross-stage hierarchy to enhance feature learning. Next, PANet (Path Aggregation Network) improves the flow of information and features from the backbone to the head, enhancing the model's ability to detect objects at different scales.. Finally, the head predicts the class probabilities, bounding boxes, and object scores.YOLOv7[24] introduces several new features that reduce computational costs while maintaining high accuracy. It focuses on optimizing the computational efficiency and learning potential of the network. ELAN (Evolved Layer Aggregation Network) is used to enhance feature extraction. The Auxiliary Head helps the model learn faster and generalize better, especially during the early stages of training. Re-parametrization techniques are used to optimize the network for faster inference by merging convolution layers at different stages.

YOLOv8 builds on the lessons learned from YOLOv5 and YOLOv7, aiming to strike the perfect balance between speed and accuracy[25]. An improved CSPNet optimizes the balance between computational cost, learning ability, and model performance. YOLOv8 also incorporates adaptive training techniques that optimize hyperparameters and model adjustments based on the data, resulting in more robust and generalized models. Figure 8 illustrated the basic structure of YOLOv8.

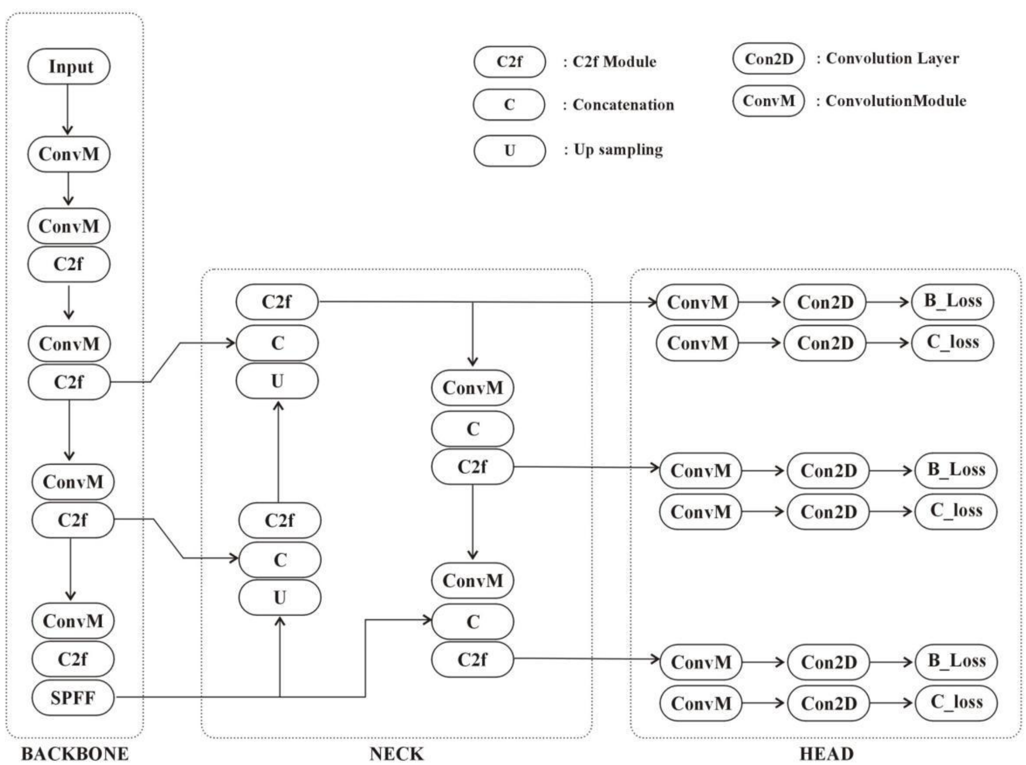

Figure 8. YOLOv8 with default structure configuration

3.3 Triple Riding Detection System –

The prototype model is specifically trained to recognize key objects: Helmets, Non-Helmets, and Motorcycles with Riders. The trained model then identifies motorcycles with riders, which is crucial for detecting the number of people riding and helps to identify triple-riding - traffic rule violations. Figure 6 illustrates the complete workflow of triple triple-riding detection system. Figure 9 shows input images and detected bounding box with class label as output. This system plays a vital role in enforcing motorcycle safety regulations by ensuring that riders adhere to safety norms, such as wearing helmets and avoiding the dangerous practice of triple riding. The accurate classification of these objects allows authorities to take necessary actions to improve road safety.

Figure 9. Input test image and outputimage indicating detection of violations (triple riding violation, helmet violation and no violation)

Algorithm 1: Triple Riding traffic rule violation detection based on bounding boxes

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Input: *bounding box, class and confidences information from object detection model*
Output: *list of traffic rule violations and counting of helmet and non-helmet*
Define function- ***is_within****(ibb, obb),* ***calculate_area****(bb) ,* ***intersection_area****(box1, box2),*
is_80_percent_within()

fun ***is_within(ibb, obb)***
x1_i, x2_i, y1_i, y2_i ← ibb
x1_o, x2_o, y1_o, y2_o ← obb
if ibb within obb:
return True, Otherwise, return False

function ***calculate_area(bb)***
x1, y1, x2, y2 ← bb
*area ← (x2 - x1) * (y2 - y1)*

function ***intersection_area(box1, box2)***
x1_i ← max(box1.x1, box2.x1), y1_i ← max(box1.y1, box2.y1) , x2_i ← min(box1.x2, box2.x2) , y2_i ← min(box1.y2, box2.y2)
if coordinate overlap or intersect
*intersection_area ← (x2_i - x1_i) * (y2_i - y1_i)*

function ***is_80_percent_within(ibb, obb):***
inner_area ← calculate_area(ibb)
inter_area ← intersection_area(ibb, obb)
if (inter_area / inner_area) >= 0.8 Then Return True, Otherwise, return False
class_boxes ← unique classes from //Initialize dictionary
Populate *class_boxes**:***
for each*box, cls in boxes, classes:*

***append**box to class_boxes[cls]*
class_1_count ← 0, class_2_count ← 0.
***for each**b_0 in class_boxes[0]*
***for each**b_1 in class_boxes[1]*
***if**is_within(b_1, b_0)**or**is_80_percent_within(b_1, b_0)*
***increment**class_1_count.*
***for each**b_2 in class_boxes[2]*
***if**is_within(b_1, b_0)**or**is_80_percent_within(b_1, b_0)*
***increment**class_2_count*
if class_1_count = 0
v1 ← "Violation -1: Helmet Violation"
if (class_1_count + class_2_count) greater than 2
v2 ← "Violation -2: Triple Riding Violation"
Else:v2 ← "No Violation"

Key component of this study to effectively extract the bounding box information of the objects belonging to classes : motorcycle with rider, helmet and non-helmet. To detect these objects we have used the state-of-art detection model YOLO. For recognition of triple riding traffic rule violations, we proposed coordinate based bounding box intersection area (BBIA) algorithm as shown above.

3.5. Experimental environment, parameter settings

The experimental results for building a deep learning model using the YOLO algorithm were conducted on Google Colab with an NVIDIA-SMI 535.104.05, featuring 12 GB of memory (K80) or 16 GB (T4) and using CUDA 11.x. . The model training parameters are set as shown in Table 2.

Table 2.list of parameter and their values

Parameters and values		**Parameters and values**	
Learning rate	0.01	Workers	4
Batch size	32	Optimizer	SGD
Image size	640 x 640	Momentum	0.937
Epochs	120	Patience	50
Weight decay	0.0005	weights	Yolov8n.pt

The triple riding detection model utilized libraries like OpenCV for image processing, NumPy for numerical tasks, and Darknet and TensorFlow for deep learning. These tools work together to analyze video data and implement advanced machine learning techniques. This combination enables effective detection of triple riding.

4. Results and discussion

This section presents the results of the proposed system. Most existing systems primarily focus on detecting helmet, non helmet, speed limit violation and counting vehicles. Few systems implements triple riding detection system that completely based on class label. Our system introduced an algorithm BBIA that specifically identifies triple riding, addressing another significant traffic rule violation based on YOLOv8. Objects such as helmet, non-helmet, bike with rider detected using YOLOv8 algorithm and using BBIA algorithm, we detect different traffic rule violations. We tested our model's effectiveness by evaluating the proposed system on images with and without triple riding, as well as those containing other violations, and presented the results in Table 3.

Table 3. Comparison table of object detection results from different YOLO version.

Model	Params/MB	Layers	Model Size /MB	Image size	Accuracy in %				
					P	R	F1-Score	mAP@0.50	mAP@0.50-0.95
YOLOv5	6.73	157	3.9	640*640	79.1	73.7	76.3	77.5	49.5
YOLOv7	142.7	415	78.4	640*640	78.4	74.5	76.4	75.4	50.5
YOLOv8	42.4	168	22.5	640*640	73.5	80.3	76.4	81.6	52.3

This study uses a total of three different version of YOLO algorithm models. The experimental results in Table 2 show that the YOLOv8 algorithm achieved good detection rate in object detection task. YOLOv8 demonstrates impressive performance metrics, including a precision of 73.5%, a recall of 80.3%, an F1 score of 76.4%, a mAP@0.5 of 81.6%, and a mAP@0.5-0.95 of 52.3%.YOLOv8 outperforms YOLOv7 and other comparable algorithms in terms of both precision and recall, demonstrating its superior effectiveness in detection tasks. Notably, it achieves a 6.2% higher mAP@0.5 compared to the second-best YOLOv7 model.

As depicted in Figure 5, the system identifies helmets, non-helmets, and bikes with riders. It counts the number of helmets and non-helmets, draws bounding boxes around them, and assigns appropriate labels. The ground truth vs violation (helmet, triple riding, no violations) detection results are shown in Figure 10.

(a) **(b)** **(c)** **(d)** **(e)**

Figure 10. Ground Truth vs Detection Result (Motorcycle with Rider, Helmet, Non-Helmet and Triple rider) on test image data. (a),(c) & (e) represents no violation, (b) & (d) represents two violations such as helmet and triple riding

The Performance of Triple riding detection model using proposed BBIA algorithm shown in Table 4. The model is evaluated for the detection of three types of violations: triple riding (V1), helmet violation (V2), and no violation. A total of 80 test images were used to validate the model's effectiveness. The algorithm achieved a correct detection rate of 74 images, with only 6 images of incorrect detection. This corresponds to an overall accuracy of 92.5%, demonstrating the robustness of the proposed approach for accurately identifying and classifying traffic violations. The object detection accuracy of our model is 81.6%, with a precision score of 0.735 and an F1 score of 0.764.

Table 4. Performance of Triple Riding Detection using proposed algorithm (BBIA)

Type of Violations detection	**Algorithm**	**Testing Data**	**Correct Detection**	**Wrong Detection**	**Accuracy**
V1: triple riding, V2: Helmet violation, No violation	YOLOv8 + BBIA	80	74	6	92.5%

Implementation of this system automate the task, enhance public awareness of traffic regulations, helps to reduce accidents and reduce human intervention. Table 5 presents comparative study of various models and proposed model with their accuracy rates.

Table 5comparative analyses with existing algorithm and proposed method

Reference	Algorithm / Model	task	Accuracy
[17]	YOLOv3	TR	91.7%
[14]	YOLOv5s-improved	HD	92.4%
Proposed	YOLOv8 + BBIA	TR + HD	92.5%

TR - Triple Riding, HD- Helmet Detection

5. Conclusion

This paper proposed an automated triple riders - traffic rules violation detection using YOLOv8 and BBIA algorithm, trained on custom datasets. The experimental results demonstrate that the proposed system is reliable when properly implemented, offering good levels of accuracy and precision. This makes it well-suited for automating tasks that are typically time-consuming, while also enabling continuous monitoring of traffic violations with minimal human intervention. Such systems play a crucial role in raising public awareness of traffic regulations and fostering consistent compliance. By automating these processes, the system not only enhances operational efficiency but also ensures round-the-clock enforcement of traffic rules, contributing to improved road safety and regulation adherence. Currently, the proposed system focuses on detecting a few traffic violations, such as triple riding and helmet use. In the future, other violations like driving on the wrong side, fancy number plate detection, and using mobile phones while driving will be integrated to make the system more comprehensive and effective. These additions would further reduce the need for human involvement in monitoring traffic, potentially automating the entire process.

References

[1] Global status report on road safety 2023. (2023, December 13). https://www.who.int/teams/social-determinants-of-health/safety-and-mobility/global-status-report-on-road-safety-2023.

[2] Road Accidents in India 2022. (2022, October 30). https://morth.nic.in/sites/default/files/RA_2022_30_Oct.pdf

[3] Laña, I., Sanchez-Medina, J. J., Vlahogianni, E. I., & Del Ser, J. (2021). From Data to Actions in Intelligent Transportation Systems: A prescription of Functional requirements for model Actionability. Sensors, 21(4), 1121. https://doi.org/10.3390/s21041121

[4] C. Chen, B. Liu, S. Wan, P. Qiao, and Q. Pei, "An edge trafficflow detection scheme based on deep learning in an intelligent transportation system," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 3, pp. 1840–1852, 2021.

[5] S. Kaffash, A. T. Nguyen, and J. Zhu, "Big data algorithms and applications in intelligent transportation system: a review and bibliometric analysis," International Journal of Production Economics, vol. 231, Article ID 107868, 2021.

[6] A. Tonge, S. Chandak, R. Khiste, U. Khan and L. A. Bewoor, "Traffic Rules Violation Detection using Deep Learning," 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2020, pp. 1250-1257, doi: 10.1109/ICECA49313.2020.9297495.

[7] P. S. Reddy, T. Nishwa, R. S. K. Reddy, C. Sadviq and K. Rithvik, "Traffic Rules Violation Detection using Machine Learning Techniques," 2021 6th International Conference on Communication and Electronics Systems (ICCES), Coimbatre, India, 2021, pp. 1264-1268, doi: 10.1109/ICCES51350.2021.9488998.

[8] M. Arshad and P. Kumar, "Detection of Two-Wheeler Traffic Rule Violation Using Deep Learning," 2022 IEEE World Conference on Applied Intelligence and Computing (AIC), Sonbhadra, India, 2022, pp. 109-114, doi: 10.1109/AIC55036.2022.9848979.

[9] Hu Y, He Q, Zhuang X, Wang H, Li B, Wen Z, Leng B, Guan G, Chen D (2013) Algorithm for vision-based vehicle detection and classification. In: 2013 IEEE International conference on robotics and biomimetics. IEEE, ROBIO, pp 568–572

[10] Vaishali, M. Ashwin Shenoy, P. R. Betrabet and N. S. Krishnaraj Rao, "Helmet Detection using Machine Learning Approach," 2022 3rd International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2022, pp. 1383-1388, doi:10.1109/ICOSEC54921.2022.9952083.

[11] R. G. Nandhakumar, K. N. Devi, N. Krishnamoorthy, S. Shanthi, V. R. Pranesh and S. Nikhalyaa, "Yolo Based License Plate Detection Of Triple Riders And Violators," 2023 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2023, pp. 1-6, doi: 10.1109/ICCCI56745.2023.10128537.

[12] K. Dahiya, D. Singh and C. K. Mohan, "Automatic detection of bike-riders without helmet using surveillance videos in real-time," 2016 International Joint Conference on Neural Networks (IJCNN), Vancouver, BC, Canada, 2016, pp. 3046-3051, doi: 10.1109/IJCNN.2016.7727586.

[13] A. Saumya, V. Gayathri, K. Venkateswaran, S. Kale and N. Sridhar, "Machine Learning based Surveillance System for Detection of Bike Riders without Helmet and Triple Rides," 2020 International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2020, pp. 347-352, doi: 10.1109/ICOSEC49089.2020.9215266.

[14] Q. An, Y. Xu, J. Yu, M. Tang, T. Liu, and F. Xu, "Research on Safety Helmet Detection Algorithm Based on Improved YOLOv5s," Sensors, vol. 23, no. 13, p. 5824, Jun. 2023, doi: 10.3390/s23135824.

[15] H. Lin, J. D. Deng, D. Albers and F. W. Siebert, "Helmet Use Detection of Tracked Motorcycles Using CNN-Based Multi-Task Learning," in IEEE Access, vol. 8, pp. 162073-162084, 2020, doi:10.1109/ACCESS.2020.3021357.

[16] Waris, Tasbeeha, Asif,Muhammad, Ahmad, Maaz Bin, Mahmood, Toqeer, Zafar, Sadia, Shah, Mohsin, Ayaz, Ahsan, CNN-Based Automatic Helmet Violation Detection of Motorcyclists for an Intelligent Transportation System,Mathematical Problems in Engineering, 2022, 8246776, 11 pages, 2022. https://doi.org/10.1155/2022/8246776

[17] Mallela, N.C., Volety, R., R., S.P. et al. Detection of the triple riding and speed violation on two-wheelers using deep learning algorithms. Multimed Tools Appl 80, 8175–8187 (2021). https://doi.org/10.1007/s11042-020-10126-x
[18] Redmon J, Divvala S, Girshick R, Farhadi A (2016) You only look once: unified, real-time object detection. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 779–788
[19] Lin TY, Maire M, Belongie S, Hays J, Perona P, Ramanan D, Dollar P, Zitnick CL (2014) Microsoft coco: Common objects in context. In: European conference on computer vision. Springer, pp 740–755
[20] Redmon (2016) Darknet: open-source neural networks in c. http://pjreddie.com/darknet/
[21] Venkatramulu, S. ., Yugasri, B. ., Sadala, T. M. ., Revathi, G. ., & Rao, V. C. S. . (2023). Violation of Traffic Rules and Detection of Sign Boards. International Journal on Recent and Innovation Trends in Computing and Communication, 11(8s), 249–255. https://doi.org/10.17762/ijritcc.v11i8s.7204
[22] R. S. Charran and R. K. Dubey, "Two-Wheeler Vehicle Traffic Violations Detection and Automated Ticketing for Indian Road Scenario," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 11, pp. 22002-22007, Nov. 2022, doi:10.1109/TITS.2022.3186679.
[23] Ultralytics, "YOLOv5: A state-of-the-art real-time object detection system," 2021. [Online]. Available: https://docs.ultralytics.com. [Accessed: 01.09.2024].
[24] C.-Y. Wang, A. Bochkovskiy, and H.-Y. M. Liao, “YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors,” arXiv.org, Jul. 06, 2022. https://arxiv.org/abs/2207.02696
[25] J. Terven, D.-M. Córdova-Esparza, and J.-A. Romero-González, “A comprehensive review of YOLO architectures in computer vision: from YOLOV1 to YOLOV8 and YOLO-NAS,” Machine Learning and Knowledge Extraction, vol. 5, no. 4, pp. 1680–1716, Nov. 2023, doi:10.3390/make5040083.