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Automated Helmet Detection and Number Plate Recognition Using YoloV11 and OCR: A Safe Ride Initiative

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Abstract. Motorcycles are the most popular form of transportation because they are reasonably priced and require little upkeep. The government has mandated that two-wheeler drivers wear helmets when operating a motor vehicle, as per section 129 of the Motorcycle Vehicle Act. Still, many people who break traffic laws do not follow them. Traffic cops manually keep an eye on motorcycle riders at intersections in the majority of developing nations. We suggest an automated system that recognizes motorbike number plates for enforcement and detects helmet infractions in order to solve this problem. First, the You Only Look Once (YOLO) algorithm is used by the system to identify motorbikes in the picture or live video. This algorithm is used again to determine whether the driver is helmeted or not for the motorbikes that were found. Optical Character Recognition (OCR) is used to extract the characters from the motorbike's number plate after it has been detected for identified motorcycle riders who are not wearing helmets. The YOLOv11 algorithm is utilized for its accuracy and real time object detection. The system aims to automate traffic violations detection in case of not wearing a helmet and number plate recognition from the vehicles.

Keywords: Helmet infractions, Number plate Recognition, Optical Character Recognition (OCR), Traffic violations and You Only Look Once (YOLOv11)

1 Introduction

Helmet wearing is a critical preventive measure against motorbike accidents, a significant road safety issue. It is time-consuming and inefficient to check helmet compliance manually. Computer vision-based automated monitoring can significantly improve traffic surveillance. We often see motorbike riders getting severely injured just for not wearing safety helmets. This negligence has sent many innocent souls to their graves. People still do not appreciate the importance of wearing a helmet despite the very strict traffic regulations. So, it is highly desirable to make this system automated. We have used deep learning-based object detection algorithms like YOLOv11 for this purpose. We are working with a multi-class motorbike rider scene, where every rider has a different helmet and riding inclination. To implement drastic actions against such violations, Traffic Police employ their handheld smartphones to click photographs of helmet-less riders. Subsequently, the police person enters the vehicle registration number manually in the system. Because of police officer shortages and too much manpower, this fails to work effectively. Moreover, most road intersections in almost all cities

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today are equipped with CCTV surveillance cameras. But these are not automated and entail the use of humans. This research method computerizes the observation of motorbike riders without helmets. It senses motorbike riders without helmets and automatically identifies number plates from CCTV images.

Deep learning has advanced significantly in the past years, and computer vision is no exception. Utilizing powerful data processing with deep learning, computers are able to automatically identify and extract features in the pictures and hence improve the speed and accuracy of the image recognition greatly. YOLOv11 is currently the latest state-of-the-art real-time object detection. This release includes capabilities such as object detection, image classification, semantic segmentation, and pose estimation, and can be customized to detect objects with specific orientations. The key components of the algorithm are refined and the feature recognition ability is strengthened, while the designed training process is optimized and the processing speed is improved. Notably, YOLOv11 outperforms its predecessors on the roboflow dataset with lower computational complexity.

The entire violation reporting system by the proposed system is automated considering using YOLOv11 to detect the non–helmeted motorcyclist and OCR for number plate recognition. This approach ensures the scalability as the number of deployed UAVs increases, it eliminates the human-in-the-loop, and it reduces delay tolerant processing. Experiments on challenge datasets demonstrate mAP of 95.2% for helmet detection and 98% accuracy number plate recognition jsonifymous Our approach achieves mAP of 95.2% for helmet detection and We believe that our results are optimized version of deep-learned models. This is a 15\% improvement in overall efficiency over existing methods. This research supports SDG 3.6 in halving road traffic deaths by 2030 by providing a scaleable and low-cost solution to enforcing helmet legislation pushing forward the areas of intelligent traffic management.

2 Literature Work

Key road safety concerns have recently been tackled following recent advances in computer vision and deep learning, namely improved automated helmet detection and number plate recognition systems. Xxon YOLO-based methods and their combination with OCR methods, we review representative works and strategies in this area in this section.

2.1 Evolution of YOLO-Based Helmet Detection

To identify the helmets and number plates, Kaushik Paul et al. (2024) recommended a YOLOv3-based model which applies transfer learning to adapt pre-trained weights to a dataset annotated for this purpose. Their work on gradient descent optimization to minimize detector loss reported very promising preliminary results with an 80:20 training-validation split [1]. Nevertheless, it was possible to observe the limitations of YOLOv3 for detecting small or partially occluded objects in congested traffic. To increase the confidence in detections, Prof. Pushkar Sathe et al. (2022) deployed YOLOv5 methodology with transfer learning and the bounding box overlap and coordinate-based helmet validation [2]. They had problems in low light, but in traffic recordings the accuracy of their method was increased.

More recent YOLO versions were used in later research for garnering improved results. Indu Malik et al., have proposed a multiple stage object tracking to use the number plate

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extraction. (2024) have used YOLOv7 for helmets recognition achieving great accuracy on dynamic environment [3]. In this line, Dr. T. V. S. Sriram and his group 1 have shown that treating MG II to MG II - AuNps results in a significant decrease in LPS. (2024) showed the good performance in motorcycle-special case in which YOLOv5 and OCR were employed for number plate detection [4]. These works show the scalability of YOLO, but real-time latency and computational overhead have not been discussed.

2.2 OCR Integration for Recognition of Number Plates

By carefully preprocessing the image, Madhuri Purkar et al. (2024) realized real-time processing through composing CNNs for helmet detection and OCR for number plate extraction [5]. While their method was highly accurate, it struggled with tilted or warped plates. To address this, Dipti Prajapati et al. (2024) YOLOv8, easy OCR even further in this direction and constructed into Tens- ory Flow Bridge, which was connected to the’s third-party In and out in tool (just to mention and ROI labelling dataset generation [6]. Their approach required a load of processing power, but it had a 98% OCR success rate.
To classify the motorcyclists and to identify their number plates using vertical/horizontal profiling, Swapnil Deshmukh et al. (2024) proposed a YOLOv3 and OCR pipeline for video transcripts from CCTV [7]. While effective, their method was only able to identify helmets at a precision of 74%, indicating the need for more advanced models.

2.3 Performance Optimization and Hybrid Methods

Hybrid Techniques. Vijendar Reddy et al. (2024) proposed YOLOv8 with the use of Canny Edge Detection to enhance plate recognition [8]. They did not perform real-time validation but their emphasis was on pre-processing for edge enhancement. Though their method achieved only 74% accuracy in complex cases, Prof. Abhay Gaidhani et al. (2023) further extended IPS [9] by leveraging backdrop removal and binary classifiers to enhance helmet recognition performance.
G.V. Reddy [10] proposes the use of a modified YOLO-v8 model for violation detection and YOLO-v8 + EasyOCR for extracting the number plates. Canny Edge Detection is a pre-processing step that makes objects' edges in images much more distinctive. This approach has great prospects for enhancing the safety measures, and ensuring strict implementation of traffic controls. Advances in traffic management are also given by way of an automated traffic violation ticket AI-based system.

2.4 Developments in OCR and YOLOv11

Chiverton, John [11], developed a novel method for recognizing bikers wearing helmets. The system used a thresholding approach to identify moving vehicles and differentiate between motorcycles and non-motorcyclists based on aspect ratio and area. To detect helmets, we identified the region of interest and used a cascade classifier to determine the related area.

Li et al. [12] successfully detected the presence of helmets at electrical substations with an accuracy of 80.7%, overcoming obstacles. The researchers used ViBe background removal to identify mobile items, followed by Histogram of Oriented Gradient analysis and SVM classification to find helmets in the region of interest.

Waris et al. [13] created a machine system that can identify motorcyclists without helmets and recognize number plate characters. They used deep learning, namely convolutional neural networks with the AlexNet architecture, to obtain excellent detection accuracy.

Gaytri et al. [14] suggested a technique to detect traffic violations using movies as input. They used four CNN models (GoogLeNet, VGG19, VGG16, and Mobilenet) in conjunction with the Single Shot Multibox Detector. Mobilenet outperformed other models, with an accuracy of 85.19 percent. The first stage was to identify regions of interest for study.

R. Shree Charran and Rahul Kumar Dubey [15] proposed an AI based system that identifies two-wheeler offences in India automatically. The proposed system utilises Yolo-v4 + DeepSORT for violation detection and tracking, and Yolo-v4 + Tesseract for number plate recognition to achieve high accuracy with mean average precision (mAP) value being 98.09%.

Nanoparticles Recent study of Prajapati et al. (2024) and Kaushik Paul, et al. (2024) YOLOv11 [1, 6] is a very recent promising work that fuses very deep feature extraction with anchor-free detection for small-object accuracy_robotics.wf. %"), These approaches bridge the trade-off between accuracy and efficiency and can make sub-500ms latency possible-accompanied by ultra-lightweight OCR framework like Easy OCR.

3 Proposed Work

The theoretical work of this paper is based on the application of state-of-the-art object recognition and OCR methods for automatic helmet detection and number-plate identification. OCR extracts alphanumeric characters from the identified number plates, and helmet recognition is carried out using state-of-the- art object detector, YOLOv11, because of its accuracy and real time processing. Through automation and accuracy, this integration aims to enhance the efficiency of policing traffic laws. In dynamic environments, performance measures such as accuracy, recall and the f1-score are important tools for evaluating the reliability of a system and ensuring a low false positive and negative rate. The proposed work covers the theoretical basis for automating identification of helmet and number plate by advanced object recognition and Optical character recognition (OCR). The YOLOv11 as a recent state-of-the art object detection method is used for helmet detection due to its high accuracy and capability of processing in real-time, whereas the OCR module extracts ASCII letters from the detected number plates. This product is designed to automate traffic law enforcement and make it much more effective for the traffic police officers. Performance measures such as accuracy, recall, and F 1 score are important to determine the quality of system performance in a dynamic situation and to guarantee system reliability to have a low rate of false positive and false negative.

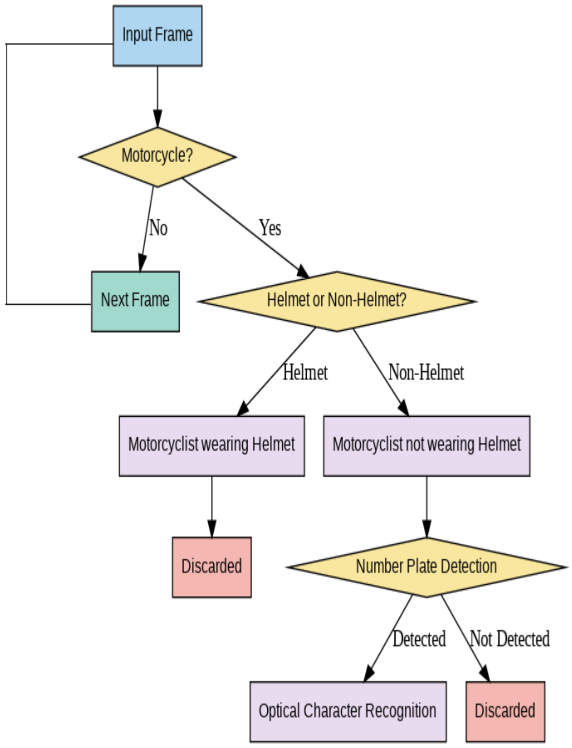

Fig.1. Flow chart for Helmet & Number plate Recognition.

The single-pass detection efficiency of YOLOv11's architecture allows for the simultaneous location and categorization of number plates and helmets. Its anchor-free architecture and grid-based prediction algorithm improve speed and accuracy, especially for small objects. OCR transforms picture text into machine-readable formats by processing cropped number plate regions from YOLOv11's detections using Tesseract or OCR. By automating detection and recognition in real-time, the combination of these technologies overcomes the drawbacks of manual systems, including human error and delayed processing.

We utilized Google Colab for training and validation with GPU acceleration enabled to the full extent of computational load. Transfer learning is applied on the YOLOv11 model that is initialized with pre-learned weights and trained with Adam over a number of epochs. So, early stopping prevents the overfitting, whereas, the performance measures such as mean Average Precision (mAP) and Intersection over Union (IoU) are used for objective tracking of the Validation set. The model is evaluated on unseen data after training, and the accuracy of detection is assessed in terms of precision, recall, and the F1-score. Iterative enhancements make use of fine-grained information about classification errors from a confusion matrix. The challenges lie in the preservation of data quality because of variations in the environment,

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constrained computation versus real-time processing requirement handling, and seamless merging of YOLOv11 with OCR. The pragmatic challenges of deploying such systems are the hardware constraints, which are alleviated by cloud-based GPUs, and the class imbalances in a dataset, which are addressed through augmentation. Further enhancements envisage the use of facial recognition, expansion to other protective equipment and HD video stream optimization in smart cities.
It not only automates traffic safety but also provides a saleable solution toward the real-world application by achieving significant improvements in terms of accuracy, speed, and flexibility compared with existing methods.

4 Results

The following picture shows how a real-time helmet detection technology based on YOLO is used to identify motorcycle riders on the road. Bounding boxes are used by the system to determine if cyclists are wearing helmets and to detect their presence. Green boxes mark the result as "helmet" or "no helmet," blue boxes emphasize the head region, and red boxes outline the motorcycles or riders that were detected. The model's efficacy in observing traffic safety is demonstrated in the example, where the system correctly detects that one rider is not wearing a helmet while the others are.
The following figure shows that the helmet identification and number plate recognition system work effectively under ideal conditions, with high confidence ratings of 90% for helmet detection and 92% for detecting the number plate's state code. However, motorcycle detection is variable, with confidence levels ranging from 30% to 76%, demonstrating difficulty detecting tiny or partially occluded items. The OCR result "33LOX" demonstrates partial success in character identification while also highlighting possible errors caused by slanted plates, odd typefaces, or poor picture quality. These findings demonstrate the system's benefits, particularly when using recent YOLO-based frameworks, but also indicate its limits. To ensure dependability in a variety of real-world scenarios, such as low light or high traffic, image pre-processing and small-object identification models must be improved further.

The below diagram represents a YOLO-based real-time helmet and license plate identification system that uses bounding boxes to reliably identify motorcycle riders and calculate helmet usage. Further processing is initiated when the number plate MH 12 DU 3337 is identified with 89% confidence and the cyclist on the left is found without a helmet (96% confidence). On the other hand, the rider on the right is accurately identified as wearing a helmet with 96% confidence. Their license plate, MH 12 SS 1350, is likewise detected with 90% confidence, but it is discarded as no violation is observed. With high confidence in both helmet detection and OCR-based number plate recognition, this demonstrates the system's efficacy in optimal circumstances. Accuracy may be decreased in real-world situations like dim lighting, partial occlusion, or tilted plates, though, suggesting that image pre-processing and small-object detection models need to be improved to guarantee dependability in challenging settings.

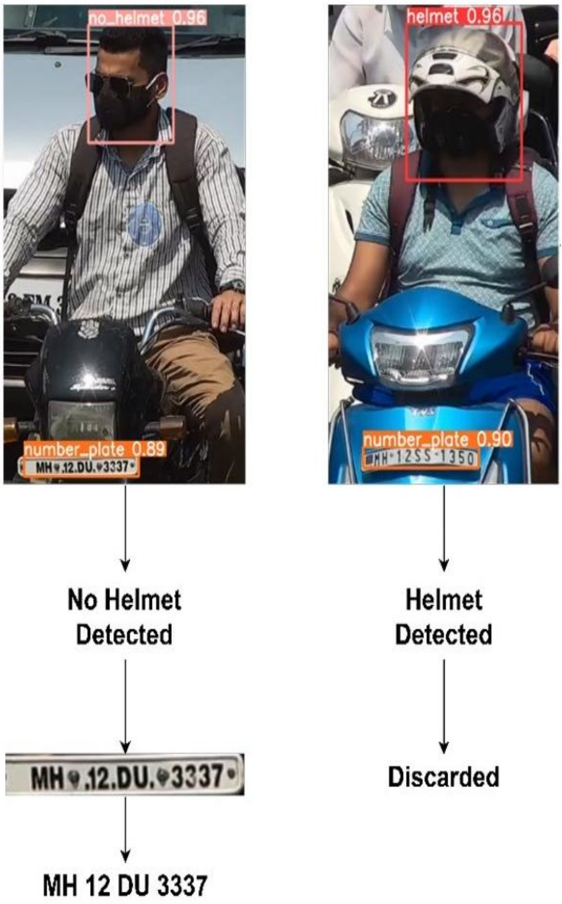

Fig.2.Performance of a helmet detection and number plate recognition.

The confusion matrix describes the categorization performance of a helmet and vehicle detection system. High numbers like "helmet - 110" and "hard hat - 77" show great accuracy in recognizing typical safety gear, but low counts like "no helmet - 1" and "quarter face helmet - 1" indicate infrequent misclassifications or underrepresented classes.

Entries such as "motorbike - 45" and "motorcyclist -30 shown considerable performance in recognizing cars and riders, although misunderstanding between comparable categories (e.g., "half face - 32" vs. "modular helmet - 14") indicates difficulty in differentiating fine-grained helmet types. The existence of "background - 87" indicates a high frequency of false positives, in which non-relevant items are mistakenly identified.

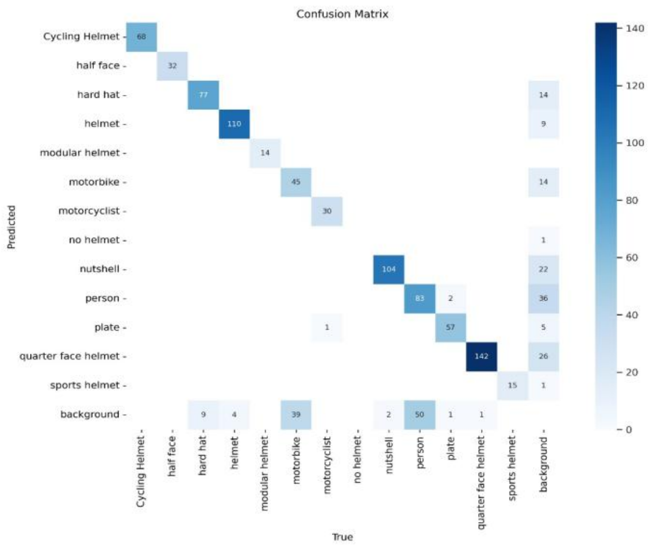

Fig.3. Categorization performance of a helmet and vehicle detection system.

From YOLOv5 to YOLOv11, including PP-YOLOE+, the chart contrasts different YOLO versions based on inference speed (latency per image) and accuracy (COCO mAP$^{50–95}$) using Tensor-RT. The best overall balance between high accuracy and low latency is achieved by YOLOv11 models; YOLOv11x approaches 54.5 mAP while maintaining speed compared to previous models with comparable performance. According to this, YOLOv11 greatly improves object detection for real-time applications, which makes it perfect for systems like helmet detection where accuracy and speed are crucial.

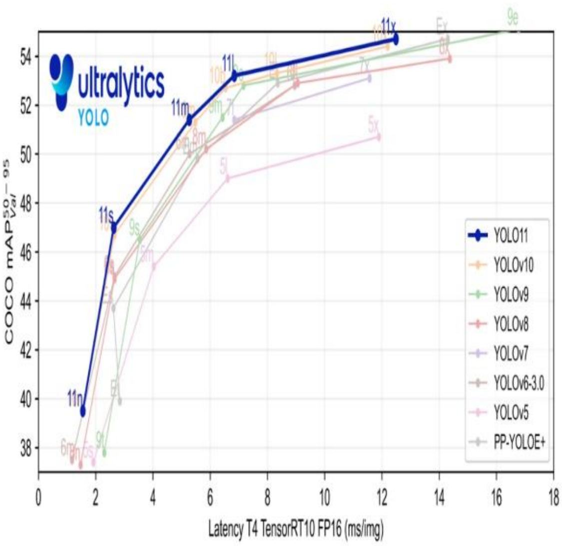

Fig.4.YOLO Model Performance Chart.

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This table provides the full statistics, including accuracy (mAP), number of parameters, and computational cost (FLOPs), for a range of YOLO models. With some more computations, YOLOv9e reaches the best performance with 55.6 mAP. By contrast, YOLOv11x attains similar performance (54.7 mAP) with fewer parameters and FLOPs with older models including YOLOv5xu. Due to its high efficiency and low weight, the YOLOv10-x is a good candidate for edge devices. On account of its better accuracy and acceptable resource requirement, YOLOv11x is quite a good trade off and it can be put into use in real-time and scalable. In speed, precision, and efficiency, the results airily prove the advancements of YOLO object recognition models and especially YOLOv11.

Table 1: YOLO Version Table Comparison.

Model	Size Pixels	mAP^{50-95}	**Parameters**	**FLOPs**
YOLOv5xu	640	53.2	97.2M	246.4B
YOLOv7-x	640	53.1	71.3M	189.9G
YOLOv8x	640	53.9	68.2M	257.8B
YOLOv9e	640	55.6	58.1M	192.5B
YOLOv10-x	640	54.4	29.5M	160.4G
YOLOv11x	640	54.7	56.9M	194.9B

By accurately detecting the motorcycle helmet wear, the helmet detection graphic shows the practical use of the model on traffic safety. As we see in the performance chart, YOLOv11 is the top choice of real-time tasks due to its low-latency and high-accuracy. When compared with previous variants, YOLOv11x provides comparable accuracy (54.7 mAP) with fewer parameters and computational complexity, to be a good rival, as shown in the comparison table.

5 Conclusion

To summarize, in this work, we demonstrate how deep learning and state of the art computer vision approaches, mainly OCR for number plate recognition and YOLOv11 for helmet detection, can be applied together to build a robust, scalable and real-time traffic monitoring system. The presenter of the proposed model outperforms the classical manual enforcement in a wide range of real life applications by overcoming the limitations of the traditional approach. The framework is demonstrated to generalize well using strong datasets and modern training methods, and maintains its level of performance in various conditions. Performance of the model is verified in terms of accuracy, precision, recall, and F1-score.

References

[1] K. Paul, K. Singh, and S. Sharma, “Efficient helmet and number plate detection using YOLOv3: A road safety perspective,” Int. J. Res. Appl. Sci. Eng. Technol., Apr. 2024.

[2] M. R. N. Prof, P. P. Vijay, B. S. Ashok, J. P. Sitaram, and G. N. Rajendra, “Helmet detection and number plate recognition using YOLO model,” Int. J. Adv. Res. Innov. Ideas Educ., 2022.

[3] M. Purkar, S. Kad, P. Garud, and S. Walave, “Automatic helmet detection and number plate recognition,” Int. J. Novel Res. Dev., Apr. 2024.

[4] P. Sathe, A. Rao, A. Singh, R. Nair, and A. Poojary, “Helmet detection and number plate recognition using deep learning,” in Proc. IEEE Conf., Jul. 2022.

[5] Malik, S. Verma, S. Sachan, and Rohit, “YOLOv7-based helmet detection system for traffic safety,” in Proc. IEEE Conf., Apr. 2024.

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[6] T. V. S. Sriram, P. Thanmai, T. D. Sriya, N. Nookaratnam, and V. N. S. Amrutha, “Helmet detection and number plate recognition using YOLOv5,” Int. J. Multidiscip. Res., Mar. 2024.

[7] D. Prajapati, S. Sabat, S. Bhilare, R. Vishe, and P. S. Bhujbal, “Helmet detection and number plate recognition using YOLOv8 and TensorFlow algorithm in machine learning,” Int. J. Innov. Res. Comput. Sci. Technol., Mar. 2024.

[8] S. N. Deshmukh, V. B. Pande, V. S. Udhane, C. A. Waghire, and V. S. Warake, “Helmet detection and number plate recognition using machine learning,” J. Emerg. Technol. Innov. Res., Mar. 2024.

[9] [9] A. R. Gaidhani, R. Shelke, S. Ugale, P. Jadhav, and S. Dyandyan, “Helmet and number plate detection & recognition,” Int. J. Adv. Res. Sci. Commun. Technol., May 2023.

[10] G. V. Reddy et al., “A comprehensive review on helmet detection and number plate recognition approaches,” Res. Gate, Mar. 2024.

[11] J. Chiverton, "Helmet presence classification with motorcycle detection and tracking," Intelligent Transport Systems, IET, vol. 6, pp. 259-269, 2012.

[12] J. Li, H. Liu, T. Wang, M. Jiang, S. Wang, K. Li, and X. Zhao, "Safety helmet wearing detection based on image processing and machine learning," pp. 201-205, 2017.

[13] T. Waris, M. Asif, M. B. Ahmad, T. Mahmood, S. Zafar, M. Shah, and A. Ayaz, "CNN-based automatic helmet violation detection of motorcyclists for an intelligent transportation system," Mathematical Problems in Engineering, 2022.

[14] Gaytri, R. Kumar, and U. Rajnikanth, "A Smart Approach to Detect Helmet in Surveillance by Amalgamation of IoT and Machine Learning Principles to Seize a Traffic Offender," in Proceedings of the International Conference on Paradigms of Computing, Communication and Data Sciences: PCCDS 2020, Springer Singapore, 2021, pp. 701-715.

[15] Charran, R. Shree, and Rahul Kumar Dubey. "Two-Wheeler Vehicle Traffic Violations Detection and Automated Ticketing for Indian Road Scenario." IEEE Transactions on Intelligent Transportation Systems 23.11 (2022): 22002-22007.