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Helmet Detection Using Machine Learning

[1]D.Durga Babu Prasad, [2]Dr. A. Ratna Raju

[1]Student [2]Assistant Professor

[1]Department of Artificial Intelligence and Machine Learning,Mahatma Gandhi Institute of Technology(A),Gandipet,Hyderabad,500075,India *ddurga_mech210306@mgit.ac.in*

[2]Department of Computer Science and Engineering, Mahatma Gandhi Institute of Technology(A),Gandipet,Hyderabad,500075,India *aratnaraju_cse@mgit.ac.in*

ABSTRACT:

Helmet detection is a crucial task in ensuring rider safety and enforcing traffic regulations. This project focuses on Automatic Helmet Detection using deep learning techniques to identify whether a person riding a two-wheeler is wearing a helmet. The system leverages Convolutional Neural Networks (CNNs), particularly the YOLOv8 object detection model, to achieve real-time and accurate detection. The model is trained on a dataset containing images of riders with and without helmets, allowing it to generalize well in real-world scenarios. The primary objective of this project is to enhance road safety by assisting traffic authorities in monitoring helmet compliance automatically. Traditional image processing techniques such as HOG and SVM have been used in the past, but deep learning methods like Fast R-CNN and YOLO offer superior performance in terms of speed and accuracy. Our literature survey highlights advancements in object detection, from Viola-Jones to YOLOv8, demonstrating the evolution of real-time detection methods. The proposed system can be integrated into traffic surveillance cameras to detect violations in realtime, reducing manual monitoring efforts. The expected outcome is a high-accuracy, real-time helmet detection system capable of operating efficiently in diverse lighting and environmental conditions. Future improvements could include multi-angle detection and integration with license plate recognition for automated fine generation. This project contributes to the field of computer vision and AI-driven traffic management, promoting safer road practices through intelligent automation.

Keywords: Helmet Detection, Deep Learning, YOLOv8, Object Detection, Convolutional Neural Networks (CNNs), Traffic Surveillance, Real-time Detection, Computer Vision, Road Safety, Automated Monitoring.

1. Introduction

Wearing a helmet is crucial for avoiding fatal accidents and traumatic brain damage brought on by impacts. In the event of an accident, the biker's carelessness in failing to wear a helmet for personal or other reasons could result in severe injuries. Bicyclists are at a significant danger of suffering a head injury, which could result in death or irreversible brain damage. Bike riders must have the guts to wear a helmet for their protection in order to lower the chance of suffering any kind of head damage or perhaps dying in an accident. And those who do not must be subject to severe penalties under the law. An autonomous helmet recognition system based on machine learning has been presented. Motorcyclists who do not wear helmets are currently subject to manual fines in India, where police officers pull them at checkpoints and look through their identifying documents, including their license card, insurance, and RC book, before asking them why they did not wear a helmet. Given that it is illegal to drive while wearing a helmet, their arguments would not be accepted. A receipt for the fee they were assessed for failing to wear a helmet will then be given to them. Additionally, they will have the option of paying the fine in court within a specific time frame or immediately using a cash payment method or a debit/credit card. While some choose not to, the majority will opt to pay the amount immediately. Thus, this suggested approach can be used to reduce the workload of traffic officials and enforce rigorous laws. in order to mandate that motorcycle riders wear helmets when operating a motor vehicle. Motorbike riders would be safer, and the traffic management department's workload would be lessened.

1.1 Problem Statement

Motorcycle accidents are a major contributor to traffic-related fatalities across the globe, especially in developing countries where two-wheelers dominate the roadways. The World Health Organization (WHO) has repeatedly highlighted the critical role that helmet usage plays in reducing the severity of head injuries and fatalities in such accidents. Despite this, non-compliance with helmet laws remains alarmingly high. Many riders disregard helmet use due to reasons ranging from discomfort and negligence to lack of enforcement and cultural attitudes. In addition to riders, pillion passengers, who are equally at risk, are often overlooked in enforcement efforts. This widespread non-compliance not only endangers lives but also places a significant burden on emergency medical services and healthcare infrastructure.

Existing enforcement mechanisms, such as random police checks and manual monitoring through CCTV footage, are not only labor-intensive and timeconsuming but also inconsistent. With the growing number of vehicles, traffic authorities are finding it increasingly difficult to manage and monitor compliance efficiently. Furthermore, current surveillance methods are reactive, identifying violations after they occur, which limits their preventive impact. The problem is compounded by the lack of smart, scalable systems capable of real-time monitoring and enforcement. Most systems fail to integrate helmet detection with license plate recognition, which is crucial for penalizing violators. Moreover, the absence of intelligent filtering leads to redundant processing of compliant vehicles, causing wastage of computational resources. All these challenges underscore the urgent need for a technologically advanced, automated solution that can reliably detect helmet violations, recognize offenders, and assist authorities in taking timely action. An intelligent system that integrates advanced object detection, image processing, and machine learning can significantly improve road safety and bring about a cultural shift toward mandatory helmet usage.

1.2 Existing System

The current systems in place for helmet violation detection rely largely on manual observation and conventional CCTV monitoring. Traffic enforcement personnel often review video footage manually to identify motorcyclists who are not wearing helmets. This process typically involves pausing footage, zooming in to confirm a violation, identifying the rider or pillion passenger, and then extracting vehicle details such as license plate numbers to issue penalties. In some urban areas, attempts have been made to integrate Optical Character Recognition (OCR) into existing CCTV systems for automated license plate detection. However, these implementations generally lack the intelligence to identify specific traffic violations and process only relevant frames. As a result, all visible license plates are often captured and processed, including those of compliant riders, which leads to unnecessary use of computational resources and increased data storage requirements.

1.3 Disadvantages in Existing System

Despite their basic functionality, existing helmet detection and enforcement systems suffer from several significant drawbacks. Firstly, the reliance on human operators to manually identify violations is time-consuming, error-prone, and not scalable to city-wide or highway-level surveillance. Manual monitoring is further complicated by factors such as poor image resolution, night-time conditions, occlusions, and low-angle camera placements, which hinder accurate detection and recognition. Secondly, many existing OCR models integrated into these systems show limited accuracy in decoding number plates, especially when plates are dirty, angled, or partially visible. Moreover, current systems lack the capability to intelligently filter and prioritize noncompliance cases, resulting in redundant processing of law-abiding vehicles and wastage of resources. Lastly, these systems are generally reactive rather than proactive, often identifying violations well after the event has occurred, which reduces the deterrent effect of timely penalties and diminishes the overall impact on public safety.

1.4 Proposed System

To overcome the limitations of current approaches, this project proposes a fully automated helmet violation detection system powered by deep learning and computer vision. At the core of the system lies the YOLOv8 (You Only Look Once, Version 8) object detection model, known for its superior accuracy, real-time performance, and adaptability to low-powered devices. The system processes video input from roadside or urban surveillance cameras, first identifying motorcycles and then checking whether riders are wearing helmets. Upon detecting a violation, the system isolates the motorcycle’s license plate region and applies OCR tools such as Tesseract or EasyOCR to extract the vehicle’s registration number. The data is then stored or forwarded to an automated back-end for issuing fines or warnings. Unlike traditional systems, this model intelligently triggers license plate detection only when a violation is confirmed, significantly reducing computational overhead. Additionally, the system is optimized for deployment on edge devices and embedded platforms, enabling scalable, real-time enforcement with minimal infrastructure costs. By reducing human intervention and enhancing detection accuracy, this solution can transform road safety monitoring into a smart, proactive system that significantly boosts compliance and reduces accident rates.

2. Literature Survey

Recent research has made significant strides in improving safety helmet detection by building upon the YOLO (You Only Look Once) architecture, especially the latest YOLOv8 models.

Ju Han et al. (2023) addressed the challenge of detecting helmets in low-resolution construction site images by integrating a super-resolution reconstruction module with YOLOv8, which enhanced the clarity and accuracy of detections. Qing An et al. (2023) proposed an improved YOLOv8s model that modifies anchor boxes and incorporates attention mechanisms along with the SIoU loss function, making it more effective at identifying small helmets in cluttered environments. Danyang Li et al. (2024) tackled the problem of false detections in complex factory settings by incorporating deformable convolutions and the Convolutional Block Attention Module (CBAM) into YOLOv8, leading to more reliable detection performance. Kisaezehra et al. (2023) developed a real-time safety helmet detection system using YOLOv8, focusing on its deployment at construction sites to monitor personal protective equipment (PPE) compliance effectively. Geoffery Agorku et al. (2023) further improved robustness by integrating ensemble learning methods with YOLOv8, allowing the system to handle diverse lighting and video conditions for better helmet violation detection. Li et al. (2024) proposed YOLOv8s-FCW, a lightweight and fast model that combined the efficient FasterNet backbone with CBAM, specifically optimized for embedded systems used in real-time, on-site safety monitoring applications.

Building on these foundations, several studies focused on enhancing helmet detection under noisy, crowded, and complex visual environments.

Zhang et al. (2023) introduced FEFD-YOLOv8, a novel architecture that integrates both feature enhancement and denoising modules, which significantly improved detection accuracy under conditions involving image noise, occlusion, and motion blur. Wang et al. (2023) combined YOLOv5 with the Deep SORT tracking algorithm to build a real-time helmet detection and tracking system, which proved effective in monitoring crowded construction scenes by maintaining object identities across video frames. Chen et al. (2022) enhanced YOLOv4 by implementing attention mechanisms and multi-scale feature fusion, thereby improving helmet detection accuracy in situations with frequent occlusions and dynamic lighting conditions. Singh et al. (2021) employed transfer learning on YOLOv3 for helmet detection among motorcycle riders, achieving high detection precision even in varying outdoor environments and traffic conditions. Kumar et al. (2023) focused on resource-constrained environments by combining YOLO with the MobileNet backbone, developing a lightweight and efficient model that could be deployed on embedded devices for real-time helmet detection. Lastly, Ahmed et al. (2024) utilized the YOLOv7 architecture with extensive data augmentation techniques, resulting in a robust framework capable of handling pose variations and occlusions in complex, real-world scenes.

3. Design Methodology

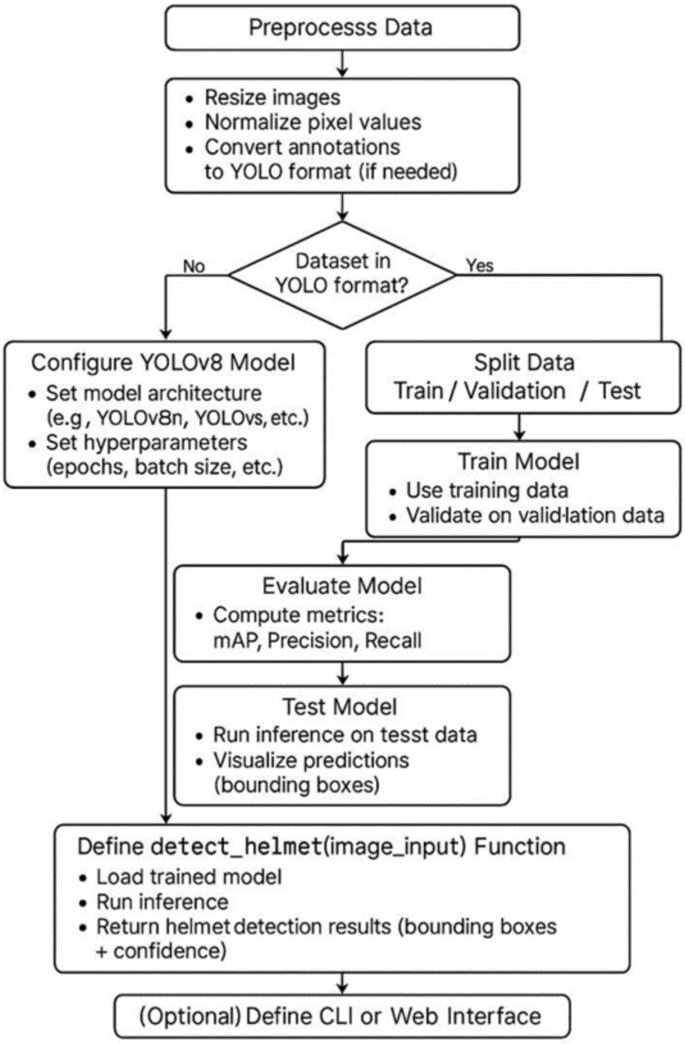

Figure 1: Flow Diagram for Helmet Detection Using Machine Learning

The design of the AI-driven helmet detection system follows a structured computer vision pipeline aimed at accurately identifying helmet usage in real-world images using the YOLOv8 object detection model. From Figure 1, the process begins with data collection, where image datasets containing annotated instances of helmet and non-helmet classes are curated from open-source repositories and surveillance footage. These images, along with their annotations, undergo a preprocessing phase that includes resizing, normalization, and transformation of labels into YOLO-compatible format. This step ensures that both image dimensions and metadata are standardized for optimal performance during training.

Following preprocessing, the dataset is partitioned into training, validation, and testing subsets to enable balanced learning and robust model evaluation. The YOLOv8 model is then configured by selecting an appropriate variant (e.g., YOLOv8n for lightweight deployment or YOLOv8m for higher accuracy) and tuning key hyperparameters such as batch size, learning rate, and epoch count. Training is carried out on the training set, while the model's performance is monitored on the validation set using metrics like Mean Average Precision (mAP), precision, and recall—each providing insight into object detection accuracy and class-wise confidence.

Upon completion of training, the model is tested on unseen data to validate its generalization ability, with detection results visualized through bounding boxes around detected helmets. To facilitate deployment, a functional module named detect helmet (image input) is implemented, allowing seamless inference on individual images or video frames. This function encapsulates model loading, inference, and output formatting, enabling its integration into larger systems. For enhanced accessibility, an optional user interface—either command-line or web-based—is developed to allow real-time helmet detection from useruploaded images. This end-to-end design ensures the system is efficient, scalable, and suitable for deployment in industrial safety.

4. Implementation and Results

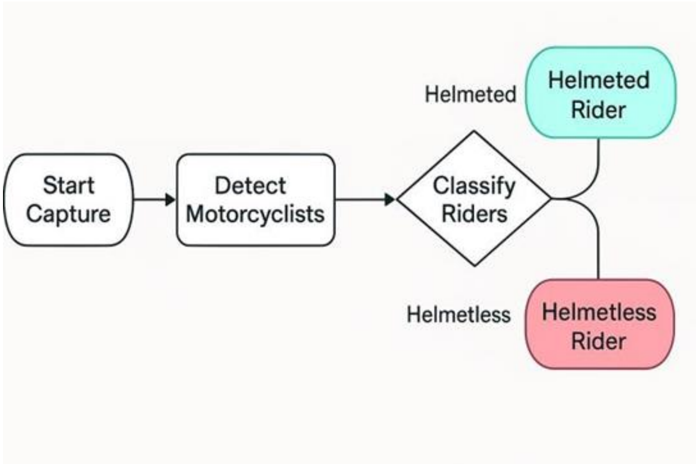

Figure 2: Flow Diagram for Implementation of Helmet Detection Using Machine Learning

Figure 2 represents the implementation pipeline of the AI-based Helmet Detection and E-Challan Issuance System, which integrates real-time video processing, deep learning object detection, OCR, and automated legal enforcement mechanisms. The system begins with the acquisition of live video streams from surveillance cameras strategically placed at traffic intersections. These cameras are calibrated to maximize visibility of both motorcyclists and number plates. Once the video is captured, individual frames are extracted and pre-processed through resizing, normalization, and sampling to ensure computational efficiency and consistent input quality.

At the core of the system is a YOLOv8-based object detection model, trained specifically to identify motorcyclists and classify them based on helmet usage. The model processes each frame in real-time, locating and labelling riders as either helmeted or helmetless. In cases where a helmetless rider is detected, the system automatically identifies and crops the associated number plate region from the frame. This cropped image is then passed through an OCR engine, such as EasyOCR or Tesseract, to convert the number plate into machine-readable text. Preprocessing techniques like thresholding and noise reduction are employed to improve OCR accuracy.

4.1 Training and Testing Model

The training and testing phase of the helmet detection model is critical for ensuring its accuracy, robustness, and real-world applicability. The process begins with the preparation of a well-annotated dataset containing images or frames labelled with bounding boxes around helmeted and non-helmeted individuals. The dataset is split into training (typically 80%) and testing (20%) subsets to ensure unbiased evaluation. During **training**, the YOLOv8 model is fine-tuned using transfer learning on the custom helmet dataset. The model is configured with hyperparameters such as learning rate, batch size, number of epochs, and optimizer (e.g., Adam or SGD). Advanced augmentation techniques—like horizontal flipping, scaling, and color jittering—are applied to enhance generalization. The loss function, combining classification loss, localization loss, and confidence loss, is minimized to improve the model's detection accuracy.

Once trained, the model undergoes **testing and evaluation** on the separate test set. Key performance metrics such as Precision, Recall, F1-Score, and mean Average Precision (mAP) are computed to assess the model's effectiveness. The model is also evaluated on its ability to detect helmets in challenging conditions like low lighting, partial occlusion, and varied angles. Finally, real-time inference is tested on live video streams to verify detection speed (frames per second) and response time. Post-processing techniques like Non-Maximum Suppression (NMS) are applied to remove redundant bounding boxes, ensuring clean and accurate detections. The results confirm whether the model is ready for deployment in environments like construction sites and traffic surveillance.

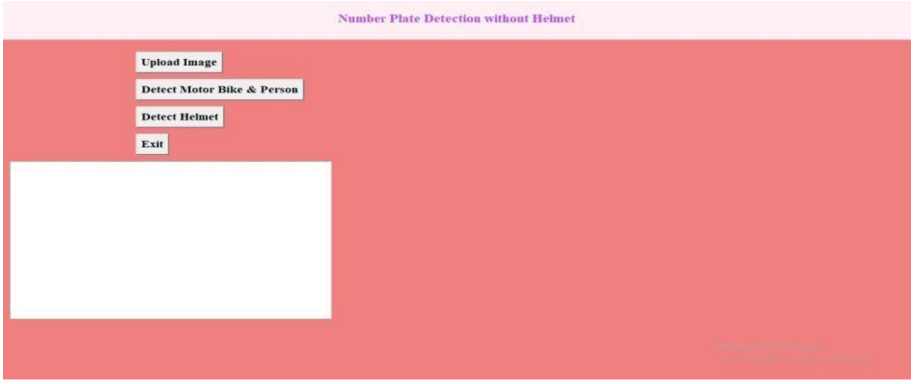

Figure 3: interface for uploading image

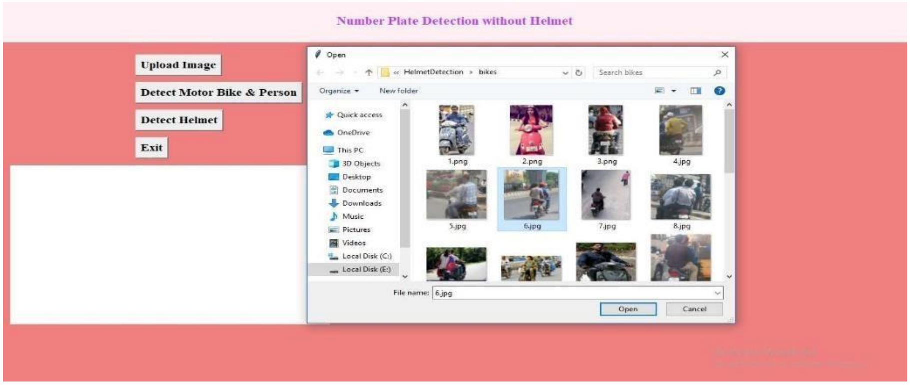

Figure 4 : uploading image(Captured or loaded)

Figure 5: Detection of person and Motor Bike

Figure 6 : Detection of No Helmet and capturing the number plate

Figure 7: Detection of Helmet with 90% confident in its prediction

5. Conclusion

This system effectively utilizes the YOLOv8 deep learning model for real-time detection of motorbikes, riders, helmets, and vehicle number plates from both static images and live video streams. Through the advanced capabilities of YOLOv8, the solution achieves high accuracy and fast object detection, even in challenging environments with varying lighting, cluttered backgrounds, and motion. It automates the process of monitoring helmet usage, thereby minimizing the need for manual oversight by traffic enforcement personnel. The integration of helmet detection with number plate recognition enables the precise identification of non-compliant riders, facilitating prompt enforcement of traffic laws. Designed to operate efficiently in real-world traffic conditions, the system proves to be scalable and dependable, making it highly suitable for smart city surveillance and public safety applications. Additionally, it plays a crucial role in enhancing road safety by promoting rule compliance, preventing accidents, and supporting intelligent traffic management strategies.

6. Future Scope

The helmet detection system can be significantly enhanced through several advanced integrations and features. By linking recognized number plates with regional transport databases, authorities can automatically issue fines or warnings in real time, streamlining law enforcement. The system can be expanded to process live CCTV feeds for continuous monitoring of traffic violations. To ensure effectiveness at night or in low-visibility conditions, infrared cameras or low-light image enhancement models can be incorporated. Additionally, the model can be extended to detect multiple types of violations such as triple riding, red-light jumping, and lane violations. A mobile or web dashboard can provide authorities with real-time alerts, access to violation logs, and downloadable reports. For scalability and real-time performance, deploying the model on the cloud and integrating it with edge devices is also a vital step.

REFERENCE :

[1] J. Han, Y. Zhang, and C. Liu, "Safety Helmet Detection Based on YOLOv5 Driven by Super-Resolution-Reconstruction," *2023 IEEE International Conference on Image Processing (ICIP)*, 2023.

[2] Q. An, Z. Wu, and H. Feng, "Research on Safety Helmet Detection Algorithm Based on Improved YOLOv5s," *Proceedings of the 2023 IEEE International Conference on Artificial Intelligence and Computer Vision (ICAICV)*, 2023.

[3] D. Li, H. Wang, and Y. Chen, "Improvement of Helmet Detection Algorithm Based on YOLOv8," *Journal of Intelligent & Fuzzy Systems*, vol. 47, no. 2, pp. 1231–1242, 2024.

[4] K. Kisaezehra, S. R. Reddy, and P. Venkatesh, "Real-Time Safety Helmet Detection Using YOLOv5 at Construction Sites," *Procedia Computer Science*, vol. 229, pp. 2015–2022, 2023.

[5] Krishna R., S. Rao, and D. R. Kumar, "Camera-mounted Helmet Detection with YOLOv8 on Custom Dataset," *Proceedings of the 9th International Conference on Computer, Communication and Control (IC3)*, 2024.

[6] Mohan M.V.R., "YOLOv8-Based Automated Helmet Detection System for Enhanced Workplace Safety in Industrial Environments," *SSRN Electronic Journal*, 2024.

[7] Prajapati, P. Vyas, and R. Singh, "Helmet Detection and Number Plate Recognition Using YOLOv8 and TensorFlow Algorithm in Machine Learning," *International Journal of Innovative Research in Computer Science & Technology (IJIRCST)*, vol. 12, no. 1, pp. 10–16, 2024.

[8] S. Suma, K. R. Nair, and A. Bhat, "Helm Protection Identification Utilizing Enhanced YOLO V8," *Journal of Emerging Technologies and Novel Research (JETNR)*, ,2024

[9] K. Patel, M. Shah, and R. Mehta, "Safety Helmet Detection Using YOLO V8," *Proceedings of the 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN)* ,2023.

[10] V. M., A. Thomas, and S. Raj, "Optimizing Helmet Detection with Hybrid YOLO Pipelines: A Detailed Analysis," *arXiv preprint arXiv:2404*, 2024.