A Deep Learning-Based System to Detect Triple Riding and Helmet Violations Through CCTV Webcam

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Abstract. The automatic recognition of motorcycle helmets and detection of triple-riding violations in real-time surveillance videos is a growing application in computer science. Deep learning techniques for object detection and classification have gained popularity due to their potential to address surveillance-related challenges. However, existing models face limitations in achieving state-of-the-art results due to low resolution, adverse weather, occlusion, and poor illumination. The critical problem of triple-riding detection remains inadequately addressed. This study proposes a deep learning-based system utilizing the YOLOv8 model for real-time detection of helmet violations and triple-riding infractions using CCTV and webcam footage. While the pre-trained YOLOv8 model is employed for triple riding detection, a custom-trained variant is developed using a dedicated helmet dataset for accurate helmet violation detection. The system processes image and video inputs, generating outputs that visually highlight detected violations. Evaluation metrics such as precision and recall ensure accuracy and reliability. This approach addresses these challenges by leveraging publicly available datasets alongside self-collected data, delivering robust performance. The proposed system represents a significant advancement in automated traffic rule enforcement, contributing to improved road safety and showcasing the potential of deep learning in surveillance applications.

Keywords: YOLOv8, Traffic violations, Real-time detection, Helmet and Triple Riding Violations, CCTV surveillance.

1 Introduction

Road accidents remain a pressing global issue, claiming approximately 1.35 million lives annually and causing injuries to over 50 million individuals, as reported in the World Health Organization's Global Status Report on Road Safety 2018. Among the most vulnerable road users are motorcyclists, cyclists, and pedestrians, who lack structural protection, making them more susceptible to severe injuries. Two-wheelers, although an affordable and convenient mode of transport, pose significant safety risks,

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especially in regions with high traffic density and limited enforcement of road safety regulations. Traffic Rule Violation Monitoring System ensures that the rules are followed strictly and reduces manual effort. The main objective of this work is to identify helmet detection and Triple Riding violations [1].

One of the leading causes of motorcycle-related fatalities is head injury, often resulting from the absence of helmets during accidents. Helmets are proven to reduce the impact of collisions, serving as an effective barrier against brain trauma [2]. Despite the critical role of helmets in mitigating injuries, compliance with helmet-wearing regulations remains low in many countries, particularly in developing nations like India and Pakistan. In these regions, factors such as rapid urbanization, insufficient road safety awareness, and unsafe practices like triple riding further exacerbate the risk of accidents.

Most nations find it essential to enforce road safety regulations but face significant challenges in doing so. Current approaches that involve manual inspections combined with human-monitored video surveillance require excessive time and resources, making them difficult to scale effectively. The implementation of artificial intelligence and deep learning advances represents a viable method to automatically detect safety violations like helmet non-compliance and triple riding in real time [3]. The paper presents an object detection system based on deep learning and YOLOv8 (You Only Look Once version 8) that addresses these challenges. The system under the proposal analyzes live video feeds from both webcams and CCTV cameras to identify motorcyclists riding without helmets and detect triple-riding scenarios. Through automation of monitoring activities, the system eliminates the need for ongoing human involvement while guaranteeing efficient and precise enforcement of road safety regulations.

Existing traffic management infrastructure integration improves both the scalability and cost-effectiveness of the system. The system will automatically send notifications like fines and alerts to individuals who break the rules, which helps ensure that people obey safety regulations while maintaining their accountability [4]. The suggested method has robust functionality in different environmental conditions due to its capacity to respond to changes in lighting, occlusions, and weather. The objective of this research is to reduce the rate of fatalities and injuries in motorcycle accidents by addressing significant safety infringements. The solution creates more intelligent and secure urban spaces through the use of advanced deep learning technologies and intelligent traffic systems and encourages the safe utilization of roads. The following studies could expand to track more traffic violations and boost system functions to create full road safety management solutions.

2 Literature Survey

Helmet Detection Based Vehicle Using Deep Learning. This study proposed a deep learning-based system to ensure vehicle safety by only allowing a vehicle to start if the driver is wearing a helmet. The system detects helmet usage using deep learning algorithms, preventing vehicle operation in the absence of proper safety gear [5]. The approach aims to reduce head injuries and fatalities in two-wheeler accidents by enforcing helmet compliance and promoting safer riding practices.

Helmet Detection Using HOG and SVM. This proposed a helmet detection system combining Histogram of Oriented Gradients (HOG) for feature extraction and Support Vector Machines (SVM) for classification [6]. This system analyzed surveillance footage to detect whether riders were wearing helmets. It achieved 88% classification accuracy with HOG and wavelet transform (WT) features but faced challenges with large-scale datasets and real-time performance with high-resolution videos.

Real-Time Helmet Violation Detection Using YOLOv5 and Ensemble Learning. This study developed a real-time helmet violation detection system using the YOLOv5 deep learning framework combined with ensemble learning techniques [7]. The model was trained on a dataset of 100 videos (10 fps) to detect motorbike riders without helmets. It demonstrated robustness across various lighting and weather conditions, achieving a mean Average Precision (mAP) score of 0.5267 on the AI City Track 5 public leaderboard. The system showed the potential to enhance road safety through automated traffic regulation enforcement.

Triple Riding and No-Helmet Detection. This research introduced a traffic rule violation monitoring system using the YOLO algorithm to detect triple riding and identify helmet usage violations[8]. The system classifies two-wheeler riders based on compliance with traffic regulations. It employs a junction-based data collection approach to improve traffic regulation enforcement and ensure the detection of violations in real time [9].

Automated Helmet Detection and License Plate Recognition Using CNN. This study introduced an automated system for detecting traffic violations, particularly focusing on helmet usage [10]. It used Convolutional Neural Networks (CNNs) for helmet detection and integrated license plate recognition for enforcement. The system processes video inputs for traffic management applications, aiming to improve compliance and safety by automatically identifying non-compliant riders.

3 Existing System

Conventional traffic monitoring systems predominantly depend on manual intervention, requiring traffic personnel to either observe CCTV footage or be physically stationed at checkpoints to detect and address violations. Although some automated solutions are available, these systems often focus on basic object detection and lack the advanced capabilities needed for specific violations such as helmet usage and triple riding. In addition, currently, existing systems have problems with regard to real-life situations such as:

Unsuccessful Real-time Detection. Factors like images or videos are not processed in real-time, leading to delays in detecting infringements, if any exist.

High False Positive and False Negative Rates. Misclassified non-riders and irrelevant objects, referred to as motorcyclists, result in frequent misclassification.
Limited Angle Coverage. Primarily, the effectiveness of the system is lower because of difficulties in recognizing riders who are not in the vertical frontal or sideways perspectives.
Irregular Detection of Moving Subjects: Inconsistency in the detection of moving objects leads to difficulty tracking moving targets in the video streams, thereby resulting in unclear and thin outputs. These all clearly underline the need for a more advanced and agile system specifically designed to tackle more sophisticated issues in real-time traffic violation detection under highly complex and dynamic situations.

4 Proposed System

The system is built on deep learning technologies and seeks to solve existing gaps in functionality. This system uses the YOLOV8 model for real-time detection of helmet violations. The system's main attributes are:

Triple Riding Violation Detection. The triple riding detection task is solved using a fine-tuning trained YOLOv8 model.
Helmet Violation Detection. The model which identifies riders without helmets is trained on a custom helmet dataset.
Performance Metrics. The use of precision and recall graphs is important for the evaluation of the accuracy and reliability of helmet violation detection.
The system takes in image data as input and generates output in the form of marked images and or videos showing the identified violations. This system tries to automate as much of the detection process as possible to minimize the need for manual effort, increase the efficiency of enforcement activities, and increase compliance with traffic laws. With new approaches to deep learning, even very difficult situations can be dealt with, making it a versatile solution for contemporary traffic control.

5 Project Methodology

The methodology for the proposed system involves the following steps:

Data Collection. Collect images from CCTV webcams in various real-world traffic scenarios. Compile a dataset for helmet violation detection, including labeled images of riders with and without helmets.
Data Preprocessing. Annotate the dataset with bounding boxes indicating helmets and riders. Normalize and augment the data to improve model robustness, including techniques like rotation, scaling, and brightness adjustments.
Model Training. Use a pre-trained YOLOv8 model for triple-riding detection. Fine-tune the YOLOv8 model on the helmet dataset to detect helmet violations. Implement

transfer learning to leverage existing knowledge from the pre-trained model for improved performance on helmet data.

Model Evaluation. Evaluate the trained models using metrics such as precision, recall, and F1-score. Analyse precision-recall curves to understand model performance under different thresholds.

System Deployment. Integrate the trained YOLOv8 models into a real-time detection pipeline. Process live images from CCTV webcams to identify and highlight violations. Output images with detected violations highlighted for review.

Performance Monitoring and Optimization. Continuously monitor system performance in real-world scenarios. Update the model with additional training data as needed to improve accuracy and adapt to new conditions.

This systematic approach ensures a robust, scalable, and efficient solution for detecting helmet and triple-riding violations, enhancing traffic safety and enforcement capabilities.

6 Architecture of YOLOV8

YOLOv8, the latest iteration of the" You Only Look Once" object detection algorithm, represents a significant advancement in real-time computer vision. By blending innovative neural network architectures and optimization techniques, YOLOv8 achieves superior performance in object detection, classification, and segmentation tasks.

6.1 Backbone

Purpose. Extracts essential features from the input image.

Technology. The backbone utilizes a modified version of CSPDarknet53 to efficiently extract multi-scale features. The use of CSPNet enhances computation efficiency by splitting the feature maps, enabling parallel processing.

6.2 Neck

Purpose. Combines features from various stages of the backbone to improve object detection capabilities.

Technology. Employs a Path Aggregation Network (PANet) to enhance feature fusion, which helps improve object detection across various scales by effectively aggregating both fine-grained and semantic features.

6.3 Head

Purpose: Estimates class probabilities, bounding boxes, and object confidence scores.

Technology: The head employs an anchor-free mechanism, which streamlines the detection process by eliminating the use of pre-defined anchor boxes. This enhances model generalization and computation during training and inference.

6.4 YOLOv8 Key Innovations

YOLOv8 encompasses numerous improvements and is an efficient and general-purpose object detection framework. The innovations are

Anchor-Free Prediction. Does away with the usage of anchor boxes, simplifying training and inference.
Dynamic Input Resizing. Makes it more robust by training on images of different resolutions, making the model robust to different input sizes.
Modular Design. Allows support for multiple tasks, like detection, classification, and segmentation, using task-specific prediction heads optimized for the specific task.
Transfer Learning Support. Allows adaptation to some custom data sets by fine-tuning pre-trained weights for better performance on specialist data.
Lightweight Architecture. Built to be very efficient for application in real-time with minimal computational resources while being very accurate.

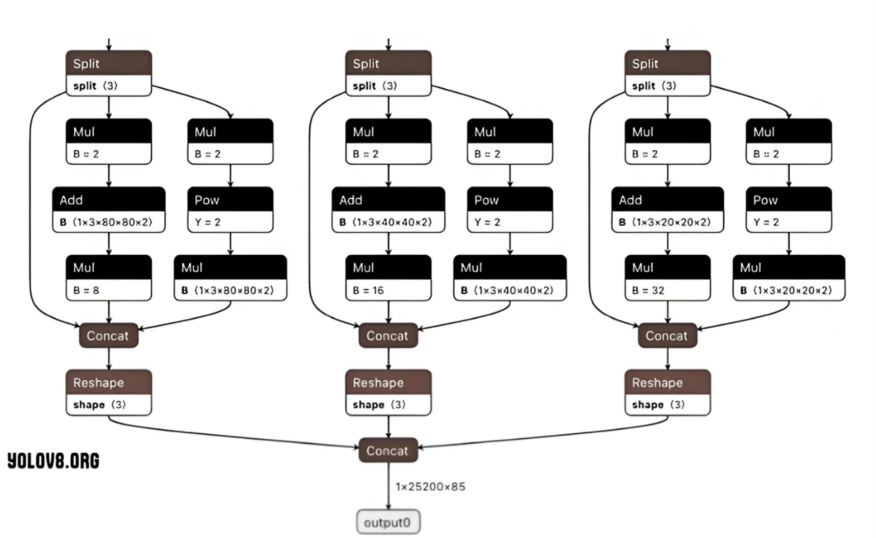

Fig. 1. YOLOv8 Framework Operation

6.5 Key Advantages of YOLOv8

YOLOv8 offers several benefits that render it an effective tool for real-time object detection:

Real-Time Performance. Equipped with high-speed processing, rendering it perfect for live use like traffic monitoring.
Accuracy. Better feature extraction and detection algorithms enhance precision and recall, offering accurate results even under difficult conditions.

Flexibility. YOLOv8 is compatible with diverse datasets and tasks, with the ability to provide customization for specialized applications like detection, classification, and segmentation.

These high-end features make YOLOv8 a state-of-the-art solution for complex object detection problems, such as helmet and triple-riding violation detection in traffic monitoring systems.

7 Workflow

From Fig. 2, the workflow represents that deep learning models were employed to detect violations regarding helmet usage and triple-riding practices. The process started with acquiring the Helmet Dataset as the primary input. A pre-trained YOLOv8 model was utilized to detect the triple riding violation depending on its power in object detection. In parallel, another model, a custom-trained YOLOv8 model, can be customized to detect the usage of a helmet accurately. Once this is done, the process moves to input, normally real-time or pre-recorded videos/images. The next step consists of the pre-processing stages to make data suitable for using detection models. The developed models for helmet detection and triple-riding violations will be applied to pre-processed data for the purpose of analysis. The output of the system could present a number of violations concerning riders without helmets or cases of triple riding. This factory-like workflow provides for an orderly and efficient pipeline to automate the detection of road safety violations, thereby supporting and enforcing road traffic laws while enhancing compliance with road safety.

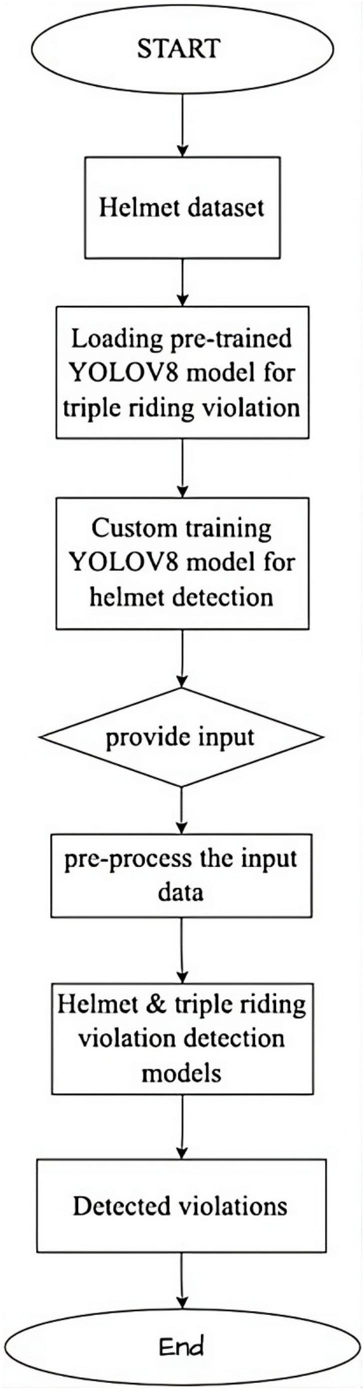

Fig. 2. Workflow Design

8 Results And Analysis

8.1 Graphical Representation

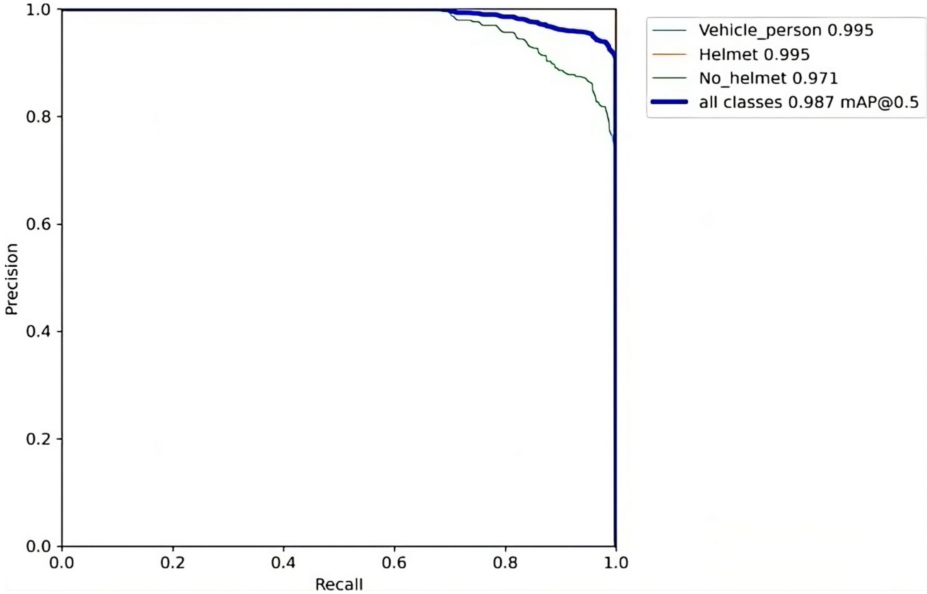

Fig. 3. Precision-Recall Curve

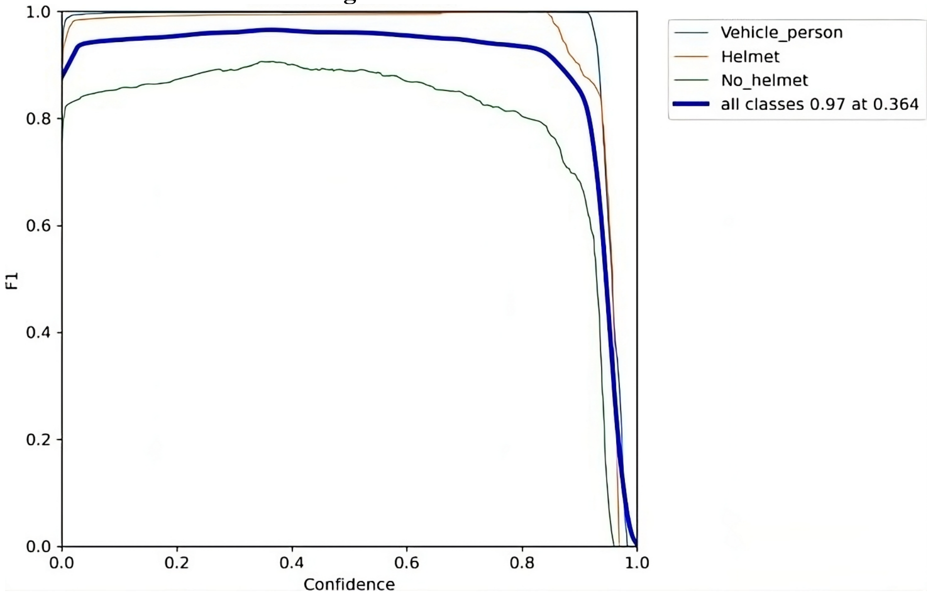

Fig. 4. F1 – Confidence Curve

8.2 Detection Results

This proposed system is very effective for real-time detection of traffic violations as it focuses mainly on the use of helmets and offenses with regard to triple-riding. Being based on the YOLOv8 model, the system has been able to detect various types of violations in real-time under different scenarios quite reliably. Indeed, it can detect vital parameters such as whether a person is wearing a helmet or not and whether triple riding is taking place by displaying the bounding boxes and confidence with the mentioned RGB colors. The following sections will show the model's detection capabilities.

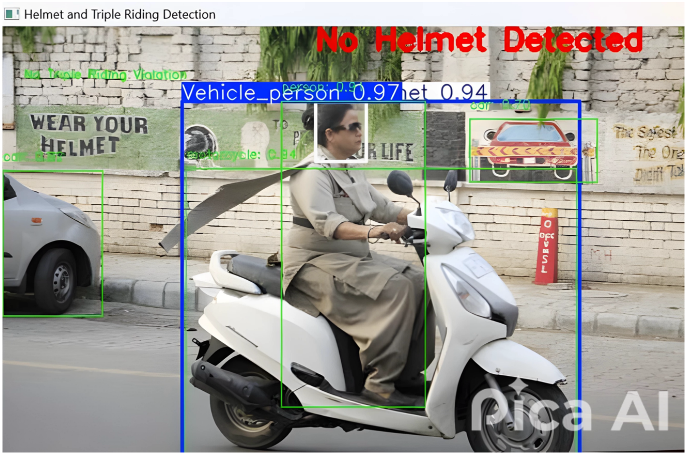

Fig. 5. Helmet Violation Detected

Fig. 6. No Helmet Violation Detected

Fig. 7. Triple Riding Violation Detected

Fig. 8. No Triple Riding Violation Detected

9 Conclusion

In this paper, we have described a particular application of deep learning for the real-time detection of wearing helmets and the violation of triple-riding. For this purpose, the pre-trained YOLOv8 model was used to identify triple riding, and an identification-specific model was trained for helmet violation detection. The technology facilitates the identification of traffic offenses by employing a pre-trained YOLOv8 model for triple-riding detection and training custom algorithms for helmet violation detection without human moderation, thus reducing the need for human supervision. The approach provides a solution to the problems faced by traditional monitoring systems, embracing human error, resource constraints, and the heavy-handed approach to enforcement. Performance outcomes of the system are monitored constantly to affirm the precision and authenticity of the model in actual working conditions. The flexibility in processing image inputs gives the model agility to be deployed in various surveillance scenarios, thus serving as a robust solution for traffic safety enforcement. Such an automated traffic law enforcement model enhances compliance with rules set because there is knowledge that someone is always watching. This results in a drastic reduction in motor vehicle crashes and fatalities.

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