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Automatic Helmet Violation Detection Using Deep Learning Techniques

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Abstract - *In India, most people prefer two-wheeler vehicles as their primary mode of transportation. It is a common form in India. This usually leads to road accidents because of not wearing helmets. In developed cities, the digital system has been used to detect non-helmet riders. Often, this reduces the number of road accidents and the rate of death. But still, in India, there are many cities, even though all rules are followed. Some of the people are not wearing helmets and following the rules. To overcome this, helmet violations have been detected using CCTV surveillance cameras and machine learning models, including deep learning object detection models. This has reduced the rate of accidents and the rate of death. 44.5% of two-wheelers, 74,897 people were killed due to this reason. In order to resolve this problem we have developed a model that is having accuracy 95.3, the model is trained on open source dataset, and used yolov8 for model training and integrated cub am for more accurate results even in low light conditions.*

Key Words: Helmet Violation Detection, Deep Learning, YOLOv8, CBAM (Convolutional Block Attention Module), Object Detection, Number Plate Recognition (OCR), CNN (Convolutional Neural Network), CCTV Surveillance, E-challah Automation, Twilit Messaging, India Traffic Safety, Performance Evaluation (Accuracy, Precision, Recall, map), Dataset Annotation and Augmentation, Smart City Deployment.

1. INTRODUCTION

Traffic accidents are happening and leading to death, especially among two-wheelers, who are highly involved in this. The two-wheeler riders are getting injured due to not wearing a helmet, which causes death worldwide. In India, over the past 10 years, non-compliance has remained a significant issue, contributing to an increased number of road accidents. Approximately 30% of total deaths on roads were caused by helmet-violating riders. [1]

To overcome this issue, digital informants have been undertaken in India. The use of technologies like CCTV cameras and artificial intelligence systems [2] automatically identifies and finds violations. In this paper, we are going to frame one solution for this. Nowadays, with the improved technologies, helmet violations are decreased using machine learning models like **YOLOv8, OCR** for Number plate Recognition, and Twilio for message alert. **You Only Look Once** is the most popular object detection model in machine learning and deep learning. [3] Over the past five years, the effectiveness of machine learning in CCTV has become more efficient. Various research papers and studies show that high.

Accuracy of detecting violations using deep learning technologies, such as CNN, i.e., Computational Neural Network, typically ranges from over 90% to 98.56% in controlled experiments.[5] The impact of ML in this is enabling automated detection and the generation of each CNN and notification, which is faster than manual monitoring. The World Health Organization data indicates a reduction in the rate of death by 42% and severe head injuries by up to 69%. This system contributes to a reduction in the deaths or injuries of life. The development of real-time solutions can reduce the number of deaths and injuries.

1.1 EXISTING SYSTEM

The existing system for monitoring helmet violations mainly relies on manual surveillance by traffic police and basic CCTV monitoring, which is time-consuming, labor-intensive, and prone to human errors. In many cases, enforcement is limited due to high traffic density, lack of continuous monitoring, and difficulty in identifying violators accurately. Some automated approaches use simple image processing or traditional machine learning techniques, but they often fail under low-light conditions, motion blur, and complex backgrounds, and usually lack seamless integration with number plate recognition and automated e-challah generation. As a result, the existing system is inefficient, less scalable, and unable to provide real-time, end-to-end enforcement of helmet safety rules.

1.2 PROPOSED SYSTEM

We developed our system using a Convolutional Neural Network (CNN) and the YOLOv8 model for object detection. This paper outlines the system's development through a structured, step-by-step methodology.

- The first step is Data Acquisition. We collected the datasets from open-source platforms such as Kaggle and Robot flow. We gathered around 1,000–1500 images and manually annotated them to create a well-structured dataset with the class label, with helmet, without helmet, rider, and number plate suitable for model training.

- The second step is Data Pre-processing. We performed data augmentation and normalization. Augmentation techniques like rotation, color adjustments, and scaling increased dataset variability. This improved the model's ability to generalize. Normalization ensured all images used consistent format during training

- The third step focuses on Helmet Detection. For this, we utilized YOLOv8, integrated with the **CBAM** (Convolutional Block Attention Module), to enhance the model's ability to focus on relevant visual features in low-light conditions. (Wu et al., 2025) This combination helped in accurately detecting whether a rider is wearing a helmet.

- The fourth step is Violation Logic and License Plate Recognition. The system applies a binary logic where '0' indicates the rider is not wearing a helmet and '1' indicates they are wearing one. Once a violation is detected, OCR is used to read the license plate number and extract it. Following this, the system will automatically initiate an e-challan generation process, and Twilio will be used to send alert notifications to the registered mobile number.

- The fifth step is performance evaluation. We evaluated the model using standard metrics such as accuracy, precision, recall, and mean average precision (mAP) to measure how effectively the system performs. (Evaluation of YOLOv8 Model for Object Detection, 2024).

- The sixth step involves classification using a **YOLOv8 with CBAM.** The attention mechanism in CBAM enhances feature extraction and improves classification performance.

- The final step is a detailed performance review. This includes accuracy graphs, confusion matrices, precision–recall curves, and other visual performance indicators to highlight the strengths and limitations of the system.

1.3 OBJECTIVES

- To develop a deep learning-based system using YOLOv8 to detect riders, helmets, and number plates in real-time traffic footage.
- To integrate CBAM for fine-grained classification of helmet usage (with/without helmet) and apply OCR for automatic number plate recognition to ensure reliable identification of violators.
- To implement a digital challan system that automatically records violations, stores evidence, and generates penalty notices integrated with a backend database for traffic management authorities.

2. LITERATURE SURVEY

Traditional traffic management was both labor-intensive and subject to human error, especially with high traffic problems. Adequate, the inadequacies of such a more automatic system that could resolve the problem. Advances in deep learning: Earlier systems for helmet prediction focused more on basic image processing, and classic machine learning models like SVM or KNN classifiers were limited to only low generalization to detect multiple persons. This improves the accuracy of detecting violations. Models like YOLO detect objects in machine learning. These models identify riders and violators in crowded scenes. The rate of accuracy of this model was above 90%. The early detection methods used by vision sensors, puzzle logic, and classical image processing could detect vehicles and riders but had slow processing and low real-time accuracy; hence, the machine learning approaches are used for automatic systems. This improves the detection accuracy.

In the year 2024, than extended the application by integrating yellow v11 with H, completing both helmet detection and number plate recognition in real time. The system efficiently minimizes the latency and bandwidth consumption, making it ideal for deployment in Smart City environments. Saravanan and Rajini, in their 2024 paper, present a three-stage automatic helmet violation detection system incorporating a mass area cylinder for segmentation and classification, like rest net and Dense, which are deep neural networks that improve the accuracy of detection.

This approach provided the most structured pipeline with the existing traffic monitoring system. This research studies collectively demonstrate the availability of use using of deep learning for helmet detection in the handling wearing angles motion blur and diverse traffic environments the current research aims to build on this foundations by developing a robust and integrity system that not only detects helmet while it is but also identify them the real license in real time together these studies underscore the shift towards more accurate and real time detection system. The current research 6 to address these limitations by developing a deep learning based solution
that integrates helmet detection with real-time number plate recognition.

Table-1: Literature Survey

Title	Authors	Methodology	Research Gap
Enhancing Helmet Violation Detection and License Plate Recognition through Optimization of YOLOv8 Models with Edge Computing Integration	H.D.N. Thanh (2024)	Optimized YOLOv8 model deployed with edge computing for real-time helmet detection and number plate recognition.	Lack of integration with automated e-challan systems and limited evaluation for Indian traffic conditions.
Comprehensive Study on the Development of an Automatic Helmet Violator Detection System (AHVDS)	M. Saravanan & G. K. Rajini (2024)	Multi-stage deep learning framework using CNN-based classifiers and structured detection pipeline.	Real-time performance optimization and SMS-based challan automation not addressed.
Real-Time Multi-Class Helmet Violation Detection Using Few-Shot Data Sampling Technique and YOLOv8	A. Aboah et al. (2023)	YOLOv8 with few-shot learning for detecting helmet and non-helmet classes in real time.	Performance degrades in dense traffic and low-light CCTV environments.
Algorithm of Helmet Wearing Detection Based on AT-YOLO Deep Model	Zhou Q. et al. (2021)	Attention-based YOLO (AT-YOLO) model to enhance helmet detection accuracy.	Tested mainly on controlled datasets with limited real-world robustness.
Helmet Use Detection of Tracked Motorcycles Using CNN-Based Multi-Task Learning	H. Lin et al. (2020)	CNN-based multi-task learning for tracking motorcycles and detecting helmet usage.	High computational cost and poor scalability for real-time urban surveillance.

3. SYSTEM REQUIREMENTS AND SPECIFICATION

The proposed system requires a standard laptop or desktop computer with sufficient processing power to handle real-time video analysis, preferably with at least 8 GB of RAM and an optional NVIDIA GPU to speed up model training and inference. It operates using the Python programming language and leverages advanced deep learning technologies such as YOLOv8 integrated with the CBAM attention module to accurately detect helmet and non-helmet riders from CCTV or recorded video feeds. Open CV is used for video processing, while Easy OCR or Teaser act is employed to extract vehicle number plate details from detected violations. To complete the enforcement workflow, the system integrates the Twilio API to automatically generate and send e-challan notifications via SMS. The overall design emphasizes high accuracy, real-time responsiveness, scalability for smart city deployment, and reliable performance across different lighting and traffic conditions, while remaining easy to maintain and upgrade as technology evolves.

4. IMPLEMENTATION

The implementation of the project starts with **collecting and annotating a diverse dataset** of traffic images, labeling helmets, non-helmet riders, riders, and number plates. These images are then **preprocessed and augmented** to make the model more robust to real-world variations. Next, the YOLOv8 model is trained and enhanced with the **CBAM attention module** to improve its focus on relevant regions, especially in low-light and cluttered scenes. Once the detection model is ready, it is integrated into a **real-time pipeline** that reads frames from CCTV or video files, runs detection, and flags violations. For every non-helmet rider detected, the corresponding number plate region is cropped and passed to **EasyOCR**, which extracts the text. This information is then used to **auto-generate an e-challan**, and the details are sent as an SMS to the vehicle owner using the **Twilio API**. Finally, the entire system is thoroughly tested using metrics like accuracy, precision, recall, and mAP to validate its performance before considering deployment.

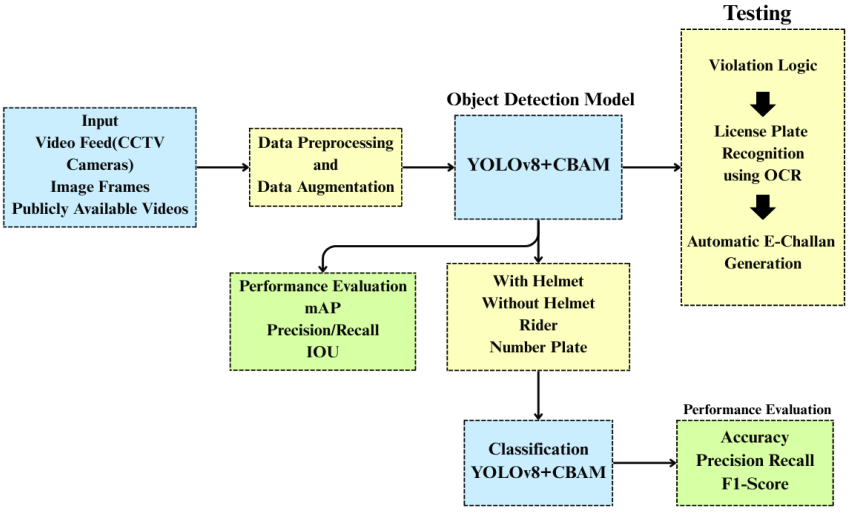

Fig-1: System Design

5. RESULTS AND EVALUATION

In this section, we will go through all the details of the experiments conducted to contribute to this work.

I. Experimental Details

Here, we have used Kaggle and Robo flow datasets. Starting learning it is 0.001429, and in each training, 20 epochs contain 300 iterations. In order to get better results, various experiments have been performed. We have changed the batch size, epoch size, and network optimizer to increase the system accuracy. For this work, we have used the most popular

Optimizer called ADAM(adaptive moment estimation) optimizer and Root mean square propagation. The training batches are set to 16.

Table-2: Training Deails

Number of epochs	20
Batch size	16
Training set	50%
Testing set	25%
Validating set	25%
Optimizer	ADAM
Activation function	ReLU

II. Evaluation Matrices:

In order to study the effectiveness of our proposed system, the different evaluation metrics have been considered. We tested our model's performance using different measures like Precision-recall, F1-score, precision, and accuracy. The evaluation metrics can be calculated as,

- $F1 = 2 * (Precision\ \ Recall)/(Precision + Recall)$
- Precision = (TP)/(TP+FP)
- Recall = (TP)/(TP+FN)

Where,

- TP = True Positives,
- FP = False Positives and
- FN = False Negatives

III. Detection Results

Table-3: Observed Result

Batch Size	16
Imgsz	640
Optimizer	Adam , SGD
Momentum	0.947
Weight_decay	0.0005

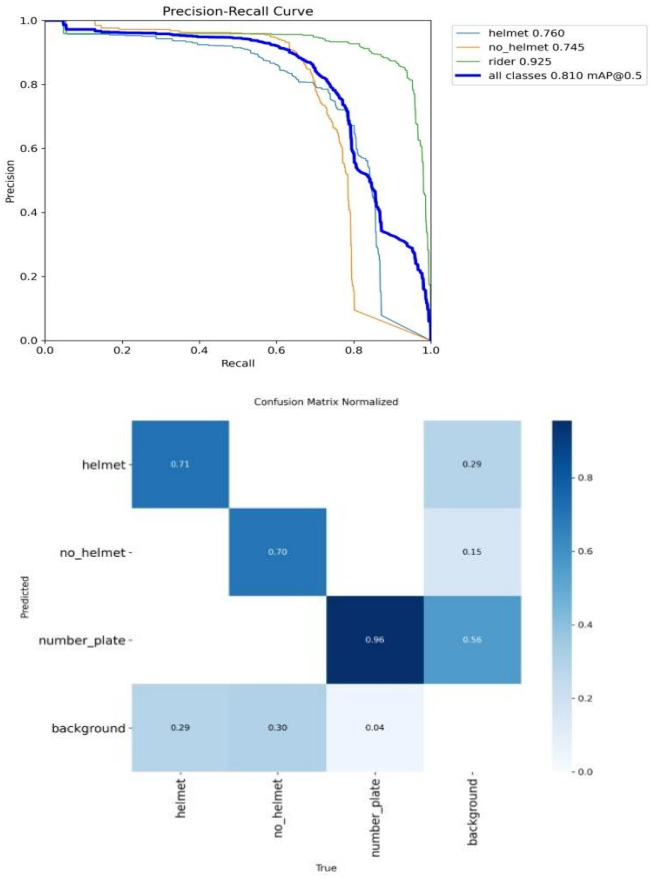

Fig-2: Confusion Matrix

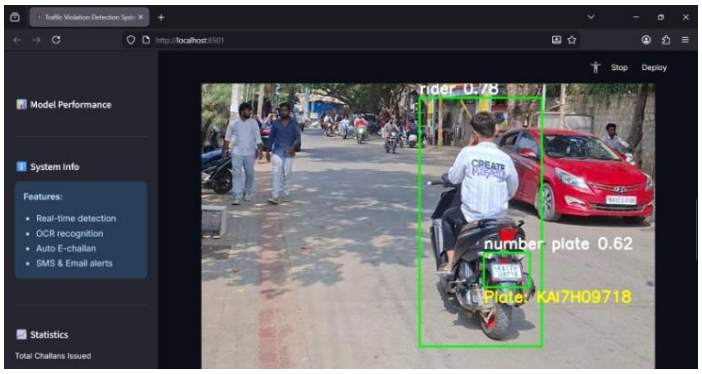

Fig-3: Detected Results

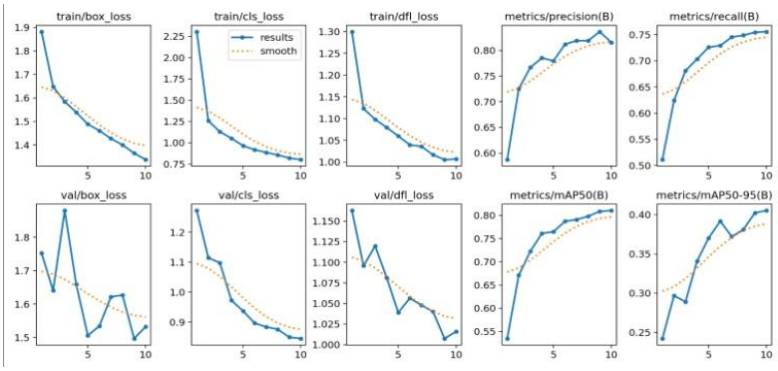

Fig-4: Training Result

6. DISCUSSION

From the literature survey, it is observed that recent research increasingly focuses on deep learning–based approaches such as YOLO and CNN models for helmet violation detection. While these methods achieve good accuracy in controlled environments, many existing systems face challenges in low-light conditions, dense traffic, and real-time deployment. Moreover, most studies primarily address detection alone and lack a fully automated end-to-end framework that integrates number plate recognition, challan generation, and user notification. These limitations highlight the need for a robust, integrated solution, which motivates the proposed system using YOLOv8 with CBAM and automated e-challan generation.

7. CONCLUSION

The proposed system successfully integrates deep learning-based object detection (YOLOv8 with CBAM) and OCR for real-time automatic helmet violation detection we achieved 95.3% of accuracy and number plate recognition using CCTV surveillance in Indian cities. By leveraging annotated datasets, data augmentation, and advanced neural network architectures, the solution achieves high accuracy in identifying violators and automates the e-challan process via SMS alerts, contributing to enhance road safety and reduced fatalities among two-wheeler riders.

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