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SafeRide AI: Helmet and Number Plate Detection

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Abstract: The rapid increase in two-wheeler usage has led to a significant rise in traffic accidents, many of which result in fatalities due to the non-compliance of safety regulations such as wearing helmets. This paper presents the design and implementation of SafeRide AI, a real-time computer vision framework designed to automate the detection of motorcyclists not wearing helmets and the subsequent extraction of their vehicle license plate numbers. By leveraging the YOLOv8 (You Only Look Once) architecture for high-speed object detection and EasyOCR for robust Optical Character Recognition (OCR), SafeRide AI provides a seamless, end-to-end pipeline for traffic enforcement. The system utilizes a specialized dataset to distinguish between "with helmet" and "without helmet" classes while simultaneously locating number plates. A sophisticated association logic is implemented to link violations directly to the corresponding vehicle identifiers. Experimental results indicate that our implementation achieves a high Mean Average Precision (mAP) for detection while maintaining real-time processing speeds of up to 30 frames per second on standard GPU hardware. This research contributes a scalable solution for urban traffic monitoring and the promotion of road safety standards through automated AI intervention.
Keywords: YOLOv8, Computer Vision, Deep Learning, Helmet Detection, OCR, Traffic Compliance, Automated Surveillance, EasyOCR.

I. INTRODUCTION

Road traffic safety is a critical global concern, with motorcyclists being among the most vulnerable road users. Statistics indicate that a large percentage of fatal road accidents involve two-wheelers, where the primary cause of death is severe head injury due to the absence of protective headgear. Despite stringent traffic laws, manual monitoring of every intersection is labor-intensive and prone to human error, specially in densely populated urban environments.

The emergence of Deep Learning (DL) and Computer Vision (CV) offers a paradigm shift in traffic management. Automated systems can monitor traffic feeds 24/7 without fatigue, identifying violations in milliseconds. However, the technical challenge lies in achieving both high accuracy (mAP) and high speed (real-time processing) while handling varying lighting conditions, camera angles, and occlusions.

SafeRide AI addresses these challenges by integrating a specialized YOLOv8 model with a multi-stage association and recognition pipeline. Unlike traditional systems that focus solely on detection, SafeRide AI bridges the gap between violation identification and violator identification by extracting license plate text in the same processing loop. This research details the architectural blueprint, the technical orchestration of model weights, and the development of a user-centric dashboard using Streamlit to democratize access to advanced traffic analytics.

II. LITERATURE REVIEW

A. Evolution of Object Detection Models

The field of object detection has evolved from traditional feature extraction methods like Haar Cascades and HOG to modern deep learning architectures. The introduction of R-CNN and its variants (Fast R-CNN, Faster R-CNN) brought high accuracy but suffered from slow processing speeds. The "You Only Look Once" (YOLO) series revolutionized the field by framing detection as a single regression problem, enabling real-time performance without sacrificing significant accuracy. The latest iteration, YOLOv8 by Ultralytics, provides state-of-the-art performance in both speed and precision, making it ideal for high-speed traffic surveillance.

B. Helmet Detection and Safety Compliance

Previous research in helmet detection often utilized smaller models like YOLOv3 or YOLOv5. While effective in controlled environments, these models often struggled with "Rider-Helmet" association in crowded scenes. Recent studies have emphasized the importance of detecting the "Rider" as a parent object and the "Helmet" or "Number Plate" as child attributes to ensure correct logical mapping—a strategy implemented in SafeRide AI.

C. Optical Character Recognition (OCR) in Traffic

Automated License Plate Recognition (ALPR) systems have traditionally relied on Tesseract OCR or specialized proprietary engines. However, EasyOCR, based on a combination of CRAFT (Character Region Awareness for Text Detection) and CRNN (Convolutional Recurrent Neural Network), has shown superior performance in handling non-standard fonts and noisy backgrounds typical of outdoor traffic environments.

D. Identified Research Gaps

Most existing solutions are fragmented; they either detect the helmet violation or recognize the number plate, but rarely perform both synchronously with high fidelity. Furthermore, many systems lack a deployment-ready interface for law enforcement. SafeRide AI fills this gap by providing an end-to-end framework—from raw video input to a structured violation log including identified plate text.

III. METHODOLOGY

The development of SafeRide AI followed a rigorous design-based research methodology, focusing on the synergy between object detection accuracy and system throughput.

A. Dataset Preparation and Model Training

The core of the system is a specialized YOLOv8 detection model. The training process involved:

- Data Collection: Gathering thousands of images of motorcycles in various traffic scenarios.
- Annotation: Labeling objects into four distinct classes: rider, with helmet, without helmet, and number plate.
- Optimization: Using a pre-trained yolov8n.pt base and fine-tuning it (Transfer Learning) on the traffic dataset for over 50 epochs to generate the best.pt weights.

B. The Orchestration Pipeline

SafeRide AI employs a Sequential Association Pipeline:

- Stage 1: Multi-Object Detection: The frame is processed by YOLOv8 to identify all riders, helmets, and plates.
- Stage 2: Spatial Association: The system checks the spatial coordinates of "without helmet" and "number plate" boxes against the "rider" bounding box. If a "without helmet" object is within the rider's vertical proximity, a violation is flagged.
- Stage 3: OCR Extraction: Once a violation is confirmed, the specific "number plate" region is cropped.
- Stage 4: Text Refinement: The crop undergoes preprocessing (grayscale, bilateral filtering, and Otsu thresholding) before being passed to EasyOCR.

C. Interface Synthesis

A responsive web dashboard was built using Streamlit. This allows users to:

- Upload individual images for deep analysis.
- Process real-time video streams or pre-recorded clips.
- Adjust confidence thresholds dynamically to minimize false positives in noisy environments.

IV. PROPOSED SYSTEM DESIGN

A. Architectural Overview

SafeRide AI uses a modular architecture comprising a Frontend Client, a Neural Core, and an OCR Engine.

- Frontend (UI/UX): Built with Streamlit and CSS, providing an interactive environment for users.
- Neural Core (Detection): Powered by Ultralytics YOLOv8, loaded on NVIDIA CUDA when available for GPU acceleration.
- OCR Engine (Recognition): Driven by EasyOCR, handling the translation of visual patterns into alphanumeric strings.

B. Technology Stack

- Language: Python 3.10+
- Deep Learning: Ultralytics (YOLOv8), PyTorch.
- Computer Vision: OpenCV (cv2), cvzone (for visualization).
- OCR Implementation: EasyOCR (Enabling stable character detection on Windows/Linux).
- Web Framework: Streamlit (for rapid deployment and interactive dashboards).

V. RESULTS AND DISCUSSION

A. *Comparative Performance Analysis*

SafeRide AI was evaluated against manual checkpoint monitoring and older YOLOv5 implementations.

Metric	Manual Monitoring	YOLOv5 Baseline	SafeRide AI (YOLOv8)
Detection Speed (FPS)	1 Frame/sec	18 - 22 FPS	28 - 35 FPS
Detection Accuracy (mAP)	High (Human)	78.5%	89.2%
Violator Traceability	Low (Paper-based)	Moderate (Manual OCR)	High (Auto OCR)

B. *Qualitative Evaluation*

The system demonstrated exceptional performance in complex scenes. The specialized training allowed the model to detect helmets even in blurred, high-speed motorcycle passes.

- Helmet Status: Correctly identified "without helmet" even with low-quality head coverings or turbans correctly excluded.
- Number Plate Precision: The OCR refinement stage (using bilateral filters) significantly improved character recognition for dust-covered or slightly tilted plates.

C. *Deployment Feasibility*

The use of **Streamlit** allowed for a lightweight deployment that doesn't require a dedicated server-side GPU for small-scale operations (CPU-only mode is supported), although a CUDA-enabled GPU is recommended for real-time intersection monitoring.

VI. CONCLUSION

SafeRide AI successfully demonstrates the viability of utilizing state-of-the-art computer vision to enhance public safety. By consolidating object detection and OCR into a unified, real-time pipeline, the platform effectively automates the enforcement of helmet compliance. The implementation of YOLOv8 ensures that the system is both fast enough for live traffic and accurate enough for legal accountability.

A. *Future Scope*

1) Automatic E-Challan Integration: Connecting the OCR output directly to regional transport databases to automate fine generation.
2) Night-Vision Optimization: Implementing thermal or infrared-tuned model weights for 24-hour monitoring.

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