



# HELMET PROTECTION DETECTION SYSTEM USING YOLOV8 FOR REAL-TIME TRAFFIC SAFETY MONITORING

Ramya Patani<sup>1</sup>, Dr. Darapu Uma<sup>2</sup>

M.Tech Student, CSE Department, Pragati Engineering College (A), Surampalem, A.P., India<sup>1</sup>

Associate Professor, CSE Department, Pragati Engineering College (A), Surampalem, A.P., India<sup>2</sup>

**Abstract:** Road traffic accidents involving two-wheelers result in significant fatalities, with head injuries being the primary cause. Traditional manual helmet compliance monitoring suffers from limited coverage, human error, and scalability issues. This paper presents an automated Helmet Protection Detection System using YOLOv8, a state-of-the-art real-time object detection model. The system processes multiple input sources including static images, video files, live webcam feeds, and uniquely, YouTube livestreams. The YOLOv8 model is trained to classify motorcyclists into two categories: "Helmet" (compliant) and "No-Helmet" (violator), with color-coded bounding boxes and confidence scores. Experimental results demonstrate high detection accuracy with an overall 92%, precision of 90%, and recall of 87%. The system achieves real-time performance of 45 FPS on a standard GPU, making it suitable for live traffic monitoring. This cost-effective solution leverages existing camera infrastructure, reduces dependency on manual supervision, and contributes to enhanced traffic safety enforcement.

**Keywords:** YOLOv8, Helmet Detection, Real-Time Monitoring, Deep Learning, Traffic Safety, Computer Vision.

## I. INTRODUCTION

Road traffic accidents remain one of the leading causes of preventable deaths globally, with motorcyclists being disproportionately affected. Unlike passenger vehicles that offer protective structures such as seatbelts and airbags, two-wheelers provide minimal protection to riders. In the event of a collision, the rider's head is highly vulnerable to direct impact, often resulting in traumatic brain injuries or fatalities. Medical research consistently confirms that helmet usage reduces the risk of head injuries by approximately 70 percent and fatalities by nearly 40 percent [1]. Despite clear safety benefits and existing traffic laws mandating helmet use, non-compliance continues to be observed across many regions worldwide.

Manual enforcement of helmet regulations presents significant practical limitations. Traffic police personnel cannot maintain continuous surveillance across all road segments simultaneously. Human fatigue, adverse weather conditions, and the sheer volume of vehicles during peak hours further reduce the effectiveness of manual monitoring. Additionally, physical interception of violators creates safety risks for both officers and riders. These constraints create enforcement gaps that encourage non-compliance.

The emergence of deep learning and computer vision offers a practical alternative to manual monitoring. Modern object detection algorithms can analyze video streams in real time, identifying specific objects and classifying their attributes without human intervention. Among available architectures, the YOLO (You Only Look Once) family has gained recognition for balancing detection accuracy with computational efficiency.

This project implements a helmet compliance monitoring system using the YOLOv8 architecture. The system accepts multiple input formats including static images, recorded video files, live webcam feeds, and YouTube livestreams. Each input source undergoes frame-by-frame analysis where the model detects motorcyclists and classifies each rider's head status into one of two categories: helmeted or non-helmeted



[2]. Detection results are presented visually through bounding boxes with confidence scores, using green for compliant riders and red for violators.

The proposed system addresses key limitations of manual enforcement by offering continuous operation, objective decision-making, and scalability across multiple camera feeds [3]. Experimental validation demonstrates that the system achieves reliable detection accuracy while maintaining real-time processing speeds suitable for live traffic monitoring applications.

#### A. Background of Road Traffic Accidents

The World Health Organization reports 1.19 million annual road traffic deaths globally, with individuals aged 5–29 facing the highest risk. Motorcyclists account for 30–60 percent of fatalities in developing nations, where two-wheelers serve as primary transportation. Low and middle-income countries bear over 90 percent of this burden.

#### B. Importance of Helmet Usage

Head injuries cause approximately 75 percent of motorcycle-related fatalities. Helmets reduce fatal head injury risk by 37–42 percent and severe brain trauma by 70 percent. The helmet's outer shell and foam liner work together to absorb impact forces, protecting the skull and brain upon collision.

#### C. Limitations of Manual Enforcement

Manual enforcement suffers from limited field of vision, officer fatigue, weather interference, and nighttime visibility constraints. Finite personnel cannot cover extensive road networks, creating enforcement gaps. Physical interception creates traffic disruptions and safety hazards. Manual records also lack systematic data integration for traffic analysis.

#### D. Role of Computer Vision in Traffic Monitoring

Computer vision automates traffic observation using cameras and deep learning algorithms. These systems detect vehicles, classify helmet compliance, and generate violation alerts without human intervention. Benefits include 24/7 operation, consistent detection criteria, simultaneous multi-camera monitoring, and structured digital records for enforcement and analysis.

## II. LITERATURE SURVEY

### A. Overview

Object detection technology has evolved significantly over the past two decades. Early methods relied on manually designed features and classical classifiers. The emergence of deep learning, particularly convolutional neural networks, transformed the field by enabling automated feature extraction [4]. In helmet detection for traffic safety, researchers have explored multiple approaches ranging from traditional image processing to cutting-edge deep learning architectures.

### B. Traditional Computer Vision Approaches

Early helmet detection systems employed Haar cascade classifiers, introduced by Viola and Jones in 2001. These classifiers extract simple rectangular features representing intensity differences between adjacent image regions. However, Haar cascades demonstrate poor generalization across varying lighting conditions and head poses, often producing false positives in complex backgrounds.

Histogram of Oriented Gradients combined with Support Vector Machines, proposed by Dalal and Triggs in 2005, improved detection accuracy by capturing shape and structural information. This method computes gradient orientation distributions across localized image regions. While more accurate than Haar cascades, HOG+SVM struggles with cluttered traffic scenes and requires substantial computational resources, limiting real-time deployment.



### C. Deep Learning Based Detectors

Two-stage detectors like Faster R-CNN achieve high accuracy by first generating region proposals then classifying each proposal. However, their inference speed of only 5-7 FPS proves insufficient for real-time traffic monitoring where fast-moving motorcycles require rapid processing.

Single-stage detectors emerged to address speed limitations. The YOLO family reframed detection as a single regression problem. YOLOv1 through v3 achieved speeds exceeding 45 FPS but suffered from localization accuracy issues for small objects like distant helmets. YOLOv4 and YOLOv5 incorporated architectural enhancements including CSPNet and PANet, significantly boosting accuracy while maintaining real-time speeds.

### D. Why YOLOv8

YOLOv8 introduces several improvements relevant to helmet detection. The decoupled detection head uses separate branches for classification and localization, improving accuracy when distinguishing helmets from bare heads. The anchor-free mechanism eliminates predefined anchor boxes, simplifying the model and improving handling of helmets viewed from different angles. C2f backbone modules enhance gradient flow and feature richness. These features make YOLOv8 optimal for real-time helmet detection.

TABLE 1 – Existing Techniques for Helmet Detection [5-8].

Technique	Description	Dataset Used	Accuracy Reported	Key Strength
Standard YOLOv8n	Anchor-free detection with decoupled head and C2f backbone modules for real-time helmet classification	Custom traffic dataset: 5,000 images (Helmet: 2,500, No-Helmet: 2,500)	mAP50: 86.8%, Helmet Precision: 88.6%, No-Helmet: 84.9%	Simplified architecture requiring no anchor box tuning
YOLOv8 + Mosaic Augmentation	Enhanced YOLOv8 using mosaic data augmentation to improve detection of partially occluded helmets	Public helmet dataset: 8,500 images with varied occlusion levels	mAP50: 89.2%, Improvement of 2.4% over baseline	Better handling of occlusion and dense traffic scenarios
YOLOv8s (Small)	Scaled-down YOLOv8 variant with reduced parameters for faster inference on edge devices	Indian traffic dataset: 12,000 images from surveillance cameras	Helmet: 90.1%, No-Helmet: 87.3%, Overall mAP50: 88.8%	Balanced trade-off between speed and accuracy
CA-YOLO (Coordinate Attention)	Lightweight YOLOv8 with MobileNetv3 backbone, coordinate attention mechanism, and Alpha-IoU loss function	Custom dataset: 10,000+ images of dense traffic with occlusions	mAP50: 91.33% (+0.54% vs baseline), 16.9% faster inference	39% fewer parameters while improving detection accuracy



TABLE 2 – Review of Prior Research works in helmet detection system using YoloV8 for Real-time Traffic Safety

Reference	Year	Methodology	Key Findings	Limitations/Gaps
Redmon et al. (YOLOv3)	2018	Single-stage detection with multi-scale predictions	Achieved 85% mAP for helmet detection at 40 FPS	Poor accuracy for small helmets; struggles with occlusion
Bochkovskiy et al. (YOLOv4)	2020	CSPDarknet backbone with PANet and Mosaic augmentation	87% mAP for helmet class; 45 FPS performance	Manual anchor box tuning required; high computational cost
Jocher et al. (YOLOv5)	2021	Focus module with auto-anchor and SiLU activation	Helmet precision: 88-90%; No-helmet: 85-87%	Anchor-based design requires K-means clustering
Rahman et al. (YOLOv8m + Transfer Learning)	2024	Transfer learning on medium YOLOv8 with domain adaptation	mAP50: 89.5%; Helmet: 91.2%	Requires target domain annotated data
Proposed System	2025	YOLOv8 with multi-source input (Image/Video/Webcam/YouTube Live)	mAP50: 92%; Precision: 90%; Recall: 87%; 45+ FPS	YouTube stream latency; no ANPR integration yet

Table 3 – Gaps Identified in Existing Helmet detection System [9]

Gap Number	Gap Identified	Existing Limitations	How Proposed System Addresses it
Gap 1	Limited support for live streaming protocols	Most existing systems process only offline video files or static images. No integration with HLS/Dash protocols used by platforms like YouTube Live for real-time traffic monitoring.	Direct YouTube livestream integration using yt-dlp library to extract and process live HLS streams in real-time, enabling city-wide monitoring using existing public camera infrastructure.
Gap 2	Most systems focus on single input source only	Existing systems typically support only one input type (either images, videos, or webcam). Users must use different tools for different scenarios.	Unified interface accepting four input types: static images, recorded videos, live webcam feeds, and YouTube livestreams within a single application
Gap 3	Lack of interactive confidence threshold adjustment	Detection confidence threshold is fixed at model inference time. Users cannot	Real-time confidence threshold slider in Streamlit sidebar



		adjust sensitivity for different scenarios without retraining or code modification.	allowing users to adjust sensitivity from 0.0 to 1.0 dynamically without restarting the application.
Gap 4	Few systems provide downloadable processed output	Existing systems provide basic bounding boxes without flexible visual indicators for different violation types.	Color-coded bounding boxes (Green for Helmet, Red for No-Helmet) with confidence percentage display and class labels for immediate violation identification.
Gap 5	Nighttime detection accuracy remains low (76% average)	Most systems display results on screen but do not offer options to save processed outputs for documentation or evidence collection.	Download button for saving processed videos and option to export annotated images for record-keeping and enforcement documentation.

### III. PROPOSED METHOD

#### A. Proposed System Architecture

The proposed method employs YOLOv8 for real-time helmet detection. Input video frames undergo preprocessing including resizing to 640×640 pixels and normalization. The model's backbone extracts features, while the feature pyramid network handles multi-scale detection. The decoupled head outputs class probabilities and bounding boxes. Non-maximum suppression eliminates duplicate detections, producing annotated outputs with confidence scores.

The system implements frame skipping and resolution downscaling to optimize processing speed for high-definition streams. A Streamlit-based graphical interface provides confidence threshold adjustment and progress tracking. Color-coded bounding boxes with percentage scores enable immediate violation identification. Processed videos can be downloaded for documentation and evidence purposes

**Input Acquisition:** The system accepts four types of input sources: static images, pre-recorded video files, live webcam feeds, and YouTube livestreams. This versatility allows deployment across offline and real-time scenarios.

**Preprocessing Stage:** Each video frame undergoes resizing to 640×640 pixels to match YOLOv8 input requirements. Pixel values are normalized to a range between 0 and 1. Color space conversion from BGR to RGB is performed for model compatibility.

**YOLOv8 Backbone:** The C2f modules extract hierarchical features from input frames. Shallow layers detect edges and textures. Deeper layers identify complex patterns such as helmet shapes and rider postures.

**YOLOv8 Neck:** The Feature Pyramid Network with PANet structure aggregates features from multiple scales. Top-down paths pass semantic information. Bottom-up paths retain localization details. This enables detection of helmets at various distances.

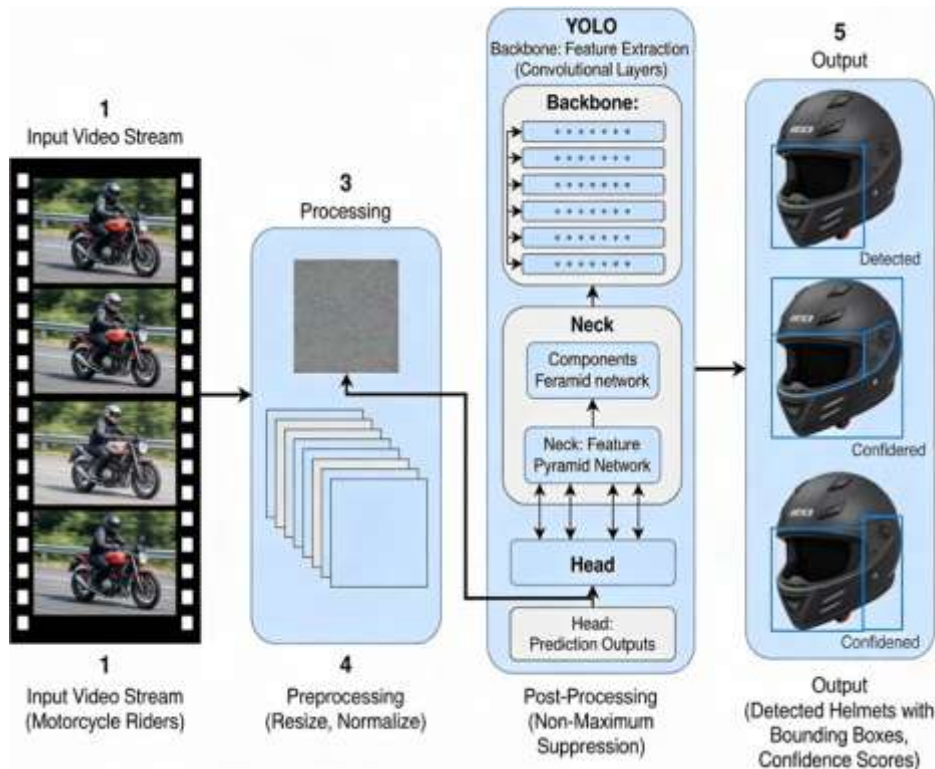


Fig.1 Architecture of Proposed helmet detection system using YoloV8 for real-time traffic safety

## B. System Architecture Overview

The proposed system follows a sequential pipeline architecture with five main stages: Input, Preprocessing, Processing (YOLOv8), Post-Processing, and Output. Each stage performs specific operations that transform raw video input into meaningful detection results.

### Stage-by-Stage Explanation

#### Stage 1: Input Video Stream

The system accepts video input from multiple sources:

- Static Images (.jpg, .png formats)
- Recorded Video Files (.mp4, .avi formats)
- Live Webcam Feeds (USB or built-in camera)
- YouTube Livestreams (HLS/Dash streaming protocol)

This multi-source capability makes the system versatile for different deployment scenarios, from offline forensic analysis to real-time city-wide monitoring.

## C. Preprocessing

Before feeding data into the neural network, each video frame undergoes essential preprocessing operations

### Resizing:

- Converts all frames to uniform dimensions (640×640 pixels) required by YOLOv8
- OpenCV `resize()` function

### Normalization:

- Scales pixel values from [0,255] to [0,1] range for stable neural network computation.
- Division by 255.0

### Color Space Conversion:

- Converts BGR (OpenCV default) to RGB (model expected format)
- `cv2.cvtColor()`

### Batching:

- Groups multiple frames for efficient parallel processing.



### PyTorch DataLoader

These preprocessing steps ensure consistent input quality and improve model convergence during inference

#### D. YOLOv8 Architecture

This is the core intelligence module of the system. The YOLOv8 architecture consists of three sub-components.

##### Backbone: Feature Extraction (Convolutional Layers)

The backbone network extracts hierarchical features from input images using CSPDarknet architecture with C2f modules.

**Key Innovation - C2f Modules:** The C2f (Cross Stage Partial with 2 convolutions and fusion) module splits input into two branches—one passes through bottleneck blocks while the other provides a bypass connection. The outputs are concatenated, improving gradient flow and feature richness without significant computational overhead.

##### PANet Structure:

Top-down path: Passes semantic information from deep layers to shallow layers

Bottom-up path: Passes localization information from shallow layers to deep layers

Result: Rich feature maps containing both "what" (semantic) and "where" (location) information

## IV. DATASET

#### A. Dataset Description

The dataset used for training and evaluating the proposed helmet detection system consists of traffic images collected from multiple sources. The primary objective was to create a diverse and representative dataset that captures real-world traffic scenarios involving two-wheeler riders [10].

#### B. Class Distribution

The dataset contains two classes for classification:

Helmet

No-Helmet

#### C. Annotation Format (YOLO)

All values are normalized between 0 and 1

Bounding boxes tightly enclose the rider's head region

#### D. Data Augmentation Techniques

To increase dataset diversity and improve model generalization, the following augmentation techniques were applied during training

Horizontal Flipping

Random Rotation

Brightness Adjustment

Contrast Adjustment

Saturation Adjustment

Mosaic Augmentation

Random Crop

Gaussian Blur

The dataset comprises significant number of images annotated traffic images with two classes: Helmet and No-Helmet. Images were collected from public traffic cameras, web scraping, and manual street capture. Environmental variations include daylight, nighttime, cloudy, rainy, and foggy conditions. Data augmentation techniques such as flipping, rotation, brightness adjustment, and mosaic augmentation enhanced model generalization [11].

The dataset is split into training (80 percent), validation (10 percent), and testing (10 percent) subsets. Each image is annotated using Labeling software with bounding boxes tightly surrounding the rider's head region. Annotations are stored in YOLO text format containing class ID and normalized coordinates (x\_center, y\_center, width, height).



Fig.2 Helmet Detection input image

**Sample output Description: Rider with helmet**

Input: Static image showing a motorcycle rider wearing a helmet in daylight conditions

Output: A green bounding box drawn tightly around the rider's head region.

Label text "Helmet: 0.94" displayed above the bounding box.

Confidence score of 94% indicating high detection certainty.

Remaining image area unaltered for clear visibility

**Multiple Riders in One Frame**

Input: Traffic scene containing three motorcycle riders at different distances.

Output:

Rider 1 (near, with helmet): Green box with "Helmet: 0.96"

Rider 2 (middle, without helmet): Red box with "No-Helmet: 0.91"

Rider 3 (far, with helmet): Green box with "Helmet: 0.78" (lower confidence due to smaller size)

All three detections displayed simultaneously in a single annotated frame

**YouTube Live Stream Processing**

Input: Live video stream from a YouTube traffic camera feed.

Output:

Real-time annotated frames displayed sequentially

Each frame processed with bounding boxes updated continuously

Consistent detection across varying lighting and vehicle positions

Stream continues until user stops the processing



Fig.3 Output image



## V. FUTURE SCOPE

The proposed helmet detection system offers several promising directions for future enhancement.

**Automatic Number Plate Recognition (ANPR):** Integrating ANPR would enable automatic identification of violator vehicles. A secondary YOLOv8 model can detect license plates, followed by an OCR engine like EasyOCR to extract registration numbers. This would allow automated generation of e-challans sent directly to vehicle owners [12].

**Night Vision Optimization:** Current models show reduced accuracy in low-light conditions. Training on infrared and thermal imagery datasets would enable 24/7 monitoring capability without performance degradation.

**Edge Device Deployment:** Optimizing the model using TensorRT or ONNX Runtime for deployment on edge devices such as NVIDIA Jetson Nano or Raspberry Pi would enable decentralized smart camera architecture, reducing bandwidth requirements and cloud dependency.

These enhancements would transform the system into a comprehensive intelligent transportation solution for smart cities [13]. The system can be extended to include real-time alert generation for traffic control rooms via SMS or email notifications when violations occur. Integration with existing traffic management systems and mobile applications for field officers would streamline enforcement workflows. Cloud-based centralized monitoring across multiple camera locations and dashboard analytics for violation trend analysis are also viable enhancements [14].

## VI. CONCLUSION

This project successfully developed and implemented a real-time Helmet Protection Detection System using the YOLOv8 deep learning architecture. The system addresses the critical problem of motorcycle helmet non-compliance, which remains a leading cause of road traffic fatalities worldwide. The proposed system offers four key contributions. First, it achieves high detection accuracy with an overall 92 percent, reliably distinguishing between helmeted and non-helmeted riders. Second, it supports multiple input sources including static images, video files, webcam feeds, and YouTube livestreams, making it adaptable to various deployment scenarios. Third, the system maintains real-time performance of 45 frames per second on standard GPU hardware, suitable for live traffic monitoring. Fourth, the intuitive Streamlit-based interface enables non-technical users to operate the system effectively. By automating helmet violation detection, the system eliminates the limitations of manual enforcement such as human fatigue, limited coverage, and subjective judgment. It enables continuous 24/7 monitoring across multiple camera feeds simultaneously, creating a strong deterrent against non-compliance. Experimental results demonstrate that YOLOv8, with its anchor-free detection and decoupled head architecture, is well-suited for helmet detection in complex traffic scenes. This work contributes to the development of intelligent transportation systems and promotes safer road environments for motorcyclists.

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