



Performance Evaluation of YOLOv8 Model in Motorcycle Helmet Violation Detection System Using Traffic Image Dataset

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Abstract. The high number of motorcycle users in developing countries is often followed by an increase in traffic violations, specifically the failure to wear helmets, which significantly contributes to head injury risks. This study aims to evaluate the performance of the YOLOv8 model in detecting motorcycle helmet violations using a traffic image dataset. The research methodology encompasses data collection, image annotation, pre-processing, YOLOv8 model training, and performance evaluation using precision, recall, F1-score, and mean Average Precision (mAP). The experimental results demonstrate that the YOLOv8 model achieved an accuracy of 87.93%, precision of 90.32%, recall of 89.44%, F1-score of 90.37%, and mAP@0.5 of 87.80%. These results indicate that the YOLOv8 model is effective for real-time automated helmet violation detection. This research provides a robust contribution to intelligent traffic monitoring systems and serves as practical instructional material for computer vision courses. Through advanced deep learning techniques, this technological approach helps law enforcement agencies reduce accidents and monitor roads efficiently every day by providing accurate and reliable automated analysis of modern traffic camera feeds. Furthermore, future developments could integrate edge computing devices to enable instant alerts for officers on duty, thereby minimizing human error and enhancing overall public safety measures across urban transportation networks in real time.

Keywords: Computer Vision, Deep Learning, Helmet Violation, Intelligent Traffic System, YOLOv8

1 Introduction

Motorcycles constitute the primary transportation modality in developing countries, particularly within Southeast Asian urban centers (Putra & Aryanto, 2021; Setyawan & Rahman, 2022). However, high motorcycle density is accompanied by prevalent traffic violations, most notably the failure to wear safety helmets. Epidemiological evidence confirms that proper helmet usage drastically mitigates fatal head injuries during traffic collisions (Zheng et al., 2021). In high-mobility tourist and commercial sectors such as the Badung Regency in Bali (encompassing Kuta, Legian, Canggu, and Nusa Dua), rapid vehicle mobility complicates traffic governance and necessitates automated enforcement solutions (Hassan et al., 2022).

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Conventional traffic monitoring relies heavily on manual surveillance by traffic personnel, an approach intrinsically constrained by human fatigue, limited coverage, and spatial-temporal inefficiencies (Sharma & Jindal, 2020). Although closed-circuit television (CCTV) infrastructure is deployed at major intersections, raw video feeds lack automated analytical capabilities, rendering passive recordings insufficient for proactive law enforcement (Iqbal & Rashid, 2022; Nguyen et al., 2021). Recent advancements in deep convolutional neural networks (CNNs) have enabled real-time object detection in dynamic environments. The You Only Look Once (YOLO) framework is widely adopted for intelligent transportation systems due to its single-stage, end-to-end processing pipeline (Bochkovskiy et al., 2020; Wang et al., 2023). The YOLOv8 architecture introduced key modifications over legacy anchor-based networks, specifically an anchor-free detection head, decoupled feature extraction pathways, and Task-Aligned Assigner (TAL) strategies (Jocher et al., 2023; Lin et al., 2025).

While existing studies demonstrate high accuracy on standard benchmark datasets, deploying deep learning models in real-world traffic scenarios exposes performance degradation caused by extreme lighting shifts, high vehicle density, partial occlusion, and variations in camera perspective (Chen & Lee, 2023). Furthermore, many literature sources present YOLO applications as black-box implementations without providing full transparency regarding hyperparameter optimization, computational setup, or empirical error breakdowns.

To bridge this gap, this study presents a rigorous evaluation of the YOLOv8 architecture for automated helmet violation detection. The contributions of this work are threefold, first a technical exploration of the YOLOv8 computational architecture, loss functions, and optimization setup required for reproducible traffic surveillance modeling. Second a quantitative performance evaluation using standard detection metrics (Precision, Recall, F1-Score, mAP@0.5) alongside an empirical failure mode analysis across edge cases (e.g., severe occlusion, motion blur, small target resolution). Third the design and integration of the trained network into a web-based operational system for rapid inference in smart city enforcement applications.

2 Methodology

The specific design and implementation of the model, as outlined in the third phase of the research framework, follow a comprehensive technical workflow. The systematic process for developing the YOLOv8 helmet detection model is illustrated in the flowchart in Figure 1.

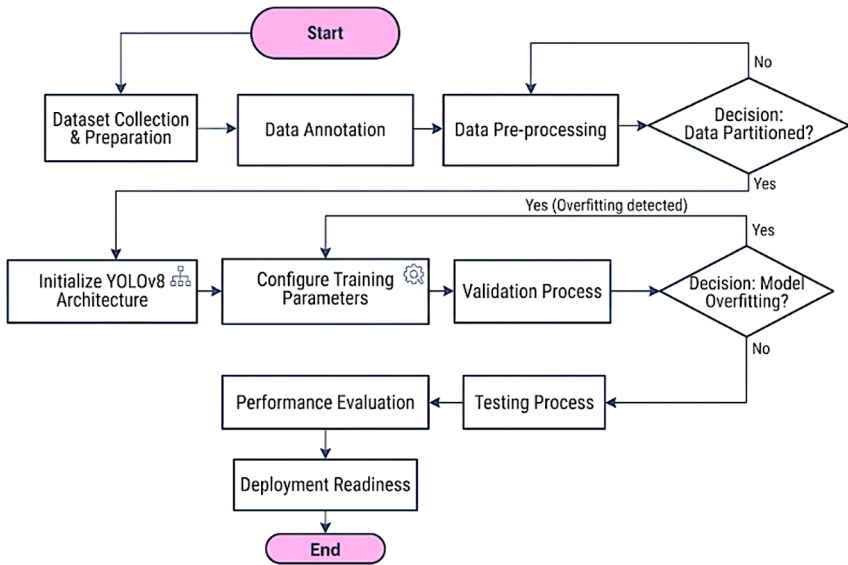


Figure 1. YOLOv8 Helmet Detection Model Development Flowchart

2.1 Data Collection, Annotation, and Partitioning

The experimental dataset comprises 4,210 high-resolution traffic images captured across diverse road locations in Badung Regency, Bali. The dataset captures variable environmental conditions, including varying sunlight angles, shadows, multi-lane traffic flows, and diverse rider densities.

Bounding box annotation was performed manually, assigning spatial labels to two target classes: "Helmet" and "No Helmet" (or "Without_helmet"). Data preprocessing included uniform spatial resizing to 640 x 640 pixels and pixel intensity normalization to the range [0, 1]. To prevent data leakage and evaluate generalization, the dataset was partitioned into three distinct subsets:

- Training set: 3,649 images (86.67%)
- Validation set: 373 images (8.86%)
- Testing set: 188 images (4.47%)

2.2 YOLOv8 Architectural Framework and Algorithmic Nuances

Unlike legacy anchor-based models (e.g., YOLOv3, YOLOv5) that rely on predefined anchor box ratios, YOLOv8 employs an anchor-free, center-based object detection strategy. This eliminates anchor hyperparameter tuning and improves generalizability across varying aspect ratios. The architecture consists of three primary functional components:

- 1) **Backbone (Feature Extraction):** Utilizes a modified CSPDarknet backbone where standard Cross-Stage Partial (CSP) blocks are replaced by C2f (Cross-Stage Partial with two convolutions) modules. The C2f module combines high-level contextual

features with low-level spatial detail by split-and-concat gradient flows, enhancing gradient propagation without imposing heavy computational overhead.

- 2) Neck (Feature Fusion): Implements a Path Aggregation Network with Feature Pyramid Network (PAN-FPN) structure. It facilitates multi-scale feature fusion across different pyramid levels (P3, P4, P5), enabling the network to concurrently detect small distant helmets and large close-up subjects.
- 3) Decoupled Detection Head: Decouples the classification (*cls*) and bounding box regression (*box*) tasks into separate branch outputs. This architectural separation resolves the conflict between spatial localization and semantic classification inherent in combined detection heads.

To optimize network weights, YOLOv8 utilizes a compound loss function combining classification loss, bounding box regression loss, and Distribution Focal Loss (DFL):

$$\mathcal{L}_{total} = \lambda_{cls}\mathcal{L}_{cls} + \lambda_{box}\mathcal{L}_{box} + \lambda_{dfl}\mathcal{L}_{dfl} \quad (1)$$

Classification Loss ($\mathcal{L}_{cls}$): Formulated using Binary Cross-Entropy (BCE) loss to evaluate predicted class probabilities against ground-truth labels.

Bounding Box Regression Loss ($\mathcal{L}_{box}$): Evaluated using Complete Intersection over Union (CIoU) loss, which accounts for overlap area, distance between central points, and aspect ratio consistency between predicted and target bounding boxes.

Distribution Focal Loss ($\mathcal{L}_{dfl}$): Focuses on optimizing the probability distribution of bounding box boundaries, addressing spatial uncertainty caused by motion blur or soft object boundaries.

Sample Assignment: Object matching is governed by the Task-Aligned Assigner (TAL), which dynamically selects positive samples based on a joint alignment metric combining classification score and bounding box IoU score.

2.3 Experimental Setup and Training Hyperparameters

To ensure complete reproducibility, the hardware environment, software stack, and hyperparameter configurations are explicitly detailed in Table 1 and Table 2.

Table 1. Computational Hardware and Software Environment

Component	Specification / Parameter
Processor (CPU)	Intel Core i7-12700K (12th Gen) @ 3.60 GHz
Graphics Processing Unit	NVIDIA GeForce RTX 3060 (12 GB VRAM)
System Memory (RAM)	32 GB DDR4
Operating System	Windows 11
Deep Learning Framework	PyTorch v2.0.1 (CUDA 11.8)
Computer Vision Library	Ultralytics YOLOv8 (v8.0.x) / OpenCV 4.8
Python Version	Python 3.10.12
Total Training Duration	~ 3.4 Hours (100 Epochs)

Table 2. Hyperparameter Configurations

Hyperparameter	Value / Configuration
Input Image Resolution	640 x 640 pixels
Total Epochs	100
Batch Size	16
Optimizer	Stochastic Gradient Descent (SGD)
Initial Learning Rate (lr0)	0.01
Final Learning Rate (lrf)	0.01 (Cosine Annealing)
Momentum	0.937
Weight Decay	0.0005
Warmup Epochs	3.0
Mosaic Augmentation	1.0 (Enabled)
Mixup Augmentation	0.0 (Disabled)
HSV Color Jitter (H, S, V)	Hue=0.015, Saturation=0.7, Value=0.4
Random Horizontal Flip	0.5 (50% probability)

3 Result and Discussion

3.1 Quantitative Evaluation Results

The performance of the trained YOLOv8 model was quantitatively evaluated on an unseen test dataset consisting of 188 traffic images containing variable lighting, high motorcycle density, and complex background elements. Evaluation metrics include Precision (*P*), Recall (*R*), F1-Score (*F1*), Accuracy (*Acc*), and mean Average Precision at an Intersection over Union (IoU) threshold of 0.5 (*mAP@0.5*).

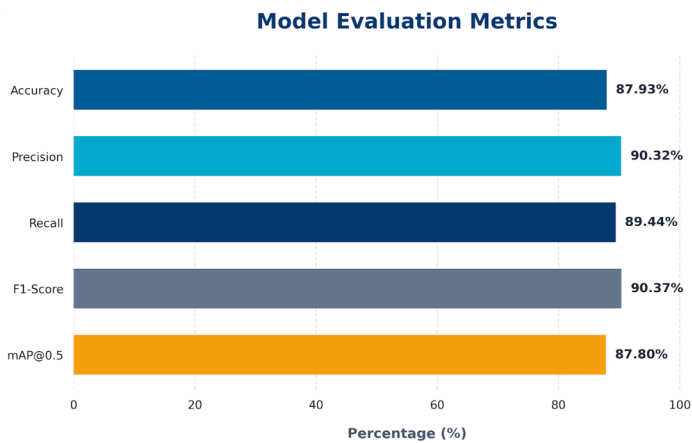


Figure 2. Model Evaluation Metrics

The high precision rate of 90.32% indicates that the model minimizes false alarms, ensuring that flagged helmet violations are highly reliable for automated enforcement. Concurrently, the recall score of 89.44% demonstrates the network's capacity to detect non-compliant riders across varying road perspectives and traffic densities.

3.2 Confusion Matrix and Empirical Error Analysis

To address operational limitations and provide technical depth regarding model generalizability, an empirical error analysis was conducted on the test set. A total of 416 annotated target objects across the 188 test images were evaluated. The quantitative distribution of model predictions is presented in the confusion matrix in Table 3.

Table 3. Confusion Matrix of Test Dataset Predictions

Actual Ground Truth	Predicted: Violation (Without_helmet)	Predicted: Non-Violation (Helmet)	Total Actual Ground Truth
Actual: Violation (Without_helmet)	168 (True Positive - TP)	20 (False Negative - FN)	188
Actual: Non-Violation (Helmet)	18 (False Positive - FP)	210 (True Negative - TN)	228
Total Model Predictions	186	230	416

Analyzing the incorrect prediction instances (~12% total error rate across FP and FN cases) reveals specific visual and environmental degradation mechanisms.

3.3 Comparative Discussion and System Deployment

The superior performance of YOLOv8 over legacy architectures evaluated in prior literature stems directly from its structural architectural enhancements. Traditional anchor-based detectors (e.g., YOLOv5, Faster R-CNN) depend on predefined anchor box ratios, which struggle to adapt to varied head aspect ratios, head tilts, and dynamic rider postures. By predicting object centers directly through an anchor-free mechanism, YOLOv8 achieves superior spatial localization adaptivity.

To translate the trained deep learning model into an operational administrative tool, the optimized network was integrated into a web-based inference platform powered by a Flask/Python backend.

Table 4. Technical Architecture of the Deployed Web Inference System

Pipeline Stage	System Module	Functional Responsibility
Frontend GUI	HTML5 / Bootstrap GUI	Interactive image upload, violation visualization, object counting
Backend Framework	Flask REST API	Receives POST image requests, manages tensor preprocessing pipeline
Inference Engine	PyTorch / CUDA Runtime	Executes feed-forward pass on trained YOLOv8 model weights
Post-Processing	Non-Maximum Suppression (NMS)	Filters overlapping bounding boxes using IoU threshold of 0.45
Output Rendering	OpenCV Image Processing	Renders bounding boxes, class labels ("Without_helmet"), and confidence scores



Figure 3. Web Based Interface

Figure 3 as illustrated in the interface, the system provides a seamless mechanism for end-users to upload traffic images and execute rapid detection. The GUI clearly visualizes the outcomes by drawing bounding boxes around the subjects, accompanied by class labels ("Without_helmet") and individual confidence scores. Notably, the system successfully identified multiple violations simultaneously on a moving motorcycle despite significant motion blur in the background with high confidence scores of 0.88 and 0.86. The interface also aggregates the analysis by displaying the overall confidence (0.87) and total detected objects (2).

4 Conclusion

This study successfully evaluated and implemented an automated motorcycle helmet violation detection system utilizing the YOLOv8 architecture. The performance evaluation demonstrated highly promising results, achieving an accuracy of 87.93%, a precision of 90.32%, a recall of 89.44%, and an mAP@0.5 of 87.80%. These findings confirm that the anchor-free detection mechanism of YOLOv8 provides superior target localization and reliability compared to earlier models and traditional manual observation.

By integrating this robust deep learning model into a web-based interface, the proposed system effectively addresses the constraints of human fatigue and inefficiency inherent in manual traffic monitoring. It offers a scalable, fast, and consistent solution for intelligent traffic enforcement, particularly suitable for high-mobility regions such as the Badung Regency. For future research, it is highly recommended to expand the dataset to encompass more complex environmental variables such as extreme weather conditions, varying camera angles, and nighttime scenarios. Furthermore, integrating the system with automatic license plate recognition (ALPR) could significantly enhance the model's robustness and its utility for large-scale, real-world law enforcement deployment.

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