Capstone Project Assignment 2 – Literature, Data, and Technology Review Submission

Group -7

Group Members

1. May Myat Noe Oo
2. Nay Chi Moe Oo
3. Min Sett Paing
4. Akeri Myint Zaw
5. May Phyo Thyu
6. Chan Aye Naing

**Literature Review**

**1. Introduction**

Road accidents, especially those involving motorcyclists, continue to pose a significant public health challenge worldwide. These incidents directly undermine Sustainable Development Goal 3 (Good Health and Well-Being) by contributing to a high number of fatalities and serious injuries. Although many regions have implemented mandatory helmet laws, enforcement often remains inadequate due to reliance on manual monitoring. Manual surveillance is time-consuming, prone to human error, and constrained by limited resources.

To address these challenges and enhance traffic safety, the adoption of intelligent, deep learning-based surveillance systems has become essential. Reviewing existing literature helps establish a solid foundation for understanding the development of object detection models in traffic safety, evaluating current performance benchmarks (e.g., mean Average Precision, , and identifying the research gap that our proposed YOLOv8-based system aims to fill. This review will examine the evolution of object detection technologies, justify the selection of the YOLOv8 architecture, and synthesize efforts toward real-world deployment of robust surveillance systems.

**2. Organization**

This literature review is structured thematically to highlight the evolution of technology and the challenges of automated traffic enforcement. The review is divided into three main sections:

1. **Model Evolution and Performance Benchmarking:** Discussing the transition from conventional detection methods to YOLO architectures and setting performance expectations.
2. **YOLOv8 and Multi-Task Integration:** Highlighting recent research demonstrating the effectiveness of YOLOv8 for complex, combined detection tasks such as helmet use, license plate recognition, and triple-riding detection.
3. **Real-World Robustness and Enforcement:** Examining strategies to improve model generalization under challenging conditions and integrating these systems into practical enforcement pipelines.

**3. Summary and Synthesis**

**3.1 Model Evolution and Performance Benchmarking**

Early deep learning systems demonstrated the challenge of real-time detection in complex traffic environments. The foundational work by Siebert and Lin (2020), which used a RetinaNet architecture on extensive **Myanmar** video data, achieved a weighted **mAP of** 72.3%. This seminal work highlighted the difficulty of the task in a high-density regional context.

The following table summarizes the key metrics, models, and data sources for the papers discussed in this review, providing a comparative overview of the field's progression toward high-accuracy, real-time violation detection.

|  |  |  |  |
| --- | --- | --- | --- |
| **Paper Title (Year)** | **Model / Framework** | **Dataset (Source / Region)** | **Performance (Accuracy / mAP)** |
| *A Deep Learning Approach for Helmet Detection and Fine Generation System* (2025) | YOLOv3 + OpenCV / OCR | Mixed COCO-style images; Kaggle dataset (>10k riders, helmet/no-helmet) | >95% overall accuracy |
| *Real-Time Helmet & Triple-Riding Detection with Email Alerts* (2025) | YOLOv5 + PaddleOCR | Custom real-time video stream | 94.1% mAP@50 |
| *Intelligent Real-Time Helmet & License Plate Device* (2024) | Modified YOLOv8 + SPP | India; roadside videos converted to images | Vehicle: 64%, Helmet: 95%, Plate: 93% |
| *Smart Traffic Violation Detection (Sri Lanka)* (2025) | YOLOv8 (n/s/m) + EasyOCR | Local Sri Lankan traffic videos | Vehicle: 93%, Helmet: 87.9%, Plate: 59.9%, Triple-rider: 80% |
| *Helmet Detection Based on Improved YOLOv8* (2024) | Improved YOLOv8 | Roboflow curated dataset (Helmet / No-Helmet / Person / Two-Wheeler) | High real-time mAP (exact % not stated) |
| *Detecting Motorcycle Helmet Use with Deep Learning (Myanmar)* (2019) | RetinaNet (ResNet-50 backbone) | Myanmar: 254 hrs video, 13 sites, ~91k frames, ~10k motorcycles | 72.3% weighted mAP, ~14 FPS |
| *AI-Driven System for Real-Time Detection of Mirror Absence, Helmet Non-Compliance, and License Plates* (2025) | YOLOv8 + EasyOCR | COCO pre-trained + custom traffic dataset | Helmet: 92%, Mirror: 89%, Plate (OCR): 85% |
| *Automatic Rider Helmet Violation Detection and Vehicle Identification in Smart City Scenarios* (2025) | NVIDIA TAO Toolkit + YOLOv8 | Custom Indian motorcycle dataset (complex conditions) | Helmet: 98.56%, Plate: 97.6% |
| *Traffic Rule Violation Detection in University Campus* (2023) | YOLOv8 | Self-generated dataset | Triple rider: 94%, Plate: 96%, Motorcycle: 97% |
| *Detection of Triple Riding and Helmet Violations Through CCTV Webcam* (2025) | YOLOv8 | CCTV webcam images in real-world traffic scenarios | 98.7% mAP@0.5 (overall) |

The field quickly shifted to more efficient single-stage detectors like the YOLO family:

* YOLOv3: Systems integrating YOLOv3 with OCR were developed to automatically detect violations and generate fines, reporting an accuracy of over 95% for helmet detection (Yadav et al., 2025).
* YOLOv5: This architecture proved its scalability by enabling multi-violation systems. For example, LG et al. (2025) successfully developed a real-time system detecting both helmet non-compliance and triple-riding, which included automated email notifications.

A key challenge identified across this early work is the need for speed without sacrificing detection accuracy in dynamic video feeds.

**3.2 YOLOv8 and Multi-Task Integration**

The introduction of YOLOv8 addressed the speed/accuracy trade-off by implementing an anchor-free design and optimized feature modules, quickly establishing it as the preferred architecture for contemporary traffic solutions. Recent research confirms its superior performance for combined tasks:

* Helmet and Triple-Riding Validation: Gayathri et al. (2025) explicitly validated YOLOv8's capability for simultaneous helmet and triple-riding detection. Their fine-tuned model achieved an outstanding overall metric of 0.987 Mean Average Precision (mAP@0.5), demonstrating the architecture's high reliability. Furthermore, their precision score for the key "Helmet" class reached 0.995.
* High-Accuracy Multi-Task Systems: Deshpande et al. (2025) showed that a two-step YOLOv8 system achieved a helmet detection accuracy of 98.56 % and a license plate detection accuracy of 97.6 %, demonstrating that the architecture can handle high-stakes enforcement tasks with very low error rates.
* Integrated Solutions: Studies synthesize violation detection with real-world infrastructure. Krishna and Karthikeya (2024) developed an intelligent traffic management system that integrated helmet compliance with traffic signal violation detection and Number Plate Identification (LPR), reinforcing the need for a comprehensive platform rather than siloed detectors.

3.3 Real-World Robustness and Enforcement

Research efforts have focused on adapting YOLOv8 to real-world deployment challenges:

* Model Optimization for Robustness: To counter issues like occlusion and low-light, Lin (2024) proposed an improved YOLOv8 model that integrated attention mechanisms to enhance feature extraction, resulting in a 1.3 % boost in mAP and increased recall over the base model. This highlights the importance of customizing the architecture for specific environmental difficulties.
* Policy and Scalability: Thilakarathna et al. (2025) provided a retrospective analysis of road traffic accidents, emphasizing the need for AI-based solutions to inform preventative policy, while Chaturvedi et al. (2023) demonstrated the system's scalability by successfully detecting violations in contained university campus environments.
* Novel Applications: The versatility of YOLOv8 extends to detecting highly specific infractions. Nishant et al. (2025) successfully utilized YOLOv8 and OCR to monitor novel violations such as mirror absence alongside helmet non-compliance, showcasing the model’s potential for broad regulatory enforcement.

**4. Conclusion**

The extensive literature confirms that deep learning, particularly the YOLOv8 architecture, is the current state-of-the-art solution for real-time traffic violation detection. The key takeaways are that contemporary models achieve extremely high accuracy (mAP scores consistently above 95 % ) and that successful systems rely on multi-task integration (helmet, LPR, triple-riding) and architectural fine-tuning for robustness.

The importance of our research is derived from the necessity to translate this global technological advancement into a highly effective, localized tool.

Our project will contribute to the existing body of knowledge by:

1. Bridging the Performance Gap: Directly replacing the outdated technology ( 72.3 % mAP) previously tested in Myanmar (Siebert & Lin, 2020) with a custom-trained, optimized YOLOv8 solution capable of achieving state-of-the-art accuracy ( >95 % mAP).
2. Delivering a Localized End-to-End System: Integrating the best practices from multi-task integration (Deshpande et al., 2025; Krishna & Karthikeya, 2024) to create a robust, end-to-end pipeline that handles detection, classification, and localized License Plate Recognition specifically for the unique traffic flow and visual environment of the target region. This will offer a highly accurate and practical template for automated enforcement, significantly enhancing road safety and compliance with traffic laws.

**Reference:**

Chaturvedi, P., Lavingia, K., & Raval, G. (2023). Detection of traffic rule violation in University campus using deep learning model. *International Journal of System Assurance Engineering and Management*, 14(6), 2527-2545.

Deshpande, U. U., Deshpande, V., Koti, R., Patil, R., Chate, R. A. A., Tandur, V. R., ... & Charantimath, V. (2025). Computer-vision based automatic rider helmet violation detection and vehicle identification in Indian smart city scenarios using NVIDIA TAO toolkit and YOLOv8. *Frontiers in Artificial Intelligence*, 8, 1582257.

Gayathri, T., Kavya, M., Sri, M. H., Harshitha, L., Sahithi, K. S. V., & Tejaswi, M. (2025). A Deep Learning-Based System to Detect Triple Riding and Helmet Violations Through CCTV Webcam. In *International Conference on Advancements in Computing Technologies and Artificial Intelligence (COMPUTATIA-2025)* (pp. 330-343). Atlantis Press.

Krishna, G. J., & Karthikeya, D. V. (2024). Intelligent Traffic Management System: An Advanced Solution for Helmet Compliance, Traffic Signal Violation Detection, Number Plate Identification. In *2024 International Conference on Electrical Electronics and Computing Technologies (ICEECT)* (Vol. 1, pp. 1-5). IEEE.

LG, R., Srinivasan, S. B., & Sundar, R. (2025). Real-Time Helmet and Triple Riding Detection System with Automated Email Notifications for Enhanced Road Safety. In *2025 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI)* (pp. 1-6). IEEE.

Lin, B. (2024). Safety helmet detection based on improved YOLOv8. *IEEE Access*, 12, 28260-28272.

Nishant, V. H., Agarwal, A., & Moharir, M. (2025). A Novel AI-Driven System for Real-Time Detection of Mirror Absence, Helmet Non-Compliance, and License Plates Using YOLOv8 and OCR. In *2025 12th International Conference on Emerging Trends in Engineering & Technology-Signal and Information Processing (ICETET-SIP)* (pp. 1-6). IEEE.

Siebert, F. W., & Lin, H. (2020). Detecting motorcycle helmet use with deep learning. *Accident Analysis & Prevention*, 134, 105319.

Thilakarathna, W. G. S. R., Thudugala, M. T. K. L., Hangilipola, W. A. C. J., Perera, W. N. S., & Paranitharan, P. (2025). Road traffic accidents in Sri Lanka: A retrospective analysis and artificial intelligence-based solutions for prevention. *Sri Lanka Journal of Forensic Medicine, Science & Law*, 16(1).

Yadav, S., Singh, S., Bedare, D., & Samel, I. (2025). A Deep Learning Approach for Helmet Detection and Fine Generation System. *International Journal of Research and Innovation in Applied Science*, 10(4), 902-910.

**Data Research Submission**

**1. Introduction and Context**

This research aims to develop and validate a multi-stage computer vision system for automated detection of motorcycle helmet use, alongside extraction of critical contextual data such as rider count and license plate recognition.The primary research question is: "How accurately and efficiently can a modular deep learning pipeline (ImageAI, YOLOv8, and OCR) simultaneously register helmet compliance, rider count, and license plate information to generate actionable road safety data?"

Addressing this question is crucial given the global shortage of comprehensive, real-time traffic safety metrics. Automation enables precise identification of non-compliant riders, including where and when violations occur, thereby supporting targeted enforcement and educational interventions. Ensuring robustness requires thorough analysis of real-world variance, including occlusion, lighting conditions, camera angles, and class imbalance.

**2. Organization of Findings**

This submission is organized thematically to present the architecture and outputs of the proposed system:

1. **Data Scope and Preprocessing**: Input sources and preparation steps.
2. **Multi-Stage System Architecture**: Integration and function of ImageAI, YOLOv8, and OCR modules.
3. **Data Extraction and Insight Generation**: Structure and utility of the final CSV output for actionable insights.

**3. Data Description**

**Dataset 1 (Contextual): Annotated Myanmar Motorcycle Traffic Videos**

* **Source**: Felix Wilhelm Siebert and Hanhe Lin (2019), covering 13 observation sites across 7 Myanmar cities.
* **Format**: Segmented 1920×1080 video clips at 10 fps, annotated frame-by-frame with bounding boxes.
* **Size**: 910 clips; 10,180 individual motorcycle tracks; 339,784 annotated frames.
* **Rationale**: Provides real-world context for model design, reflecting high rider density, variable visibility, and challenging traffic conditions.

**Dataset 2 (Primary Training/Testing): Local Images & Roboflow Dataset**

* **Source**: Combination of locally collected traffic images and global helmet detection data from Roboflow.
* **Format**: Labeled JPG/PNG images.
* **Size**: Approximately 10,000 images (variable depending on final selection).
* **Preprocessing**: Includes resizing, normalization, and data augmentation to enhance model generalization.
* **Rationale**: Serves as primary training material. Combining global and local data ensures transfer learning efficacy and optimal performance in the target environment, which is particularly important for license plate recognition.

**4. Data Analysis and Proposed System Methodology**

The system applies a modular, multi-step pipeline to sequentially extract metrics:

1. **Motorcycle Detection (ImageAI)**: Detects motorcycles and riders to define regions of interest (ROI) for downstream processing.
2. **Helmet Classification and Rider Counting (YOLOv8)**: Processes the ROI to simultaneously:
   * Classify helmet presence (Helmet/Non-Helmet).
   * Count the number of riders on each motorcycle.
3. **License Plate Recognition (OpenCV + Tesseract OCR)**: Applies image preprocessing (filtering, thresholding) to isolate plates, then uses OCR to extract text for unique identification.

**5. Conclusion**

**Key Findings and Expected Outcomes**

1. **Viable Automation**: The integrated YOLOv8 and ImageAI pipeline is expected to achieve high accuracy in real-time, suitable for deployment in surveillance systems.
2. **Comprehensive Data**: Outputs a normalized CSV consolidating helmet status, rider count, and license plate data, converting raw video into actionable insights.
3. **Scalability**: Modular design enables component upgrades without system-wide redesign.

**Significance to Project Goals**  
The proposed system addresses the global lack of structured road safety data. By automating helmet compliance monitoring, rider counting, and license plate recognition, it provides a holistic dataset that supports data-driven enforcement and intervention strategies, ultimately contributing to injury prevention.

**Reference:**

Siebert, F. W., & Lin, H. (2019). Detecting motorcycle helmet use with deep learning. *Accident Analysis & Prevention*, 124, 146–150.

# **Technology Review Submission**

## **1. Introduction and Context**

This technology review provides context for the advanced computer vision and deep learning tools selected to build an automated system for motorcycle helmet use detection and road safety data extraction. The system is modular, integrating YOLOv8, ImageAI, OpenCV, and Tesseract OCR.

The importance of this technology review is twofold: it justifies the selection of specific tools based on performance, speed, and scalability requirements, and it establishes a foundation for the system's architecture. For critical, real-time traffic analysis, the chosen technologies must be proven to be fast and accurate.

The review’s relevance to our project and research goal is direct: the system's primary goal is to transform raw video footage into actionable, multi-metric safety data (helmet status, rider count, license plate ID). The selection of YOLOv8 ensures high-speed, accurate detection, while the inclusion of ImageAI and Tesseract OCR enables the necessary end-to-end data extraction capability outlined in the project proposal.

## **2. Technology Overview**

### A. YOLOv8 (You Only Look Once, Version 8)

|  |  |
| --- | --- |
| **Feature** | **Description** |
| **Purpose** | Single-stage object detection, image classification, and segmentation. |
| **Key Features** | High speed (inference time), excellent balance between speed and accuracy (mAP), anchor-free detection mechanism, modern architecture (CSPDarknet/Darknet) for improved feature extraction. |
| **Common Use** | Real-time video analysis, drone surveillance, production-line quality control, and advanced traffic monitoring (e.g., classifying vehicles, pedestrian tracking). |

YOLOv8 is the latest iteration in the YOLO series, designed for high-performance, real-time object detection. Its single-stage approach allows it to simultaneously predict bounding boxes and class probabilities across the entire image in one pass, making it significantly faster than two-stage detectors like R-CNN.

### B. ImageAI (Integration Framework)

* **Purpose:** A high-level Python library that simplifies implementing deep learning models (like YOLO, RetinaNet, etc.) for pre-trained detection and easy transfer learning.
* **Key Features:** Minimal code requirement for object detection, seamless model integration, and easy generation of Regions of Interest (ROI).
* **Common Use:** Rapid prototyping of computer vision systems, educational purposes, and quickly integrating detection results into larger Python workflows.

### C. Tesseract OCR and OpenCV (Auxiliary Tools)

* **Tesseract OCR:** An open-source Optical Character Recognition engine. Its purpose is to convert images of text (in our case, license plates) into digital text.
* **OpenCV:** A comprehensive library for classic computer vision tasks. Its purpose here is to perform image manipulation (e.g., filtering, warping, thresholding) to isolate and prepare the license plate image for optimal Tesseract performance.

## **3. Relevance to Your Project**

The selected technologies are relevant because they form a modular pipeline designed to address the project's specific **multi-metric data collection** needs:

|  |  |  |
| --- | --- | --- |
| Project Challenge | Relevant Tool(s) | How the Challenge is Addressed |
| Real-time processing | YOLOv8 | Its high FPS capability ensures the system can process video streams faster than they are recorded, preventing backlogs. |
| Isolating target objects | ImageAI | Used for initial Motorcycle Detection, acting as a rapid filter to define the ROI before passing the image to the more complex YOLOv8 model, thus improving overall efficiency. |
| Helmet Classification | Fine-tuned YOLOv8 | Directly trained to distinguish between the two primary classes (Helmet/No-Helmet) and count riders, achieving high accuracy simultaneously. |
| Data Extraction | OpenCV + Tesseract OCR | These tools handle the necessary text recognition on license plates, converting the image data into a unique CSV identifier, which is essential for actionable enforcement data. |

## **4. Comparison and Evaluation**

We evaluated YOLOv8 against other state-of-the-art detection models, focusing on performance in a real-time, resource-constrained environment.

|  |  |  |  |
| --- | --- | --- | --- |
| Factor | YOLOv8 | YOLOv5 | Two-Stage (e.g., Faster R-CNN) |
| Performance (mAP) | Very High | High | Highest (Best Accuracy) |
| Speed (FPS) | Extremely High | High | Low (Slowest) |
| Ease of Use | High (Excellent community support and pre-trained weights) | High | Moderate (Complex implementation) |
| Scalability | Excellent (Models come in N, S, M, L, X sizes) | Excellent | Moderate |
| Suitability for Project | Optimal. Best balance of speed and accuracy for real-time video processing. | Good, but YOLOv8 offers marginal speed and mAP improvements. | Unsuitable for real-time video streams due to slow inference time. |

YOLOv8 is the most suitable choice due to its superior speed-to-accuracy trade-off. While two-stage models like Faster R-CNN might offer marginally better accuracy (mAP), their low Frames Per Second (FPS) make them impractical for continuous traffic surveillance. YOLOv8's speed is essential for mitigating the computational burden of the entire pipeline, especially when combined with the computationally intensive task of License Plate Recognition.

## **5. Use Cases and Examples**

The technologies selected have been successfully deployed in numerous projects involving real-time analysis:

* **Traffic Surveillance and Enforcement (YOLO/OCR):** Organizations worldwide use YOLO variants and OCR for automated speed enforcement and toll collection. For example, systems are deployed in China and India to monitor traffic violations, including seatbelt and mobile phone usage, demonstrating the capability to handle challenging occlusions and high traffic density similar to our project.
* **Industrial Inspection (YOLOv8):** Companies like Amazon use YOLO models for quality control on conveyor belts, where real-time defect detection (classification) and counting are mandatory, proving the model's reliability in a high-throughput environment.
* **Research (ImageAI/Tesseract):** Researchers frequently use the ImageAI wrapper to quickly test and deploy models, while Tesseract is the de-facto open-source standard for document and image OCR, including applications in cultural heritage digitalization and vehicle recognition projects.

## **6. Identify Gaps and Research Opportunities**

While powerful, these technologies present specific limitations that require custom development for our project:

|  |  |  |
| --- | --- | --- |
| Limitation/Gap | Description | Required Customization/Opportunity |
| Imbalanced Data Classes | The core data (from the Siebert & Lin paper) has very few examples of motorcycles with 3+ riders or complex helmet compositions, leading to low accuracy for these classes. | Custom Training and Augmentation: Aggressively augment the Roboflow/local dataset to generate synthetic examples of rare multi-rider configurations to balance the training data. |
| OCR Reliability | License Plate Recognition (Tesseract) is highly sensitive to blur, motion, low lighting, and non-standard plate formats. | Custom OpenCV Preprocessing: Develop a specialized OpenCV pipeline tailored to the local license plate structure and anticipated camera noise (blur, fogging, etc.) to maximize Tesseract's input quality. |
| Modular Integration Overhead | The handoff between modules (ImageAI YOLOv8 OpenCV) introduces potential latency and error accumulation if not managed efficiently. | Latency Optimization: Implement efficient threading or asynchronous processing to minimize delays between stages, ensuring the final output remains close to real-time. |

## **7. Conclusion**

This technology review confirms that the multi-stage pipeline utilizing ImageAI, fine-tuned YOLOv8, OpenCV, and Tesseract OCR provides the optimal framework for our project.

The key takeaway is that the speed of YOLOv8 allows us to build a complex, multi-functional system that remains efficient and scalable, a crucial advantage over slower, high-accuracy alternatives. By integrating OCR, we transition this from a mere detection system into a powerful data extraction tool.

This chosen technology benefits our research by maximizing the value of collected data. Instead of simply reporting a compliance rate, we gain the ability to link helmet status directly to unique vehicle identifiers, enabling specific, verifiable, and highly impactful road safety interventions—the core goal of the project.

## **Reference:**

**[OpenCV]** Bradski, G. (2000). The OpenCV Library. Dr. Dobb's Journal of Software Tools.

**[ImageAI]** Moses, T. A., et al. (2018). ImageAI. GitHub repository.

**[Tesseract OCR]** Smith, R. (2007). An Overview of the Tesseract OCR Engine. Ninth International Conference on Document Analysis and Recognition (ICDAR).

**[YOLOv8]** Jocher, G., et al. (2023). YOLOv8: Ultralytics. GitHub repository.

**[Contextual Reference]** Siebert, F. W., & Lin, H. (2020). Detecting motorcycle helmet use with deep learning. Accident Analysis & Prevention, 134, 105319.

Chaturvedi, P., Lavingia, K., & Raval, G. (2023). Detection of traffic rule violation in University campus using deep learning model. International Journal of System Assurance Engineering and Management, 14(6), 2527-2545.

Deshpande, U. U., Deshpande, V., Koti, R., Patil, R., Chate, R. A. A., Tandur, V. R., ... & Charantimath, V. (2025). Computer-vision based automatic rider helmet violation detection and vehicle identification in Indian smart city scenarios using NVIDIA TAO toolkit and YOLOv8. Frontiers in Artificial Intelligence, 8, 1582257.

Gayathri, T., Kavya, M., Sri, M. H., Harshitha, L., Sahithi, K. S. V., & Tejaswi, M. (2025). A Deep Learning-Based System to Detect Triple Riding and Helmet Violations Through CCTV Webcam. In International Conference on Advancements in Computing Technologies and Artificial Intelligence (COMPUTATIA-2025) (pp. 330-343). Atlantis Press.

Krishna, G. J., & Karthikeya, D. V. (2024). Intelligent Traffic Management System: An Advanced Solution for Helmet Compliance, Traffic Signal Violation Detection, Number Plate Identification. In 2024 International Conference on Electrical Electronics and Computing Technologies (ICEECT) (Vol. 1, pp. 1-5). IEEE.

LG, R., Srinivasan, S. B., & Sundar, R. (2025). Real-Time Helmet and Triple Riding Detection System with Automated Email Notifications for Enhanced Road Safety. In 2025 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI) (pp. 1-6). IEEE.

Lin, B. (2024). Safety helmet detection based on improved YOLOv8. IEEE Access, 12, 28260-28272.

Nishant, V. H., Agarwal, A., & Moharir, M. (2025). A Novel AI-Driven System for Real-Time Detection of Mirror Absence, Helmet Non-Compliance, and License Plates Using YOLOv8 and OCR. In 2025 12th International Conference on Emerging Trends in Engineering & Technology-Signal and Information Processing (ICETET-SIP) (pp. 1-6). IEEE.

Thilakarathna, W. G. S. R., Thudugala, M. T. K. L., Hangilipola, W. A. C. J., Perera, W. N. S., & Paranitharan, P. (2025). Road traffic accidents in Sri Lanka: A retrospective analysis and artificial intelligence-based solutions for prevention. Sri Lanka Journal of Forensic Medicine, Science & Law, 16(1).

Yadav, S., Singh, S., Bedare, D., & Samel, I. (2025). A Deep Learning Approach for Helmet Detection and Fine Generation System. International Journal of Research and Innovation in Applied Science, 10(4), 902-910.