**SafeRide AI: Helmet**

**Violation Detection with Plate Recognition**

**A Capstone Project by**

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DEDICATION

This portion is optional but perhaps you have someone or some people who have inspired you to push on with your studies. A dedication would be a fitting way to acknowledge their impact on your success.

ACKNOWLEDGMENTS

The road to this point in your studies couldn’t have been travelled alone. Along the way, someone somewhere helped you. This is your chance to thank them.

By the way, exercise the liberty to be personal to reflect the sincerity of your gratitude.

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ABSTRACT

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# INTRODUCTION

## Background of the Study

Motorcycle-related road accidents remain a pressing concern in the Philippines, where non-compliance with helmet requirements continues to contribute to preventable injuries and fatalities. These accidents not only endanger the lives of riders but also place a significant burden on the healthcare system and the broader economy. Strengthening motorcycle riding safety also aligns with Sustainable Development Goal (SDG) 9, which emphasizes the promotion of innovative and sustainable infrastructure to ensure safer mobility for all road users.

The primary risk factors contributing to motorcycle accident fatalities in urban areas with populations exceeding 100,000 residents remain a significant concern in road safety research. Research on motorcycle safety reveals significant differences between urban and rural areas across multiple countries. In Thailand, both urban and rural motorcycle riders experience near-miss incidents influenced by control errors, violations, and safety equipment use, though distinct environmental conditions contribute to different riding behaviors between areas (Sajjakaj Jomnonkwao et al., 2023). Indonesian data shows higher road traffic accident prevalence in urban areas (34.1%) compared to rural areas (28.2%), with age and helmet use being common risk factors, while sex was significant in urban areas and mental disorders in rural areas (Intan Zainafree et al., 2022).

In China, illegal motorcyclist behaviors such as unlicensed riding, drunk riding, and improper overtaking were found to significantly increase the likelihood of serious or fatal injuries, with young riders showing higher propensity for illegal behaviors and older riders facing greater risks of severe outcomes (Li et al., 2022). Similarly, in Thailand, recent findings indicate that factors such as the absence of a valid driver’s license, exceeding speed limits, and male driver involvement significantly elevate the probability of fatal outcomes in motorcycle crashes, particularly among young adult riders on urban roads (Thanapong Champahom et al., 2023).

The enforcement of helmet laws in the Philippines still relies largely on manual observation by traffic enforcers, a method that struggles to keep pace with the growing number of motorcycles on the road. Research on helmet law enforcement reveals significant differences between manual and automated methods for identifying violations in traffic environments. Manual monitoring by traffic police at intersections requires substantial human effort and intervention, with enforcement often limited due to the demanding nature of continuous surveillance (Kale, 2023; Godbole, 2024). In many developing countries where motorcycles are the primary mode of transportation, helmet non-compliance remains a leading contributor to road fatalities (Kale, 2023).

In contrast, automated systems utilizing machine learning and computer vision technologies can process real-time video feeds or CCTV footage to detect non-helmeted motorcyclists and extract license plate information using OCR algorithms, thereby reducing the human effort required for enforcement while improving compliance monitoring (Kale, 2023; Virutkar et al., 2024). A systematic review found that while enforcement of mandatory helmet laws was ineffective in reducing road traffic deaths, it proved effective in decreasing injuries and increasing compliance with road safety laws (Gupta & Bandyopadhyay, 2020). Automated enforcement systems, including camera-based detection, demonstrated effectiveness in improving road users' compliance with safety regulations, suggesting that technology-enhanced approaches may offer advantages over traditional manual enforcement methods in busy traffic environments.

With traffic enforcers struggling to monitor helmet compliance in congested roads and poor visibility conditions, researchers have increasingly turned to AI-driven automated detection systems to enhance road safety and enforcement efficiency. These systems primarily utilize deep learning techniques, particularly YOLOv8 for object detection, to identify motorcyclists not wearing helmets from surveillance camera footage (Angayarkanni et al., 2024; K. Yasoda et al., 2024). The automated approach addresses the limitations of manual enforcement, including human error, fatigue, and the challenge of monitoring high traffic volumes (Angayarkanni et al., 2024; Agrahari & Singh, 2020).

Moreover, these systems integrate helmet detection with license plate recognition using technologies like EasyOCR, enabling automatic identification and penalization of violators (Angayarkanni et al., 2024; Agrahari & Singh, 2020). They have demonstrated reliability across various challenging conditions, including poor lighting, occlusion, motion blur, and adverse weather such as rain, fog, and snow (Angayarkanni et al., 2024; K. Yasoda et al., 2024). By supporting scalable, real-time traffic monitoring, these solutions contribute to intelligent transport systems while also addressing privacy and legal compliance considerations (Angayarkanni et al., 2024).

Traffic enforcers face the difficulty in spotting helmet violators during periods of heavy traffic congestion, at night, and under poor visibility conditions, where manual monitoring becomes less reliable. Manual enforcement is often hindered by human error, fatigue, and the overwhelming volume of vehicles, which allows many violators to go unrecognized (Angayarkanni et al., 2024; Vijendar Reddy et al., 2024). Studies note that “excess traffic and limited traffic personnels” contribute to these enforcement gaps, leaving violations undetected (Vijendar Reddy et al., 2024).

Environmental challenges further intensify the problem, as research highlights that automated detection systems need to account for conditions like poor lighting, occlusion, and motion blur—factors that also obstruct manual spotting (Angayarkanni et al., 2024). Supporting this, one study achieved 81% detection accuracy for motorcyclists during both daytime and nighttime conditions, but only 74% accuracy specifically for helmet violation detection (Wonghabut et al., 2018), underscoring the difficulty of identifying violators in real-world scenarios. Collectively, these findings suggest that manual enforcement is least effective during rush hours, nighttime, and in high-traffic areas, which are precisely the conditions automated systems are designed to overcome.

Recent research has focused on AI-powered systems for detecting and enforcing helmet compliance in urban transportation settings. Multiple studies have implemented computer vision technologies, particularly YOLOv5 and YOLOv3 models, to achieve real-time helmet detection with high accuracy rates, including a reported 97% precision (Garad et al., 2024). These systems integrate various enforcement mechanisms: traffic signal control that dynamically adjusts based on helmet detection (Garad et al., 2024), IoT-enabled automated penalty systems using Raspberry Pi and camera modules (Kumar et al., 2025), and comprehensive violation processing with license plate recognition using Optical Character Recognition (OCR) technology (Shetty et al., 2024; Rocque et al., 2023).

The enforcement capabilities include automated fine collection, SMS/email notifications to violators, license and insurance validity checks, and potential license suspension for repeat offenders (Kumar et al., 2025; Rocque et al., 2023). These technological implementations aim to reduce manual intervention while enhancing road safety compliance in urban environments.

Despite the Motorcycle Helmet Act of 2009 (RA 10054), helmet law enforcement in Malaybalay City remains inconsistent, with many riders failing to comply (VeraFiles, 2019). While the city’s Traffic Management Center enforces Ordinance No. 900, Series of 2019, limited resources and growing transport demands weaken its effectiveness (Bukidnon Online, 2019). These challenges create a pressing need for stronger, technology-driven mechanisms to ensure helmet compliance and improve road safety.

These challenges in Malaybalay City highlight the urgent need to strengthen helmet law enforcement, especially in mid-sized urban areas where traffic congestion and limited resources make monitoring difficult. As non-compliance continues to put riders at risk, it is important to examine how current enforcement methods address helmet violations and where gaps remain. This concern provides the foundation for the statement of the problem of this study.

## Statement of the Problem

Motorcycle accidents are one of the main causes of death in mid-sized urban cities with populations over 190,000. One reason for this is the failure of riders to follow helmet laws. The Motorcycle Helmet Act of 2009 (RA 10054) requires all riders and passengers to wear standard protective helmets to reduce serious injuries and deaths. However, many riders still do not wear helmets, which puts them at greater risk during accidents and shows the need for stronger enforcement.  
 At present, helmet law enforcement depends mostly on traffic enforcers. This manual method is often limited and inconsistent, especially during rush hours, in crowded areas, or at night. Because of these challenges, many violators are not caught. While some larger cities adopt automated systems to detect helmet violations, most mid-sized cities do not, leaving gaps in enforcement and allowing preventable accidents and deaths to continue.

This study has identified research questions related to the implementation of helmet compliance laws.

1. What are the main reasons why motorcycle accidents cause deaths in mid-sized urban cities with populations over 100,000 people?
2. How do manual versus automated enforcement methods compare in identifying and addressing helmet law violations in busy traffic environments?
3. When and where do traffic enforcers face the most difficulty in spotting helmet violators without automated systems (e.g., rush hours, nighttime, or high-traffic areas)?
4. What systems have been implemented in the past to detect non-wearing of helmets in large cities?

This study examines the challenges of helmet law enforcement and the potential of automated systems to improve compliance, aiming to reduce motorcycle-related deaths in mid-sized cities.

## Objectives of the Study

General Objective

This study aims to develop a system that detects helmet non-compliance and related violations using image processing and computer vision techniques.Specifically, it intends to:

* Gather data on the different helmet law enforcement practices, challenges, and compliance data from mid-sized urban cities.
* To design and develop a system that detects helmet non-compliance using image processing and computer vision techniques, specifically the YOLOv8 object detection algorithm for helmet detection and Optical Character Recognition (OCR) for license plate recognition.
* To test the system in terms of functionality, security, and accuracy, with specific emphasis on image detection and the performance of YOLOv8 algorithm.
* To evaluate the system in terms of reliability, responsiveness, and usability to determine its overall performance.

## Significance of the Study

The development of this study focusing on Road Safety and Traffic Law Enforcement has the potential to benefit specific individuals, groups, or organizations. In general, the study’s outcomes are highly advantageous to the following:

Local Government Units and Traffic Management Center. The system enables traffic offices to monitor helmet compliance more effectively, even in congested or high-risk areas. It helps them optimize enforcement schedules and create targeted road safety campaigns.

Motorcycle Riders and Passengers. This study holds significance for the riders and passengers as it promotes safety awareness and compliance with helmet regulations. By encouraging proper helmet use, it helps prevent severe injuries and fatalities while fostering a culture of discipline and responsibility on the road.

Urban Communities. This study holds significance for the general public because fewer motorcycle accidents mean reduced traffic disruptions, lower healthcare costs, and safer commuting environments. Safer roads enhance community well-being and contribute to the overall security of urban areas.

Future Researchers. This study is significant to future researchers and developers as it can serve as a foundation for further innovations in artificial intelligence, smart city technologies, and intelligent transportation systems. It may also serve as a useful reference for related studies, offering insights and guidance for future academic and technological projects.

## Scope and Delimitation

The study also involves gathering comprehensive data on existing helmet law enforcement practices, challenges, and compliance levels from selected small urban cities. This includes obtaining perspectives from traffic enforcement agencies, local government units, and motorcycle riders to capture a holistic view of current implementation. Additionally, secondary data such as accident reports, violation records, and policy documents will be examined to identify gaps and recurring issues. These insights will provide a contextual foundation for designing a system that addresses both enforcement needs and user compliance behavior.

It also covers the design and development of a system that detects helmet non-compliance using image processing and computer vision techniques, specifically the YOLOv8 object detection algorithm for helmet detection and Optical Character Recognition (OCR) for license plate recognition. In addition, the study includes testing the system in terms of functionality, security, and accuracy, with emphasis on image detection and the performance of the YOLOv8 algorithm, as well as evaluating its reliability, responsiveness, and usability to determine overall performance.

This study clearly defines its boundaries and focus. First, the data gathering on helmet law enforcement practices, challenges, and compliance is limited only to selected mid-sized urban cities, which means the results may not fully represent the situation in larger metropolitan areas or rural communities. Second, the system is designed specifically to detect helmet non-compliance and perform license plate recognition, thereby excluding other types of traffic violations or broader road safety concerns. Third, the evaluation of the system is confined to controlled test environments and does not extend to full-scale real-world deployment, where external factors including varying weather conditions, heavy traffic, or infrastructure limitations may affect performance. Lastly, the study focuses only on the YOLOv8 algorithm and OCR technology, and does not include comparisons with other object detection or recognition methods.

# REVIEW OF RELATED LITERATURE

This chapter presents related literature and studies gathered from previous research, scholarly articles, books, and journals relevant to the proposed study. It serves as a foundation for understanding existing works on helmet law enforcement, image processing, and object detection technologies. This review provides the researchers with both direct and indirect references that guide the conduct of the present study, the development of the proposed helmet detection system, and the analysis of its results. The materials and studies included in this chapter offer essential background information and insights that support the overall development and objectives of the research.

### 2.1 Related Studies

Various studies have been conducted to promote road safety, strengthen traffic law enforcement, and integrate technology into accident prevention efforts. These studies highlight how data analytics, automation, and artificial intelligence can contribute to safer and more efficient traffic management systems. Collectively, they present a comprehensive approach to reducing accidents and improving compliance among road users.

**2.1.1 Helmet Law Enforcement**

Road safety compliance remains a pressing issue in many low- and middle-income countries, often due to weak enforcement and limited public awareness. According to (Al-Hajj et al., 2022), a cross-sectional study in Lebanon found that only 38.9% of motorcycle riders wore helmets, 37.4% of adults used seatbelts, and 25.8% of children were properly restrained. The study also reported that compliance varied across demographics, with females and middle-aged adults more likely to follow safety regulations than males, rural residents, and lower-income groups. The authors concluded that targeted interventions, stricter law enforcement, and sustained awareness campaigns are essential to improve compliance and reduce traffic-related injuries.

According to (Calderón Ramírez et al., 2023), road safety remains a critical global concern, with over 1.25 million fatalities and 20 to 50 million non-fatal injuries reported annually from traffic accidents. The authors highlighted the role of Road Safety Audits (RSA) as a systematic approach to evaluating existing and future road conditions to ensure optimal safety standards. Their literature review, conducted using the PRISMA-ScR methodology, identified the ten most widely applied RSA guidelines worldwide, four of which relate to human factors and six to road infrastructure. The study emphasized that geometric design, signage, and safety devices are the most commonly used elements in RSA, but also noted a lack of standardized methodology, as countries often adopt their own methods or checklists to guide audits. These findings underscore the importance of consistent and evidence-based auditing practices to improve road safety outcomes globally.

In addition, (Setty et al., 2020) investigated effective helmet use among 3,499 motorcyclists in Mysuru, India. They found that although 82% of riders reported wearing helmets, only 28% demonstrated proper usage of standard, full-face, and firmly strapped helmets. Compliance was higher among riders than pillion passengers, and female riders exhibited greater adherence than males. The study also noted that individuals using motorcycles for work or school were more likely to comply, and those recently stopped by traffic authorities showed higher rates of effective helmet use. These findings underscore the importance of consistent enforcement and monitoring combined with public awareness campaigns to enhance helmet compliance.

Furthermore, (Suleman Bajwa et al., 2021) examined the effect of helmet law enforcement on traumatic brain injury (TBI) cases in Lahore, Pakistan. Their mixed-method study revealed that enforcement led to significant improvements in clinical outcomes, including higher Glasgow Coma Scale scores, increased survival rates, and reduced severe TBI and intracranial hemorrhage cases. However, challenges such as poor helmet quality, partial policy implementation, and limited protection for pillion riders persisted. The study concluded that strong, comprehensive enforcement coupled with quality regulation and awareness programs can substantially improve road safety.

Additionally, (Zhou et al., 2022) assessed the impact of helmet-wearing policies on e-bike riders in Ningbo, China. The study found that helmet usage increased from 33.21% to 51.44% following policy enforcement, while riders who never wore helmets dropped to 4.01%. The authors noted that factors such as time of day, weather, and prior habits influenced compliance. Stricter enforcement and behavioral monitoring were associated with reduced crash risk, demonstrating the importance of policy intensity and consistent enforcement in promoting helmet use.

Similarly, (Choi & Kim, 2021) reviewed technological advancements in smart helmets across industries from 2009 to 2020. Their analysis of 103 publications showed that most applications targeted motorcyclists, focusing on helmet detection, accident prevention, alcohol monitoring, and emergency response. Furthermore, the integration of IoT technologies, including microcontrollers and wireless communication, enabled real-time monitoring and enforcement capabilities. The study suggested that smart helmet technology can support automated enforcement systems to enhance compliance and improve road safety outcomes.

According to (Ahmad et al., 2023), helmet use significantly reduces the severity of head injuries in motorbike accidents. Their study of 400 patients in Karachi, Pakistan, showed that non-helmeted riders had longer hospital stays, higher ICU admissions, greater mortality, and worse overall outcomes compared to helmeted riders. The findings emphasize that wearing a helmet is crucial for preventing severe traumatic brain injuries and improving recovery.

Furthermore, (Blanco Magdalena et al., 2020) studied the impact of an unexpected helmet law enforcement change in Uruguay. Their natural experiment revealed a sharp rise in compliance from approximately 30% to over 80% and a reduction in serious or fatal motorcycle accidents by five percentage points. Young and male riders, typically at higher risk, benefited most from the change. The study emphasized that stricter fines, vehicle impoundment, and public awareness campaigns produced immediate and sustained improvements in safety outcomes at minimal enforcement costs.

In addition, (Bolly & Trajanus Laurens Yembise, 2024) conducted a survey of motorcycle riders and passengers along the Jayapura City Ring Road in Indonesia. Observing 6,411 motorcycles and 18,602 individuals over 14 days, the study found low helmet compliance, particularly during peak afternoon traffic. High-risk groups had non-compliance rates exceeding 70%, while moderate-risk groups reached 290%. The authors concluded that helmet non-compliance significantly increases head and craniofacial injury risks and highlighted the urgent need for stricter enforcement, public education, and targeted safety interventions.

Finally, (Lepard et al., 2021) conducted a systematic review and meta-analysis of 25 studies across high- and low-/middle-income countries. Their findings showed that mandatory helmet laws significantly increased helmet use and decreased motorcycle fatalities and traumatic brain injuries, with greater effects observed in high-income countries. The study concluded that while helmet laws are globally beneficial, LMICs require additional measures, including enhanced public education and stronger enforcement, to maximize compliance and road safety outcomes.

**2.1.2 Helmet Detection and License Plate Recognition Using Image Processing and YOLO Algorithms**

Recent studies have focused on developing automated systems that use computer vision and image processing to detect helmet non-compliance and recognize vehicle license plates. (Patel et al., 2023) introduced a system using the YOLOv8 model for helmet detection, proving its ability to identify riders wearing or not wearing helmets in real time. Their study highlighted how advanced object detection algorithms like YOLOv8 can improve monitoring efficiency in safety enforcement. Similarly, (Agorku et al., 2023) developed a real-time helmet detection system for traffic law enforcement using YOLOv8, trained with over a thousand images. Their work demonstrated the feasibility of deploying deep learning models in actual traffic settings, addressing issues such as lighting and image imbalance.

(Prajapati et al., 2024) extended the concept by combining helmet detection with license plate identification using YOLOv8, focusing on parking area surveillance. Their system captured and analyzed real-time footage, allowing better management of rider compliance and vehicle tracking. (Suma, 2024) also improved YOLOv8 by adding attention mechanisms and structural optimizations, which increased precision and recall in detecting small or partially hidden helmets. This showed that even minor enhancements to model architecture can greatly improve performance in complex environments.

(Purkar et al., 2024) proposed a system that detects riders without helmets and extracts license plate information using Optical Character Recognition (OCR). Their research emphasized automation in traffic monitoring and demonstrated how integrating object detection with OCR can assist authorities in enforcing road safety. Similarly, (Mahaboob Basha et al., 2024) designed a convolutional neural network (CNN)-based helmet detection system that also identifies vehicle plates. Their study showed how CNNs can support reliable detection under different angles and motion conditions.

In another study, (Nayagam et al., n.d.) applied machine learning techniques to simultaneously detect helmets and locate license plates. Their system combined image classification and OCR to enhance accuracy in recognizing violations. (Liu et al., 2024) also explored helmet and plate detection through computer vision, emphasizing that combining these functions leads to a more efficient and effective enforcement system. They noted common challenges such as poor lighting, motion blur, and occlusion that affect accuracy in real-world settings.

(Gupta & Bandyopadhyay, 2020) implemented YOLOv3 and CNNs for helmet and license plate detection, showing that even earlier YOLO versions can achieve good accuracy for traffic monitoring. However, they pointed out that newer models like YOLOv8 deliver higher detection rates and faster processing speeds. Finally, (Deng et al., 2024) presented YOLOv8s-SNC, an enhanced version of YOLOv8 for small-object detection. By introducing new modules such as SPD-Conv and SEResNeXt detection heads, they significantly improved precision and recall, making it ideal for dense or complex scenes.

**2.1.3 YOLOv8 Based Helmet Detection and Number Plate Recognition**

The growing number of motorcycle-related fatalities has prompted researchers to explore automated systems for helmet detection. (Mukul, 2021) designed a real-time helmet detection system using the YOLO algorithm to automatically identify riders not wearing helmets. Their findings indicated that two-wheelers accounted for 37% of road accident deaths in India, highlighting the importance of automated monitoring for enforcement .

Earlier, (Allamki et al., 2019) developed a machine learning-based helmet detection and license plate recognition system utilizing the YOLO framework. Their approach integrated deep neural networks with Optical Character Recognition (OCR) to identify helmetless riders and extract license plate numbers from CCTV feeds. The study emphasized the potential of computer vision to improve road safety through real-time monitoring .

Similarly, (Kharate Aditi et al., 2024) proposed a computer vision-based helmet detection system capable of continuous monitoring using CCTV and webcam feeds. The study introduced an automated approach using deep learning and OCR, allowing traffic authorities to enforce helmet laws efficiently while minimizing manual labor.

(Kale, 2023) advanced the integration of helmet detection and license plate recognition using convolutional neural networks (CNN) and OCR. Their model processed CCTV footage in real time to identify riders without helmets and retrieve their license plate numbers. The study discussed environmental challenges such as lighting and camera angle, emphasizing the need for robust algorithms .

In another related study, (Minavathi, 2022) proposed a non-helmet driver detection approach utilizing the YOLOv3 algorithm and OCR. Their system followed a four-step process—detecting riders, motorcycles, helmets, and license plates—before using OCR to extract vehicle registration numbers. The study demonstrated the feasibility of implementing such systems for automated traffic law enforcement

(Tirpude et al., 2022) further refined this approach using a combination of YOLOv2 and YOLOv3 models for multi-level detection. Their real-time system achieved a 98.52% license plate detection accuracy, validating the effectiveness of deep learning-based multi-stage architectures in dynamic road environments .

Recent studies have leveraged the power of YOLOv8, the latest version of the You Only Look Once model, which provides superior speed and precision. (Satheesh et al., 2024) introduced an Automated Helmet Monitoring System combining YOLOv8 and EasyOCR to detect helmet compliance and extract vehicle license numbers. The integration of OpenCV improved performance under varying lighting conditions, ensuring stability in real-world deployment

(Prajapati et al., 2024) also utilized YOLOv8, TensorFlow, and EasyOCR to develop an automated detection system capable of generating e-challans for traffic violators. Their study demonstrated the potential of deep learning frameworks in supporting government law enforcement by automating helmet violation detection

Similarly, (Venkateswarlu et al., 2023) implemented a smart traffic assistance platform using YOLOv8 and OCR for helmet and number plate detection. Their system was designed for real-time monitoring using traffic cameras and drones, capable of issuing alerts and enhancing road safety across different environments

While helmet detection has been a primary focus, license plate recognition (LPR) systems have also evolved. (Mulia et al., 2024) conducted a performance evaluation of YOLOv8 and Faster R-CNN models for LPR, integrating super-resolution (SRGAN) to enhance low-quality images. Their results revealed that YOLOv8 achieved 93% accuracy, outperforming Faster R-CNN. The integration of SRGAN significantly improved OCR character accuracy, underscoring the importance of high-resolution image processing in traffic surveillance

**2.1.4 Evaluation of System Performance in Terms of Reliability, Responsiveness, and Usability**

Zia et al. (2025) in their study *Advancing Road Safety: A Comprehensive Evaluation of Object Detection Models for Commercial Driver Monitoring Systems* evaluated AI-based object detection models such as Faster R-CNN, RetinaNet, and YOLOv5 using performance metrics like model size, mAP@IoU 50%, and FPS. The findings revealed that YOLOv5 achieved the best performance, obtaining an mAP of 93.6% and 125 FPS on a dataset of 4,966 images, providing a balance between accuracy, speed, and model efficiency. The system’s deployment on a mini-CPU demonstrated not only its high reliability and responsiveness but also its usability in practical, cost-effective environments, making it suitable for real-world monitoring applications. This study serves as a strong benchmark for evaluating detection performance and real-time responsiveness in systems focused on traffic safety and surveillance.

Similarly, Devera et al. (2025) in Smart *Helmet Detection System for Road Safety Using YOLOv8* proposed a system that detects helmet usage in real-time surveillance of motorcycle riders. The study reported an accuracy of 75%, recall of 78%, and overall system accuracy of about 70% across varying environmental conditions. Although detecting non-helmeted individuals remained challenging, the implementation of YOLOv8 demonstrated notable improvements in real-time detection reliability and law enforcement applicability. The researchers emphasized that further enhancements such as dataset expansion and real-world integration could improve detection accuracy and adaptability. This study aligns directly with the objective of evaluating system performance in terms of reliability, responsiveness, and usability, offering valuable insights for developing and refining AI-based helmet and license plate detection systems.

In the same context, Thakre et al. (2024) in their research Automatic Helmet Detection and License Plate Recognition for Electric Bicycles Using YOLOv8 developed a hybrid model that integrates helmet detection and license plate recognition to improve traffic monitoring efficiency. The study utilized a modified YOLOv8n backbone that enhances small-object feature extraction, making it suitable for detecting small targets like helmets and license plates under different lighting and motion conditions. The model achieved a mean average precision of 91.8% for helmet detection and 89.4% for license plate recognition, surpassing traditional methods such as Haar Cascade and CNN-based models. The researchers highlighted that the system’s lightweight architecture allows deployment in embedded systems, providing real-time, high-accuracy detection for electric bicycle safety enforcement. This research aligns with the present system’s goal of enhancing road safety through AI-based detection of helmets and license plates, demonstrating that YOLOv8-based architectures can effectively balance model size, speed, and detection precision for real-world applications.

Moreover, Wani et al. (2025) in their study *Automatic Detection of Helmet Violations Using YOLO-based Detection* explored multiple YOLO versions (YOLOv8, YOLOv9, YOLOv10, and YOLOv11) to detect helmet usage, two-wheelers, and number plates under real-world traffic conditions. Their comparative evaluation used precision and recall as primary performance metrics, yielding 99.1% precision for motorcycle detection using YOLOv11, 91% for helmet detection using YOLOv8, and 98.5% for number plate detection using YOLOv9. The system also employed PaddleOCR for extracting number plate information, outperforming EasyOCR and Tesseract OCR in character recognition accuracy. The study highlights the reliability and responsiveness of YOLO-based architectures in complex, high-density urban environments and demonstrates their usability in real-time surveillance applications. This research supports the evaluation of system performance based on reliability, responsiveness, and usability core elements in ensuring effective AI-driven traffic monitoring and safety enforcement.

Furthermore, Sanchana and Eliyas (2023) in their study *Automated Motorcycle Helmet Detection Using the Combination of YOLO and CNN* introduced an automated helmet detection system that combines the strengths of You Only Look Once (YOLO) and Convolutional Neural Network (CNN) architectures. The integration of these image processing techniques enabled the system to accurately identify helmet usage with a high accuracy rate of 94.29%. The study highlights how combining deep learning models can enhance the system’s reliability and detection precision, making it applicable in intelligent transportation and traffic monitoring systems. This approach demonstrates the potential of hybrid models to improve responsiveness and usability in real-world safety applications, aligning with the objective of evaluating system performance based on reliability, responsiveness, and usability.

In the same context, Arun and Jaitly (2024) in their paper *Helmet Detection System Using YOLOv2* proposed a robust method for real-time helmet detection leveraging the YOLOv2 architecture. Their system achieved a 96.72% mean Average Precision (mAP), demonstrating high reliability and precision in diverse environmental conditions. The study also emphasized the responsiveness of the YOLOv2 model in processing image data efficiently and its usability for real-world enforcement of safety compliance. This work reinforces the relevance of evaluating AI-based detection systems through reliability, responsiveness, and usability key metrics that align closely with the objectives of the present study.

Moreover, Desai et al. (2024) in their study *Helmet and Number Plate Detection using YOLOv8* developed an intelligent system designed to automate the monitoring of traffic rule violations. Utilizing the YOLOv8 object detection algorithm, the researchers trained their model on a dataset of 3,000 real-world traffic images, achieving a precision rate of 92.55% for helmet detection and high accuracy in number plate recognition. The system demonstrated robustness under varying lighting and traffic conditions, highlighting its reliability and adaptability. Furthermore, the integration of an API for number plate recognition enhanced the system’s responsiveness and usability, enabling efficient identification and processing of violations. This study supports the evaluation of AI-driven detection systems in terms of reliability, responsiveness, and usability, aligning closely with the objectives of the present research.

Similarly, SenthilPandi et al. (2023) in their study *Object Detection using Learning Algorithm and IoT* proposed an intelligent helmet detection system that integrates YOLO-based object detection with Internet of Things (IoT) technology to enhance road safety. The system uses a Raspberry Pi 3 and a real-time camera to identify whether a motorcyclist is wearing a helmet before enabling the engine ignition. When a rider fails to wear a helmet, the system automatically prevents the engine from starting and transmits the captured data to a central computer for further processing using YOLO and CNN models. The model achieved a detection reliability of over 95%, demonstrating high accuracy and responsiveness in real-world scenarios. The use of affordable hardware and IoT integration highlights the system’s usability and feasibility for practical deployment. This study reinforces the importance of evaluating system performance through reliability, responsiveness, and usability metrics in developing intelligent road safety systems.

In the same line, Kumar et al. (2024) in their study *Real-Time Helmet Detection System with Vehicle Number Extraction for Two-Wheeler Vehicles using YOLOv8* proposed a three-stage system integrating YOLOv8 for helmet and vehicle detection with EasyOCR for number plate extraction. The system achieved accuracy rates of 64% for vehicle detection, 78% for helmet detection, and 92% for number plate recognition, demonstrating its reliability in diverse traffic conditions. By operating in real time, the model effectively responds to live video feeds, ensuring prompt and accurate detection essential for traffic monitoring and enforcement. Additionally, its implementation emphasizes usability through its application in real-world traffic management and road safety operations. This study aligns closely with the goal of evaluating system performance in terms of reliability, responsiveness, and usability, offering practical insights for developing AI-based helmet and license plate detection systems.

Mathew et al. (2023) in their study *Real-Time Number Plate and Helmet Detection of Motorcyclists using YOLOv5 and ResNet-50* developed an automated system that integrates the YOLOv5 algorithm with the ResNet-50 deep learning model to detect helmet usage and identify vehicle number plates from CCTV footage. The proposed model achieved a high mean average precision (mAP) of 98.89%, an F1-score of 94.6, and a detection speed of 130 frames per second, indicating superior reliability and responsiveness. The system effectively distinguishes helmeted and non-helmeted riders while extracting number plate information for enforcement purposes. By leveraging transfer learning and real-time object detection, the study demonstrated practical usability in intelligent traffic surveillance and safety management. This research aligns with the objective of evaluating system performance in terms of reliability, responsiveness, and usability, providing a benchmark for real-time AI-based traffic safety applications.

**Table 2.1. Compilation of Algorithms/Approach/Solution**

Field of Study: Helmet and Plate Detection using Computer Vision

| Algorithm | Strength | Weakness | Application (Cited) |
| --- | --- | --- | --- |
| YOLOv8 (You Only Look Once Version 8) | High accuracy and real-time object detection; lightweight and optimized for helmet and plate detection (Song et al., 2025; Wang et al., 2024; Ultralytics, 2025) | Requires large annotated datasets and high GPU performance for training | Helmet and license plate detection in traffic monitoring systems |
| Convolutional Neural Network (CNN) | Excellent feature extraction and classification ability for image recognition tasks (Shorten & Khoshgoftaar, 2025) | Computationally expensive and prone to overfitting without data augmentation | Helmet classification and object recognition |
| Optical Character Recognition (OCR) with EAST + CRNN | Effective for reading license plates in real-time (Zhou et al., 2025) | Sensitive to poor lighting and blurred images | Plate number recognition and text extraction |

## Table 2-1 summarizes the algorithms used in the SafeRide AI: Helmet Violation Detection with Plate Recognition system. YOLOv8 offers high accuracy and real-time detection for identifying helmets and license plates but requires large datasets and powerful GPUs (Song et al., 2025; Wang et al., 2024; Ultralytics, 2025). CNN improves image classification and feature extraction but can be computationally demanding (Shorten & Khoshgoftaar, 2025). OCR with EAST and CRNN accurately reads license plates in real time but performs less effectively under poor lighting (Zhou et al., 2025). Combined, these algorithms enhance detection accuracy and promote road safety.

## Table 2.2 List of Modifications to Chosen Algorithm/Solution

## Field of Study: Helmet Violation Detection and Plate Recognition

| Name of Modification | Author/Year (Cite) | Description | Strength | Weakness |
| --- | --- | --- | --- | --- |
| YOLOv8 Improvement with Transfer Learning | Jocher et al. (2025); Wang et al. (2024) | Enhances helmet and plate detection accuracy using pre-trained YOLOv8 weights on large traffic datasets. The model quickly adapts to new images with limited data. | Higher detection accuracy, faster training convergence, lightweight deployment | Requires extensive annotated datasets for fine-tuning |
| Two-Stage Detection (Helmet + Plate) | Liu et al. (2025) | Separates detection into two independent stages: one for helmet detection and another for license plate recognition. This improves reliability and minimizes false positives. | Reduces false detection rate and increases confidence in multi-object detection | Slightly increases processing time |
| CNN Optimization with Data Augmentation | Shorten & Khoshgoftaar (2025) | Uses flipped, rotated, and scaled images to improve model generalization and reduce overfitting. | Better performance on diverse lighting and angle variations | Requires longer training time and storage |

Table 2.2 summarizes key modifications that enhance the SafeRide AI: Helmet Violation Detection with Plate Recognition system. YOLOv8 with Transfer Learning improves accuracy and adaptability using pre-trained weights (Jocher et al., 2025; Wang et al., 2024). Two-Stage Detection increases reliability by separating helmet and plate detection, reducing false positives (Liu et al., 2025). CNN Optimization with Data Augmentation enhances model generalization through varied image transformations (Shorten & Khoshgoftaar, 2025). Together, these modifications boost detection performance and overall system efficiency.

## 2.2 Related System

This section presents various existing systems and technological frameworks developed to improve public transportation efficiency and commuter connectivity through the integration of real-time information, data analytics, and intelligent decision-support technologies.

Recent work in automated helmet and license-plate detection systems has increasingly focused on integrating deep-learning object detection models and OCR (optical character recognition) for enhanced traffic-safety enforcement. Prajapati et al. (2024) developed *Helmet Detection and Number Plate Recognition Using YOLOv8 and TensorFlow Algorithm in Machine Learning*, a system using YOLOv8 for identifying motorcyclists without helmets and EasyOCR for extracting license-plate characters. The authors demonstrate how combining these technologies enables effective real-time monitoring of riders and automated identification of traffic violations.

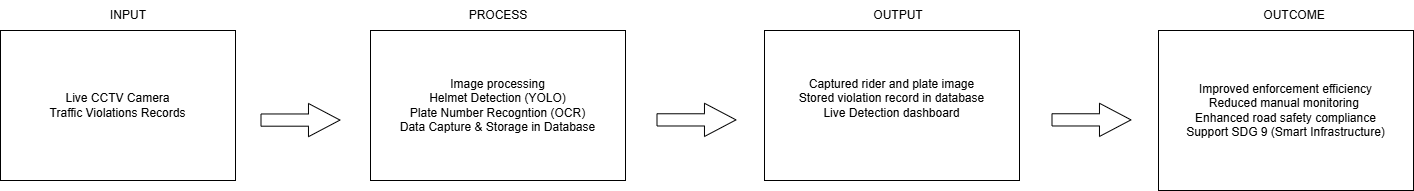
In a related study, Gopinath et al. (2024) present *Detection of Helmet and License Plate Using Machine Learning* which works in two phases: first detecting helmet usage via convolutional neural networks, then locating and reading the vehicle’s license plate if the rider violates the helmet rule. Their research highlights the practical value of linking helmet-detection with license-plate recognition in realistic traffic environments.

Agorku et al. (2023) introduced *Real-Time Helmet Violation Detection Using YOLOv5 and Ensemble Learning*, which focuses on detecting non-helmeted riders using YOLOv5 and ensemble techniques. Although it doesn’t explicitly include license-plate recognition, its emphasis on real-time performance under varying lighting and weather conditions offers valuable lessons for systems that must operate in tough traffic environments.Another relevant work by Wang et al. (2024), *A Safety Helmet Detection Model Based on YOLOv8-ADSC in Complex Working Environments*, addresses helmet detection in industrial (rather than traffic) settings by improving YOLOv8’s architecture with attention modules and enhanced small-object detection layers. While its application domain differs, the model optimization techniques it introduces are transferable to helmet-detection tasks on motorcycles.

Lastly, Aboah et al. (2023) in *Real-Time Multi-Class Helmet Violation Detection Using Few-Shot Data Sampling Technique and YOLOv8* propose a framework designed for helmet violation detection with limited labeled data using YOLOv8 and a few-shot sampling strategy. This study shows how robust detection can be achieved even when data is scarce—a key consideration for building custom datasets in your capstone.

These studies provide a robust base for designing a system that detects helmet non-compliance and captures license-plate data. They demonstrate how the integration of YOLO-based object detection and OCR techniques not only boosts accuracy and automation potential, but also addresses real-world deployment challenges such as lighting variation, occlusion, and limited data. These insights are directly relevant to the proposed system’s goals and methodology.

## 2.3 Concept of the Study



**Figure 2-3.** Conceptual Framework

The conceptual framework illustrates how real-time CCTV footage is processed to detect riders without helmets, recognize their plate numbers, and store the data for law enforcement. The system starts with live video input, which undergoes image processing and computer vision techniques, followed by helmet detection using the YOLOv8 model and plate recognition through OCR. The results captured rider and plate images with corresponding violation records are saved in a database and displayed on a live monitoring dashboard. Overall, the framework demonstrates how AI and computer vision can automate traffic monitoring, enhance road safety, and support smart transportation systems.

## 2.4 Definition of Terms

Helmet Violation – The act of riding a motorcycle without wearing a helmet, which is considered a traffic offense under Philippine law.

Automatic Number Plate Recognition (ANPR) – A technology that uses computer vision and Optical Character Recognition (OCR) to automatically identify vehicle license plates from images or video footage.

Artificial Intelligence (AI) – A branch of computer science that enables machines to simulate human intelligence, including learning, reasoning, and problem-solving.

Computer Vision – A field of AI that enables computers to interpret and process visual data from the real world, such as images or videos, to identify objects, patterns, or violations.

Image Processing - A technique used to analyze and interpret digital images or video frames to extract meaningful information, often used for object detection, recognition, and enhancement in visual data.

YOLO Algorithm (You Only Look Once) – An advanced real-time object detection algorithm that quickly identifies and classifies multiple objects within an image or video frame.

Convolutional Neural Network (CNN) – A deep learning architecture designed to automatically and efficiently process visual data, commonly used for recognizing and classifying objects in images.

Optical Character Recognition (OCR) – A technology used to convert images of text, such as license plates, into machine-readable text.

Real-Time Monitoring – The process of continuously observing traffic and identifying helmet violations as they occur, allowing immediate notification to traffic authorities.

Traffic Management Center (TMC) – A local government unit or office responsible for monitoring and managing traffic flow, enforcing traffic laws, and ensuring road safety compliance.

Motorcycle Helmet Act of 2009 (RA 10054) - A Philippine law that mandates all motorcycle riders and passengers to wear standard protective helmets while driving, to reduce injuries and fatalities caused by accidents.

# METHODOLOGY

## Materials

### Software

Describe all the software that you used including names and other details.

### Hardware

Describe the hardware that you used.

### Data

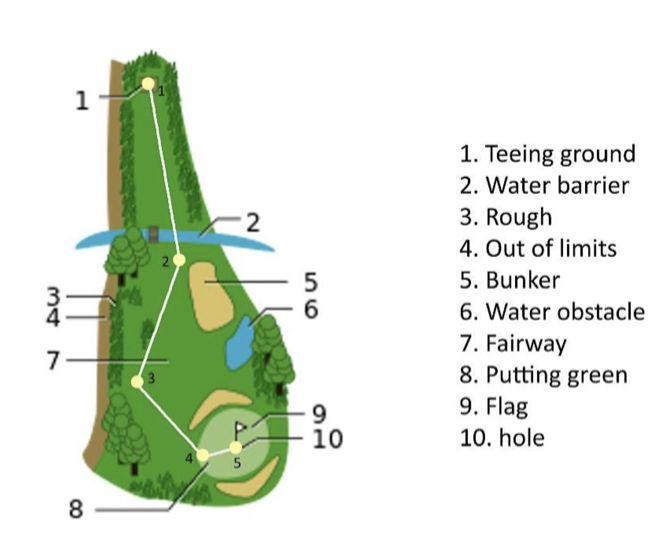
Indicate the source of the data, type of data, year of acquisition, and other pertinent details.

## Methods

The headings given here for the methods are only suggestive. Adopt what is appropriate for your research. For example, you would have experimental design if you used one such as multivariate method and the like which would describe the number of tests you did and the conditions for testing.

### Research Design

### Process Model



**Figure 3-1.** Golf course tricks.

### Procedures for the different phases

Phases be as follows depending on the methods used:

* Use Case Diagram
* Data Flow Diagram
* System Architecture
* Flowchart
* Database Schema
* Etc.

### Evaluation

# RESULTS AND DISCUSSION

## Results by phase of study

Name the phases of your study and give the results. Have as many headings as necessary depending on the number of experiments or studies you did. Provide the discussions. It may have one-to-one correspondence with your specific objectives.

## Verification studies

The headings above are only suggestive. Follow what is appropriate for your research work.

# SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

## Summary

Provide a rather concise summary of the research work.

## Conclusions

The conclusions are direct statements that would prove the achievement of the specific objectives. The conclusions should have one-to-one correspondence to the specific objectives, i.e. if you have 4 specific objectives (a to d) then you should have 4 conclusions (1 to 4).

## Recommendations

Number the recommendations and start the statement with action word.

REFERENCES

Use APA formatting for all references (in the body and in the listing here).

Use Mendeley software for easy referencing (mandatory).

APPENDICES

##### <Appendix A:> <Title>

Place your appendices here. Please be sure that these have been referenced in the body of document.

CURRICULUM VITAE

Name:

Address:

Contact Number:

Email Address:

Educational Attainment:

Membership in Organization:

Skills: