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HELMET COMPLIANCE DETECTION USING COMPUTER VISION FOR SAFER ROADS

A Thesis Project
presented to the Faculty of
College of Computer Studies

In Partial Fulfillment of the Requirements
for the degree Bachelor of Science in Computer Science

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May 2025

APPROVAL PAGE

In partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science, this research entitled **HELMET COMPLIANCE DETECTION USING COMPUTER VISION FOR SAFER ROADS** prepared and submitted by **Dela Justa, Aina Mae F.**, **Epres, Caren Joy L.**, **Matubis, Maria Angela N.**, , has been examined and is recommended for approval and acceptance.

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DEDICATION

Ad Majorem Dei Gloriam

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ABSTRACT

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CHAPTER 1

INTRODUCTION

This chapter will introduce the study, which will address the issue of motorcycle accidents that will be caused by riders who will not wear helmets. It will outline the proposed Helmet Compliance Detection Using Computer Vision for Safer Roads, along with its objectives, significance, scope, and key terms.

Background of the Problem

Motorbike accidents have been steadily increasing worldwide, leading to severe injuries and fatalities. One major contributing factor is the lack of helmet compliance and the dangerous practice of triple riding. In India alone, over 37 million individuals own and operate two-wheelers, making it critical to implement an effective monitoring system to enforce safety regulations and reduce accidents. A webcam is used for real-time video input, capturing and processing images to detect violations. The trained neural network then analyzes the webcam input, providing output based on the learned data. The system achieves an estimated 70% accuracy, with future improvements aimed at enhancing detection precision and real-time performance.[12]. Many motorcyclists frequently violate traffic rules by not wearing helmets, and enforcement by traffic police is often limited due to the demanding nature of manual monitoring. This automated helmet detection prototype has the potential to enhance traffic law enforcement and reduce human intervention, leading to safer road environments [5].

The requirement for ongoing surveillance, particularly in busy locations or along lengthy stretches of road, exacerbates this problem. The safety of motorcycle riders is directly put at risk by the ineffectiveness of the enforcement procedures. The creation of an automated, vision-based safety identification and monitoring that can precisely identify the presence or absence of helmets in real-time is required to solve this issue [11]. Given the significant portion of traffic-related fatalities attributed to motorcycle accidents resulting from non-compliance with helmet regulations. Acknowledging the critical role of helmets in rider protection, this paper presents an innovative approach to helmet violation detection using deep learning methodologies [19].

Deep learning is a subset of machine learning that uses artificial neural networks to learn from large amounts of data. In automatic helmet detection, deep learning models are trained using large datasets of helmet-wearing and non-helmet-wearing people. The neural networks learn to recognize the features that distinguish helmet-wearing one from non-helmet-wearing one . Once trained, the deep learning model can be used to automatically detect whether one is wearing a helmet or not [21].

Motorcycle-related accidents have become a growing concern worldwide, significantly contributing to road injuries and fatalities. According to the World Health Organization (WHO), more than 1.35 million people die annually due to road crashes, with motorcycle riders being among the most vulnerable. One of the leading causes of these accidents is the failure to wear helmets, which serve as a critical protective measure against head injuries. Despite laws mandating helmet use, non-compliance remains a widespread issue, exacerbated by weak enforcement and inadequate monitoring. In the Philippines, motorcycle accidents have significantly increased over the years, making it one of the leading causes of road fatalities. According to the Metropolitan Manila Development Authority (MMDA), in 2022, motorcycle-related accidents accounted for more than 30% of road crash incidents in Metro Manila alone, resulting in severe injuries and fatalities and reported a 17.3 percent increase in motorcycle-related road crashes in 2023. Based on the data from its Road Safety Unit, the MMDA said that a total of 26,599 motorcycle-related crashes were recorded in 2022 [14].

Republic Act No. 10054, also known as the Motorcycle Helmet Act of 2009, mandates that all motorcycle riders and their passengers wear standard protective helmets while on the road. This law aims to reduce head injuries and fatalities by ensuring that helmets meet specific safety standards. Despite the implementation of Republic Act No. 10054, also known as the Motorcycle Helmet Act of 2009, which mandates all motorcycle riders to wear standard protective helmets, many riders continue to violate this law, leading to preventable deaths [17].

A major challenge in enforcing helmet compliance is the reliance on manual monitoring by law enforcement officers, which is often inconsistent and inefficient. Traditional methods such as road checkpoints and manual inspections require significant resources and are prone to human error. Moreover, with the increasing number of motorcyclists on the road, it has become nearly impossible for authorities to monitor helmet compliance effectively. The absence of a scalable and automated monitoring system contributes to the ongoing problem, creating a need for technological solutions that ensure stricter enforcement of traffic laws.With advancements in artificial intelligence (AI) and computer vision, deep learning technologies have emerged as powerful tools for automating helmet compliance detection. Deep learning, a subset of AI, enables machines to process vast amounts of visual data, recognize patterns, and make accurate classifications. Technologies such as YOLO (You Only Look Once), OpenCV, and TensorFlow allow for real-time helmet detection with high precision, making them ideal for traffic monitoring applications. These technologies have been widely implemented in smart surveillance systems for vehicle detection, passenger counting and now, helmet compliance monitoring.

To address the limitations of manual enforcement, this research proposes the development of a Helmet Compliance Detection prototype using computer vision and deep learning algorithms to automatically detect whether motorcycle riders are wearing helmets correctly. The prototype focuses on enhancing helmet compliance monitoring through several key features. It can accurately determine if a rider is properly wearing a helmet on their head and not just carrying it, it will also verify if the helmet is securely fastened and correctly positioned. Helmets can generally be classified into several categories based on their structure and intended use. The prototype will concentrate on the standard motorcycle helmet, which covers the entire head and includes a chin strap and often a visor. This type of helmet offers the most protection and is typically required by law in many regions.The prototype also includes vehicle filtering which identifies if a vehicle is a motorcycle or not. If yes, it will proceed to helmet detection. In helmet detection we have 3 classes such as person with no helmet, person with proper helmet and Person with wrong helmet use. In Person with wrong helmet use category it includes improper use of a helmet such as not fastened correctly, just holding the helmet or wearing the wrong helmet such as bicycle helmets, construction helmets or other helmets that are not proper for motorcycles. This helps prevent the use of improper or mismatched helmets, which are flagged as violations to promote stricter adherence to safety standards. Moreover, the prototype enforces passenger limits by counting riders to ensure no more than two people are on a motorcycle at any time, any overloading is automatically flagged as a violation. Upon detecting any violations, a red warning is displayed on the system monitor, and the prototype automatically saves short video clips as evidence, supporting authorities in tracking and penalizing repeat offenders. By integrating these features, the prototype aims to improve road safety, assist law enforcement in effectively implementing helmet laws, and ultimately reduce motorcycle-related accidents and fatalities.

Statement of the Problem

Many motorcycle riders do not follow helmet laws, which can lead to a high risk of accidents, serious injuries, or even death. Traffic officers currently face challenges in manually checking whether motorcycle riders are wearing helmets, as the process is time-consuming and requires significant effort. Since officers cannot monitor every rider, many violations go unnoticed, making the enforcement of helmet laws difficult. Identifying helmet usage under various conditions will be a challenge for the proposed prototype. In poor lighting such as at night or in dark areas the prototype may struggle to clearly identify the rider's head. Similarly, in adverse weather conditions like fog or heavy rain, recognizing helmets will be difficult. When there are large numbers of motorcycles, it will be hard to check if each rider is wearing a helmet. Because of these challenges, the proposed prototype will need to be tested to ensure it can accurately detect helmets and provide reliable results. It will be evaluated under different conditions such as varied weather and lighting. Its speed and real-time detection performance must also be assessed to ensure it will be reliable in supporting road safety efforts.

Objectives of the Study

This section outlines the study's objectives in developing an AI-based helmet detection prototype to improve road safety.

General Objective

The main objective of this study will be to design and develop a Helmet Compliance Detection Using Computer Vision for Safer Roads that will effectively monitor and detect helmet violations among motorcycle riders using Artificial Intelligence (AI), Deep Learning, and Computer Vision. This prototype will aim to provide an accurate and automated solution for identifying non-compliance with helmet regulations, reduce the reliance on manual monitoring, and enhance the enforcement of road safety laws.

Specific Objectives

The specific objectives of this study are as follows:

1. Implement deep learning models using YOLO for object detection, and OpenCV for image and video processing.

2. Develop an Artificial Intelligence-based prototype integrating the implemented models for helmet detection.

3. Evaluate the performance of the designed helmet detection prototype under different conditions such as lighting variations, weather changes, and multiple riders.

Significance of the Study

This study will focus on applying Artificial Intelligence in traffic law enforcement, particularly in monitoring motorcycle helmet compliance. It will benefit the following stakeholders:

- **Students.** Particularly those studying Computer Science can gain valuable insights into the practical applications of AI in traffic law enforcement. This study serves as a reference for developing intelligent transportation systems and encourages innovative approaches to road safety.

- **Motorcycle Riders.** By ensuring helmet compliance, the prototype promotes rider safety, reducing the risk of severe injuries or fatalities. It encourages responsible riding behavior and contributes to safer roads.

- **Law Enforcement.** The prototype automates helmet compliance monitoring, reducing manual inspections and improving accuracy. It enhances efficiency, minimizes human error, and provides valuable data for road safety policies.

- **Camarines Sur.** The implementation of this prototype can benefit Camarines Sur by improving road safety and reducing motorcycle-related accidents. Local authorities can use this technology to enhance traffic enforcement, ensuring compliance with helmet laws and fostering a safer commuting environment for residents.

- **Researcher.** This research establishes a foundation for AI-driven traffic monitoring, enabling further studies in deep learning, object detection, and real-time surveillance, advancing smart city technologies.

- **Future Researchers.** The study lays the foundation for further research on AI-driven law enforcement systems, enabling advancements such as database integration and expanded traffic violation detection.

Scope and Limitation

This study will aim to develop and implement an AI-based prototype that uses YOLOv8 with TensorFlow for detecting motorcycles, e-bikes, and bicycles, as well as helmet usage. OpenCV will be used for real-time video and image processing, and the prototype will identify whether riders are wearing helmets properly. In addition, it will count the number of passengers on each vehicle to ensure compliance with road regulations, particularly limiting motorcycle passengers to two. The prototype will be deployed along Nabua Highway. The implementation will involve capturing real-time video through strategically placed surveillance cameras. The captured data will be processed using a Raspberry Pi 4 or NVIDIA Jetson Nano, running the trained YOLOv8 model to detect safety violations.

The prototype's outputs including flagged violations such as no helmet, improper helmet use, or overloading will be stored as video clips for review by authorities. These outputs will be used to support law enforcement in improving road safety and compliance. However, the prototype has limitations. It will only function effectively in areas covered by surveillance cameras. Its accuracy may decline in low-light or adverse weather conditions such as rain or fog. Recognizing helmet status and differentiating among similar vehicle types (e.g., between tricycle, e-bikes and motorcycles) may introduce errors. The prototype will not be connected directly to enforcement systems during the pilot implementation phase and will initially function as a standalone prototype. Future integrations may include cloud- based databases, vehicle registration systems, and mobile alert features for violations.

Project Dictionary

To avoid problems in understanding the terms used, the following technical terms are conceptually and operationally defined to provide better understanding.

- **AI (Artificial Intelligence).** The simulation of human intelligence in machines that enables them to perform tasks such as learning, reasoning, and visual recognition [18]. In this study, the prototype integrates AI-powered computer vision models to automatically analyze video data, detect helmets, count passengers, and recognize plate numbers without human intervention.

- **Algorithm.** A set of well-defined instructions or rules used to solve a specific problem or perform a computation [1]. In this study, the prototype uses machine learning and image processing algorithms to detect helmets, count passengers, and recognize plate numbers from camera feeds.

- **Accident Prevention.** Encompasses strategies and measures aimed at reducing the occurrence of unintended events that result in injury, death, or property damage. It involves identifying potential hazards, assessing risks, and implementing interventions to mitigate these risks [8]. In this study, accident prevention refers to the deployment of artificial intelligence (AI) and computer vision technologies to monitor and analyze real-time data from surveillance prototypes. The goal is to detect and alert authorities about potential accidents or safety violations, thereby enabling timely interventions to prevent incidents.

- **Computer Vision.** A field of artificial intelligence that enables computers and systems to derive meaningful information from digital images, videos, and other visual inputs [20]. In this study, the prototype processes video feeds from cameras to automatically detect helmets, count passengers, and recognize plate numbers without manual intervention.

- **Dataset.** A structured collection of data used to train or evaluate machine learning models. In computer vision, datasets consist of labeled images or videos [2]. In this study, the prototype utilizes a dataset containing images of motorcycle riders with and without helmets, plate numbers, and various riding conditions to train the object detection model. These datasets can be sourced from public datasets or collected manually for model training and validation.

- **Deep Learning.** A subset of machine learning involving neural networks with multiple layers that learn patterns and representations from large datasets [7]. In this study, AI models will be used to detect helmets in video using deep neural networks.

- **Helmet.** A protective covering for the head, typically made of a hard material, used as part of safety gear to prevent head injuries [13]. In this study, it is what the prototype will identify in real-time using computer vision techniques and ensures that the riders wear it properly.

- **Helmet Compliance.** Wearing of a helmet the right way and following the law when riding a motorcycle [23]. It helps prevent injuries and deaths in road accidents. In this study, helmet compliance is the main focus. The system uses YOLOv8 to check if riders are wearing helmets properly and to spot those who are not, to help make roads safer using technology.

- **Helmet Detection.** A computer vision task that involves identifying and verifying the presence of a helmet on a person in images or videos [9]. In this study, the prototype detects helmets in real-time using computer vision algorithms and determines if they are worn on the head and not held or carried by the riders.

- **Image Processing.** The manipulation of images through computational algorithms to enhance quality or extract useful information [6]. In this study, image processing techniques will analyze video footage to detect helmets, license plates and passenger counting, ensuring compliance with safety regulations and identifying violations.

- **Law Enforcement.** Refers to the system and practices used by government agencies to ensure public order, uphold laws, and prevent or investigate criminal activities [3]. In this study, AI-driven surveillance aids authorities by detecting violations, gathering evidence, and enhancing enforcement efficiency through real-time monitoring.

- **Object Detection.** A computer vision technique that identifies and locates objects within an image or video [22]. In this study, object detection can be used to recognize motorcyclists and determine whether they are wearing helmets by analyzing real-time footage from surveillance cameras or traffic monitoring.

- **Passenger Counting.** The process of counting the number of passengers in a vehicle using sensors or computer vision techniques [10]. In this study, the prototype employs image processing and object detection to count passengers and compare this number with detected helmets to ensure compliance.

- **Road Safety.** The methods and measures used to prevent road users from being killed or seriously injured, including regulations, infrastructure, and education [15]. In this study, road safety includes enforcing helmet laws, using an AI-powered monitoring prototype, improving traffic management, and promoting awareness campaigns to reduce head injuries and fatalities among motorcyclists.

- **Traffic Monitoring.** The systematic observation and recording of vehicular movement and flow on roads, often used to manage congestion and improve traffic systems [4]. In this study, traffic monitoring involves using AI-powered cameras and sensors to detect motorcyclists, assess helmet usage, and identify potential violations in real time.

- **YOLO (You Only Look Once).** A deep learning-based object detection model that processes an image in a single pass to detect multiple objects in real time [16]. In this study, the prototype employs YOLOv5 or YOLOv8 to efficiently detect helmets on motorcycle riders, identify passengers, and locate the motorcycle's plate number within video footage.

Notes

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CHAPTER 2
RELATED LITERATURE AND STUDIES

This chapter presents a review of both international and local literature relevant to the research topic. The researcher collected information using the college library, the internet and various other references that will assist them in their study.

Helmet Detection using Computer Vision

Helmet detection using computer vision involves automatically identifying helmet use among motorcyclists through AI and image processing. Using deep learning models like YOLO and tools like OpenCV, this prototype detects violations in real-time. It enhances road safety, supports law enforcement, and reduces manual monitoring in traffic surveillance applications.

According to Afzal et al. [2021] they developed a deep learning-based automatic helmet detection system for real-time videos. They used various models, with Faster R-CNN and Region Proposal Network (RPN) addressing challenges like low resolution, weather, occlusion, and illumination. The model was retrained on a self-generated dataset from three locations in Lahore, Pakistan. The system achieved an impressive accuracy of 97.26%, demonstrating its potential to improve authorities' ability to monitor motorcyclists violating traffic laws [1]. Another review from Singh [2024] emphasizes how computer vision improves helmet compliance in dangerous industries by using AI-powered detection to monitor safety in real-time, enforce compliance, and reduce workplace dangers [25]. Furthermore, Siebert et al. [2024] developed a low-cost and affordable computer vision method to check if helmets are used by motorcycle riders in five cities in Southeast Asia using crowdsourced images from Mapillary. They trained their algorithm on over 800,000 images and it achieved high accuracy and detected over 1.3 million motorcycles. The results show that drivers are more often to wear helmets than passengers and people wear helmets more on big roads than small roads. This approach is helpful because it is accurate and useful without the need for people to go out and collect data [24].

According to Giron et al. [2020] the no helmet no ride law that was implemented in the Philippines is still not working because many motorcycle riders are not following it. The government has partnered with De La Salle University to fix this issue by using artificial intelligence. They used Computer Vision to automatically check if riders are wearing helmets or not. The system uses deep learning, especially Convolutional neural networks to improve detection accuracy [7]. According to Soltanikazemi et al. [2023] , the helmet violation detection system was YOLOv5-based and it is developed using genetic algorithm optimization to monitor in real-time. The model achieved a high accuracy, and it was ranked 4th in the AI City Challenge in 2023. The study shows the advantages of deep learning and discusses how it is more effective than the traditional methods in ensuring helmet compliance and enhancing motorcycle safety in roads [26].

The work of Mutyala et al. [2023], introduces a real-time helmet detection warning system that is powered by Detection Transformers (DETR) for improving detection precision and operational effectiveness in improving motorcycle safety. The system detects motorcycle riders that are not using and wearing helmets in real time, and it will generate alerts to improve the road safety. DETR uses a self-attention mechanism to capture complex relationships in image sequences, allowing accurate helmet detection even in difficult conditions like poor lighting. The system combines video feed analysis with DETR's object detection features, ensuring minimal processing delay. Testing results show the system's high precision and recall rates in different situations. This solution can be customized to send alerts to authorities or directly notify and inform riders, this might decrease violations and promote safety [15]. Tomas and Doma [2023], used the YOLOv5 algorithm in their study, YOLOv5 is used to detect helmets, and it classifies their usage among motorcycle riders in the Philippines. They are processing video footage from Makati City, and they optimized model hyperparameters for better accuracy. They suggest enhancing the data consistency and to use separate models for detection and classification tasks. Their findings show best results in helmet detection that could contribute more to road safety [28].

Object Detection Models and Image Processing Techniques

Object detection models like YOLO are widely used for real-time detection tasks. YOLO, combined with OpenCV for image processing and TensorFlow for model training and deployment, offers efficient and accurate object recognition. These tools work together in applications such as traffic monitoring, helmet detection, and safety compliance systems. Image processing techniques are fundamental in preparing and enhancing visual data for analysis by machine learning models. In this study, several image processing methods were applied to ensure that the system accurately detects whether an individual is wearing a helmet. These techniques help in improving the quality of the input data, extracting relevant features, and enabling more accurate and efficient model training.

The YOLO (You Only Look Once) is a deep learning-based object detection model that can detect multiple objects in real-time with high speed and accuracy. According to the study of Jiang et al. [2022] , the YOLO algorithm was improving and evolving from time to time, and it makes object detection faster and more accurate. It compares different YOLO versions and explains its performance compared to traditional methods like Convolutional Neural Networks (CNNs). They highlight that YOLO is still improving and evolving and it is very useful in areas like in security, finance, and other applications [9]. Similarly Terven et al. [2022] discuss the evolution of YOLO from its first version to YOLOv8, YOLO-NAS, and YOLO with transformers. It highlights its improvements in architecture, accuracy, and speed. They compare YOLO with different models like R-CNN and SSD and they explore its applications in fields of robotics, healthcare, security, and traffic monitoring. Future research aims to improve YOLO's real-time detection and its efficiency [27]. YOLO (You

Only Look Once) was introduced by Joseph Redmon and his team in 2015 to address the limitations of earlier object detection models like Fast R-CNN. While Fast R-CNN was accurate, it was too slow for real-time applications, taking 2–3 seconds to process a single image. In contrast, YOLO performs detection with just one forward pass through the network, enabling much faster and real-time predictions [6]. With the increasing number of motorcycle users and the issue of helmet non-compliance, Kumar et al.[2024] developed a Real-Time Helmet Detection System to improve road safety by detecting helmet violations and capturing vehicle license plates. The system uses YOLO for object detection and a mechanism for license plate recognition, consisting of three steps: identifying motorcyclists, verifying helmet usage, and capturing the license plate. It achieved 64% accuracy in vehicle identification, 78% in helmet detection, and 92% in license plate recognition [12]. In Addition, Muhammad et al. [2024] designed a real-time helmet detection system using YOLOv8, deployed on edge devices to enhance the safety of motorcyclists in Indonesia. During testing, the model demonstrated strong performance in detecting helmets (91.1% F1 score), riders (81.7%), and non-helmeted riders (33.0%). They also evaluate the system's CPU usage (78%), RAM (77.4%), temperature (33°C–65°C), and power consumption (6.5 W). This system shows potential for integration into smart city infrastructure, improving the efficiency of traffic law enforcement [14]. Furthermore,Choubey et al. [2025] introduces a YOLOv3-oriented model created for identifying license plates and helmets within images. They improved data quality and variety by pre-processing and created a tailored annotated dataset for helmets and license plates. The model underwent training through a multi-phase approach [4].

OpenCV is an open-source library that provides a vast collection of tools for computer vision tasks, including image processing, feature extraction, object recognition, and real-time video analysis. According to Satheesh et al. [2024] using OpenCV, a publicly available computer vision library. For the goal of observing objects, attributes for extraction and image preprocessing, OpenCV offers a broad array of tools and functionalities. By utilizing

OpenCV, we will guarantee consistency and reliability when managing various real-world situations, encompassing various lighting situations, obstructions, and vehicle angles [22].

TensorFlow is an open-source machine learning library developed by Google. It is widely used for training deep learning models, including convolutional neural networks (CNNs), which are essential for object detection. In this study of Kumar et al. [2023] , TensorFlow, a deep learning framework, will be utilized to create, develop, and assess a vision-based safety identification and monitoring system. The aim of the research is to enhance motorcycle safety by automating the identification and enforcement of helmet usage. This system is designed to offer a reliable, cost-effective, and expandable solution to assist transit agencies, road safety groups, and the biking community as a whole [13]. Another review from Sharma [2024] the fundamental intelligence of the tensorflow module is illustrated by a machine learning model that has been created using tensorflow's robust machine learning framework. To achieve object detection, it is essential to precisely recognize and tag road signs, vehicles, pedestrians, and other items [23].

Vehicle Classification

According to Chandrika et al. [2020], the growing number of vehicles—exceeding 1 billion globally makes it difficult for authorities to manage traffic and provide sufficient infrastructure. Their study introduces a vehicle detection and classification system using image processing, broken into six stages: image acquisition, analysis, object detection, counting, classification, and result display. The proposed system helps monitor traffic flow, detect rule violations, and classify vehicles into categories such as motorcycles, cars, vans, and trucks, thereby supporting better traffic planning and management [3].

Similarly, Ong et al. [2022], vehicle classification plays a key role in enhancing security, managing traffic congestion, and preventing road accidents. One challenge in this process is the poor image quality from video sources, which makes object recognition difficult. To address this, their study implemented and compared YOLOv5 and Faster R-CNN algorithms for classifying vehicles into five categories: motorcycle, car, van, bus, and lorry. The results showed that YOLOv5 outperformed Faster R-CNN, achieving a mean average precision (mAP) of 0.91, precision of 0.81, and recall of 0.86, making it more suitable for accurate vehicle classification using video-based image data [16].

In line with this,Sanjana et al. [2021], vehicle detection and classification have become increasingly important due to the growing number of vehicles, traffic violations, and road accidents. Their review explores various methodologies that have evolved over the years, shifting from basic image processing to machine learning approaches. This progression has led to the integration of helmet detection and license plate recognition, using object detection and text recognition models that are now easier to implement through built-in frameworks or customizable tools [21].

Moreover, Espinosa et al. [2021] , motorcycles are classified as Vulnerable Road Users (VRUs), alongside bicycles and pedestrians, and are among the most frequently involved in urban traffic accidents. To address this issue, their study reviews the use of automatic video processing techniques—particularly leveraging CCTV surveillance systems—for the detection and tracking of motorcycles. The authors emphasize the effectiveness of deep learning algorithms within the field of computer vision for these tasks. Additionally, they discuss the use of standard performance metrics, introduce the Urban Motorbike Dataset (UMD) for evaluation purposes, and outline current challenges and potential future research directions in this emerging field [5].

Passenger Counting

Passenger counting systems utilize sensors and computer vision models to automatically count individuals boarding or exiting vehicles. These prototypes often use YOLO for real-time detection and OpenCV for image processing. They help optimize public transport operations, monitor capacity, and improve service efficiency in buses, trains, and other mass transit systems.

The study of Rendon et al. [2023], which introduced a computer vision method using deep learning to detect, count and estimate the number of passengers in Bogota's Trans-Milenio stations, this study shows how accurate passenger counting in public transport systems is important. They analyzed images with nearly 900,000 labeled heads and achieved a very accurate result, with an error of only one person per image. This is better than counting them by hand. This method is scalable and low-cost, and it is useful for improving the planning and running of public transport systems [19]. The paper by Radovan et al. [2024] discusses different passenger counting systems, comparing traditional technologies like RFID and infrared sensors with newer methods using image processing and machine learning. It explores the advantages and disadvantages of each system and how to improve these. It also discusses concerns under GDPR. The authors propose some improvements for passenger counting solutions and suggest ways to enhance public transport operations to make it more effective [18].

According to the study by Bhatt et al. [2024] , wearing a helmet when motorcycling is important because it helps reduce the likelihood of serious head injuries in accidents. With the help of modern technology such as real-time surveillance and computer vision, it is now possible to automatically determine whether riders are wearing a helmet using video footage on the road. The aim of this system is to strengthen the implementation of road safety laws by detecting not only the driver but also the passenger if they are wearing a helmet. Based on a report by the World Health Organization (WHO) in 2023, the correct use of a helmet reduces the risk of death by 42% and the risk of head injury by 69% [WHO, 2023] [2].

Evaluation Metrics of YOLOv8

YOLO (You Only Look Once) is a real-time object detection algorithm that offers a faster and more efficient alternative to traditional detection methods. Specifically, as a single-stage detector, YOLO employs a convolutional neural network (CNN) to predict both bounding boxes and object classes directly from input images. It achieves this by dividing the image into a grid, which enables the detection of multiple objects in a single pass [11].

In this context, several studies have evaluated the performance of YOLO and its variants in terms of speed, accuracy, and adaptability. According to Prakash and Palanivelan [2024], YOLO revolutionized object detection by enabling real-time performance through its single-pass, grid-based prediction approach [17]. Moreover,Karthika et al. [2024] assessed YOLOv8 for its high precision and speed, highlighting its effectiveness across static images, video streams, and live feeds [10]. Furthermore,Varghese and Sambath [2024] demonstrated that YOLOv8 outperforms earlier versions by integrating attention mechanisms, dynamic convolution, and voice recognition, which results in improved accuracy and computational efficiency [29]. Similarly, Safaldin et al. [2024] proposed an enhanced YOLOv8 model tailored for detecting moving objects in dynamic environments. Through architectural and preprocessing modifications, their model improved motion sensitivity and achieved strong results on datasets such as KITTI, LASIESTA, PESMOD, and MOCS—recording 90% accuracy, 90% mAP, 30 FPS, and 80% IoU [20]. However,Hussain [2024] conducted a comparative analysis of YOLO architectures, noting that YOLOv8 features enhanced feature extraction and anchor-free detection, while YOLOv10 achieves even greater real-time performance by incorporating large-kernel convolutions and eliminating non-maximum suppression [8].

Synthesis of the State-of-the-Art

The reviewed literature highlights the growing importance and effectiveness of computer vision and deep learning techniques in addressing road safety concerns, particularly in enforcing helmet compliance, identifying plate numbers, and counting passengers in real-time.

International and local studies consistently emphasize the role of helmet detection systems using deep learning models such as YOLO (You Only Look Once), Faster R-CNN, and Detection Transformers (DETR). Afzal et al. [2021] demonstrated a highly accurate system using Faster R-CNN, achieving 97.26% accuracy despite challenges like occlusion and weather conditions [1]. Complementing this, Singh [2024] and Giron et al. [2020] recognized the potential of AI in improving helmet compliance in both traffic and industrial settings [25], [7]. Further innovations were noted by Siebert et al. [2024] , who employed crowdsourced images for a low-cost helmet detection approach, and by Soltanikazemi et al. [2023] , whose YOLOv5-based system earned top ranks in the AI City Challenge. Mutyala et al. [2023] introduced DETR-powered real-time systems with alert features, while Tomas and Doma [2023] highlighted the importance of model optimization in improving helmet detection in the Philippines [24], [26], [15], [28].

The integration of object detection and image processing tools YOLO, OpenCV, TensorFlow has been fundamental in enabling real-time, accurate, and resource-efficient systems. Jiang et al. [Jiang et al.] and Terven et al. [2022] chronicled the evolution of YOLO from its initial versions to YOLOv8 and YOLO-NAS, highlighting architectural improvements and broader applications across various fields [9], [27].

YOLO (You Only Look Once) is a real-time object detection algorithm that efficiently detects multiple objects in a single pass using a grid-based CNN approach. Studies highlight its speed, accuracy, and adaptability, especially in its latest version, YOLOv8.Prakash and Palanivelan [2024] emphasized its real-time performance, while Karthika et al. [2024] noted its high precision in various visual inputs [17], [10].Varghese and Sambath [2024] showed improvements in YOLOv8 through added attention mechanisms and voice recognition, and Safaldin et al. [2024] reported strong performance in dynamic environments [29], [20].Hussain [**c**ompared YOLO versions, noting YOLOv8's enhanced detection and YOLOv10's improved performance using large-kernel convolutions and anchor-free techniques [8].Kumar et al. [2023] and Muhammad et al. [2024] demonstrated real-world implementations that integrate YOLO yielding high recognition rates and strong performance on edge devices [13], [14]. Similarly, Choubey et al. [2025] emphasized dataset preparation and multi-phase training in developing a YOLOv3 model for detecting helmets and plates [4].

The utility of OpenCV was established by Satheesh et al. [2024] , who showed how it aids in preprocessing, feature extraction, and robustness in varied real-world conditions [22]. In tandem, TensorFlow emerged as a powerful framework for training and deploying models, with Kumar et al. [2024] and Sharma [2024] showcasing its flexibility in creating cost-effective and scalable safety monitoring systems. [12] [23]

Several studies highlight the importance of vehicle classification in improving traffic management, security, and accident prevention. Espinosa et al. [2021] focus on tracking motorcycles using deep learning, while Sanjana et al. [2021] highlight the shift from traditional image processing to integrated helmet and plate detection using modern frameworks [5], [21]. Ong et al. [2022] show YOLOv5's superior accuracy over Faster R-CNN, and Chandrika et al. [2020] propose a full system for detecting, counting, and monitoring vehicles [16], [3]. Despite varying approaches, all studies support the effectiveness of computer vision in traffic-related applications.

The literature also covers passenger counting systems, crucial for optimizing transport services. Rendon et al. [2023] developed a deep learning method for head counting in Bogotá, yielding minimal errors and proving useful for transit planning [19]. Radovan et al. [2024] compared traditional methods like RFID with modern image processing approaches, offering improvements under regulatory frameworks such as GDPR [18]. Bhatt et al. [2024] expanded on this by developing a real-time system that also includes helmet detection for both drivers and passengers, echoing the WHO's findings on the life-saving importance of helmets [2].

In summary, the reviewed studies underscore a significant trend: AI-powered computer vision prototypes are revolutionizing public safety enforcement. Tools like YOLO, TensorFlow and OpenCV when integrated with real-time video analysis form the backbone of intelligent traffic monitoring systems. These systems not only automate compliance checks but also promise scalability, cost-efficiency, and broad applicability in smart city infrastructures.

Gap Bridged of the Study

The existing helmet detection systems mostly focus on identifying if the motorcycle driver is wearing a helmet, often ignoring the passenger. These systems are usually made for controlled or international settings and do not consider the real traffic conditions in the Philippines, such as poor lighting, blurry movements, and blocked views in live road situations. Many of these systems also check only if a helmet is present, without checking if it is worn properly or securely fastened. In some cases, riders just carry the helmet instead of wearing it, and these systems cannot tell the difference. Also, most existing systems do not check if the rider is using the correct helmet type for the motorcycles.. Another issue is that they do not detect overloading, where more than two people are riding a motorcycle, something that is common but often ignored.

To address these problems, this study presents a real-time helmet compliance monitoring prototype designed specifically for Philippine roads like the Nabua Highway. The prototype uses the YOLOv8 object detection model to detect if helmets are being worn correctly by both drivers and passengers, checks if the helmet matches the type of vehicle, counts the number of riders to spot overloading, and saves short video clips of violations as evidence. This offers a more complete, localized, and practical way to support traffic law enforcement and improve road safety.

Notes

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CHAPTER 3
METHODOLOGY

This chapter explains the methods used to develop the Helmet Compliance Detection Using Computer Vision. It includes data collection, prototypes development using the YOLO algorithm, integration of added features, and testing to ensure the prototype performs well in real-time detection of traffic violations.

Research Design

Constructive research design involves the development of new prototypes or solutions based on existing knowledge and theories. This methodology enables researchers to create practical, functional solutions that can be implemented in real-world scenarios. It focuses on addressing real-world challenges by combining theoretical insights with practical applications. In fields such as technology and computer science, constructive research typically involves the creation of software or systems that enhance or refine existing solutions, all while building on established principles to improve functionality and effectiveness [1].

This study will use a constructive research design to develop a real-time helmet compliance detection prototype that enhances road safety monitoring through the use of AI powered technologies. This research design is appropriate for the study because it focuses on building a functional and innovative prototype that integrates computer vision compo nents to address the identified gaps in traffic law enforcement. This study will develop an intelligent detection prototype that is capable of identifying motorcycle riders without helmets, improper helmet usage, overloading of passengers, and missing or unreadable license plates. The protoype will use the YOLOv8 object detection algorithm for real-time identification, OpenCV for visual processing. It will also trigger alerts and automatically record violations for documentation and enforcement purposes. The prototype is designed for use along Nabua Highway,Camarines Sur, the prototype aims to function effectively even in varying lighting and weather conditions. By constructing and evaluating this prototype, the study contributes a practical and scalable solution to improve road safety compliance using modern AI techniques. Adopting constructive research allows this study to develop a practical solution for improving road safety. In everyday life, many accidents happen because riders don't wear helmets. To address this issue, this study will build a prototype that automatically checks if riders are wearing helmets using computer vision. The prototype will use a detection algorithm to identify helmets in real-time. Through testing and collecting more data, the prototype will be improved to make it more accurate. The goal is to build a prototype that traffic authorities can use to check helmet compliance and improve road safety. This study will help to make the roads safer and can help prevent accidents and save lives.

Theorems, Algorithm and Mathematical Framework

In the field of computer vision, algorithms and mathematical models are important in developing systems e for real-time object detection. This study uses a YOLOv8-based approach to detect helmet usage, count motorcycle passengers, and recognize license plates. YOLO (You Only Look Once) is a single-stage object detection algorithm known for its speed and accuracy, making it suitable for deployment in real-time environments.

YOLOv8 Object Detection Algorithm

YOLOv8 is the latest version of the YOLO family of algorithms, designed for fast and accurate object detection. Unlike previous versions, YOLOv8 introduces an anchor-free architecture, improved feature extraction, and decoupled detection heads for classification and localization, making it more flexible and precise. According to Muhammad et al.

[2024] YOLOv8 was used for real-time helmet detection in Indonesia, achieving a 91.1% F1 score for helmet detection and 81.7 % accuracy for rider detection [2]. This study highlights YOLOv8's effectiveness in real-world applications, emphasizing its potential for smart city integration and law enforcement, particularly in monitoring motorcyclist safety.

YOLOv8 works by predicting bounding boxes and class probabilities directly from full images in one evaluation, treating detection as a regression problem. As illustrated in Figure 1, the algorithm follows a streamlined architecture composed of an input layer, backbone, neck, and prediction head, resulting in accurate and real-time object detection. It employs advanced loss functions, such as Complete Intersection over Union (CIoU), to improve bounding box accuracy. The algorithm also utilizes Non-Maximum Suppression (NMS), which filters overlapping bounding boxes and retains only the most confident predictions. Furthermore, YOLOv8 outputs are detected only when the confidence score exceeds a predefined threshold, reducing false positives.

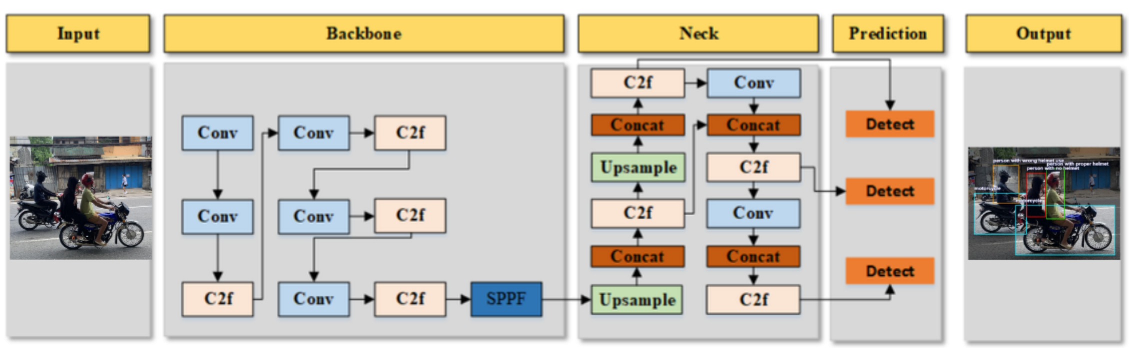


Figure 1: **Yolov8 Object Detection Architecture**

Figure 1 illustrates the YOLOv8 architecture, where the input image is first resized and normalized, then passed through the backbone for feature extraction using convolutional layers and C2f blocks, followed by the neck that refines and fuses multi-scale features through concatenation and upsampling, and finally through a decoupled prediction head for separate classification and localization, producing bounding boxes and labels.

Detection Mechanism of Yolov8

Bounding Box Prediction

YOLOv8 predicts the center coordinates (x_{pred}, y_{pred}), width (w_{pred}), and height (h_{pred}) for each object within a grid cell.

The confidence score, used for evaluating bounding box accuracy, is given by the formula:

$$Confidence = P_{object} \times IOU_{pred,truth} \tag{3.1}$$

Class Probability Prediction

YOLOv8 outputs a probability distribution across multiple object classes. For each bounding box, the network predicts the likelihood that it belongs to a particular class (e.g., helmet, rider, license plate).

Complete Intersection over Union (CIoU)

To optimize bounding box predictions, YOLOv8 utilizes the Complete Intersection over Union (CIoU) loss function, which improves upon the standard IoU by considering not only the overlap area but also the distance between the center points of the predicted and ground truth boxes, as well as the consistency of their aspect ratios. This enhancement leads to more precise and reliable bounding box regression, resulting in improved overall performance for object detection tasks.

Intersection over Union (IoU), on the other hand, serves as a fundamental evaluation metric for object detection models, as it measures the degree of overlap between predicted and ground truth bounding boxes. A higher IoU indicates more accurate localization, while lower values reflect poor alignment. The following figure illustrates how IoU is computed and highlights its role in assessing detection accuracy, with emphasis on YOLOv8's refined approach.

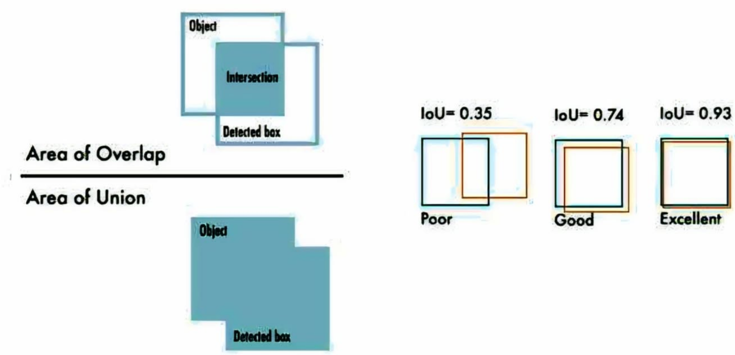


Figure 2: **Intersection over Union (IoU)**

As illustrated in Figure 2, IoU is computed by dividing the overlapping area of two boxes by their total combined area, indicating how closely the predicted box aligns with the ground truth. A higher IoU value signifies a better overlap between the predicted bounding box and the actual object. The figure further demonstrates this concept through three examples showing IoU values of 0.35, 0.74, and 0.93, corresponding to poor, good, and excellent box alignment, respectively. An IoU closer to 1 means the model has predicted the object's location with high precision, while lower values indicate weaker performance. [3]

This metric is essential in evaluating object detection models since it provides a quantitative measure of localization accuracy. For instance, many detection frameworks set a minimum IoU threshold (commonly 0.5) to determine whether a prediction is classified as a correct detection (true positive) or a missed/incorrect detection (false positive).

Non-Maximum Suppression (NMS)

YOLOv8 employs Non-Maximum Suppression (NMS) to efficiently eliminate redundant bounding boxes that predict the same object. After the model generates multiple bounding boxes, NMS ranks them according to their confidence scores, identifying how likely each box contains an object. The algorithm then selects the highest-scoring box and suppresses any overlapping boxes whose Intersection over Union (IoU) with the selected box exceeds a predefined threshold. This process ensures that each detected object is represented by only one bounding box, reducing clutter and improving the clarity of detection results. The following figure demonstrates how NMS improves detection clarity and reduces overlap.

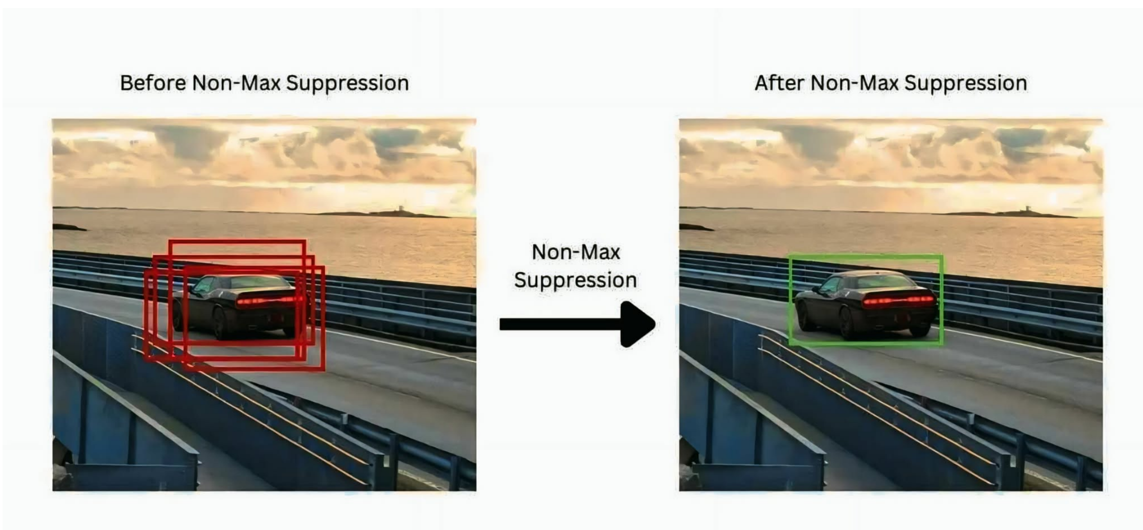


Figure 3: **Example of Non-Maximum Suppression**

Figure 3 effectively highlights the importance of Non-Maximum Suppression (NMS) in enhancing the quality of object detection results produced by YOLOv8. Without NMS, as shown in the left image, the model outputs numerous overlapping bounding boxes for a single object, which can compromise the interpretability of the results and the accuracy of object localization. The right image, after NMS is applied, displays a single, highconfidence bounding box, illustrating the algorithm's ability to reduce redundancy and improve detection clarity. This reduction in noise not only improves precision but also lowers computational load during post-processing, making the system more efficient.

In our study, the use of NMS was particularly important in refining predictions in complex scenes involving multiple or closely spaced objects—such as identifying several riders or helmets in traffic scenarios. The figure provides clear visual evidence of how NMS strengthens both the robustness and operational efficiency of the YOLOv8-based detection pipeline [4].

Materials and Statistical Tools/Evaluation Methods

This section provides detailed information on the materials, statistical tools, and evaluation methods employed in the development and assessment of the Helmet Compliance Detection Using Computer Vision for Safer Roads. It includes the hardware and software components, the process followed to implement the prototype, the sampling technique, the statistical tests used for performance evaluation, and the methods employed for evaluating the prototype's effectiveness.

The section covers the hardware, software, and tools used in developing the prototype, along with the workflow for implementation, data sampling methods, and evaluation. It highlights the use of statistical techniques such as accuracy, confusion matrices, and error rate analysis, and explains how effectiveness was assessed through detection accuracy, response time, and reliability under real-world conditions.

Test Case

The test cases briefly assess the Helmet Compliance Detection prototype's performance by simulating a variety of real-world scenarios, including different rider counts, helmet usage patterns, lighting conditions, and visibility challenges.

These tests are designed not only to verify the accuracy of helmet and passenger detection but also to evaluate the system's robustness and responsiveness under diverse traffic situations. By highlighting both strengths and potential areas for improvement, the test cases provide valuable insights for refining the prototype and ensuring reliable performance in practical deployment.

Table 1
Helmet Detection Prototype Test Cases

Test Case	Scenario Description	Expected Output	Actual Output
TC01	1 rider with proper helmet	Person with proper helmet	Person with proper helmet detected
TC02	1 rider without helmet	Person with no helmet	Person with no helmet detected
TC03	1 rider with helmet worn incorrectly	Person with wrong helmet use	Person with wrong helmet use detected
TC04	1 rider with bicycle helmet	Person with wrong helmet use	Person with wrong helmet use detected
TC05	2 riders, both with proper helmets	2 persons with proper helmets	2 persons with proper helmets detected
TC06	2 riders, only one with helmet	1 proper helmet + 1 no helmet	1 proper helmet + 1 no helmet detected
TC07	2 riders, no helmets	2 persons with no helmet	2 no helmet detected
TC08	1 rider with helmet worn backward	Person with wrong helmet use	Person with wrong helmet use detected
TC09	3 riders, all with proper helmets	Overloading violation (more than 2 riders)	3 persons with proper helmets → Violation flagged
TC10	3 riders, only one with helmet	Overloading + helmet violations	1 proper helmet + 2 no helmets detected
TC11	3 riders, mixed: 1 proper, 1 wrong, 1 none	Overloading + mixed helmet violations	3 persons with mixed violations
TC12	1 rider not wearing helmet (carrying it instead)	Person with wrong helmet use or no helmet	Person with no helmet detected
TC13	2 adults + 1 child, only adults with helmets	Overloading + partial helmet usage	2 proper helmets + 1 no helmet detected

The test cases for the Helmet Compliance Detection prototype cover various realistic motorcycle riding scenarios to ensure comprehensive evaluation of the system's capabilities. TC01 confirms that the system correctly detects a single rider wearing a proper motorcycle helmet. TC02 checks whether the system properly identifies and flags a violation when a single rider has no helmet. TC03 evaluates detection when a helmet is worn improperly, such as not fastened or secured correctly, and ensures this is flagged as wrong helmet use. TC04 tests the system's ability to differentiate and flag non-standard helmets like a bicycle helmet as improper helmet use. TC05 examines detection of two riders both wearing proper helmets, ensuring correct identification of compliant riding. TC06 validates the detection of partial compliance, where only one of two riders wears a helmet, ensuring the system outputs one proper helmet and one no helmet.

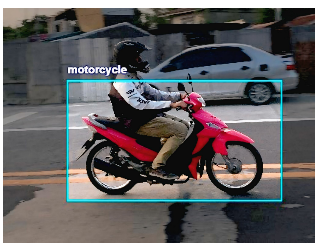
Also, TC07 confirms detection when both riders have no helmets, expecting the system to identify both violations. TC08 tests for improper helmet use when a rider wears the helmet backward, which should be detected as wrong helmet use. TC09 checks overloading detection, where three riders are on a motorcycle, all with proper helmets, but a violation is flagged due to exceeding the legal number of passengers. TC10 ensures the system detects both overloading and missing helmets when only one of three riders wears a proper helmet. TC11 verifies detection of mixed violations among three riders—one with a proper helmet, one with wrong helmet use, and one with no helmet—along with overloading. TC12 evaluates if the system correctly identifies violations when the helmet is present but not worn, such as when carried in hand or placed on the motorcycle. Finally, TC13 tests overloading combined with partial helmet use when two adults wear helmets but a child passenger does not. Overall, these test cases demonstrate the prototype's ability to detect proper helmet use, identify different violation scenarios, and monitor overloading, ensuring road safety compliance and pinpointing areas for refinement.

Instrument

The research tool used by the researchers to carry out the study was described in this section, including its design, purpose, and role in collecting and analyzing data for the evaluation of the Helmet Compliance Detection prototype. It also explains how the tool was applied during testing, the parameters it measured, and the way it supported the assessment of the system's accuracy, reliability, and effectiveness in real-world conditions.

Dataset

The dataset used in this study was custom-created and annotated by the researchers. It contains five classes: motorcycle, not motorcycle (for vehicle filtering), person with no helmet, person with proper helmet, and person with wrong helmet use. The dataset was specifically collected to support helmet compliance monitoring and accurate motorcycle detection using YOLOv8. Passenger counting was excluded, as this feature is handled directly in the system's code by detecting the number of riders per motorcycle and flagging violations if more than two are present. Images were gathered from diverse real-world scenarios to ensure that the trained model can reliably differentiate between helmet compliance cases, while also maintaining accurate motorcycle and non-motorcycle classification.



(a) **Motorcycle**

(b) **Person with no helmet**

(c) **Person with wrong helmet use**

(d) **Person with proper helmet**

(e) **Not Motorcycle**

Figure 4: **Samples of Dataset: Motorcycle, person with no helmet, person with wrong helmet use, person with proper helmet and not motorcycle.**

The image above illustrates the Helmet Compliance Detection Using Computer Vision prototype trained on a unified dataset with four main classes: (a) Motorcycle, which enables the system to correctly identify and recognize motorcycles on the road; (b) Person with No Helmet, which allows the system to detect riders who are not wearing helmets (c) Person with Wrong Helmet Use, which identifies riders wearing helmets incorrectly, and (d) Person with Proper Helmet, which confirms compliance with safety regulations. These four classes help the prototype detect motorcycles, identify helmet compliance, and overloading. Additionally, a separate Vehicle Filtering Dataset is used, which contains a single class labeled as (e) not motorcycle. This dataset enables the prototype to filter out non-motorcycle vehicles before proceeding to helmet and passenger compliance detection, thereby ensuring more accurate and reliable results.

Procedure / Process

Data Collection

Video footage is live along the Nabua Highway under various traffic and lighting conditions to capture real-world motorcycle scenarios. These videos serve as the primary input for detecting helmet usage.

Data Preprocessing

The collected data were processed using OpenCV to resize frames, enhance image quality, and normalize the input. This step ensures that the data is clean and ready for analysis by the detection model.

Model Training

The YOLOv8 model was trained using labeled data to identify whether the rider and passenger are wearing helmets. The model was tested with a separate dataset to ensure its accuracy in helmet detection.

Vehicle Filtering

As vehicles pass through the camera, the system first filters and detects whether the vehicle is a motorcycle. Only motorcycles are analyzed for helmet compliance.

Helmet Detection

Once a target vehicle is identified as a motorcycle, the system proceeds to detect whether the rider is wearing a helmet. If a passenger is also detected, the system checks whether the passenger is wearing a helmet or merely holding one or with wrong helmet use.

Real-time Monitoring

All detection processes run in real time, ensuring continuous monitoring and immediate feedback on helmet law compliance.

Real-time Violation Alert

If any person on the motorcycle (rider or passenger) is detected without a helmet or with wrong helmet use, a real- time violation alert pops up on the monitoring screen. This allows for immediate awareness and potential enforcement.

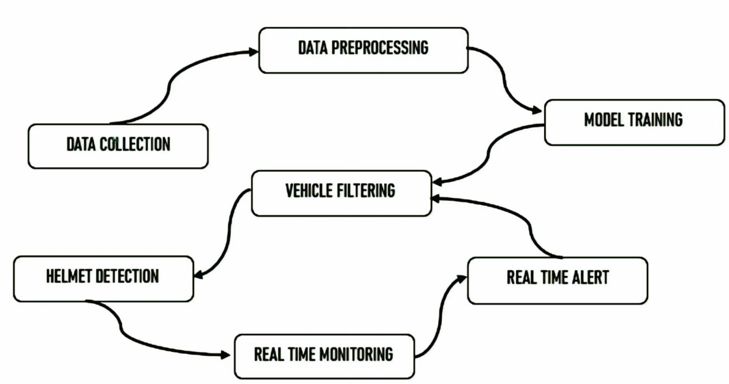


Figure 5: **Prototype of Flowchart**

The diagram presents a real-time helmet detection system workflow. It starts with video data collection and preprocessing to prepare frames for analysis. A YOLOv8 model is trained to detect helmets on motorcycle riders and passengers. During real-time operation, the system filters vehicles to focus on motorcycles, then checks for helmet compliance. If a violation is found, an alert is triggered and displayed and saves a video clip of the violation. The system continuously monitors and loops back to analyze the next vehicle, ensuring ongoing detection and enforcement of helmet laws.

Normalized Value

The normalized value is used to standardize the raw user feedback scores, transforming them into a range between 0 and 1. The formula for normalization is:

$$\text{Normalized Value} = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{3.2}$$

Where:

- X is the raw score obtained from user feedback.
- $\min(X)$ is the minimum possible value (typically 0.0).
- $\max(X)$ is the maximum possible value (typically 1.0).

After applying this formula, the normalized values are mapped to the ranges in Table 3, allowing the responses to be categorized according to satisfaction levels. This normalization ensures that the feedback is consistent and comparable across different system components. Furthermore, the final categorized feedback provides a clear understanding of user satisfaction and highlights areas where the prototype may need improvement or refinement, thereby serving as a valuable guide for system evaluation and future enhancements.

Evaluation Method

To evaluate the performance of the proposed Helmet Compliance Detection Using Computer Vision for Safer Roads, several standard evaluation metrics were utilized. These metrics assess the system's accuracy in detecting helmet usage, counting passengers, and identifying violations in real time. The evaluation was based on comparing the model's predictions against manually annotated ground truth data using test video segments.

Accuracy

Accuracy measures the overall effectiveness of the prototype by calculating the percentage of correctly identified objects (motorcycles, helmets and overloading violations) as well as correctly filtered non-motorcycle vehicles. It provides a general view of the system's performance across all detection tasks.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.3}$$

Where:

- **TP (True Positives):** Instances where motorcycles, helmets, passengers, overloading violations, or non-motorcycles were correctly detected or filtered.
- **TN (True Negatives):** Instances where non-violations or non-motorcycle objects were correctly ignored.
- **FP (False Positives):** Instances where incorrect objects were detected, such as misclassifying a non-motorcycle as a motorcycle or falsely detecting a helmet violation.
- **FN (False Negatives):** Instances where motorcycles, helmets, passengers, overloading violations, or non-motorcycles were missed.

Precision: Precision measures the ability of the system to correctly identify positive cases out of all instances that the system marked as positive. In the context of this prototype, it evaluates how often the model correctly identifies helmet violations, motorcycles, or overloading instances compared to the total number of predicted positives. A high precision indicates that the system rarely produces false alarms.

$$Precision = \frac{TP}{TP + FP} \tag{3.4}$$

Where:

- TP = True Positives (correct helmet detections)
- FP = False Positives (incorrect helmet detections)

Recall: Recall evaluates the ability of the system to detect all actual positive cases. For example, it shows how effectively the prototype detects all instances of helmet violations, motorcycles, or overloading occurrences from the ground truth. A high recall ensures that the system captures most or all violations, minimizing missed detections.

$$Recall = \frac{TP}{TP + FN} \tag{3.5}$$

Where:

- TP = True Positives (correct helmet detections)
- FN = False Negatives (missed helmet detections)

F1-Score: The F1-Score is the harmonic mean of precision and recall, providing a single metric that balances the system's ability to avoid false positives while capturing as many true positives as possible. It is particularly useful when the dataset is unbalanced, such as when the number of riders violating helmet rules is much smaller than the number of riders wearing helmets correctly.

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{3.6}$$

Mean Average Precision (mAP)

Mean Average Precision (mAP) evaluates both the precision and localization accuracy of the predicted bounding boxes across all object classes (motorcycle, person with no helmet, person with proper helmet, person with wrong helmet use). It integrates the precision-recall curve for each class and averages the results to provide a comprehensive measure of detection quality. A higher mAP indicates more reliable and accurate object detection.

- **Mean Average Precision (mAP):** The mean of average precision across all object classes.

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{3.7}$$

  Where:

  - N = Number of object classes
  - AP_i = Average Precision for the i-th class

Confusion Matrix:

The confusion matrix is a table summarizing the counts of True Positives, False Positives, True Negatives, and False Negatives for all detection tasks, including helmets, overloading, and vehicle filtering. This allows detailed insight into which types of detections are most accurate and which areas may require improvement.

The confusion matrix:

Table 2
Confusion Matrix Representation

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

- **FPS (Frames Per Second):** FPS measures how fast the system processes the video frames. It is calculated as:

$$FPS = \frac{\text{Number of Processed Frames}}{\text{Time Taken (in seconds)}} \tag{3.8}$$

Theoretical Framework

This section outlines the theoretical underpinnings guiding the development of the Helmet Compliance Detection Prototype using computer vision. The framework integrates four key theories: Computer Vision Theory, Automated Law Enforcement Theory, Surveillance Theory, and Real-Time Embedded Systems Theory.

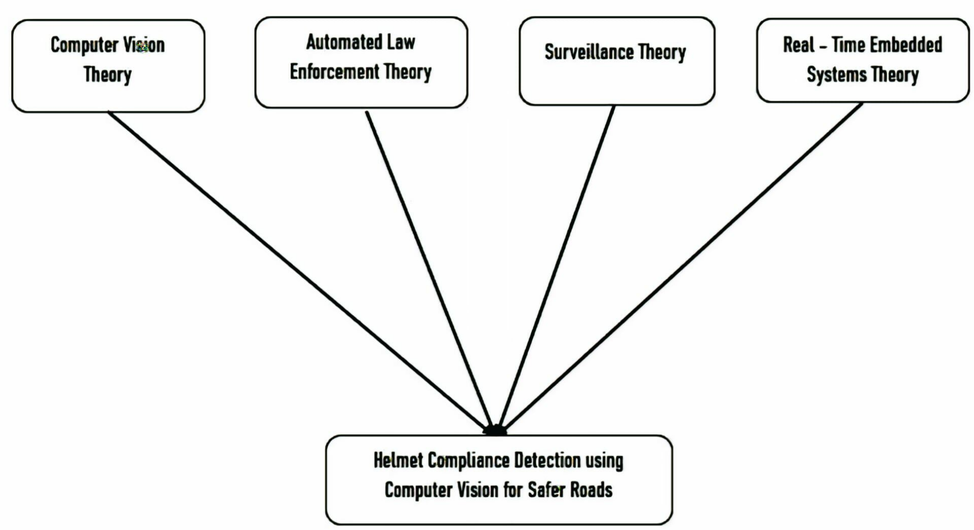


Figure 6: **Theoretical Framework of the Helmet Compliance Detection**

Figure 6 presents a simplified visual representation of the theoretical framework guiding the development of the Helmet Compliance Detection Prototype. The theoretical framework is supported by four foundational theories: Computer Vision Theory, Automated Law Enforcement Theory, Surveillance Theory, and Real-Time Embedded Systems Theory. Each of these theories is directly connected to the framework, illustrating how they collectively inform and strengthen the system's design and functionality. The layout emphasizes the multidisciplinary nature of the project, integrating both technical and sociological perspectives to ensure operational efficiency, real-time performance, and social relevance.

Computer Vision Theory

This theory provides the foundation for interpreting and processing visual inputs (video or image data) to extract meaningful patterns. In this prototype, YOLOv8 is applied to enable real-time detection of motorcycles, riders' helmet compliance, and overloading violations.

Automated Law Enforcement Theory

This theory emphasizes the role of intelligent systems in supporting or replacing human roles in enforcing regulations. In the context of traffic compliance, the integration of technologies such as OpenCV and YOLOv8 aligns with the principles of automation for more accurate, consistent, and scalable monitoring.

Surveillance Theory

Surveillance Theory explains the sociotechnical importance of systematically observing and recording behaviors to ensure safety and rule compliance. This theory justifies the deployment of camera-based monitoring systems in public spaces to detect and deter traffic violations, promoting accountability and public safety.

Real-Time Embedded Systems Theory

This theory supports the technical design of prototypes that process data and respond within strict time constraints. It underpins the implementation of real-time detection features in the system, enabling low-latency processing of live video feeds through optimized algorithms and embedded computing environments.

Notes

[1] Casper Lassenius, Timo Soininen, and Jari Vanhanen. 2001. Constructive research. In *Proceedings of the 26th Information Systems Research Seminar in Scandinavia (IRIS 26)*. Accessed: 2025-04-22. https://www.pm.lth.se/fileadmin/_migrated/content_uploads/3._constructive_research.pdf.

[2] Fadil Muhammad, Ismail Bintang, Rian Fahrizal, Ceri Ahendyarti, Romi Wiryadinata, and Imamul Muttakin. 2024. Real-time motorcyclist helmet detection using yolov8 on edge device. In *Proceedings of the 2024 International Conference on Informatics Electrical and Electronics (ICIEE)*. IEEE, (Dec. 2024). DOI: 10.1109/ICIEE63403.2024.10920426.

[3] Juan Terven, Diana-Margarita Córdova-Esparza, and Julio-Alejandro Romero-González. 2023. A comprehensive review of yolo architectures in computer vision: from yolov1 to yolov8 and yolo-nas. *Machine Learning and Knowledge Extraction*, 5, 4, (Nov. 2023), 1680–1716. DOI: 10.3390/make5040083.

[4] ThePythonCode. 2021. Non-maximum suppression using opencv in python. https://thepythoncode.com/article/non-maximum-suppression-using-opencv-in-python. Accessed: 2025-04-22. (2021).

CHAPTER 4

RESULTS AND DISCUSSION

The data gathered during the study are presented and evaluated in this chapter. A discussion and thorough analysis of helmet compliance, wrong helmet use, and motorcycle overloading are also included in this chapter.

1.Data Collection

Data Gathering

The researchers searched for datasets that included motorcycles, not motorcycles, persons with no helmet, persons with proper helmets, and persons with wrong helmet use. While it was easy to find images for motorcycles, not motorcycles, no-helmet, and proper-helmet categories, finding enough images for wrong helmet use was challenging. To create the dataset, the researchers used a phone to capture images of riders and used some images from the internet. In total, the dataset consists of around 1,133 images covering all categories. Before training the model, the images were preprocessed. This included resizing all images to a standard input size, labeling each image with bounding boxes for motorcycles and riders, and applying data augmentation techniques such as flipping, blurring, rotation, brightness adjustment, adding noise, and cropping to increase variability. The pixel values of the images were normalized to improve model training, and the dataset was split into training, validation, and test sets to allow proper evaluation of the model's performance.

Motorcycle	Not motorcycle	Person with no helmet
		

Person with proper helmet	Person with wrong helmet use
	

Figure 7: **Examples of Datasets.**

Data Pre-Processing

A total of 1,133 images were collected and fully processed using Roboflow, where they were uploaded, annotated into five classes relevant to helmet compliance detection, and organized into a complete dataset. All images were properly labeled, ensuring no unannotated data remained. To support effective model training and evaluation, the dataset was

Figure 8: **Data Pre-processing**

divided into 793 images for training, 227 for validation, and 113 for testing. This split allowed the model to learn from the majority of the data while its accuracy was assessed on separate validation and testing sets.

In Roboflow, the images were preprocessed by applying auto-orientation to correct rotation errors and resizing them to 640×640 pixels, the standard input size required by the YOLOv8 model. To improve model performance and adaptability to real-world scenarios, several data augmentation techniques were applied. These included horizontal flipping to simulate different orientations, random cropping of up to 15% to represent objects at varying distances, rotation adjustments between -15° and +15° to account for tilted camera angles, brightness variations of ±15% to handle different lighting conditions, and blurring of up to 2.5 pixels to increase resilience to motion blur. These preprocessing and augmentation steps enriched the dataset, enabling the YOLOv8 model to generalize better and perform more reliably during testing and deployment.

Model Training and Evaluation

The model was trained using a dataset with five classes: motorcycle, not motorcycle, person with no helmet, person with proper helmet, and person with wrong helmet use. The dataset was divided into training, validation, and test sets to evaluate the model. Before training, images were resized, normalized, and augmented using flipping, blurring, rotation, brightness changes, noise, and cropping to improve learning. The model was trained with the YOLOv8 algorithm for 150 epochs using batch processing, which allowed many images to be processed at once. It learned to detect and classify objects using the labeled bounding boxes. The model's performance was measured using precision, recall, F1-score, and mean Average Precision (mAP) to show how accurately it detects helmet use and violations.

```
for i, name in results.names.items():  # results.names = {0: "motorcycle", 1: "not motorcycle", ...}
    print(f"{name} -> Precision: {results.box.p[i]:.3f}, Recall: {results.box.r[i]:.3f}, "
          f"F1: {results.box.f1[i]:.3f}, mAP50: {results.box.map50[i]:.3f}, mAP: {results.box.map[i]:.3f}")

Ultralytics 8.3.198 🚀 Python-3.12.11 torch-2.8.0+cu126 CPU (AMD EPYC 7B12)
Model summary (fused): 72 layers, 3,006,623 parameters, 0 gradients, 8.1 GFLOPs
val: Fast image access ✅ (ping: 14.0±30.1 ms, read: 8.8±9.2 MB/s, size: 74.0 KB)
val: Scanning /content/drive/MyDrive/helmetdetectiondataset/valid/labels.cache... 227 images, 0 backgrounds, 0 corrupt: 100% ━━━━━━━━ 227/227 303.7Kit/s
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% ━━━━━━━━ 15/15 0.3it/s 51.4s
                   all        227        624      0.804      0.795       0.81      0.459
            motorcycle        172        205       0.97      0.956      0.976      0.669
        not motorcycle         55         93      0.911      0.978      0.968      0.778
  person with no helmet        52         73      0.699      0.671       0.71       0.26
person with proper helmet        119        168      0.662      0.676      0.653      0.251
person with wrong helmet use         61         85      0.776      0.691       0.74      0.337
Speed: 7.3ms preprocess, 206.4ms inference, 0.0ms loss, 1.1ms postprocess per image
Results saved to /content/runs/detect/val9
Overall Metrics:
Mean Precision: 0.8036871252620568
Mean Recall: 0.7945242195745195
mAP50: 0.8095097082298446
mAP [0.5:0.95]: 0.4589114873864753
```

Figure 9: **Model Training**

Model Evaluation

Model evaluation results showing per-class performance on the validation dataset. The model achieved high precision and recall for detecting motorcycles, while helmet-related classes ("person with no helmet," "person with proper helmet," and "person with wrong helmet use") had moderate performance. Overall mean precision and recall were approximately 80%, with mAP50 at 0.81 and mAP@[0.5:0.95] at 0.46, indicating that the model is effective in identifying helmet compliance but has more difficulty with strict detection of

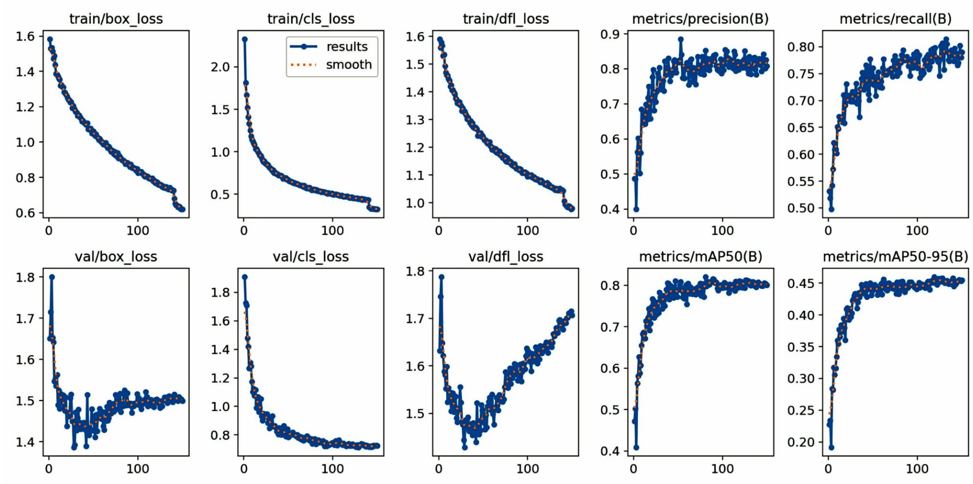


Figure 10: **Model Evaluation**

helmet violations.

Training Results

The training results show that the model learned effectively as the box, classification, and DFL losses decreased over time. Both precision and recall stabilized around 0.8, which means the model is good at correctly detecting objects and finding most of them. For overall detection performance, the model achieved about 0.8 mAP@50 and 0.45 mAP@50-95, showing strong accuracy though performance decreases under stricter evaluation. Validation results also suggest minor signs of overfitting, but the model still demonstrates reliable performance in identifying and classifying objects.

Confusion Matrix

The confusion matrix shows that the model performs very well in identifying motorcycles (96%) and non-motorcycles (98%). However, it has moderate accuracy in detecting helmet-related classes, with 73% for no helmet, 77% for proper helmet, and 72% for wrong helmet use. Misclassifications often occur between proper and wrong helmet use, or between no helmet and background. This means the model is strong in detecting motorcycles

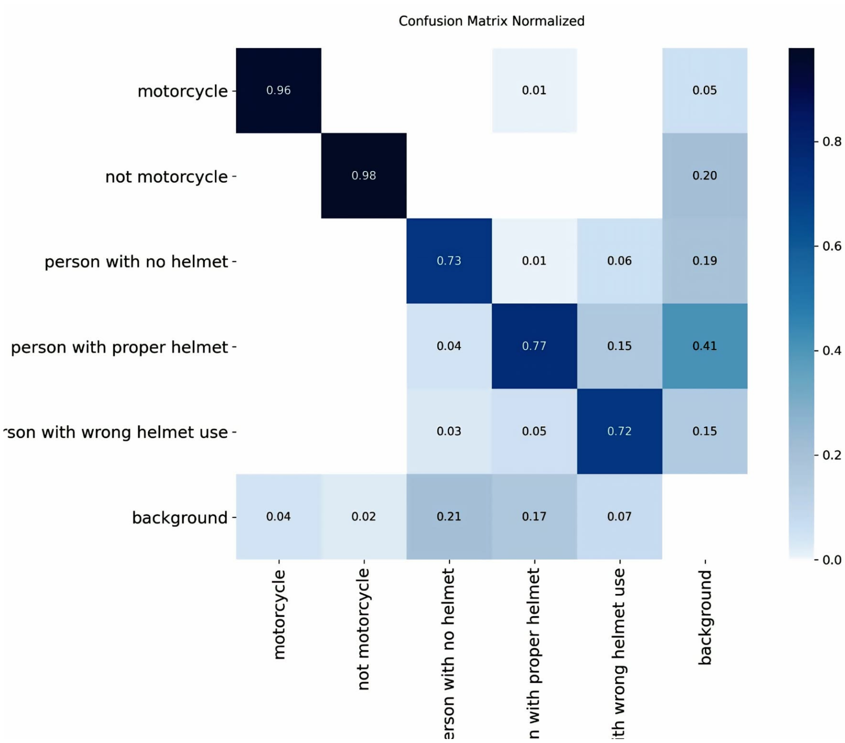


Figure 11: **Training Results**

but still struggles with fine distinctions in helmet usage and separating persons from the background.

Dataset Visualization

The dataset visualization highlights the distribution and positioning of the annotated classes. The bar chart shows that motorcycles (2022 instances) and persons with proper helmet use (1519 instances) dominate the dataset, while wrong helmet use (864 instances) is the least represented, indicating some class imbalance. Persons without helmets (1062) and non-motorcycle objects (1091) also contribute significantly to the dataset. The bounding box heatmap suggests that most objects are centered in the images, which may help the model focus on relevant regions. Additionally, the width and height distribution indicates that many objects are relatively small, with fewer larger ones, which may influence detection accuracy. Overall, the dataset provides a strong foundation for training but requires atten-

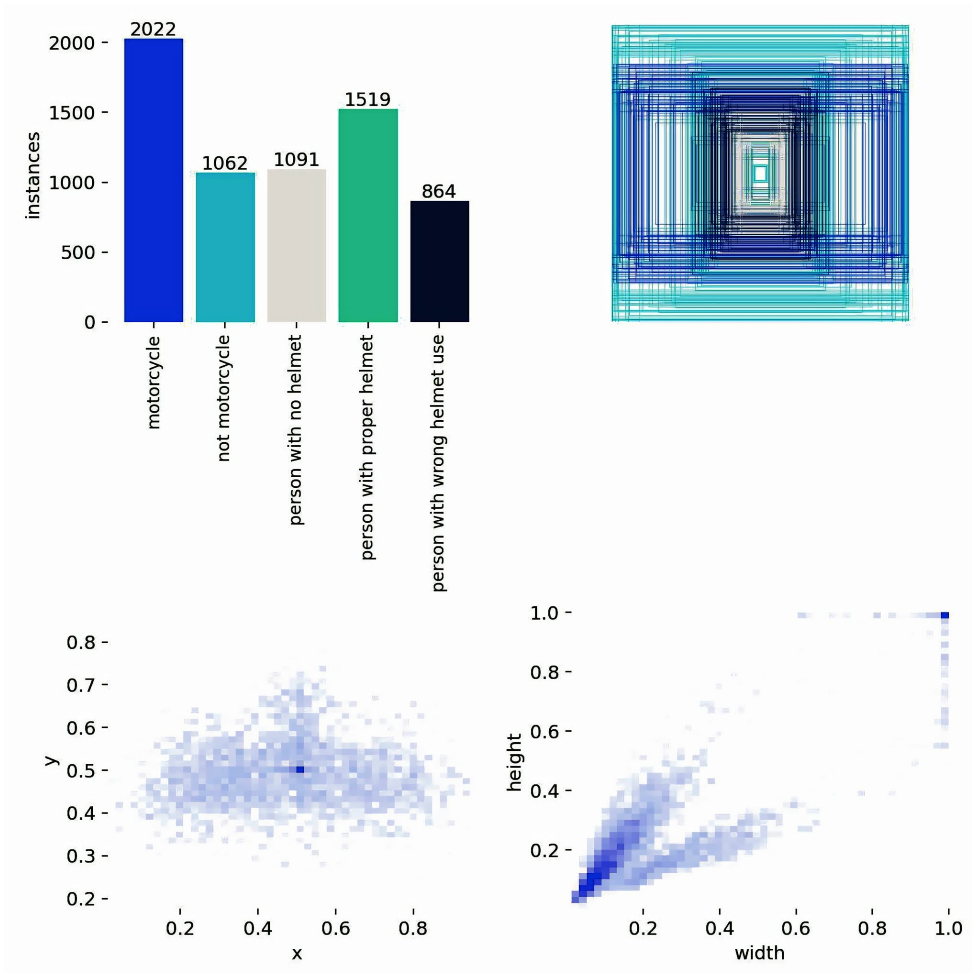


Figure 12: **Confusion Matrix**

tion to class imbalance to ensure balanced performance across all categories.

figures/Fig 17.jpg

Figure 13: **Dataset Visualization**

Box Curve

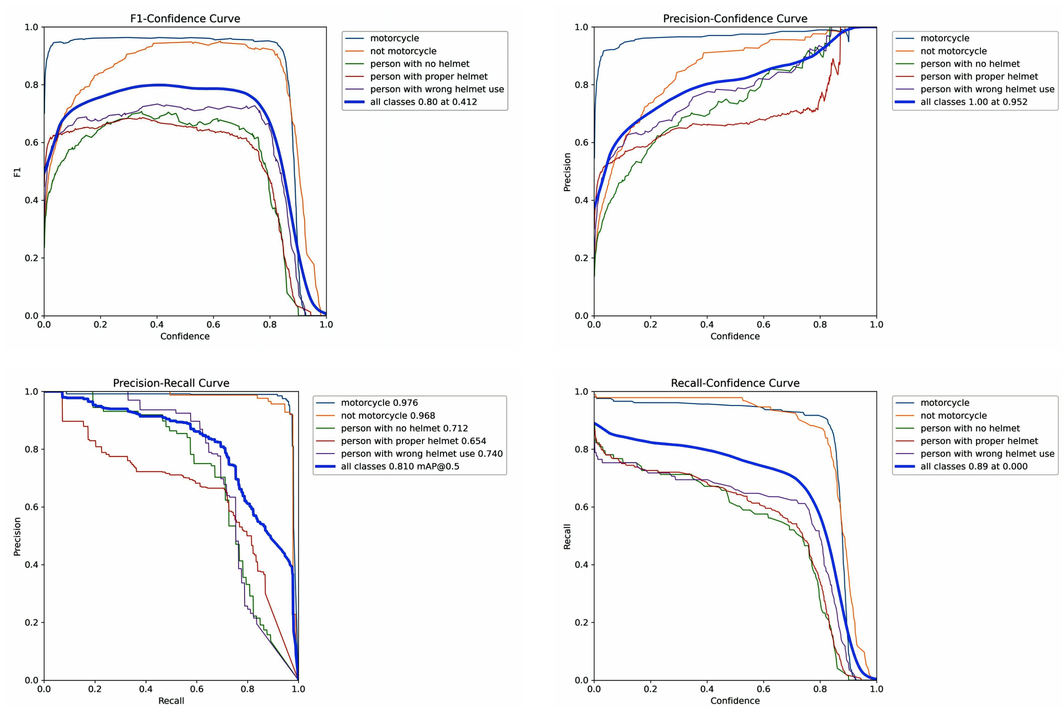
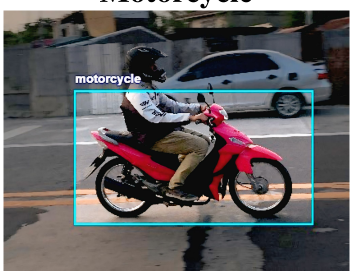


Figure 14: **Box Curve Results**

The performance evaluation graphs provide insights into how well the model detects motorcycles and helmet usage. In the F1-Confidence Curve (Graph A), the model achieves its best balance between precision and recall at a confidence threshold of around 0.41, with an overall F1 score of 0.80. The classes motorcycle and not motorcycle consistently achieve higher F1 scores compared to the helmet-related classes. The Precision-Confidence Curve (Graph B) shows that precision improves as the confidence threshold increases, with motorcycle and not motorcycle approaching near-perfect precision at high thresholds, while helmet-related classes such as proper helmet use and no helmet show lower precision values. The Precision-Recall Curve (Graph C) highlights that the model performs very well in detecting motorcycles (0.976) and non-motorcycles (0.968), but has lower average precision scores for helmet-related categories, with no helmet at 0.712, proper helmet use at 0.654, and wrong helmet use at 0.740, resulting in an overall mean Average Precision (mAP@0.5) of 0.810. Lastly, the Recall-Confidence Curve (Graph D) indicates that recall is highest at lower confidence thresholds, with an overall recall of 0.89, but gradually decreases as confidence increases, showing that while the model can detect most objects at low thresholds, higher thresholds ensure more reliable but fewer detections.

Motorcycle



Not motorcycle

Person with no helmet

Person with proper helmet

Person with wrong helmet use

Figure 15: **Detection Results**

The results present sample outputs of the model using images from the validation set as well as real-time video captured through a webcam. Each output shows detected objects along with their predicted classes, including motorcycles, not motorcycles, persons with no helmet, persons with proper helmets, and persons with wrong helmet use. These outputs demonstrate how the model identifies helmet compliance in different scenarios, providing clear visual evidence of its performance. The prototype is integrated into a web-based interface, which allows users to view live detection results directly from the webcam feed. Frames are processed instantly by the model, enabling real-time monitoring of helmet usage and motorcycle presence. This setup highlights the model's accuracy, detection capability, and practical applicability for continuous, real-time helmet compliance monitoring in various conditions.

Vehicle Filtering

Before detecting helmets, the prototype first identifies motorcycles in the camera feed. This is important because helmet detection only applies to motorcycles, not to bicycles, tricycles, e-bikes or other vehicles. The YOLOv8 model detects different types of vehicles, and only the motorcycles are selected for helmet detection. By filtering out non-motorcycle vehicles, the prototype reduces errors and ensures that helmet detection is faster and more accurate. This also allows the prototype to focus on relevant vehicles, which is important for real-time performance.

Helmet Detection

After motorcycles are filtered from the camera feed, the prototype detects the helmet status of each rider. The YOLOv8 model was trained to classify riders into three categories: person with no helmet, person with proper helmet, and person with wrong helmet use.

By focusing only on motorcycles, the prototype reduces false detections and ensures accurate helmet compliance monitoring. The model processes the video feed in real-time, highlighting each rider and indicating their helmet status. Violations, such as riders without helmets or wearing them incorrectly, can be logged or trigger alerts, enabling timely monitoring and reporting of non-compliance.

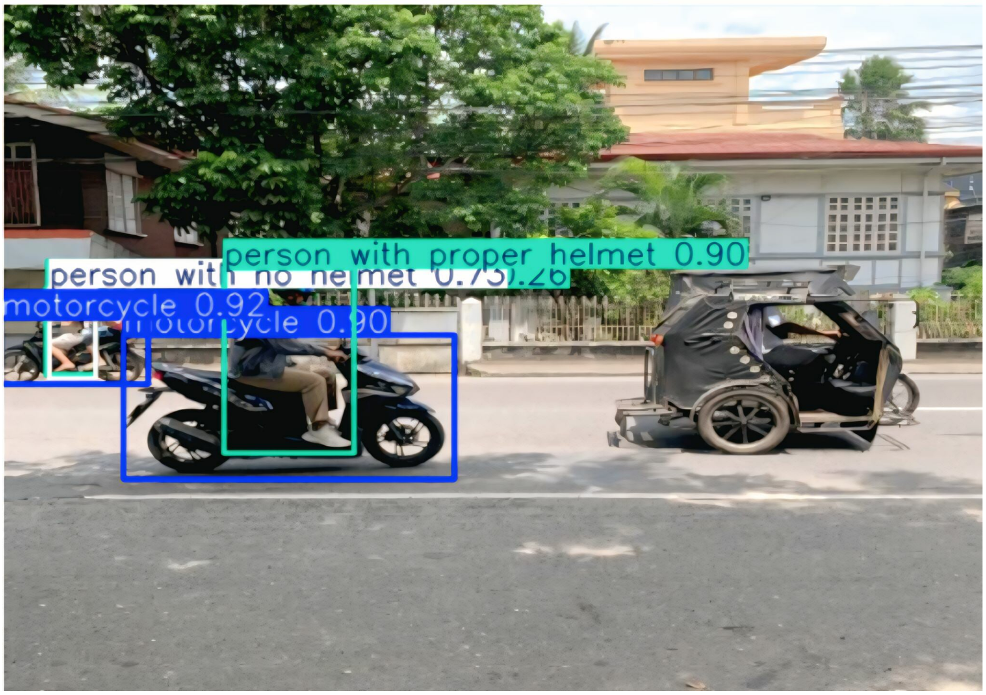


Figure 16: **Helmet Detection**

Real Time Monitoring

The prototype performs helmet detection on motorcycles in real-time by processing live camera feeds. After vehicle filtering, each rider is classified as person with proper helmet, person with wrong helmet use, or person with no helmet. Violations are immediately highlighted, logged, or trigger alerts, enabling timely and accurate monitoring. This real-time processing ensures the prototype can be effectively deployed for on-road helmet compliance enforcement.

Real Time Violation Alert

The prototype provides immediate alerts whenever a helmet violation is detected. When a rider is identified as not wearing a helmet or wearing it incorrectly, a red warning alert appears on the monitor displaying “Violation Detected.” At the same time, the prototype automatically saves a video clip of the violation for documentation and reporting purposes.

Figure 17: **Real Time Violation Alert**

This feature ensures timely detection, accurate recording of violations, and supports effective enforcement of helmet compliance.

CHAPTER 5

CONCLUSION

This chapter provides an overview of the research project "Helmet Compliance Detection using Computer Vision for safer roads" utilizing YOLOv8 model, including its results, conclusions, and recommendations.

Summary

The study "Helmet Compliance Detection using Computer Vision for Safer Roads" was conducted to provide a practical solution to the increasing number of motorcycle-related accidents in the Philippines. Many of these accidents are caused by riders who do not wear helmets properly and by motorcycles carrying more passengers than allowed. Although the Motorcycle Helmet Act of 2009 requires the use of standard protective helmets, enforcement has remained weak because manual monitoring is limited and prone to human error. To address this problem, the researchers developed an artificial intelligence–based prototype focused specifically on motorcycles and motorcycle riders. The prototype was designed using the YOLOv8 object detection model together with OpenCV to process video feeds and monitor riders in real time.

A dataset of motorcycle riders with helmets, without helmets, and with improper helmet use was collected, annotated, and used to train the YOLOv8 model. To further improve accuracy, a vehicle filtering feature was added so that the prototype only detects motorcycles and excludes other types of vehicles. The trained model was then integrated into the prototype to identify correct and incorrect helmet usage, detect motorcycles with more than two riders, and record short video clips of violations for evidence. Initial tests conducted on sample videos showed that the prototype can reliably detect different types of violations in real time, particularly under normal lighting conditions. Some limitations were observed in low-light and unfavorable weather simulations, which reduced accuracy. Despite these challenges, the study demonstrated that computer vision and deep learning can effectively support helmet law enforcement. Overall, the prototype shows strong potential to improve road safety by focusing on motorcycle riders and may serve as a foundation for future enhancements and real-world deployment in AI-based traffic monitoring

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APPENDICES

Appendix A

Language Editing Certification

This is to certify that the undersigned has reviewed and went through all the pages of the Bachelor of Science in Computer Science thesis manuscript titled

”Helmet Compliance Detection Using Computer Vision”

of **Dela Justa, Aina Mae F.**, **Epres, Caren Joy L.**, **Matubis, Maria Angela N.**, as against the set of structural rules that govern research writing in accord with the composition of sentences, phrases, and words in the English language.

JUAN DE LA CRUZ

Language Editor

Date:______________________

Appendix B

Secretary's Certification

This is to certify that the undersigned has provided accurate recommendations, suggestions, and comments unanimously agreed and approved by the panel of examiners during the oral examination of the thesis titled

"ENTER YOUR TITLE HERE"

prepared and submitted by **AuthorName1**, **AuthorName2**, **AuthorName3**, and that the same have not been amended, modified or obliterated.

MS. MARIA DAISY R. BELARDO

Secretary

Date:______________________

Appendix C

JOINT AFFIDAVIT OF UNDERTAKING (Plagiarism)

JOINT AFFIDAVIT OF UNDERTAKING

Vita

figures/person-icon.png

- **Joseph Jessie S. Oñate** is a faculty member of the College of Computer Studies. He finished his Master of Science in Computer Science degree at Ateneo de Naga University. His research interests focused on Intelligent Systems, Algorithm and Complexity, Web Technologies, Computer Vision, and Graphics.

figures/person-icon.png

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