MOTORBIKE IMAGE RECOGNITION USING YOLO

MR.PHASIN PLOYPICHA
MR. PIYAKORN RODTHANONG
MR.SOPON PLEANGNOI

A PROJECT REPORT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE BACHELOR OF ENGINEERING IN COMPUTER ENGINEERING

FACULTY OF ENGINEERING & INTERNATIONAL COLLEGE
MAHIDOL UNIVERSITY

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Computer Engineering Project
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was submitted to the Faculty of Engineering & International College,
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on
July 25, 2025

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บทคัดย่อ

บทคัดย่อภาษาไทย (not required for your project proposal, but it is mandatory for the black book)

คำสำคัญ : ลาเท็ก / วิทยานิพนธ์ (~5 คำ)

41 หน้า

MOTORBIKE IMAGE RECOGNITION USING YOLO

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DATE OF GRADUATION	July 25, 2025

ABSTRACT

The paper describes an implemation of system to help in detection of motorbike, person using YOLO in combination with a custom model to detect head and helmet. In order to count these classes and document the class entering University gates through surveillance camera. The data is to be recorded throgh google sheet API, taking snapshot of a specific scenario where a civillians using motorbike are not wearing helmet. YOLOv8 is used as the main framework for it performances and continuous supports from developers as well as its accessibility. The custom model for helmet and head detection are trained, annotated through ROBOFLOW program, and the datasets are from the university's cctv camera. Five model has been trained and, one of the five has been choosesn for their perfromace to be implemented for the detections. The product is a system that detects motorbike, person, helmet and head. Using BotSort tracker in conjunction to aid in the counting algorithm. To evaluate the performance of our detection and counting system, we analyzed pre-recorded CCTV footage using various YOLO-based models. Detection accuracy was benchmarked against manual counts, with person and motorbike detections remaining consistently high due to the use of pretrained models. Helmet detection accuracy showed substantial improvement —from 42% in the initial model to 96% in the final version—by optimizing confidence thresholds. Counting performance was assessed using both a double-line method for helmet and head detection and the BoT-SORT tracker for motorbike and person tracking.

While short line lengths (150 pixels) minimized counting errors in the double-line method, some over- and undercounting still occurred due to overlapping objects or missed detections. BoT-SORT achieved relatively accurate results, though minor discrepancies were noted due to ID switches and tracking drift. Overall, the system demonstrated reliable detection and counting capabilities, with notable advancements in helmet detection accuracy through iterative model refinement.

KEYWORDS : YOLOv8, Bot_SortTracker, Roboflow,Region of Interest(ROI), Counting Algorithm.

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CHAPTER 1
INTRODUCTION

1.1 Background

Urban traffic congestion and road safety, particularly for motorbikes, remain major issues. Motorcycles, due to their mobility, contribute greatly to traffic flow. However, they are also prone to violations, such as not wearing helmets or using the wrong lane, which increase the chance of an accident. Traditional traffic management systems lack the ability to detect and address such specific breaches in real time.

AI technologies, like as YOLO, a deep learning model for object detection, have showed potential in traffic surveillance but have not yet been routinely used to identify helmet use or lane breaches. Previous research has shown that YOLO is good for vehicle detection, but there is a gap in its use for targeted motorbike detection and safety compliance.

This research seeks to close this gap by utilising YOLO to detect motorcycles, check for helmet use, and identify lane violations. By focussing on these critical aspects, the system will improve road safety and aid in more effective traffic enforcement.

1.2 Objective

1. To detect motorbike, person, helmet and non-helmet user.
2. Count motorbike, person, helmet and non-helmet users efficiently.
3. Upload system up to university's server.

1.3 Scope

1. Develop system to detect motorbike, person, hemet and non-helmet user.
2. Display annotated video.
3. Count all the essentails and display real time.
4. University server running on system efficiently.

1.4 Expected Results

1. To reduce illegal activities of riders.
2. To ensure both safety of rider and pedestrian.
3. To spraed safety awareness.
4. Has more than 80 percent accuracy .

1.5 Timeline

Table 1.1 Project Timeline

Plan	Timeline											
	2024									2025		
	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep
Wrting Proposal												
Review Paper and Methodology												
Data Gathering												
Start Training Model												
Finalize Training Model												
Prepare University Server Specs												
Deploy and connect to database												
Presentation												

CHAPTER 2
LITERATURE REVIEW

The papers in the literature review are used as a foundation to guide, the thesis, this included inspiration, the methodoly, and expected results.

2.1 Video Image Recognition of Car Track Characteristics at Intersections [6]

The system relies on machine learning algorithms to interpret video data in real-time, helping to optimize traffic signal control, reduce congestion, and enhance safety. The study emphasizes its application in intelligent transportation systems and urban traffic flow optimization.

The use of YOLOv8, a popular deep learning model for object detection, because it offers a balance of speed and accuracy. YOLOv8 is efficient in processing real-time video streams, which is crucial for tracking vehicles at intersections. It excels in recognizing objects (like cars) in complex environments, and its architecture allows it to detect vehicles quickly while maintaining high precision.

2.2 A Lightweight Remote Sensing Small Target Image Detection Algorithm Based on Improved YOLOv8 [3]

The authors optimize the YOLOv8 architecture by refining the feature process and introducing techniques like multi-scale detection, anchor box adjustments, and a better feature fusion method. This helps the algorithm perform better with small targets. ensuring more accurate detection without significantly increasing computational cost.

they conclude that, this makes it suitable for real-time applications in remote sensing, where detecting small objects like vehicles, ships, or buildings in satellite imagery is critical. The enhancements lead to better precision and recall.

2.3 Traffic Detection and Enhancing Traffic Safety: YOLO V8 Framework and OCR for Violation Detection Using Deep Learning Techniques [5]

The YOLOv8 algorithm is a deep learning model that uses a convolutional neural network (CNN) to detect and classify objects in input images. It uses bounding box regression and class prediction to identify objects and assign class probabilities.

The model is pre-processed by converting the input video into frames, extracting features, and detecting objects. The YOLOv8 model then uses a grid to track objects, predicting bounding boxes and class probabilities. The model is fine-tuned on specific object classes and implemented for tracking, counting, and speed estimation.

This project consists of two main modules: one for vehicle count and speed detection, which uses a dataset of 800 images and video clips, and the other for number plate recognition. The first module uses computer vision techniques to accurately count vehicles and calculate speeds. The second module uses a Roboflow website dataset to extract license plate information, useful for applications like parking management and traffic monitoring.

This project aims to create two modules with distinct functions in traffic monitoring. The number plate recognition module enhances functionality for recognizing and tracking vehicles based on their number plates, while the vehicle count and speed detection module provides insights into traffic flow and speed trends.

The study on traffic detection using the YOLOv8 framework and Optical Character Recognition (OCR) has shown promising results. The system accurately detects traffic violations in real-time, while OCR enhances its ability to identify and classify violations like illegal parking or speeding.

YOLOv8 and OCR provides a robust solution for automating violation detection processes, demonstrating the effectiveness of deep learning methodologies in enhancing traffic safety and enforcing traffic regulations.

2.4 Smart Traffic Management System for Efficient Mobility and Emergency Response [1]

The proposed solution combines AI with real-time data analytics to improve traffic light management. It incorporates real-time congestion response, algorithmic optimization, data-driven decision making, and feedback loop integration.

The system uses a vast dataset of lane-specific traffic information to inform real-time adjustments. The Traffic Light Control System (OF) is activated, and the dataset undergoes preprocessing to ensure compatibility with the algorithms. A predictive model is trained using machine learning techniques, and a feedback loop is implemented to continuously evaluate the effectiveness of the decisions.

The AI system also optimizes traffic flow during emergencies, adjusting timings to prioritize passage and ensure smooth traffic flow. This innovative approach aims to alleviate congestion and improve overall traffic flow, ultimately leading to sustainable and safer cities.

2.5 Utilizing Image Processing and the YOLOv3 Network for Real-Time Traffic Light Control [2]

The paper presents the creation of a traffic light control system which is aimed at relieving congestion in urban areas. The system is designed based on the YOLOv3 object detection algorithm and is capable of counting both vehicles and pedestrians at intersections in real time using a Jetson Nano board for data processing. The research further shows that traffic lights can be controlled by taking into consideration factors such as the number of vehicles that have stopped, the number of vehicles that are crossing over and the number of pedestrians thereby enhancing the efficiency of the system which in turn reduces negative impacts on the environment.

The authors note the cost entailed in relief from congestion in UK being in the region of £37.7 billion per year and admonish that such inefficient delay is caused by the inadequate control of traffic lights that energy loss is also the outcome of that inefficient management of the traffic signal is responsible. The developed system loks set to achieve average precision with average vehicle counting for 95 percent as supported by this research.

2.6 Research on Vehicle Lane Change Warning Method Based on Deep Learning Image Processing [4]

The paper presents the progress in work which is falling into the category of the development of the low-cost lane-changing warning system which works in the efforts to improve driving safety through monocular camera and deep learning algorithms. The main aim of the study is to detect when there is a pole vehicle-user behavior who would be changing the existing lane as this is paramount to mitigate risk of collision, consequently enhance safety of roads.

As a result, the authors enhanced the Mask Region-based Convolutional Neural Network (Mask R-CNN) aiming towards a vehicle target seeker. They used the K-means clustering technique to identify appropriate proportions of anchor frames for vehicle targets, which facilitated more precise candidate box generation without degrading the performance of the network. This led to introduction of a fresh anchor set and mAP increased by about 2.6 percent thanks to about 26 percent in the mean average precision improvement.

The system was trained in a vernacular fashion with a full with 66,389 vehicle targets which were adequately annotated for target annotation assuring their appropriate performance. The authors performed various evaluations and recorded an accuracy of 94.5 percent for detection of lane changing after identifying and validating marked images of lane changing sequences. This high accuracy demonstrates the effectiveness of the proposed system in real time applications.

2.7 Summary

The reviewed studies highlight innovative uses of AI and deep learning for traffic management and safety. One study employs the YOLOv8 framework and Optical Character Recognition (OCR) to detect traffic violations in real-time, using modules for vehicle counting, speed estimation, and license plate recognition, achieving effective enforcement of traffic regulations. Another study integrates AI with real-time analytics to optimize traffic light control, dynamically responding to congestion and prioritizing emergency vehicles, thereby improving urban mobility and sustainability. Similarly, a traffic light control system based on YOLOv3 counts vehicles and pedestrians at intersections, achieving 95 percent accuracy in optimizing traffic flow and reducing urban congestion. Lastly, a lane-change warning system utilizing Mask R-CNN and K-means clustering achieves 94.5 percent accuracy in detecting lane changes, offering a cost-effective solution for collision risk mitigation and enhanced road safety. These approaches collectively demonstrate the transformative potential of AI in traffic management.

CHAPTER 3
METHODOLOGY

3.1 System Design

The purpose of the helmet detection system is to track helmet use from CCTV footage on a college campus. Three primary phases of the system comprise data preparation, model training and system implementation. The first step involves converting campus CCTV video footage into image frames, which are subsequently labelled with helmet and unhelmeted head information using Roboflow. A customised YOLOv8 object detection model that is tuned for real-time performance is trained using the annotated dataset. After training, the model is incorporated into a real-time system that recognises and categorises heads and helmets by processing incoming video frames. In order to provide real-time statistics that facilitate safety compliance monitoring, a counting mechanism is integrated to monitor the quantity of helmets and heads seen within a designated area of interest.

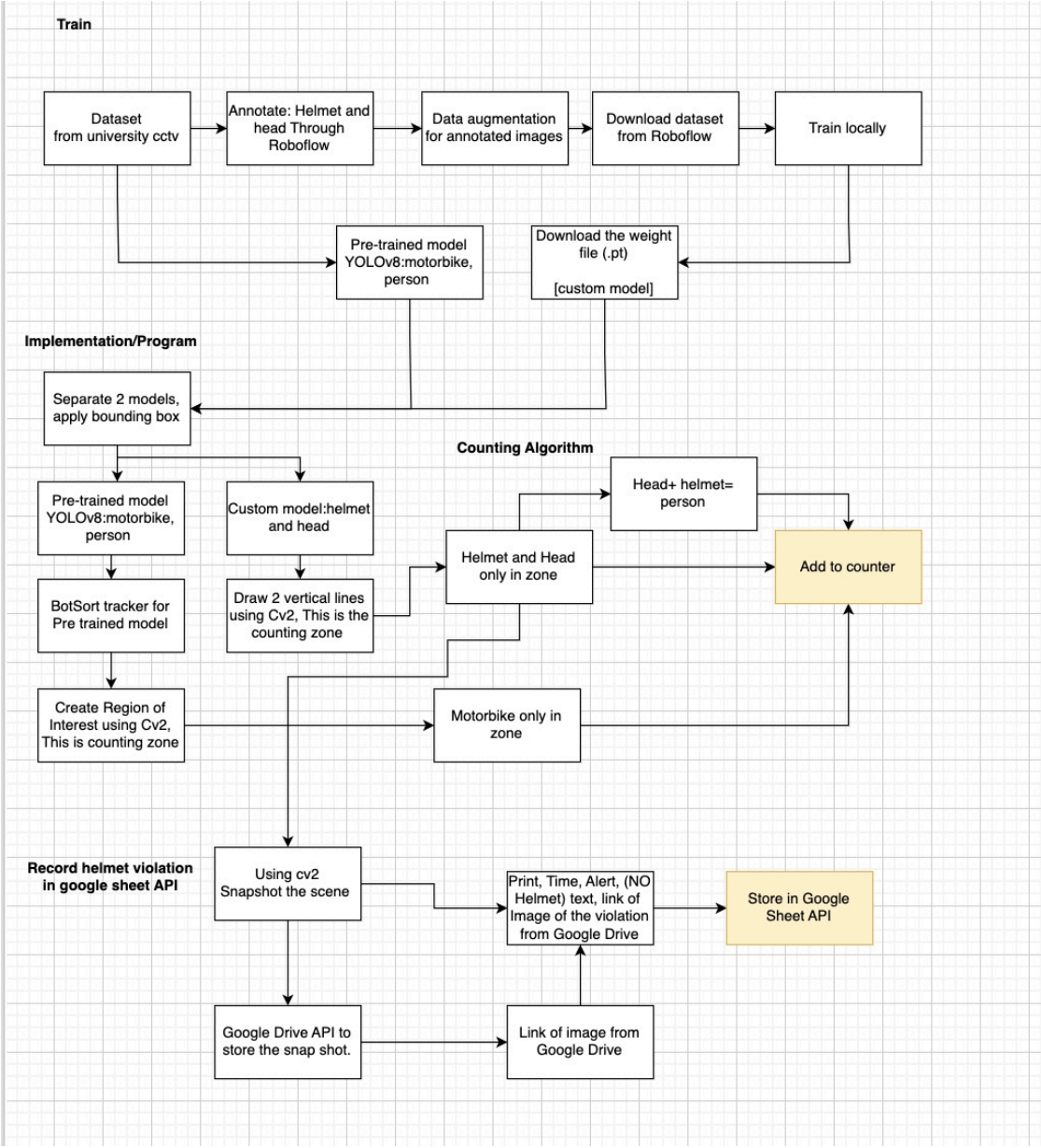

Figure 3.1

The flowchart in the figure 3.1 illustrates the overall workflow of the system. First, the dataset is obtained from the footages of a cctv camera of Mahidol university. The video footages are split into 3 frames per second using Roboflow. Then annotate each frames splited, the annoated items are helmet and head, then using data augmentations from Roboflow. Then we can downlaod the datasets. Finally, using dataset downloaded we can train locally through data.yaml, the data augmentations details are to be

specified in Chapter 3. After the training the weights of the trained model are obtained in a .pt file, the file is the model that will be used in the system in conjunction with the pre-trained model from YOLOv8. The Implementation phase is to apply the custom trained model called best_17, work with the video stream input. The bounding box and region of interest seen in figure 3.2.made from cv2.

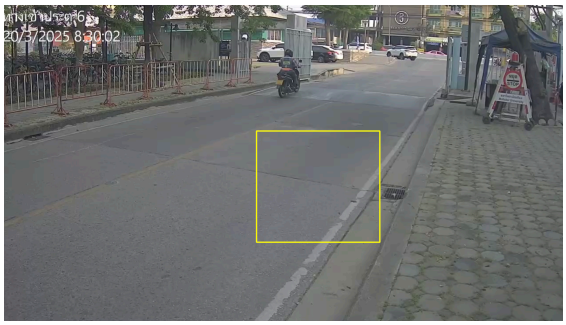

Figure 3.2: Dataset Image `

Using these zone we speparate the counting zone for helmet, head, and another zone to count person and helmet. As for the person we decided to count the head and the helmet to total to person as there are issues about the camera angel limiting the accuracy of the person detection.

After implementing the program with the model, we use cv2 to take snapshot of the frame as when helmet violation occur. The system links and uses Google API, to store the detection evidence of the scenario. The Google Sheet API will append new rows each time a head detection occur. The image are visible, and stored by Google Drive API, to check the instances where it happens.

3.2 Data

Dataset: videos of the entrance which contain motorcycle coming in and out the campus, collected from local sources which is gate six Mahidol University CCTV camera. The videos are split into frames using Roboflow and then each frame are use for annotations.

Annotations: Create two classes. first class containing the bouding box of helmet user only and the second class containing head(which is non-helmet user.)

Preprocessing: Includes resizing images to 640x640 pixels, normalizing pixel values, and applying augmentations (e.g., rotation, scaling, and brightness adjustments).

3.3 Custom Model

YOLOv8 Architecture: YOLOv8 (You Only Look Once version 8), developed by Ultralytics, is known for its streamlined architecture and improved detection performance over its predecessors (e.g., YOLOv5, YOLOv7), particularly in low-light or occluded environments—conditions often encountered in real-world surveillance footage. The YOLOv8 architecture is used for this project due to its state-of-the-art performance in object detection, offering a balance between real-time inference speed and high accuracy. Specifically for this project, YOLOv8 is a tool that is important for training and differentiating helmet and head classes easily. Additionally YOLOv8 is easier to set up and supported by developers and communities in a larger scale than other YOLO versions.

Despite the availability of newer object detection models such as YOLO-NAS or YOLOv9, YOLOv8 remains a highly reliable and widely supported choice. In this project, YOLOv8 was used to create a custom-trained model that focuses on five specific object classes: motorcycles, helmets, crosswalks, pedestrians, and lanes. However, the two most critical objects for our safety analysis—helmet and head—were prioritized in both annotation and evaluation.

To obtain the custom model for "head", and "helmet" detection we must first upload the datasets into Roboflow website in figure 3.1. Roboflow will allow users to specifically annotate desired classes, which after annotating said datasets, we can download directly from Roboflow the annotated datasets which we can train locally. Training can be done localy or through Google Collab. However due to limitations we used Vistual Studio as a medium to train the datasets from Roboflow.

Training Process: The goal of the training process for our custom YOLOv8 model was to develop a high-accuracy object detection system specifically tailored to key safety-related classes: helmet, head (non-helmeted rider), motorcycle, and pedestrian. By fine-tuning the YOLOv8 architecture with annotated CCTV footage, the objective was to enable the model to accurately distinguish between helmeted and non-helmeted motorcyclists under real-world conditions such as varying lighting, occlusion, and motion blur. The expected outcome was a model that not only generalizes well across diverse scenarios but also minimizes false positives and false negatives—particularly for helmet and head detection, which are not part of the default YOLO classes. This improved detection performance would then serve as the foundation for a reliable counting mechanism, supporting downstream analytics such as helmet usage rates. Ultimately, the training process aimed to contribute to traffic safety initiatives by enabling automated and scalable monitoring of motorcyclist behavior using CCTV footage.

- **Data Collection:** The dataset was compiled from real CCTV footage recorded on campus at Mahidol University's Faculty of Engineering. The footage was collected over a span of seven days during the morning rush hour (8:00–10:00 AM), totaling approximately two hours. This time window was chosen to capture peak motorcycle and pedestrian traffic for accurate helmet usage monitoring. Figure 3.2 is an example of a snapshot from the dataset, the actually dataset is a video as mention.

Figure 3.2: Dataset Image

- **Frame extraction:** Using the cv2 module from OpenCV, video footage was processed and extracted into still frames. To ensure computational efficiency while retaining sufficient information, frames were sampled at a rate of 3 frames per

second (FPS). The extracted images were then uploaded to Roboflow, a computer vision dataset platform, for annotation and augmentation. However for Roboflow, it provides a frame splitting function within the website and aternatively, the frame splitting can be done here directly. In the figure 3.3 is an example of frame extraction function after uploading the datasets into Roboflow. Extracting the video datasets into frames, means that we can annotate each frames specifically we have three frames across one second. This is to also ensure that we do not have to much datasets, and it also depends on how much the desire classes appears on the videos. For our case there are enough objects across three frames per second to annotate.

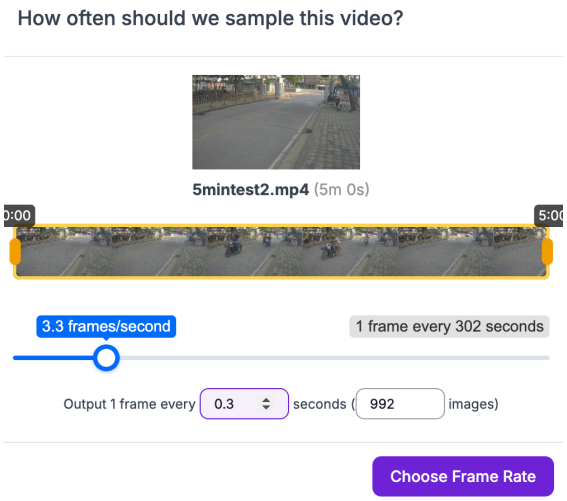

Figure 3.3: Frame Extraction Image

- **Annotation:** Within Roboflow, bounding boxes were manually drawn around the target to create accurate ground truth data for supervised learning. In this project context, head and helmets are used to differentiate between a person with a helmet on and a person without a helmet on. Annotations were carefully reviewed to ensure consistency, especially in challenging cases such as partial occlusions or non-standard helmet designs. The figure 3.4 show an example how we draw the bounding boxes for the classes. The bounding boxes allow to make an area of detection to be easily differentiate between different classes. Therefore, the bounding box, which has to be drawn manually require to draw closely to the objects, which in this case is the head of the riders. Therefore, the differentiation

between heads without helmet can be distinct from the head with helmet with minimal background. To ensure optimal detection performance, we recommend drawing bounding boxes as tightly as possible around the objects. This guideline is particularly important for researchers or practitioners who intend to follow a similar training approach or replicate our methodology.

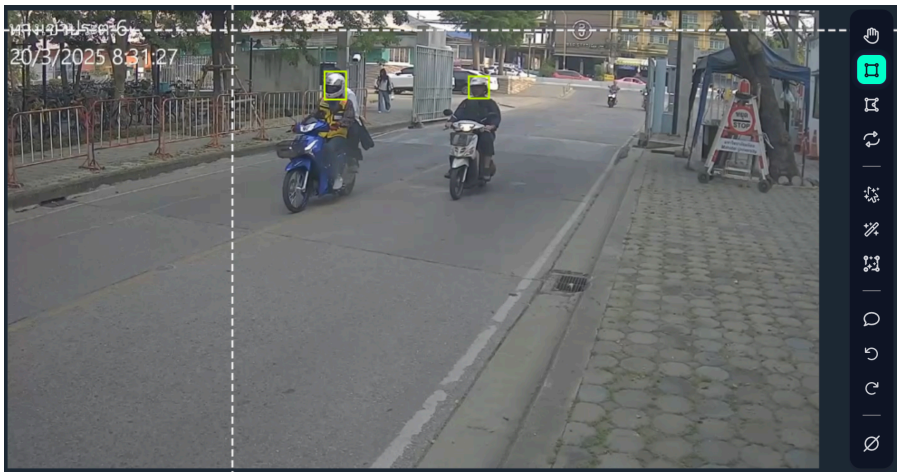

Figure 3.4: Annotation Image

- **Dataset Splitting:** The annotated dataset was divided into three subsets shown in figure 3.5: training, validation, and testing, following a common 70%–20%–10% split. This allocation was selected to ensure a sufficient volume of data for effective model training, while also preserving dedicated sets for model evaluation and tuning. Specifically, 70% of the data was used for training, providing the model with enough examples to learn relevant patterns and features from the annotated objects. The validation set, comprising 20% of the data, played a critical role in monitoring the model's performance during training and guiding hyperparameter tuning to mitigate overfitting. Overfitting occurs when a model learns the training data too well, resulting in poor generalization to unseen data. The remaining 10% of the data was reserved as a test set, which serves as an unbiased benchmark to evaluate the final model's performance. This partitioning strategy is widely adopted in machine learning workflows as it offers a balanced and effective framework for training, validating, and testing models. The dataset split was performed following the completion of the annotation process.

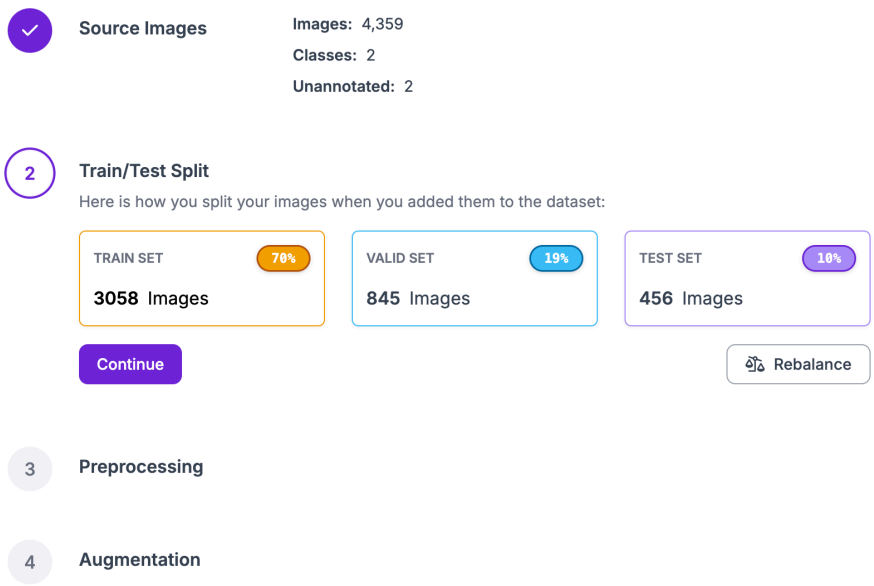

Figure 3.5: Spliting Datasets Image

Figure 3.6 illustrates the data augmentation techniques used during the model training process. These augmentations are divided into two categories: image-level augmentations and bounding box-level augmentations.

The image-level augmentations applied include horizontal flipping, rotation, grayscale conversion, and exposure adjustment. These transformations alter the appearance of the entire image, thereby increasing the model's robustness to variations in lighting, contrast, orientation, and color. Such augmentations simulate real-world environmental changes, helping the model generalize better across diverse scenes captured by CCTV footage.

Bounding box-level augmentations, although not all applied in this study due to premium feature restrictions (as indicated by the "Upgrade" tags), would typically involve transformations such as crop, rotate, and shear applied directly to annotated objects. These operations preserve the alignment between bounding boxes and their corresponding objects, making them highly valuable in maintaining annotation integrity during geometric changes.

In this project, specific augmentations such as horizontal flip, contrast enhancement, and brightness variation were implemented to improve detection performance under fluctuating lighting conditions and camera perspectives. These augmentations contributed to building a more resilient model capable of operating accurately across diverse visual inputs encountered in real-world traffic monitoring scenarios.

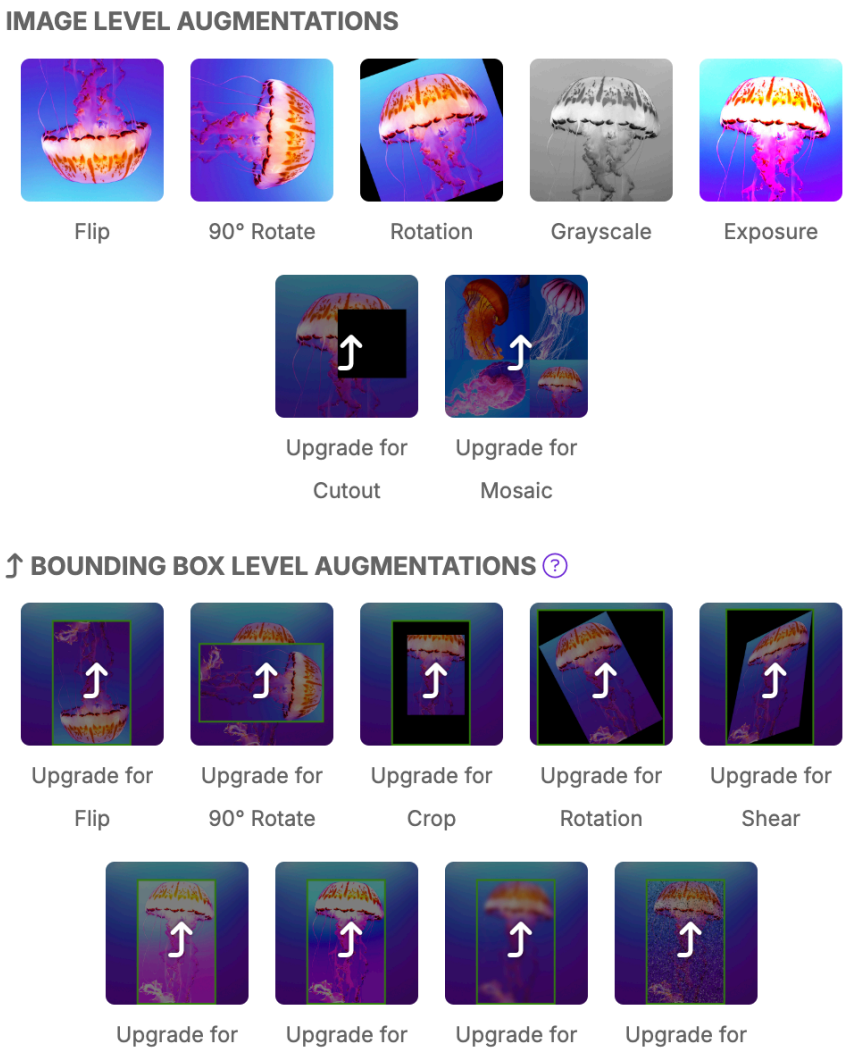

Figure 3.6: Augmentation Image

- **Data Configuration and Training:** The dataset used in this project consisted of 4,359 annotated images, divided into training, validation, and testing sets at a ratio of 70%, 20%, and 10%, respectively. This split ensures a balanced distribution of data across the learning, tuning, and evaluation phases, supporting both model generalization and performance assessment.

  A data.yaml file was configured to organize the dataset structure and define training parameters. This configuration file specifies the relative paths to each data split, the number of object classes, and the corresponding class names used in the detection task. It acts as the main reference for the YOLOv8 framework to interpret dataset composition during training.

Once the dataset and configuration were defined, the training process was initiated using the YOLOv8 framework. The training pipeline was guided by key hyperparameters—such as epoch count, image size, batch size, and learning rate—which were carefully chosen to match the dataset characteristics and available computational resources. These settings were not only critical to detection accuracy but also influenced the efficiency and stability of the model training process. Detailed descriptions and justifications of these hyperparameters are provided in the Hyperparameter Configuration section of this report.

Upon completion of training, the model outputs a .pt file, which contains the learned weights, model architecture, and training metadata. This file represents the finalized version of the trained YOLOv8 model and can be used for real-time inference or integrated into post-processing tasks such as counting and visualization pipelines.

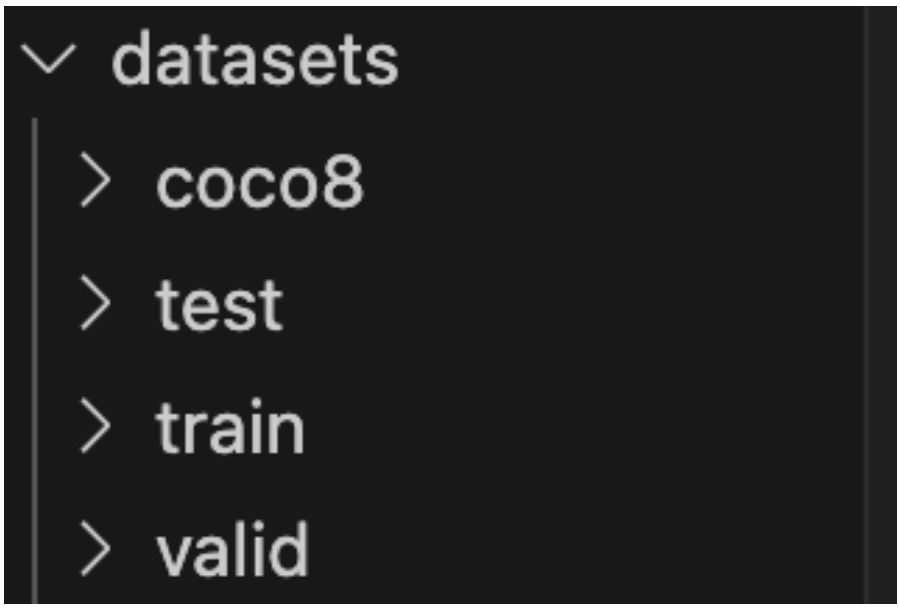

Figure 3.7: Files from downloaded Dataset

```python
results = model.train(
    data='data.yaml',
    epochs=500,                # Updated
    imgsz=640,                 # Image resolution
    batch=32,                  # Updated batch size
    patience=50,
    save=True,
    save_period=10,
    device='cpu',              # Use 'cuda' if you have GPU
    workers=4,
    resume=True,
    exist_ok=True,
    name='helmet_continued',
    pretrained=True,
    optimizer='Adam',
    lr0=0.005,                 # Updated learning rate
    project='runs/detect',
    save_dir=output_dir
)

# === Save the final combined model ===
output_path = os.path.join(output_dir, 'weights', 'final_model.pt')
os.makedirs(os.path.dirname(output_path), exist_ok=True)
model.export(format='pt', filename=output_path)

print(f"Training completed. Model saved to: {output_path}")
```

Figure 3.8: Data.yaml file in VS

3.4 Counting System

3.4.1 Helmet and Head

After customizing our YOLOv8 model, which is called best_17, by training with the dataset we have collected from CCTV footages, we implemented a counting system to track the number of helmets and unhelmeted heads by using double line counting method, while persons and motorcycles used Bot_Sort tracker to detected in the video.

For helmet and head counting, we applied a double-line counting method. This defines a "counting zone" using two vertical lines, and only counts detections whose bounding box centers fall within the zone. To prevent duplicate counting across frames, we used a rolling memory of the last ten frames. If a new detection is within a set distance (e.g., 30 pixels) of a previously counted object of the same type, it is ignored. This method improves reliability by reducing overcounting and stabilizing results, especially for slow-moving or flickering detections. The final counts are updated in real time and displayed on the video, offering a clear summary of helmet usage and safety

compliance.

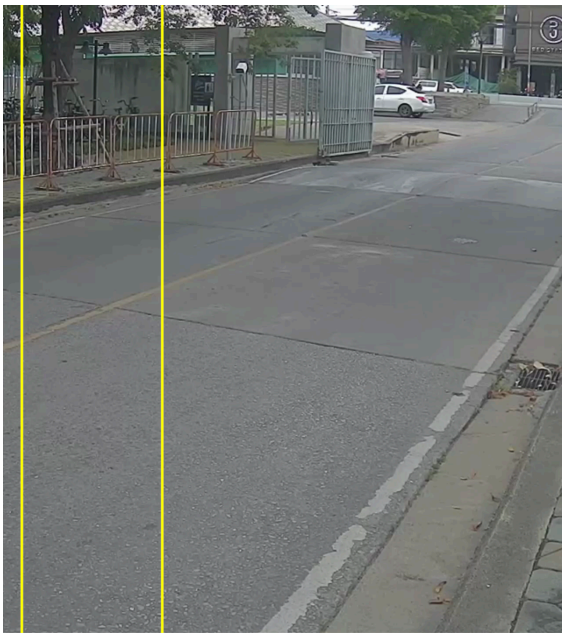

Figure 3.9

Figure 3.9 illustrates the designated counting zone used for helmet and head detection. The image shows two vertical yellow lines placed 150 pixels apart, which define the area for double-line counting. When an object passes through both lines in sequence, it is registered as a valid count. This method helps reduce duplication or false counts caused by temporary detection overlaps or brief tracking loss.

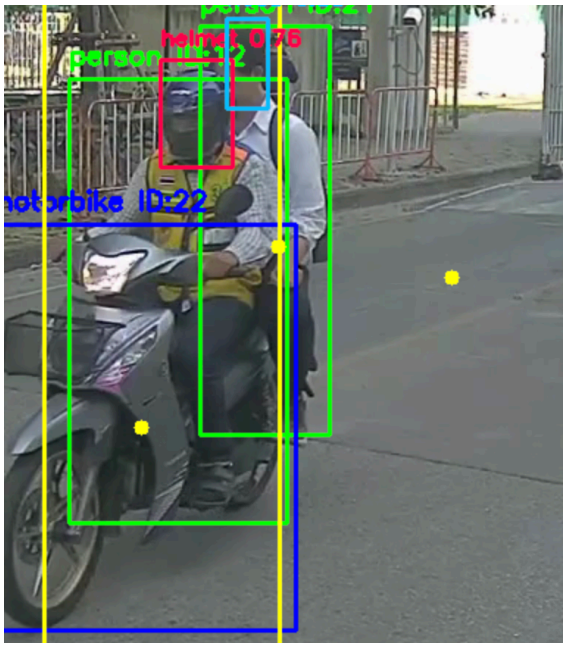

Figure 3.10

Figure 3.10 shows an example of the double line counting system in action when objects, such as a helmet and/or a head, enter the counting zone. As seen in the image, the objects are detected and labeled with text and different colors while passing through the two vertical lines, triggering the counting logic. Two yellow vertical lines are the double counting line which are the region to only count head and/or helmet passing by. Green are the bounding box color of person, dark blue are bounding box color of motorcycle. Red are the bounding box of helmet and light blue are the bounding box of head(non-helmet). This illustrates how the system identifies and differentiates helmeted and non-helmeted riders within the defined zone.

Figure 3.11

Figure 3.11 displays the result of the helmet and head counting process, shown at the top-right corner of the screen. These values are updated in real-time after the system detects and counts objects passing through the counting zone. This visual feedback confirms the detection and classification outcome for each rider, distinguishing between

helmeted and non-helmeted individuals.

3.4.2 Person and Motorbike

However as for the Person, and Motorbike detection we can use the Yolov8s.pt model, class 0(person), and class 3(motorbike), as their model are well polished for tracking. For the tracking use Bot-sort tracker, obtain through Roboflow ultralytics/trackers/bot_sort.py. The tracker will be use to create specific id number for each class that has been detected. Using these id we will create center point of each classes which will be important in the counting method.

For the counting method, we can create a region of interest, through using open CV. From there we create a condition, to store the track id with track history. track_history = function will store the position cx, cy of the tracked object. We will use this value to identify its current and previous position to ensure that when object inside the Region of Interest, position compare is is greater than the current position objected will not be used to count, while if the current position of the tracked id compared to stored id is less than it, it can be counted inside the ROI. This is to ensure that the person, and motorbike can be counted by by what it can be tracked. The detection should look similiar to figure1.

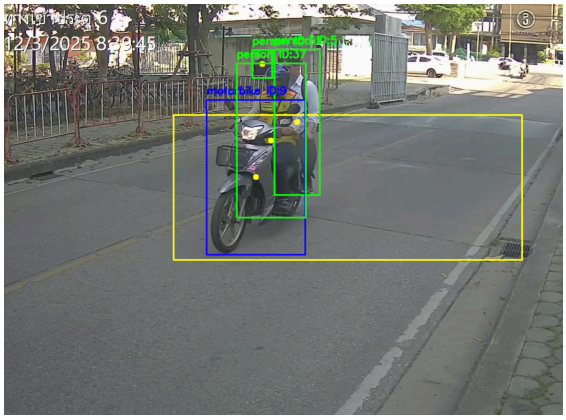

Figure 3.5

3.4.3 Output Generation

The output generation phase transforms the detection and counting results into a visual and interpretable format. For each processed video frame, the system overlays bounding boxes and labels indicating the object class (helmet, head, person, or motor-

cycle), along with live counts displayed on the top-left corner using OpenCV. These real-time visual indicators allow users to monitor helmet usage compliance at a glance. Additionally, the system can produce an annotated video file as output, which includes all detections and updated counts across the entire duration. This output is valuable for both immediate observation and later review or reporting, providing a clear and documented summary of safety compliance in the monitored area. The images below shows the output of the system which after we run the program, will show live dection of the video input, and the save video file after the program completed the detection, we save it as a way to easier analyse and observe the detection through video playback, as analysing it live while running maybe not be as efficient.

Figure 3.4.1: Saved output Video

Figure 3.4.2: Live Output Generation

3.4.4 Storing Output in Google Sheet API

After the output has been generated, we store the detection into a log using Google API from the video steam. The Google API integration is used for logging and evidence storage for helmet violation cases. Firstly as mention the two model, YOLOv8 pre-trained model, and custom model for head/helmet detection. How the system is works is, when a head is detected within the zone. The frames will be stored, using cv2 to snap-shot the specific frame of head detection. We log the detections events to Google Sheet, it records, the timestamp, head detection, alert, and link to Google Drive file to the captured image.

The credentials.json file can be obtained through Google API, the system will connect to pre-defined Google Sheet as we name them(Data log) and appneds the new rows with each detection events that occurs, the image are uploaded to Google Drive using the

Drive API, and public access links are generated per log. This implementation allows users to store datas of the detection, this is to allow scalable and automated solution for monitoring helmet violations. The result is as seen in the figure below.

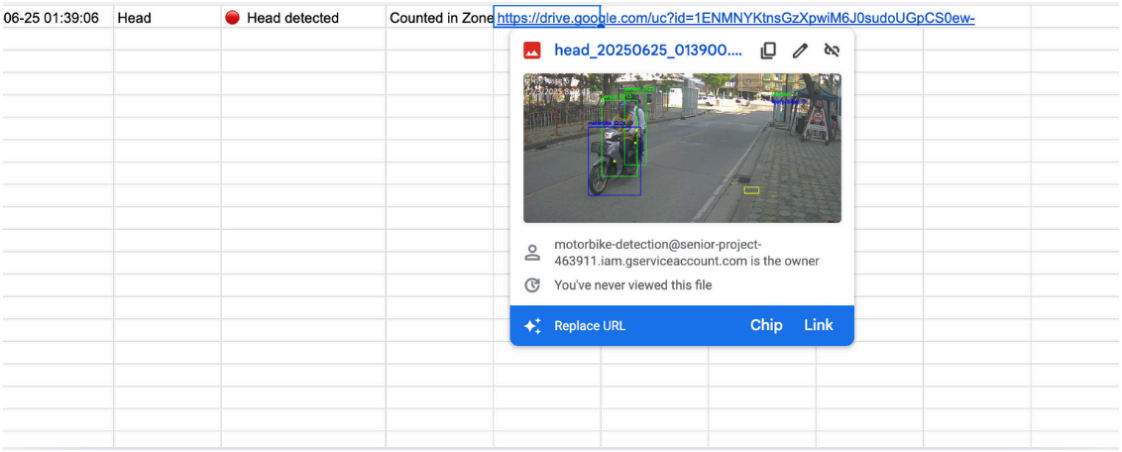

Figure 3.6

3.5 Tools and Frameworks

- **YOLOv8 Framework**: For object detection.
- **Libraries**: Python libraries such as ultralytics, opencv-python, numpy, collections.
- **Annotation Tools**: Roboflow.

3.6 Hyperparameter Configurations

During the training process, serveral key herparameters were manually selected to balace the performce, the model accuracy and accordingly to our local computation resrouces.

Epochs = 500, this is to ensure suffieicent exposeure to the training datasets. It will allow the model to learn patterns, and improve generalization overtime. However we can stop the early depending on our resources and depending on overfitting.

Image Size imgsz = 640 (image resolution) 640x640 pixel is most commonly use parameter. This will also help decrease the traning time. However for smaller objects like head and helmet detection. Training them on 640x640 is enough, however in some circumstances when training very far, helmet and head that are annotated are risk to

losing fine-grained details. This is important as it is very essential for detecting small overlapping objects. For our case we annotate them after they pass the bumper, we have checked that at this area before hand that when resolution was 640x640, it was not too grainy for traing. The image belows shows the annotated image that was resized to 640x640 for training.

Figure 3.6.1: Resized Image

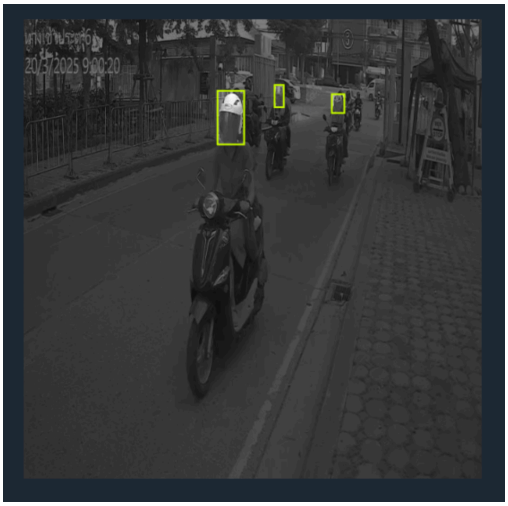

Figure 3.6.2: Resized Image

Batch Size =32, this is due to primarily contrained by the GPU, as larger batches can lead larger samples, and faster convergency. Nonetheless, batch size 32istill alowws for reasonable effieicnt traning and consistent model updates. This value can be changed depending on the GPU memory. While a larger batch size could have potentially accelerated training and stabilized gradient updates, our hardware limitations required a compromise at 32 images per batch.

Learning Rate = 0.005. Setting it to this value helps to cacilitate steady learning without causing instability. If it was too high, it could result in model to overshoot the optimal solution during traning. This value is also recommended by YOLOv8.

3.7 Performace Evaluation

The trained YOLOv8 models were evaluated using standard object detection metrics: **mean Average Precision (mAP)**, **precision**, and **recall**. These metrics provide a quantitative assessment of detection accuracy and were used to track the progression

and performance of each model iteration. The primary metric, **mAP**, measures the area under the precision-recall curve and is defined as:

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i$$

where AP_i represents the Average Precision for class i, and N is the total number of classes. mAP offers a comprehensive evaluation by considering both false positives and false negatives, making it a reliable indicator of overall model accuracy.

Precision, defined as

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}},$$

measures the proportion of correctly predicted positive detections among all predicted positives. High precision indicates that most detections are correct, which is crucial for reducing false alarms in safety-critical applications like helmet detection.

Recall, defined as

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}},$$

reflects the model's ability to correctly identify all relevant objects in the frame. High recall ensures that few objects are missed, which is particularly important for applications where under-detection can compromise system reliability.

Together, these metrics were used to compare multiple trained models, guiding the selection of the best-performing version for downstream tasks such as accurate counting of helmets and heads in real-world traffic footage.

Metric	all	Helmet	head
Images	814	622	321
Instances	1084	715	369
Precision (P)	**0.901**	0.934	0.869
Recall (R)	**0.862**	0.913	0.811
mAP@0.50	**0.924**	0.959	0.889
mAP@0.50:0.95	**0.497**	0.512	0.482

Figure 3.7

The evaluation results in figure 3.7 demonstrate that the best custom YOLOv8 model performs strongly in detecting both helmet and heads(non-helmet), with particularly high accuracy in helmet detection. Overall, the model achieved a precision of 0.901 and recall of 0.862 across all classes, indicating reliable and consistent predictions. For the helemt class specifically, the model attained satisfying performance with a precision of 0.934, recall of 0.913, and a high mAP@0.50 of 0.959. This suggests that the model can effectively identify helmets with minimal false positives and false negatives. In comparison, the head class yielded slightly lower results, with a precision of 0.869, recall of 0.811, and mAP@0.50 of 0.889, reflecting more variation or complexity in detecting uncovered heads. The overall mAP@0.50:0.95 score of 0.497, while moderate, still indicates acceptable performance under stricter localization conditions. These results affirm the model's suitability for real-time helmet usage monitoring, particularly in scenarios where accurate helmet detection is critical.

Head_Model

	Precision	Recall	mAP50
All	0.871	0.859	0.891
Helmet	0.867	0.885	0.907
Non-helmet	0.876	0.833	0.875

Figure 3.8

Figure 3.8 shows the previous model performace evaluation, which is call Head_model. In comparing the performance of the updated helmet and head detection model, which is figure 3.7, to the previous version, several improvements are evident.

The current model achieves an overall precision of 0.901 and recall of 0.862, both higher than the previous model's precision of 0.871 and recall of 0.859, suggesting better accuracy and detection coverage. Helmet detection has particularly improved, with the current model reaching a helmet precision of 0.934, recall of 0.913, and mAP@0.50 of 0.959, outperforming the previous model's respective values of 0.867, 0.885, and 0.907. Head detection has also seen slight gains, with the current model achieving 0.869 precision, 0.811 recall, and 0.889 mAP@0.50, compared to 0.876, 0.833, and 0.875 in the earlier version. Additionally, the current model maintains a solid mAP@0.50:0.95 of 0.497 overall, indicating better localization performance under stricter IoU thresholds. These enhancements reflect a more robust and reliable detection system, making the current model better suited for real-world deployment in helmet compliance monitoring scenarios.

CHAPTER 4
RESULT

We have used pre-recorded footage from CCTV cameras to analyze and compare the performance and accuracy of the detection and counting system.

4.1 Model Result

Table 4.1

Model Name	Person	Motorbike	Helmet
BestV8	87%	96%	42%
Best21			72%
Helmet_model			82%
Head_model			86%
Best17			95%

To evaluate the accuracy of the model, we compared detection counts with manual counting over a ten-minute span of one video with every model we have. The aim of this is to see the accuracy and improvement of our model. The results in Table 4.1 shows the accuracy results of different models. Person and motorbike used YOLO pretrain model to detect these two classes, so the accuracy and considered constant throughout different models. Helmet detection rises from 42% to 96%, which is 54% improvement from the first model to latest model. The calculation method of finding helemt detection accuracy across different models is to find the total ground truth and detection of the train model, then divide it to find the accuracy. We find the best confident for each model by comparing confident of 0.15 and 0.3 to find the best accuracy. Best17 model have the ground truth helmet of 60, we have the confident set to 0.15 and detected the detection number to be 55, which is 90%. On the other hand, we change the confident to 0.3 and the results of the detection is 58, which is 95% resulting in a better accuracy.

Table 4.1 presents the detection accuracy of various models across three object

categories: person, motorbike, and helmet. The accuracy values for person and motorbike detection remain constant across models—87% and 96% respectively—because these classes were detected using the pretrained YOLO model without additional fine-tuning. In contrast, the helmet detection results vary significantly between models, as each represents a different version of a custom-trained helmet detection model.

After evaluating the model's detection accuracy, we proceeded to assess the performance of the counting system. This analysis was conducted using two pre-recorded CCTV footage videos. Tables 4.2 and 4.3 present the counting accuracy for helmeted and non-helmeted (head) riders, derived from Video 1 and Video 2 respectively. These tables utilize a double-line counting method.

4.2 Counting Result

Table 4.2

	Double Line Counting		Ground Truth	
Video 1	Head	Helmet	Head	Helmet
	25	26	25	25

Table 4.2 shows the counting results for Video 1 using the double-line method compared to the ground truth. The system accurately counted heads (25 vs. 25) but slightly overcounted helmets (26 vs. 25), likely due to duplicate detections or crossing artifacts.

Table 4.3

	Double Line Counting		Ground Truth	
Video 2	Head	Helmet	Head	Helmet
	29	24	32	29

Table 4.3 shows the double-line counting results for Video 2. The system counted 29 heads and 24 helmets, while the ground truth recorded 32 heads and 29 helmets. This indicates undercounting in both categories, which could be due to missed detections or

rapid movements causing objects to skip the counting lines.

For the helmet and head detection specifically, we experimented with adjusting the length of the double-counting lines to evaluate their impact on counting accuracy. For instance, we tested line lengths such as 300 pixels for Line X and 450 pixels for Line Y, along with several other variations. The results indicated that optimal performance occurs when the length of the double lines is kept within approximately 150 pixels. Longer lines tended to increase the likelihood of multiple or false counts due to prolonged object overlap with the counting zone.

Table 4.4

Video 1	BotSort Counting		Ground Truth	
	Head	Helmet	Head	Helmet
	25	26	25	25

Table 4.4 presents BotSort counting results for Video 1. The system detected 52 persons and 32 motorbikes, compared to the ground truth values of 51 persons and 30 motorbikes. This reflects a small overcount in both categories, likely due to brief tracking ID switches or overlapping detections in crowded scenes.

Table 4.5

Video 2	BotSort Counting		Ground Truth	
	Head	Helmet	Head	Helmet
	29	24	32	29

Table 4.5 summarizes the BotSort results for Video 2. The model counted 56 persons and 44 motorbikes, while the ground truth showed 60 persons and 34 motorbikes. This indicates slight undercounting of persons and significant overcounting of motorbikes, which may result from false positives or tracking drift over longer video durations.

In contrast, Tables 4.4 and 4.5 focus on motorbike and person counting accuracy, also based on video 1 and video 2. However, these use the BotSort tracking and counting method instead of the double-line approach. This separation allows us to compare the performance of different counting techniques across differents object categories and scenarios.

To evaluate counting accuracy, we use a relative error formula to calculate the percentage difference between the counted value and the ground truth. This approach provides a clear measure of overcounting or undercounting, allowing us to identify and analyze overflow or missed counts in the system.

Table 4.6

Motorbike	Person	Head	Helmet
93%	95%	88%	91%

Table 4.6 presents the overall performance accuracy of the detection and counting system across four object categories: motorbike, person, head (non-helmeted), and helmet. The results reflect the combined effectiveness of both the object detection model and the counting mechanism (BoT-SORT for motorbike and person, and double-line counting for head and helmet).

The system achieved the highest accuracy in detecting and counting persons (95%), followed by motorbikes (93%). These results align with the use of pretrained

YOLO models, which provided stable and reliable detection performance. Helmet detection yielded an accuracy of 91%, demonstrating strong performance from the custom-trained model, especially after multiple iterations and confidence threshold optimization. Head detection (88%) exhibited slightly lower accuracy, likely due to the challenge of distinguishing non-helmeted heads in varying lighting and occlusion conditions.

Overall, the results confirm that the system performs with high accuracy across all critical object categories, validating its applicability for real-world motorcycle safety monitoring tasks.

CHAPTER 5
CONCLUSION AND DISCUSSION

5.1 Conclusion

This project presents a helmet and head detection system developed using a custom-trained YOLOv8 model, integrated with a counting mechanism applied to university CCTV footage for real-world evaluation. The final model demonstrated significant improvements in detection accuracy, achieving up to 95% accuracy in helmet detection and an average of 91.75% across all object classes in the test videos.

The implementation of the double-line counting method proved effective in reducing duplicate counts and stabilizing detection outputs, particularly for slow-moving or partially occluded objects. For person and motorbike tracking, the BoT-SORT tracking algorithm delivered reliable performance under low-overlap conditions, supporting accurate and consistent count results. Challenges in person detection—such as undetected children and overlapping riders—were addressed by aggregating helmet and head detections to approximate the total number of individuals, a decision supported by the high precision of the helmet and head models. Additionally, flickering and inconsistent detections in motorbike tracking were mitigated through the use of tracker history, which preserved object IDs across frames and allowed for movement-based counting based on bounding box center positions. This approach enhanced stability and reduced false counts. A defined Region of Interest (ROI) was also applied to ensure that only relevant objects within the designated monitoring area were included in the count, avoiding erroneous detections from peripheral motion. Overall, the system demonstrates strong potential for practical applications in automated helmet usage monitoring and traffic safety analytics.

To effectively use this helmet and head detection and counting system, several key components and considerations should be followed. The core of the system is a custom-trained YOLOv8 model, which achieved high detection accuracy across all classes, with helmet detection reaching up to 95% and an overall average accuracy of 91.75%. For

counting, the system employs two methods: a double-line counting mechanism for helmets and heads, which effectively reduces duplicate counts in cases of slow movement or occlusion, and the BoT-SORT tracking algorithm for person and motorbike counting, which improves consistency by tracking object IDs across frames. In scenarios where person detection is unreliable—such as detecting children or overlapping riders—the counts of helmet and head detections are combined to estimate the number of persons, leveraging the accuracy of the custom-trained models. To handle flickering or missed detections, the system uses the track history feature of the tracker, which compares the current position of an object with its previous location to ensure continuity in tracking. Additionally, a Region of Interest (ROI) should be defined to limit the detection and counting zone, preventing errors caused by objects entering or leaving the frame. This system is most effective when applied to CCTV footage in controlled environments with stable camera positions and clearly defined detection areas.

5.2 Discussion

5.2.1 Model Improvement

Table 4.1 highlights the performance improvement of various helmet detection models, while person and motorbike detection accuracies remain constant across all models at 87% and 96%, respectively. This consistency is expected, as all models use the original YOLOv8 architecture for detecting persons and motorbikes. The main focus of model optimization lies in helmet detection, which has undergone several iterations of training using custom datasets. The earliest version, BestV8, achieved only 42% accuracy in helmet detection, likely due to limited training data or suboptimal labeling. This was significantly improved in Best21, which reached 72% accuracy. Subsequent models, such as Helmet_model and Head_model, showed further improvements to 82% and 86%, respectively, indicating better dataset quality and fine-tuning strategies. The most refined version, Best17, achieved a 95% helmet detection rate, demonstrating the effectiveness of progressive model training, class balancing, and more consistent annotation.

5.2.2 Helmet and Head Double Line Counting

In the first video which is table 4.2, the accuracy of our helmet and head detection are very precise, since the video displays a clear bounding box of head and helmet detection and no overlapping with other head and helmet. Table 4.2 showing the accuracy of non-helmet to be at 100%, but there are minor flaws in helmet accuracy as it exceed the ground truth. The reason there are 26 helmets being displayed from the counting system is because the person who is in the front often blocks out the person who is in the back and this can cause false detection, classifying people who are not wearing a helmet as wearing it.

In the second video which is table 4.3, the accuracy went down compared to the first video. The reason is that there are many occasions where multiple motorbikes come through at the same time, causing confusion of our model and causing many overlapping bounding boxes of head and helmet. This makes the accuracy of helmet detection to 82% and non-helmet to 90%.

5.2.3 Person and Motorbike BotSort Counting

Table 4.4 shows the accuracy of person detection to be 98% and motorbike accuracy to be 93%. this result is being tested on video 1, which is the video where overlapping hardly appear, making the result satisfying.

Table 4.5 which is being tested on the second video where this video overlapping appears often more than the first video resulting in lower accuracy comparing to the first video. As person accuracy drop down to 93% and motorbike drop to 77%. Occasionally motorbike with two person on it can cause confusion in bounding boxes and it can appear to detect one person instead of two person, since the people who is driving and riding is really close to each other. Our BotSort method works well with less overlapping of bounding boxes, and as the more over-lapping occur, it causes a confusion of unique ID tracking system when it is in the counting zone. Causing a new unique ID to be create eventhough it is consider the same person or motorbike proceeding throughout the frame.

5.3 Limitation

Figure 5.1

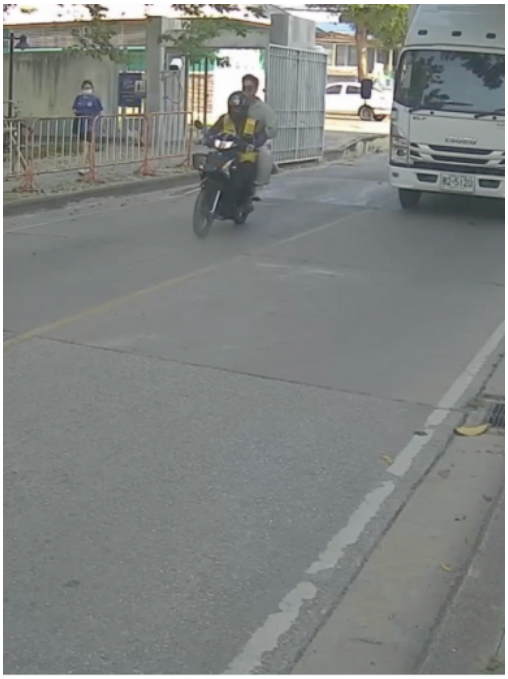

Figure 5.2

During system development and testing, the main challenge involved dealing with overlapping bounding boxes, particularly when multiple motorcycles and riders appeared close together. This sometimes led to incorrect object counts or detection errors, such as merging two people into one or misidentifying a detection. The tracking system also struggled when many objects entered the counting zone at once, occasionally creating new IDs for the same object however we uses Bot_sort Tracker to help minimize the flickering as possible, as when they enter the counting zone, if object is redetected there are chances new ID will appear and our system could not reidentify the object, it would count that object base on the new ID.

These issues were more pronounced in crowded scenes and highlight the limitations of relying on bounding box-based tracking in complex real-world environments. which can be seen in Figure 5.1. This sometimes led to incorrect object counts or detection errors, because there are another object blocking another object in the counting zone.

In Figure 5.2 another flaw showing the struggle of tracking system when an object appear to be on another lane, causing it hard for our model to detect an object, especially

when it appear to far from the annotation point.

5.4 Future Work

In future improvement, the focus will be on improving both the detection model and the tracking accuracy. Training with more diverse and balanced data will help the model generalize better across various environments and video conditions. Further enhancement of the counting and tracking logic is also planned to address issues with ID switching and occlusion. Additionally, while deployment to the university server is not yet complete, it remains a key objective for real-time monitoring in a practical setting. These improvements will support the goal of developing a more accurate, stable, and scalable helmet compliance monitoring system.

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