Assessing the driving behaviour of motorcyclists to improve road safety

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Abstract: Traffic violations by motorcycle riders pose a significant risk to urban road safety. In this paper, we present a novel approach that utilizes computer vision algorithms to detect and quantify traffic violations committed by motorcycle riders. These violations include non-compliance with helmet regulations, illegal lane changing, wrong way driving, weaving between vehicles, and running red lights. To enhance the awareness of motorcycle riders regarding the infractions they commit and the potential hazards these pose to road safety, we have developed a mobile application. This application not only provides riders with valuable feedback but also encourages them to be more conscientious and responsible for their actions. A series of experiments was conducted in the city of Marrakech, Morocco, demonstrating the system's effectiveness in positively influencing the behavior of motorcyclists on urban roads.

Keywords: Road safety, Traffic violations, Motorcycles, Object detection, License plate recognition

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1 Introduction

Urban traffic is characterized by a significant presence of various types of vehicles, including a substantial number of motorcycles. The rapid increase in the motorcycle population within urban areas has given rise to numerous challenges for residents and other road users. At times, motorcycles occupy up to 70% of urban road space, leading to traffic congestion and a surge in accidents, primarily involving motorcycle riders [Wahab and Jiang, 2019].

Motorcycle riders exhibit a wide spectrum of riding behaviors, with some choosing to ride at high speeds while others adopt a more cautious approach. This variability is influenced by factors such as the chosen route, the rider's experience level, road-specific infrastructure conditions, and more. Consequently, motorcyclists often display distinct travel patterns in terms of speed, following distance, longitudinal and lateral movement,
which differ from those of other vehicle types [Hsu and Wen, 2019] and [Chang and Chen, 2019].

According to the World Health Organization [World Health Statistics, 2023], riding a motorcycle is associated with a significantly higher risk, being 10 times riskier per kilometre and around 20 times riskier per hour of driving compared to operating a private car [Bartolomeos et al., 2017]. Furthermore, when compared to drivers of other vehicle categories, motorcyclists face a 34-fold higher risk of fatalities and an 8-fold higher risk of injuries [Anaya et al., 2017]. Notably, groups of motorcyclists account for 16% of all road traffic fatalities in EU-24 countries [Yannis et al., 2015].

In today's urban traffic landscape, motorcycles have come to dominate the roadways. Their ability to choose varied routes contributes to unpredictable traffic patterns. This lack of adherence to established driving norms often leads to traffic congestion. However, it's worth noting that traffic congestion can be mitigated if motorcyclists, who increasingly dominate the traffic scene, adhere to traffic rules, and speed limits. The result would be reduced travel times and costs.

Unfortunately, urban areas often bear witness to the presence of reckless motorcyclists, contributing to the overall lack of traffic control, especially at intersections [Kota et al., 2019]. Motorcycle-related accidents pose a substantial issue, irrespective of a country's development status. According to [Ospina-Mateus et al., 2019], there are an estimated 770 million motorcycles on roadways worldwide. Regrettably, motorcycling carries a significant safety risk, with motorcyclists accounting for over 380,000 deaths each year. In fact, motorcyclists represented 28% of all global road fatalities in 2016. This figure indicates a rising trend in accident rates [Sivasankar et al., 2014].

Research by [Govinda et al., 2022] and [Awad et al., 2018] reveals that 95% of road accidents and 77.58% of traffic injuries can be attributed to driver behavior. Human error plays a pivotal role in most motorcycle accidents. This encompasses various aspects of the riders' actions, including their speed, alcohol intoxication, fatigue, inattention, substance use, seat belt usage, fluorescent clothing choices, and helmet utilization. Much of the observed reckless behavior in motorcyclists, not just in Marrakech but worldwide, includes riding in large groups, often leading to traffic jams and various degrees of road accidents.

Excessive and inconsistent speeds, frequently observed among motorcyclists, contribute to traffic collisions. Inconsistent speeds can result in startled reactions, compelling other drivers to overreact. Another common issue is riding on the wrong side of the road or failing to adhere to designated lanes. Additional problematic behaviors include driving on sidewalks and, in some instances, traveling against the designated flow of traffic on sidewalks.

One of the concerning behaviors frequently exhibited by two-wheeler drivers involves abrupt lane changes. Many motorcyclists in Marrakech, and indeed worldwide, tend to disregard traffic rules, often switching lanes without utilizing turn signals. Such a practice significantly contributes to severe, often fatal accidents. Another prevalent issue is the failure to obey traffic signals and a propensity for running red lights, resulting in fatal accidents, not limited to Marrakech but seen globally. Collisions frequently occur when vehicles attempting lane changes encounter two-wheelers unexpectedly. Furthermore, unpredictable maneuvers at roundabouts and intersections are notorious for causing traffic gridlocks in Marrakech.
The core objective of this paper is to develop methods which can raise awareness among motorcyclists regarding these perilous behaviors that lead to traffic accidents and congestion. To achieve this aim, the proposed approach has a dual focus. First, it involves the detection of motorcycle behaviors through cameras and the identification of motorcycle licenses. Second, it encompasses the analysis of these behaviors to uncover the root causes and understand their repercussions on other road users. On the other end of this approach, motorcyclists can address the issues they face via an Android application, using their license plate number for incident reporting.

This paper is structured into four main sections. The first section, "Related Work," offers an overview of existing literature and studies related to motorcycle behavior analysis, traffic congestion, and accident prevention. In the second section, "Proposed Approach," we outline the methodology, which includes camera-based detection and analysis techniques for assessing motorcycle behavior and the development of an Android application for reporting incidents. The third section, "Results and Analysis," presents a comprehensive analysis of the identified motorcycle behaviors, their underlying causes, and the impact of these behaviors on traffic flow and safety. Finally, the "Conclusion and Discussion" section summarizes the key findings, discusses their implications, and underscores the importance of raising awareness among motorcyclists, implementing traffic safety measures, and reducing congestion. The section also explores future research recommendations and potential interventions.

2 Related Work

Studies on motorcycle-involved accidents provide compelling evidence that motorcycles and their riders are often difficult for drivers of larger vehicles to spot, especially in heavy traffic conditions or when issues related to visibility come into play. Drivers of other vehicles frequently claim that they didn't see the motorcycles or their riders, or they realized it too late, leading to accidents. In nearly half of these incidents, drivers of other vehicles failed to identify the motorcycles in a timely manner, resulting in collisions. In other cases, various obstacles in the traffic flow may have obstructed the view of the motorcyclist. This difficulty in detecting motorcycles on the road is often referred to as conspicuity.

Conspicuity is the term used to describe the ability of road users to identify or detect motorcycles. Motorcycles occupy less space in comparison to cars or larger vehicles, making them challenging to spot, particularly when they are traveling at high speeds.

Size is another critical factor associated with conspicuity. The front-on silhouette area of a motorcycle is only about 30-40% of that of a typical car when considering the angle of approach [Zhang et al., 2018]. During daylight hours, motorcycles can be spotted from a distance because their size allows drivers to take evasive actions when they are within sight. However, motorcycles are relatively smaller, and they can only be detected when they are in close proximity. Additionally, people often rely on the physical characteristics of objects to identify them. When motorcycles are at a considerable distance, they can appear similar to pedestrians or bicycles, with their speed being the primary distinguishing factor. At greater distances, it becomes challenging for drivers of larger vehicles to differentiate between these road users.
To comprehend the factors contributing to motorcycle accidents and to formulate strategies for accident prevention, researchers frequently conduct crash type analyses. This method involves an examination of the crash type, factors involved, and the severity of injuries sustained. An example of such a study was conducted in Los Angeles from 1976 to 1981, focusing on motorcycle crashes and their underlying causes. The findings revealed common causes of motorcycle accidents, including speeding, alcohol and drug use, lane splitting, distracted driving, inexperienced riders, adverse weather conditions, and failure to wear protective gear. By identifying these factors, policymakers, law enforcement, and other stakeholders can develop strategies and countermeasures to prevent motorcycle accidents and enhance road safety for all road users.

In another study conducted in Victoria, Australia, as documented in [Yousif et al., 2020], researchers delved into the details of various motorcycle crash types. Additionally, a comprehensive crash typology study, as presented in [Preusser et al., 1995], utilized data from the National Highway Traffic Safety Administration’s Fatal Accident Reporting System. The results of this study revealed that a majority of accidents occurred due to collisions between motorcycles and different vehicles, particularly cars. However, concerning fatal accidents, the most common type involved two-wheelers running off the road, accounting for 41% of total fatalities. These incidents often transpired late at night and on weekends, primarily involving intoxicated motorcyclists. Overall, these findings underscore the significance of conspicuity issues, while also highlighting the heightened risks posed by impairment to motorcyclists.

When addressing road accidents or traffic crashes, the traffic behaviors of pedestrians, cyclists, and motorcyclists are identified as significant contributing factors. According to statistics from the World Health Organization [World Health Statistics, 2023], these cyclists and motorcyclists constitute more than 50% of road accident fatalities. Furthermore, over 90% of these fatalities occur in low-income and middle-income countries. This trend can be attributed to the fact that these countries represent nearly 60% of the world’s vehicles [Bartolomeos et al., 2017]. These statistics provide insight into the extent of traffic congestion on roadways. In the specific context of Marrakech, it is often referred to as the “motorcycle capital” of Morocco. While motorcycling is faster than driving cars, it is accompanied by a higher risk of road accidents, primarily affecting motorcyclists [Bazargan-Hejazi et al., 2018]. However, traffic issues caused by these motorcyclists, including speeding, overtaking, and disrupting the flow of cars at start-up, result in more fatalities among car occupants. In these scenarios, motorcyclists often escape unscathed, leaving car occupants to bear the brunt of the fatal consequences [Flannigan and Khayesi, 2021].

There has been a substantial body of research focusing on the application of computer vision and machine learning techniques to detect traffic violations from camera videos. This area of study has gained increasing significance as cameras are more frequently used to monitor traffic and enforce traffic regulations. The primary objective of this research is to develop algorithms capable of automatically detecting violations, such as running red lights or speeding, from videos recorded by traffic cameras.

In a study by [Allamki et al., 2020], the authors introduced a deep learning-based approach for real-time detection of helmet usage on motorcycle riders in video streams. Their approach combined Convolutional Neural Networks (CNNs) and Recurrent
Neural Networks (RNNs) to detect and classify helmet usage, resulting in high accuracy in detection and classification.

Another noteworthy study, conducted by [Talaulikar et al., 2019], presented a machine learning-based approach for detecting and classifying traffic violations in video streams. They applied Principal Component Analysis (PCA) to derived features to identify and classify various traffic violations, including illegal lane changes and running red lights. The study demonstrated the approach's effectiveness in achieving high accuracy for detecting and classifying violations in real-world scenarios.

Furthermore, [Xuan Can et al., 2021] proposed a comprehensive framework for the detection and counting of motorcycles in video content. This framework harnessed a combination of object detection, tracking, and event recognition techniques to identify and categorize motorcycles in video streams. The results showcased the framework's capacity to attain high accuracy in detecting and counting motorcycles in real-world settings.

In the work by [Vasanthakumar et al., 2021], a helmet detection and classification system using deep learning was introduced. They employed Recurrent Neural Networks (RNNs) to discern and classify riders wearing or not wearing helmets in videos. The system yielded remarkable accuracy in helmet violation detection.

[Nadeem et al., 2022] presented a real-time system designed to detect and classify zigzag riding violations using deep learning. This system leveraged a pre-trained model based on the German traffic-sign dataset to detect zigzag riding in images. Despite using a relatively small dataset from Pakistan, the study demonstrated the system's high accuracy in detecting zigzag riding violations. It offers real-time monitoring capabilities for traffic and the detection of such violations.

Lastly, the work by [Suttiponpisarn et al., 2021] introduced a road surveillance system focused on identifying wrong-way driving using deep learning. The system employed the YOLOv4-tiny algorithm and the Deep SORT tracking algorithm to filter out roadside noise. The results showed that the system provided satisfactory and accurate detection of wrong-way driving and moving objects on the sidewalk. This system can be implemented for real-time road monitoring, helping reduce the risk of accidents resulting from this type of traffic violation.

The approach presented in [Suresh Kumar et al., 2021] introduces a real-time triple-riding detection system employing deep learning. They applied the faster R-CNN technique to detect instances of triple-riding in videos. The results demonstrated that the system achieved a high level of accuracy in detecting triple-riding violations.

In other research by [Xu et al., 2021], a multi-task deep learning approach was proposed for real-time traffic violation detection, encompassing the detection of various violation types, including impolite pedestrian behavior and red-light running. The study showed that the multi-task approach enhanced the overall accuracy of the system and had the potential to significantly reduce costs compared to physical equipment-based monitoring.

Furthermore, [Shubho et al., 2021], [Yan et al., 2022], and [Franklin and Mohana, 2020] presented deep learning-based approaches for real-time detection of various vehicle types and traffic violations in video streams. These approaches leveraged YOLOv4 as the object detector and consistently achieved high accuracy in real-time detection and classification of vehicles and violations. Implementing these systems for traffic monitoring and enforcement could substantially contribute to traffic management.
These studies collectively illustrate the diverse methods proposed for traffic violation detection using camera videos, each with its unique focus, dataset, and evaluation metric.

While these studies have made substantial contributions to the field of traffic violation detection using deep learning techniques such as CNNs (Convolutional Neural Network) and RNNs (Recurrent Neural Network), there are certain limitations to consider. One limitation is the narrow focus of many studies, concentrating on one or two specific violations, like helmet non-compliance or illegal lane-changing. This limited scope may not be sufficient for a comprehensive traffic violation detection system.

Additionally, these studies do not address the crucial aspect of providing a mechanism for motorcycle riders to check for any violations they may have committed. Enabling riders to take responsibility for their actions and make necessary adjustments to enhance road safety is an essential consideration.

In light of these limitations, there are potential areas for future research to explore. One area could involve developing a system that allows motorcycle riders to input their license plate number and view any detected violations associated with it. This would provide riders with valuable feedback and empower them to take responsibility for their actions.

Another promising research avenue could focus on developing a system capable of detecting multiple violations simultaneously, rather than solely concentrating on one or two specific violations. Such an approach would enhance the system's overall effectiveness and provide a more comprehensive view of traffic violations on the road.

Upon observing traffic and analyzing the behavior of two-wheeler riders on the streets of Marrakech, it becomes evident that motorcycle drivers often neglect proper turning procedures. Their mistakes include driving on the wrong side of the road and even on sidewalks, leading to accidents and traffic collisions on the opposing side of the road, as well as potential hazards for pedestrians.

An analysis of the behavior of two-wheeler riders on the streets of Marrakech reveals several noteworthy findings. Many motorcycle drivers appear to lack careful planning when making turns. This often leads to a critical mistake: driving on the wrong side of the road or even on sidewalks, resulting in accidents, traffic collisions on the opposing side of the road, and hazards for pedestrians.

Another observed behavior relates to how motorcycle drivers position themselves at red lights. They tend to leave no space, neither in front nor at the rear of cars, filling every available gap they can find. Unfortunately, this practice contributes to an increase in traffic delays.

The study also examined the dangerous act of zigzag maneuvers executed in heavy traffic conditions. These erratic movements led to significant collisions and disruptions in the flow of traffic.

In Marrakech, an additional two-wheeler behavior under scrutiny was the tendency of motorcycles to mix with parked vehicles in designated lanes. This behavior resulted in frequent conflicts with other vehicle drivers. Riding on sidewalks was another unsafe practice observed, presenting substantial challenges for pedestrians sharing the same walkways with two-wheelers.

Furthermore, the research uncovered another common behavior at traffic signals: motorcyclists often attempt to squeeze into gaps at the front of the queue, instead of waiting behind four-wheel vehicles or other traffic. This not only extends startup time
but also complicates the estimation of green light durations for the traffic queued behind the motorcycles.

3 Proposed Approach

The proposed approach for detecting motorcycle traffic violations is a cutting-edge and comprehensive system that leverages advanced technologies to enhance road safety. This approach comprises five pivotal steps, each of which plays a crucial role in precisely detecting and forecasting traffic violations.

The first step of the approach relies on pre-trained weights acquired from the COCO dataset [Lin et al., 2014], a widely used resource for object detection tasks. This initial phase is paramount for identifying motorcycles at the current intersection, laying the foundation for subsequent analysis and prediction. The pre-trained weights are fine-tuned on a vast and diverse dataset, ensuring the system's ability to accurately detect motorcycles, irrespective of their make or model.

Moving on to the second step, the approach entails the extraction of depth features, including target position, size, and direction. Long Short-Term Memory (LSTM) techniques are employed to establish temporal connections between frames [Tan et al., 2019]. These depth features provide supplementary information that significantly improves the accuracy of the detection and prediction processes. The LSTM model excels in capturing sequential patterns within the data, enabling the system to recognize and anticipate the movements of motorcycles over time.

The third step of the approach employs EASYOCR to recognize license plate numbers. This stage is pivotal in distinguishing individual motorcycles and assessing whether they've committed any traffic violations. EASYOCR stands out as an advanced optical character recognition system that harnesses machine learning algorithms for precise character and number recognition from images.

In the fourth step of the approach, the focus shifts to predicting mistakes and violations. This includes assessing the position and direction of traffic for each individual motorcycle. Building on the data collected in the preceding steps, machine learning algorithms are employed to analyze and forecast motorcycle behavior. The predictions generated in this phase play a vital role in identifying potential violations, such as running a red light or making an illegal turn.

Finally, the last step of the approach entails storing motorcycle license plate recognition and detected traffic violations in a database. This step serves the essential purpose of enabling motorcycle drivers to review and comprehend their mistakes and violations. By facilitating this feedback loop, the approach contributes to enhancing road safety by increasing awareness among motorcycle drivers and encouraging adherence to traffic rules and regulations.

In conclusion, the proposed approach for detecting traffic violations by motorcycles is an innovative and efficient system that harnesses advanced technologies to elevate road safety. This approach is rooted in a thorough analysis of motorcycle behavior and is designed to accurately detect and predict traffic violations. Through the identification of potential violations and the promotion of rule-abiding behavior among motorcycle drivers, this system holds the potential to significantly reduce accidents and foster safe driving practices.
3.1 Data and Motorcycles Detection

3.1.1 Data collection and pre-processing

The data used to develop the algorithm consists of captured video sequences from three different intersections, denoted as A, B, and C, situated within the city of Marrakech. These specific intersections were chosen because they are emblematic of typical scenarios in developing countries where two-wheeled vehicles, particularly motorcycles, constitute a significant portion of road users [Goyal et al., 2019]. In Marrakech, motorcycles account for over 60% of road users, and this figure has exhibited a steady rise in recent years [Azmi et al., 2022].

To record the traffic at each of these intersections, we utilized camera phones equipped with high-resolution capabilities and a frame rate exceeding 8 frames per second. The recorded footage varied in duration, amassing over 2 hours of video for each intersection. In total, we had access to 7 hours of video data for this study, providing a substantial dataset for the algorithm to acquire knowledge from.

To ensure the algorithm's training encompassed a diverse array of scenarios, the video footage was captured from different angles, as demonstrated in Figure 3. This approach enabled the system to develop expertise in detecting and predicting traffic violations from various vantage points and perspectives. The use of multiple angles also broadened the scope for capturing a wide spectrum of motorcycle movements and behaviors, thereby enhancing prediction accuracy and overall system performance.

In summary, the dataset utilized for our algorithm development consists of recorded video footage obtained from three distinct intersections in Marrakech, deliberately selected for their representativeness of developing countries characterized by high motorcycle usage. The high-quality camera phones used to record the footage provided a substantial amount of valuable information for the algorithm to learn from, ensuring its ability to effectively detect and predict traffic violations.
In this study, mobile phones were chosen as our primary data collection devices due to the specific requirements of data collection in Morocco, which necessitated authorized access. Mobile phones were not only readily available but also allowed for efficient and cost-effective data collection. However, it’s imperative to discuss the choice of cameras for potential future real systems.

In future iterations of our research, where authorization requirements might not be a limiting factor, the selection of cameras will be a critical consideration. We acknowledge that mobile phones may have limitations when compared to dedicated traffic cameras typically employed in actual traffic management systems. These limitations might encompass factors like image quality, field of view, and durability.

Figure 2: The tree intersections are selected for this study
The algorithm employed an object detection approach to identify motorcycles within the traffic footage, using the improved YOLO-V7 architecture, as described by [Wang et al., 2022]. This approach leverages a real-time object detection method, employing model scaling techniques to enhance accuracy. Pre-trained weights were harnessed for the detection of motorcycles, helmets, and license plates within each frame of the footage.

To visually illustrate the detection process for motorcycles, the algorithm delineated rectangular bounding boxes around each individual motorcycle present in the frame, as depicted in Figure 4. This bounding box strategy ensured that each detected object was encapsulated within its distinct box, enabling precise identification and tracking. Furthermore, the algorithm incorporated techniques for the detection of helmets and license plates, further enhancing its capacity to recognize and trace individual motorcycles.

Through the utilization of pre-trained weights and the creation of bounding boxes encompassing each detected object, the algorithm achieved accurate motorcycle detection within the traffic footage. This approach facilitated real-time processing and laid the foundation for subsequent algorithmic steps, including the prediction of...
mistakes and violations. In summary, the object detection approach represented a pivotal component of the algorithm, empowering it to effectively identify and track individual motorcycles within the traffic footage.

![Figure 4: An example of a motorcycle bounding box. An individual motorcycle (marked in light yellow rectangles)](image)

3.1.3 License Plate Recognition

License Plate Recognition (LPR) is the procedure of identifying and extracting license plate information from an image. This is conventionally accomplished through the use of computer vision algorithms such as YOLOv7 and Optical Character Recognition (OCR) tools, such as EasyOCR. In the initial phase of license plate detection, YOLOv7 is employed to detect the license plate region within an image. Subsequently, EasyOCR is utilized to extract the characters from the detected license plate image and transcribe them into text. This resulting text can then be employed to ascertain the vehicle and its owner.

Once the YOLOv7 model is trained, it becomes capable of promptly detecting and recognizing license plate numbers in real-time, whether from new images or video streams. The YOLOv7 model adeptly identifies license plates and employs EasyOCR to interpret the characters on the license plate, ultimately extracting the license plate number, as visually represented in Figure 5.

It's crucial to acknowledge that LPR represents a multifaceted undertaking, necessitating a high-quality dataset and meticulous model fine-tuning to achieve a commendable level of accuracy. The figure visually encapsulates the intricacies of the license plate recognition process.
3.2 Motorcycle tracking

The proposed approach employs YOLOv7-DeepSORT, as delineated in Figure 7. Multiple Object Tracking (MOT) is a commonly utilized technique in applications like autonomous driving, intelligent surveillance, behavior identification, and more. The prevalent MOT method used in industry is Detection Based Tracking (DBT), and the effectiveness of these methods largely hinges on their object detection networks.

Figure 6 illustrates the operational process of YOLOv7-DeepSORT. To locate the targets, input is fed into YOLOv7. The output of YOLOv7 then undergoes transformation into a distinctive feature embedding for the ReID (Person Re-Identification) model. The Kalman filter is a recursive mathematical algorithm that utilizes a series of measurements observed over time to estimate unknown variables and predict future states (Welch, 2021). It is employed to predict the trajectory of each target, and the Hungarian algorithm is a combinatorial optimization algorithm that provides an efficient solution to the assignment problem [Jonker & Volgenant, 1986]. It is used to match the outputs of YOLOv7 and the Kalman filters for trajectory determination. These operations are visually depicted in Figure 6. The final step in this process produces the output, providing valuable information such as the position, dimension, and other parameters including Frame, Tracking ID, Helmet, Person, X position, Y position, Width, Height, and Traffic light. This detailed output contributes to the comprehensive dataset, enriching the information available for analysis and further enhancing the algorithm's capabilities.

The input to the YOLOv7 algorithm consists of an image or video frame, and its output comprises a collection of bounding boxes with associated class labels and confidence scores. Each bounding box represents a detected object, with the class label indicating the object type (e.g., motorcycle, car, person). The confidence score reflects the model's certainty in the predicted class for the detected object. These bounding boxes have diverse applications, including object tracking and recognition. In the proposed approach, the output of YOLOv7 is further converted into a feature embedding that distinguishes well for the ReID model, facilitating real-time tracking of multiple motorcycles.
Figure 6: The operation process of YOLOv7-DeepSORT
Motorcycle riding is undeniably a popular and thrilling pursuit, but it does not come without its associated risks. Among the paramount safety measures for motorcycle enthusiasts, the use of a helmet stands as a vital safeguard. However, it is disconcerting to note that helmet violations are a recurring issue in this context. Regrettably, the realm of unsafe motorcycle practices encompasses a spectrum broader than just helmet negligence. These practices encompass perilous maneuvers like weaving through traffic, venturing onto sidewalks, and daringly taking on the wrong side of the road. Such actions, while injecting an element of thrill, impose substantial risks not only upon the rider but also upon other motorists and pedestrians who share the road. This paper delves into an exploration of the prevalence of these motorcycle violations and the potential consequences that riders may face for their engagement in such perilous behaviors. Moreover, it seeks to chart a course towards possible solutions, aiming to curtail the number of motorcycle accidents stemming from these infractions.

### 3.3.1 Helmet violations

Helmet violations occur when motorcycle riders operate their vehicles without wearing appropriate head protection. This issue is prevalent in many countries, posing a substantial risk of severe injuries or even fatalities in the event of an accident. To effectively address this concern, a dedicated detection algorithm proves invaluable in identifying instances of helmet non-compliance among motorcycle riders. Notably, one
such algorithm capitalizes on the capabilities of YOLOv7, a real-time object detection system. This algorithm can be fine-tuned to discern the presence or absence of helmets on riders [Charran & Dubey, 2022].

The operational sequence of this algorithm can be outlined as follows:

1. **Motorcycle Detection**: Initially, the algorithm identifies motorcycles within the traffic footage using an object detection mechanism.
2. **Region of Interest Identification**: For each recognized motorcycle, the algorithm pinpoints regions of interest where the rider's head is likely to be positioned. This determination relies on the predicted motorcycle and rider bounding boxes.
3. **Region Expansion**: The regions of interest are subsequently expanded to encompass the entire rider's head, ensuring comprehensive coverage.
4. **Helmet Detection**: A distinct, pre-trained detector comes into play, tasked with assessing whether a helmet is present within each expanded region of interest.
5. **Violation Detection**: If a helmet is not detected within the expanded region, the motorcycle is marked as violating helmet use laws.

In essence, this algorithm provides a robust mechanism for identifying cases where motorcycle riders forego helmet usage during vehicle operation, facilitating the enforcement of helmet-related regulations. It leverages the YOLOv7 object detection algorithm and a dedicated helmet detector to ensure the accuracy of these determinations.

### 3.3.2 Triple-riding Violations

Triple-riding, the practice of carrying more passengers on a motorcycle than legally allowed, poses a significant risk that can lead to accidents and injuries. Detecting instances of triple-riding using YOLOv7 involved the utilization of video footage of motorcycles as training data. The model underwent training to recognize distinctive patterns of movement and the count of riders on a motorcycle, indicative of this unsafe behavior. During the inference phase, the model scrutinizes the positions of bounding boxes enclosing motorcycles and riders in new video footage to flag instances of triple-riding.
This identification process is accomplished by counting the number of riders within these bounding boxes, enabling the model to discern triple-riding occurrences and categorize them as violations. This innovative approach ensures accurate detection of this perilous conduct, contributing significantly to enhancing road safety.

The diagram illustrates the workflow for identifying and tallying multiple violations, such as triple-riding and helmet violations, through a data-video learning-based detector:

1. **Motorcycle Identification (a):** The initial step involves pinpointing motorcycles within the video frame and marking them with bounding boxes.

2. **Detection and Counting Module (b):** Subsequently, the detection and counting module analyzes the bounding boxes, generating outputs. These
outputs encompass overlaid detections and violation counts superimposed on the frame.

3. **Violations**: They are exemplified by orange trapeziums, indicating rider or head occlusions, as well as red boxes (c), as showcased in Figure 8.

This comprehensive process is instrumental in identifying and recording instances of triple-riding, a practice that endangers road safety. It employs YOLOv7 and data-video learning-based techniques to yield precise results, making our roads safer for everyone.

### 3.3.3 Zigzagging between vehicles

Detecting the zigzagging of motorcycles between vehicles using YOLOv7 involves training the model to recognize specific movement patterns characteristic of this behavior. Instead of relying on GPS data, this is achieved by providing the model with video footage depicting motorcycles zigzagging between vehicles as training data. Subsequently, the trained model is employed to analyze the positions of bounding boxes enclosing motorcycles in new video footage.

The model discerns zigzagging instances by closely evaluating the trajectory of the bounding box over time. Detection can occur through the identification of abrupt changes in the bounding box's position or the detection of erratic movements within the frame. To ensure precise results, fine-tuning the YOLOv7 model for the specific task of detecting motorcycle zigzagging between vehicles is imperative.

For the visualization of zigzagging detection using YOLOv7, we employed a line graph to depict the bounding box's position over time. The x-axis represents time, while the y-axis corresponds to the bounding box's position within the frame. Zigzagging instances manifest as sharp peaks or valleys on the graph, which indicate sudden changes in the bounding box's position. This graphical representation facilitates the straightforward identification of zigzagging behavior.

Alternatively, a scatter plot was utilized to represent zigzagging detection. In this representation, the x-axis indicates the x-position of the bounding box within the frame, while the y-axis signifies the y-position of the bounding box within the frame at different time points. When a motorcycle is zigzagging, the points on the scatter plot disperse in various directions, reflecting the motorcycle's movement. This approach, like the line graph, simplifies the identification of zigzagging behavior, providing multiple visual cues for precise detection.

To employ YOLOv7 for detecting zigzagging motorcycles between vehicles, you can follow these steps:

1. **Collect Training Data**: Gather video footage showcasing motorcycles zigzagging between vehicles. This footage will serve as the training data for the YOLOv7 model.

2. **Model Training**: Train the YOLOv7 model using the collected training data. The objective is to teach the model to recognize movement patterns that signify zigzagging behavior.

3. **Inference on New Footage**: Utilize the trained YOLOv7 model to analyze the bounding box positions of motorcycles in new video footage.
4. **Visualize Bounding Box Positions**: Create visual representations of the bounding box positions over time. You can choose to use either a line graph or a scatter plot for this purpose.

5. **Identify Sudden Changes**: While analyzing the visual representation, be on the lookout for abrupt changes in the position of the bounding box. These sudden alterations indicate instances of zigzagging behavior.

6. **Fine-Tune the Model**: To ensure accurate detection of zigzagging motorcycles between vehicles, consider fine-tuning the YOLOv7 model for this specific detection task.

By following these steps, you can effectively utilize YOLOv7 to detect motorcycles engaging in zigzagging behavior between vehicles.

3.3.4 driving up the wrong side

To detect motorcycles driving against the flow of traffic using YOLOv7, we employed the following approach, which can also identify motorcycles on sidewalks:

1. **Collect and Pre-process Training Data**: Gather video footage of motorcycles, which will serve as training data. Pre-process the data, which may involve cropping, resizing, and annotating bounding boxes around the motorcycles.

2. **Train YOLOv7 Model**: Train the YOLOv7 model using the pre-processed training data. The goal is to teach the model to recognize movement patterns indicative of driving against traffic or on sidewalks.

3. **Inference Stage**: Use the trained YOLOv7 model to analyze new video footage of motorcycles.

4. **Bounded Box Extraction**: For each frame in the video, extract the bounding box positions of the motorcycles.

5. **Direction Analysis**: Analyze the movement direction of these bounding boxes to identify instances where a motorcycle is moving against the flow of traffic or on sidewalks.

6. **Violation Flagging**: When such instances are detected, flag them as violations and store the relevant data for further analysis.

7. **Repeat for the Entire Video**: Apply this process to the entire video footage.

Our algorithm goes beyond detecting wrong-way driving and considers various movements, such as motorcycles occasionally using the sidewalk to bypass barriers and access the opposing lane. This behavior is often influenced by road infrastructure, including barriers and road design inadequacies.
Our algorithm's ability to detect and track motorcycles on sidewalks provides valuable data for understanding the extent of this issue and informs future infrastructure improvements. By addressing these concerns, we aim to enhance road safety and create a more efficient traffic flow for all road users. This approach can significantly contribute to safer and more organized roadways.

3.3.5 red-light running

Running red lights is a grave traffic violation that substantially jeopardizes the safety of all road users. Motorcycles, in particular, are more vulnerable to being involved in red-light violations due to their compact size and enhanced maneuverability. This issue is especially pronounced in developing countries where the enforcement of traffic regulations can be lax. In this study, we introduce the utilization of YOLOv7, a cutting-edge object detection algorithm, for real-time detection of motorcycles running red lights in video footage.

To tackle the problem of motorcycles disregarding red lights, our approach comprises the following key steps:

1. **Video Capture**: Record video footage at an intersection using a camera.

2. **Pre-processing**: Prepare the video by cropping the Region of Interest (ROI) around the traffic light.

3. **YOLOv7 Detection**: Utilize YOLOv7 to identify motorcycles within the ROI.

4. **Traffic Light Region Extraction**: For each identified motorcycle, isolate the region containing the traffic light within the frame.

5. **Color Detection**: Apply image processing techniques to determine the color of the traffic light (red or green).

6. **Violation Identification**: If the traffic light is red, and a motorcycle is detected within the ROI, mark it as a red-light violation.

7. **Frame-wise Repetition**: Repeat steps 2 through 6 for each frame in the video.

8. **Violation Count**: Compile and report the total number of red-light violations detected.

This comprehensive approach not only uses advanced technology to pinpoint red-light violations by motorcycles but also focuses on enhancing road safety for all. It offers a systematic method to monitor and identify violations, which can be instrumental in maintaining traffic discipline and ensuring the safety of road users.
In Figure 9, we are presented with an example of red-light running. Our objective is to specifically identify elements in the frame as follows:

1. **Motorcycle Detection**: Locate the motorcycle with the unique identifier (ID) of 53 within the yellow bounding box in frame 1.
2. **Traffic Light Detection**: Detect and highlight the traffic light within the red bounding box.
3. **Pedestrian Path**: Illustrate a line representing the pedestrian path, as visible in frame 2.

This analysis serves to clearly demonstrate that the motorcycle bearing ID 53 crossed the pedestrian path during a red-light signal, establishing a conclusive case of red-light violation.

### 3.4 User Interface

Our application harnesses the power of YOLOv7, an advanced object detection model, to meticulously spot infractions and errors committed by motorcycle riders in video footage. With an extensive range of violations under its purview, including helmet violations, weaving through traffic, sidewalk riding, wrong-way driving, triple-riding, and more, the application delves into the bounding box positions of motorcycles and
their riders within the video content. Furthermore, the application boasts the capability to swiftly identify motorcycle license plates from the video, streamlining the process of singling out the offending vehicles.

The wealth of data accumulated by the application finds its home in a well-organized database. This database is readily accessible via a user-friendly application designed for motorcycle riders. This feature empowers riders to peruse their past mistakes and violations and, in turn, take the necessary steps to rectify them in the future.

The application itself is crafted using Flutter, a renowned open-source framework for constructing mobile applications. It seamlessly integrates with APIs, ensuring users receive real-time updates and access to the most up-to-date information.

At its core, this application strives to elevate road safety. It does so by endowing drivers with the means to not only identify their errors but also rectify them, all the while equipping authorities with the indispensable data required to enforce traffic regulations effectively.

The Android application is tailor-made for motorcycle riders who wish to inspect any traffic violations they may have incurred. It supports an intuitive interface featuring a lone input field for riders to input their license plate number. Upon entering this number and hitting the "search" button, the application dispatches a post request to the database, which then furnishes information regarding any infractions linked to the provided license plate number. This information comprises specifics such as the date, time, location, and nature of the violation. The application lays out these infractions in a neatly organized list, each entry showcasing the date, time, location, and type of violation. The application additionally tallies the total number of violations and the associated fines. In cases where a rider has committed multiple violations simultaneously, the application efficiently enumerates each one. This application emerges as an invaluable resource for riders keen on reviewing their traffic records and ensuring they adhere to traffic laws. For a visual representation of the application's user interface, please refer to Figure 10.
Traffic violations committed by motorcycle riders are a pressing issue in cities across the globe. The precise identification of these violators holds paramount importance for the enforcement of traffic regulations and the enhancement of road safety. A common technique employed for this purpose is license plate recognition technology. Nonetheless, this method comes with its share of challenges. In this study, our objective was to gather data on traffic violations among motorcycle riders using camera phones and apply license plate recognition technology to discern these violations.

Our endeavor encountered a significant hurdle: the accurate detection of license plate numbers, primarily due to the camera’s positioning during video recording. The camera was situated to the left or right of the route, rather than behind the motorcycles. This unfavorable placement impeded the capture of clear images of the motorcycles’ license plates, a critical component for precise identification of the vehicles. This challenge had a substantial impact on the data accuracy and the efficacy of license plate detection as a means of identifying violators.

In response to these impediments, we opted to shift our focus towards the detection and quantification of violations without relying on license plate recognition technology. Instead, we harnessed the potential of machine learning algorithms to identify other types of violations, including helmet violations, triple-riding, or weaving through traffic. These methodologies dispensed with the need to capture license plate numbers.
and could be complemented with additional data, such as location and time, to pinpoint the violators.

The table provided, Table 1, serves as a concise overview of observed traffic violations at various intersections (A, B, and C, as illustrated in Figure 2) during distinct time intervals (10:00-10:10, 12:30-12:40, 15:00-15:10, and 18:30-18:40). The table is inclusive of data regarding the count of motorcycles present at each intersection during these time frames, alongside the tally of violations encompassing helmet usage, triple-riding, weaving between vehicles, and wrong-way driving.

For instance, within the 10:00-10:10 time slot at intersection A, 62 motorcycles were present, with 9 violations pertaining to helmet use, no instances of triple-riding, 5 cases of weaving between vehicles, and 3 violations for wrong-way driving. The table essentially offers a snapshot of traffic violations at specific intersections during specified time intervals, serving as a valuable resource for identifying patterns or hotspot areas of violations.

<table>
<thead>
<tr>
<th>Time</th>
<th>Intersection</th>
<th>Motorcycles number</th>
<th>Violation type</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Helmet use</td>
<td>Triple-riding</td>
</tr>
<tr>
<td>10:00-10:10</td>
<td>A</td>
<td>62</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>56</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>71</td>
<td>13</td>
</tr>
<tr>
<td>12:30-12:40</td>
<td>A</td>
<td>92</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>89</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>102</td>
<td>30</td>
</tr>
<tr>
<td>15:00-15:10</td>
<td>A</td>
<td>54</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>49</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>68</td>
<td>12</td>
</tr>
<tr>
<td>18:30-18:40</td>
<td>A</td>
<td>111</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>99</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>114</td>
<td>25</td>
</tr>
</tbody>
</table>

**Table 1: Summary of Traffic Violations counter at Intersections A, B, and C**

According to Figure 11, a discernible upswing in the motorcycle count is evident at intersections A, B, and C during the time windows of 12:30-12:40 and 18:30-18:40. Particularly striking is the surge in the number of motorcycles at intersection A during these time intervals, closely paralleling a rise in the observed violations at that specific intersection.

Several factors could account for the escalation in both motorcycle numbers and violations during these periods. One plausible explanation is the alignment of these time slots with rush hour traffic, prompting more individuals to opt for motorcycles as a quicker and more efficient mode of transportation. It’s also feasible that these time frames correspond to the conclusion of the workday, leading to an increased reliance on motorcycles for commuting.

In terms of the spatial clustering of violations towards the end of the day, psychological factors like fatigue and stress may be contributing to this phenomenon. As people grapple with fatigue and stress at day’s end, their ability to maintain focus while driving and make sound decisions may be compromised. Consequently, this compromises road safety, raising the likelihood of violations and accidents.
For example, fatigued and stressed drivers might be more inclined to speed, disregard traffic signals, and engage in other risky behaviors that elevate accident risks. Furthermore, they may succumb to distracted driving behaviors such as texting or phone calls, further amplifying accident risks.

Hence, it is imperative for traffic safety professionals to acknowledge the potential role of psychological factors in the spatial concentration of violations at day's end. This could entail crafting targeted interventions to aid drivers in managing stress and fatigue, as well as fostering awareness about the perils tied to driving under such conditions.

On the whole, the concentration of violations at specific intersections during certain time windows underscores the importance of adopting a comprehensive approach to traffic safety, one that accounts for both physical and psychological factors. By tackling these factors comprehensively, there is a prospect of diminishing accident rates, curbing violations, and enhancing overall road safety.

![Figure 11: The number and type of violations for each intersection](image)

5 Conclusion and Discussion

In this study, our primary objective was to employ camera phones for gathering data on traffic violations committed by motorcycle riders. Despite the challenges we encountered, particularly with detection angles, we managed to achieve satisfactory results. A significant hurdle we faced revolved around accurately identifying license plate numbers, primarily because of the camera's positioning during video recording. Specifically, the cameras were oriented to the side of the road rather than behind the motorcycles, making it challenging to capture clear images of license plates essential for accurate detection and identification of vehicles.

This issue undeniably influenced the accuracy of the collected data and the overall effectiveness of using license plate detection as a means of identifying violators. Notably, we sought to address this challenge by exploring cameras with higher
resolutions and enhanced image processing capabilities. However, these cameras can be costlier and more complex to install.

It's worth emphasizing that this challenge is not unique to our study; it's a recurrent issue when utilizing side-positioned cameras for data collection on traffic violations. This underscores the significance of conscientiously considering camera positioning and technology when embarking on data collection endeavors to enhance data accuracy and research effectiveness.

To mitigate this limitation, we opted to leverage machine learning algorithms for the detection of other violation types, such as helmet violations, triple-riding, or zigzagging between vehicles. These methods do not hinge on capturing license plate numbers and can be harmonized with supplementary data such as location and time to identify violators effectively. This approach permits a comprehensive review of traffic dynamics at specific locations, offering prospects for potential urban mobility redesign.

In conclusion, while using camera phones for data collection on traffic violations among motorcycle riders presents certain limitations, our study underscores that it is feasible to glean valuable insights into traffic violations and identify violators using alternative techniques. Nevertheless, it remains imperative to acknowledge the constraints of the data and the potential errors stemming from camera positioning.

References


