Enhancing Road Safety: Automated Traffic Violation Detection and Counting System Using YOLO Algorithm

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***Abstract*—Ensuring compliance with traffic regulations, such as wearing helmets and obeying traffic signals, is crucial for enhancing road safety, particularly among motorcycle riders. In this study, we propose an automated approach for detecting helmet wearing and traffic light violations using computer vision techniques. Our methodology involves leveraging the YOLO-v8 object detection model pretrained on the COCO dataset to identify motorcycles, persons, traffic lights, and helmets in video footage captured at intersections in Marrakech. We conducted manual counting as a benchmark for evaluating the performance of our automated system. Our results demonstrate a strong alignment between our automated approach and manual counting for both helmet detection and traffic light violations. However, occasional discrepancies were observed, particularly during specific time slots characterized by high motorcycle speeds. Contextual factors such as traffic density and vehicle speed were identified as influencing factors. Despite these challenges, our automated system shows promise as a valuable tool for monitoring and enforcing traffic regulations. Ongoing refinement and optimization are essential to address these challenges and enhance the accuracy and reliability of automated detection systems. Our study highlights the potential of automated technologies in improving road safety measures and underscores the importance of considering contextual factors in interpreting detection results.**

Keywords— Traffic safety; Helmet detection; Traffic light violations; Automated detection; Computer vision.

I. INTRODUCTION

This With the rapid urbanization and economic development witnessed in Marrakech, Morocco, over recent years, there has been a notable increase in the number of motorcycles on the city's roads. This surge in motorcycle ownership and usage reflects not only the city's growing population but also the increasing demand for affordable and convenient modes of transportation in urban areas. However, along with the proliferation of motorcycles comes a host of challenges, particularly concerning traffic safety and congestion [1].

The influx of motorcycles in Marrakech has brought about significant changes in the dynamics of traffic flow within the city [2]. Motorcycles, known for their maneuverability and agility in navigating congested urban streets, have become an integral part of Marrakech's transportation landscape. However, their presence also poses unique challenges, including increased vulnerability to accidents and violations of traffic regulations.

One of the most pressing issues associated with the rising number of motorcycles in Marrakech is the problem of traffic violations, particularly concerning helmet usage and adherence to traffic signals. Non-compliance with helmet-wearing regulations not only poses a risk to the safety of motorcycle riders but also undermines efforts to improve road safety outcomes in the city. Additionally, violations such as running red lights or disobeying traffic signals contribute to traffic congestion and disrupt the smooth flow of traffic, further exacerbating the challenges of urban mobility in Marrakech.

The main contribution of this paper lies in the empirical analysis of motorcycle violations, focusing on helmet non-compliance and traffic light infractions, through the application of computer vision technology using YOLO-v8. By leveraging this approach, we provide accurate detection and counting of violations, offering valuable insights into the prevalence and patterns of motorcycle-related traffic violations. This research not only enhances our understanding of traffic safety issues but also presents a scalable and efficient method for monitoring and enforcing traffic regulations in urban environments.

This paper is structured into five main sections to provide a comprehensive analysis of motorcycle safety and traffic management in urban environments, with a focus on Marrakech. The "Literature Review" section offers an overview of existing research on motorcycle safety and helmet detection systems, setting the context for the proposed approach. In "Data Collection," the methodology for gathering real-time data on motorcycle behavior, including helmet usage, is outlined. The "Proposed Approach" details the development and implementation of a YOLO-v8-based framework for motorcycle detection and helmet classification, along with any enhancements made to the architecture. "Results and Discussion" presents the findings of the study, including the accuracy and effectiveness of the helmet detection models, and discusses their implications for motorcycle safety and traffic management. Finally, the "Conclusion" section summarizes the key findings, suggests avenues for future research, and recommends strategies for implementing motorcycle safety measures in urban environments like Marrakech.

II. LITERATURE REVIEW

The related work in the field of traffic violation detection and motorcycle safety encompasses various approaches and methodologies. Notable studies include a system employing the YOLO algorithm for traffic violation detection, achieving high accuracy rates in detecting violations, particularly focusing on license plate recognition [3].Additionally, research efforts aimed to automate the detection of motorcyclist violations and plate recognition using Deep Learning algorithms, showcasing effectiveness in real-time surveillance video analysis [4].Furthermore, advancements in Computer Vision and Deep Learning techniques have led to the development of systems capable of automatically detecting helmet usage by motorcycle riders from video data, offering promising solutions for improving road safety and reducing fatalities in traffic accidents [5] [6].

In countries like India, where two-wheeler vehicles dominate transportation but safety remains a concern, there's a need for robust measures to enforce traffic laws and ensure rider safety. However, the lack of detailed data on critical safety metrics like helmet usage hinders effective policymaking and outreach campaigns [7]. To address this, we developed a deep learning model utilizing Convolutional Neural Networks (CNN) to automatically detect motorcycle riders and their helmet usage from video data. With helmet usage reducing the risk of fatal injury by 42%, our model aims to enhance road safety by accurately identifying helmet-wearing riders. Experimental results demonstrate an 85% accuracy in helmet detection, offering a promising solution to improve motorcycle safety and prevent fatalities in traffic accidents [8].

Automated detection of traffic rule violations, particularly helmet non-usage by motorcycle riders, is crucial for enhancing road safety in densely populated countries like India. This paper presents a framework utilizing YOLOv3 for motorcycle rider detection and a Convolutional Neural Network (CNN) for helmet detection. The proposed model shows promising results in accurately identifying single or multiple riders traveling without helmets in traffic videos, offering a valuable tool for enforcing safety regulations and reducing the risk of head injuries in motorcycle accidents [9][10].

This paper presents a novel framework for video surveillance-based automatic detection of motorcycle helmet usage, aiming to strengthen road safety initiatives. Unlike existing methods, our framework focuses on individual motorcycles and accurately differentiates between riders and passengers regarding helmet usage. The proposed classification approach showcases improved efficiency, evident in its exceptional accuracy score of 0.7754 on the AI City 2023 Challenge Track 5 public leaderboard [11].

While the aforementioned studies make significant contributions to safety violation detection and counting, they exhibit certain limitations and areas for enhancement. Notably, some studies rely on outdated object detection frameworks like YOLOv5, potentially overlooking recent advancements in accuracy and speed. Moreover, the absence of real-time detection capabilities in certain studies may restrict their practical utility, particularly in dynamic settings such as road traffic management. Additionally, the lack of real-world data from field environments like signalized intersections or construction sites raises concerns regarding the generalizability and effectiveness of proposed methods in real-world scenarios. Hence, future research endeavors should focus on addressing these limitations by integrating state-of-the-art detection frameworks, enabling real-time detection, and leveraging diverse and representative datasets from actual field environments to ensure the robustness and reliability of safety violation detection and counting systems.

III. DATA COLLECTION

For the data collection phase of our study, we selected intersections in Marrakech as our primary observation sites. Marrakech, being a vibrant city with a diverse mix of road users, offers an ideal setting to investigate motorcycle violations, particularly regarding helmet use and adherence to traffic signals.

Our data collection strategy involved utilizing phone cameras to record video footage at selected intersections during three distinct time periods across three days of the week. Specifically, we conducted observations during the morning rush hour (9:00 - 9:30), the midday period (12:00 - 12:30), and the afternoon rush hour (3:00 - 3:30). These time slots were chosen to capture variations in traffic volume and behavior during different times of the day when motorcycle violations might occur. In total, we gathered 1,250 unique instances of traffic violations, including both helmet and traffic light violations, which were meticulously analyzed to ensure a comprehensive representation of traffic patterns.

To ensure comprehensive data collection, we implemented this observation schedule on Monday, Thursday, and Sunday. These days were chosen strategically to represent both weekdays and weekends, considering potential differences in traffic patterns and compliance with traffic regulations on different days of the week. Regarding the technical setup, the video data were collected using high-definition phone cameras mounted at strategic locations. The data were then processed using a dedicated workstation equipped with an NVIDIA GTX 1080 Ti graphics card, 32 GB of RAM, and an Intel i7-8700K CPU. This setup ensured efficient handling and processing of the video data for training and testing the YOLO-v8 model, facilitating robust real-time detection and analysis capabilities.

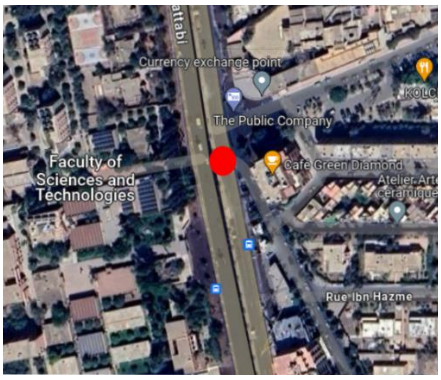

Figure 1: Study Locations - Intersection Map of Marrakech [12]

By recording video footage at multiple intersections during various times of the day and days of the week, we aimed to obtain a holistic understanding of motorcycle violations in Marrakech. This approach allowed us to gather rich observational data that could reveal insights into the frequency, nature, and contributing factors of violations related to helmet use and traffic signal adherence among motorcycle riders at intersections in the city.

This figure 1 illustrates the selected intersections in Marrakech where data collection for the study was conducted.

The intersections were selected based on criteria such as traffic volume, diversity of road users, and relevance to the study's focus on motorcycle violations, including helmet non-compliance and traffic signal infractions.

IV. Proposed Approach

In our proposed approach, we aim to leverage the advanced capabilities of the YOLO-v8 [13](You Only Look Once version 8) model, combined with pretraining on the COCO [14] (Common Objects in Context) dataset, to detect motorcycles, persons, traffic lights, and helmets in the video footage collected from intersections in Marrakech. YOLO-v8 is renowned for its efficiency in real-time object detection tasks, making it a suitable choice for our study, where prompt and accurate identification of relevant objects is crucial. By utilizing the COCO dataset for pretraining, our model benefits from a diverse range of annotated images containing various objects, including motorcycles, persons, traffic lights, and helmets, thereby enhancing its ability to recognize these objects in different contexts and under varying environmental conditions.

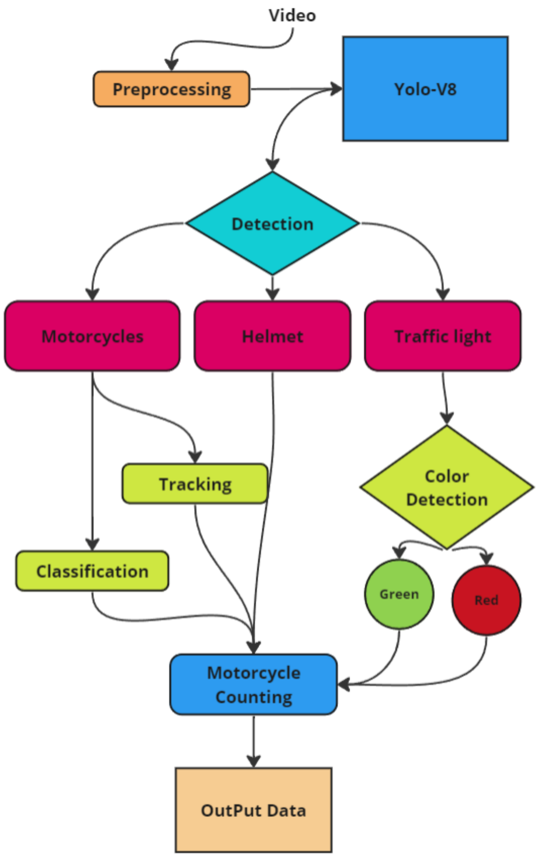

Figure 2: Architecture of the Proposed Approach for Motorcycle Detection and Violation Counting

The proposed approach involves adapting the pretrained YOLO-v8 model to our specific task of detecting motorcycle violations, such as helmet non-compliance and traffic light infractions, in Marrakech intersections. This adaptation may include fine-tuning the model parameters, adjusting the input data preprocessing pipeline, and possibly incorporating additional training data specific to our study context. Through this process, we aim to optimize the model's performance and ensure its effectiveness in accurately detecting motorcycles, persons, traffic lights, and helmets from the video footage captured at the selected intersections.

Figure 2 illustrates the architecture of our proposed approach for the detection and counting of motorcycles, as well as violations related to helmet wearing and traffic light infractions. The process begins with input video footage captured from intersections in Marrakech. This footage undergoes preprocessing to enhance quality and standardize format for compatibility with the subsequent stages. Subsequently, the preprocessed video frames are fed into the YOLO-v8 model, which performs object detection. Specifically, the model identifies motorcycles, helmets, and traffic lights within the video frames. For traffic lights, an additional step of color detection is applied to determine whether the light is green or red (including orange, representing the transitional phase). The output of the model includes the detection results, including the number of motorcycles and any violations detected, such as instances of helmet non-compliance and traffic light infractions. These results are then aggregated to provide counts of motorcycles and their respective violations, facilitating a comprehensive analysis of intersection activity and compliance with traffic regulations.

A. *Helmet Detection*

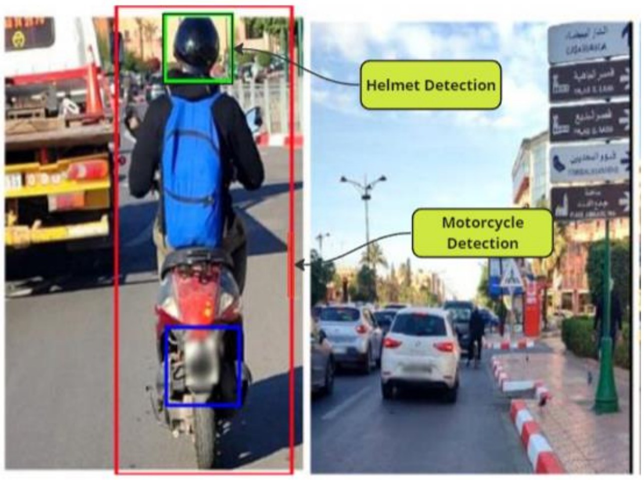

Figure 3: Example of Helmet Wearing Detection in Motorcycle Riders

In the process of helmet detection, we initially employ YOLO to detect motorcycles and persons within the captured video frames. Once these objects are identified, bounding boxes are drawn around them to delineate their spatial extent accurately. Subsequently, we focus on the region within these bounding boxes, which represents both the motorcycles and their riders. Utilizing this cropped image, we employ a secondary detection mechanism to identify helmets specifically. This involves applying a helmet detection algorithm to the extracted regions of interest, aiming to accurately discern whether motorcycle riders are wearing helmets. By segmenting the image into relevant subsets corresponding to motorcycles and their riders and then specifically targeting the detection of helmets within these subsets, our approach ensures a focused and precise analysis of helmet compliance among motorcycle riders figure 3.

B. *Traffic signal infractions*

In our approach to detecting traffic signal infractions, we utilize YOLO to initially identify motorcycles and persons within the captured video frames. Following this detection, bounding boxes are applied around these objects to precisely delineate their spatial extents. Concurrently, we employ a separate module to detect and isolate the traffic light within the video frame. Once the traffic light is identified, its bounding box is sent to a color detector, which discerns whether the signal is emitting a green, red, or orange hue. If the detected color corresponds to red or orange, indicative of a stop signal, and a motorcycle fails to halt, this is flagged as a traffic light violation, indicating that the motorcycle has run the red light or disregarded the stop signal, thus constituting a violation figure 4.

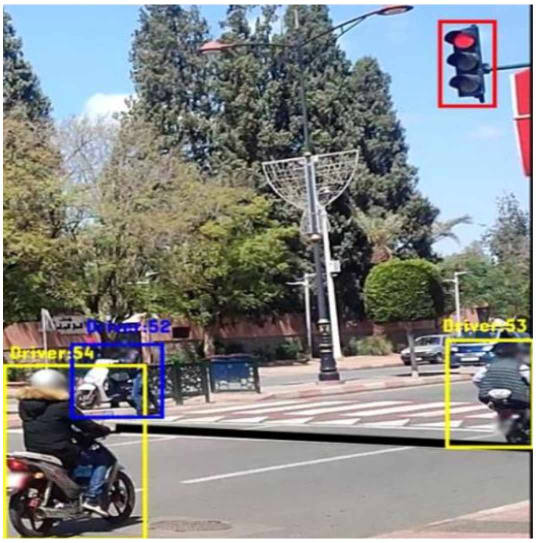

Figure 4: Example of Traffic Light Violation (Running Red or Orange Light)

V. RESULT AND DISCUTION

In order to assess the effectiveness and accuracy of our proposed approach, we conducted manual counting for helmet wearing and instances of traffic light running. This manual counting served as a benchmark against which we compared the results obtained through our automated detection and analysis system. By comparing the outputs of our approach with the manually counted data, we were able to evaluate the performance and reliability of our methodology in detecting helmet wearing and traffic light violations.

The comparison between our automated approach and manual counting for helmet detection, as presented in Figure 5, illustrates a notable alignment between the two methods across various days and time slots. For example, during the morning period on Monday (09:00 - 09:30), our automated approach detected six instances of helmet wearing, closely matching the manual count of five. This consistency extends to different days and times, such as the morning slot on Thursday (09:00 - 09:30), where both methods recorded four instances of helmet usage.

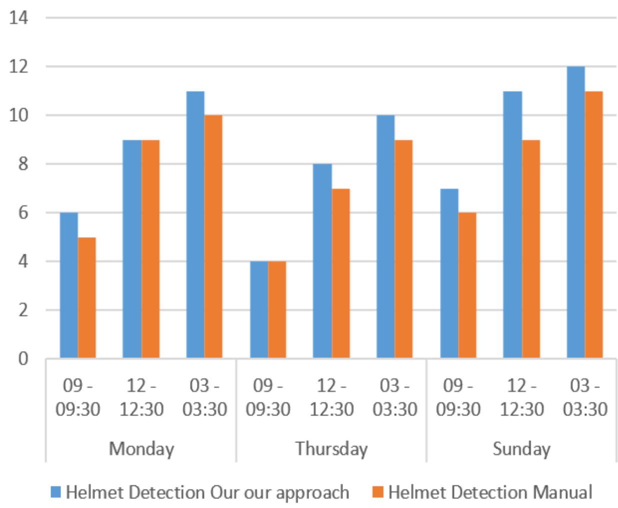

Figure 5: Comparison between Automated Approach and Manual Counting for Helmet Detection

However, discrepancies were observed in certain instances, notably during the afternoon period on Sunday (12:00 - 12:30). Here, our approach detected 11 motorcycles without helmets, while manual counting reported only 9 instances. A similar discrepancy arose during the 03:00 - 03:30 time slot. Upon scrutinizing the video footage, we identified a contributing factor to these differences: motorcycles tended to accelerate during these time slots due to reduced traffic volume, making it more challenging for our automated system to accurately detect helmet usage.

These findings underscore the importance of considering contextual factors, such as traffic density and vehicle speed, when interpreting automated detection results. While our approach generally exhibits strong alignment with manual counting, occasional discrepancies may occur due to such factors. Thus, ongoing refinement and optimization of our automated system remains crucial for ensuring reliable and precise detection of helmet compliance among motorcycle riders.

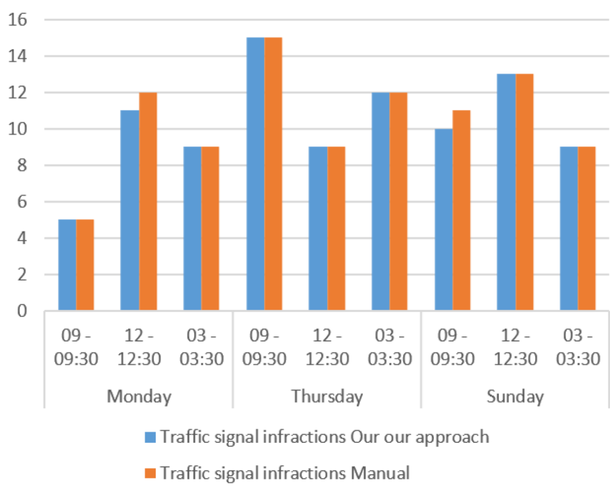

Figure 6: Comparison between Automated Approach and Manual Counting for Traffic Light Violations (Running)

The figure 6 provides a comparison between our automated approach and manual counting for traffic light violations (running) across different intersections and times of the day. The figures indicate the number of traffic signal infractions detected by both methods for each time slot on Monday, Thursday, and Sunday.

Upon analysis, it's evident that there is a close alignment between the results obtained through our automated approach and those derived from manual counting. For instance, during the morning time slot (09:00 - 09:30) on Monday, both methods detected five instances of traffic light violations. Similarly, for the same time slot on Thursday and Sunday, the counts obtained through our approach closely matched those from manual counting.

Overall, the comparison demonstrates the reliability and accuracy of our automated approach in detecting traffic light violations. The minor discrepancies observed between the two methods can be attributed to factors such as variations in lighting conditions, occlusion of traffic signals by other objects, or differences in the interpretation of video footage between automated and manual analyses. However, these differences are relatively small and do not significantly affect the overall agreement between the two methods.

VI. Conclusion

Our study demonstrates the effectiveness and reliability of our proposed automated approach for detecting helmet wearing and traffic light violations among motorcycle riders. Through manual counting, we established benchmarks against which we compared the results obtained from our automated detection system. While our approach generally showed strong alignment with manual counting, occasional discrepancies were observed, particularly during specific time slots where motorcycles tended to accelerate due to reduced traffic volume.

Despite these minor discrepancies, our automated system proved to be a valuable tool for monitoring and enforcing helmet compliance and traffic regulations at intersections. The close alignment between our automated approach and manual counting highlights the potential of automated detection systems in enhancing road safety measures. However, ongoing refinement and optimization of our system are essential to address challenges such as variations in lighting conditions and vehicle speed.

Overall, our study underscores the importance of considering contextual factors when interpreting automated detection results. By leveraging advanced technologies and methodologies, we can continue to improve the accuracy and reliability of automated systems for monitoring and enforcing traffic regulations, ultimately contributing to safer road environments for all road users.

Reference

[1] A. Charef, Z. Jarir, and M. Quafafou, "Influence of Pedestrian Crossings on Speed Characteristics and Capacity of a Roundabout," *researchgate.netZJ Ayoub Charef, M QuafafouTuijin Jishu/Journal of Propulsion Technology•researchgate.net*, vol. 44, no. 6, pp. 1001–4055, 2023, doi: 10.52783/tjjpt.v44.i6.4718.

[2] R. George, *Pikala Bikes, Marrakesh, Morocco: a social entrepreneurship company*. Edward Elgar Publishing, 2024. Accessed: Feb. 15, 2024. [Online]. Available: https://www.elgaronline.com/edcollchap/book/9781803923857/book-part-9781803923857-20.xml

[3] R. Ferdian and T. P. Sari, "Identification of Motorcycle Traffic Violations with Deep Learning Method," *Proceeding - 2022 International Symposium on Information Technology and Digital Innovation: Technology Innovation During Pandemic, ISITDI 2022*, pp. 146–149, 2022, doi: 10.1109/ISITDI55734.2022.9944502.

[4] A. Afzal, H. U. Draz, M. Z. Khan, and M. U. G. Khan, "Automatic Helmet Violation Detection of Motorcyclists from Surveillance Videos using Deep Learning Approaches of Computer Vision," *2021 International Conference on Artificial Intelligence, ICAI 2021*, pp. 252–257, Apr. 2021, doi: 10.1109/ICAI52203.2021.9445206.

[5] A. Goyal, D. Agarwal, A. Subramanian, C. V. Jawahar, R. K. Sarvadevabhatla, and R. Saluja, "Detecting, Tracking and Counting Motorcycle Rider Traffic Violations on Unconstrained Roads." pp. 4303–4312, 2022. Accessed: Feb. 15, 2024. [Online]. Available: https://github.com/iHubData-Mobility/public-motorcycle-violations

[6] M. M. Bachtiar, A. R. Mawardi, and A. R. A. Besari, "Vehicle Classification and Violation Detection on Traffic Light Area using BLOB and Mean-Shift Tracking Method," *3rd International Conference on Applied Science and Technology, iCAST 2020*, pp. 94–98, 2020, doi: 10.1109/ICAST51016.2020.9557628.

[7] M. M. Bachtiar, A. R. Mawardi, and A. R. A. Besari, "Vehicle Classification and Violation Detection on Traffic Light Area using BLOB and Mean-Shift Tracking Method," *3rd International Conference on Applied Science and Technology, iCAST 2020*, pp. 94–98, 2020, doi: 10.1109/ICAST51016.2020.9557628.

[8] D. A. Naik, P. Naik, and S. O. Reddy, "Traffic Rule Violation Detection System using Surveillance Videos in real-time," *Ann Rom Soc Cell Biol*, vol. 25, no. 6, pp. 17865–17873, Jul. 2021, Accessed: Feb. 15, 2024. [Online]. Available: https://www.annalsofrscb.ro/index.php/journal/article/view/9150

[9] M. Dasgupta, O. Bandyopadhyay, and S. Chatterji, "Automated helmet detection for multiple motorcycle riders using CNN," *2019 IEEE Conference on Information and Communication Technology, CICT 2019*, Dec. 2019, doi: 10.1109/CICT48419.2019.9066191.

[10] T. Waris *et al.*, "CNN-Based Automatic Helmet Violation Detection of Motorcyclists for an Intelligent Transportation System," *Math Probl Eng*, vol. 2022, 2022, doi: 10.1155/2022/8246776.

[11] N.-N. Duong *et al.*, "Robust Automatic Motorcycle Helmet Violation Detection for an Intelligent Transportation System." pp. 5341–5349, 2023.

[12] A. Charef, Z. Jarir, and M. Quafafou, "Smart System for Emergency Traffic Recommendations: Urban Ambulance Mobility," *IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 13, no. 10, p. 2022, Accessed: Jan. 07, 2024. [Online]. Available: www.ijacsa.thesai.org

[13] J. Terven, D.-M. Córdova-Esparza, and J.-A. Romero-González, "A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS," *Machine Learning and Knowledge Extraction 2023, Vol. 5, Pages 1680-1716*, vol. 5, no. 4, pp. 1680–1716, Nov. 2023, doi: 10.3390/MAKE5040083.

[14] Z. Ge, S. Liu, F. Wang, Z. Li, and J. Sun, "YOLOX: Exceeding YOLO Series in 2021," vol. 5, p. 12, Jul. 2021, Accessed: Feb. 15, 2024. [Online]. Available: https://arxiv.org/abs/2107.08430v2