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Technologies for Safety Helmet Detection on Motorcycles

María del Carmen Rey Merchán[1], Antonio López Arquillos[1], Jesús Gómez de Gabriel[2], and Juan Antonio Fernández Madrigal[2]

[1]Business Administration and Marketing Dpt, Universidad de Málaga, Málaga, Spain
[2]System Engineering and Automation Dpt, Universidad de Málaga, Málaga, Spain

ABSTRACT

Motorcycle-related accidents remain a significant global public health concern, with helmet use playing a crucial role in mitigating injury severity. Despite the presence of helmet legislation, compliance remains inconsistent, and traditional enforcement methods are labor-intensive and error-prone. Recent advancements in computer vision, machine learning, and embedded systems have enabled the development of automated helmet detection systems, primarily focused on static, motorcycle-based scenarios. This study provides a comprehensive review of existing helmet detection technologies and evaluates their applicability to motorcycle contexts. It highlights the limitations of current approaches—particularly in terms of hardware constraints, camera placement, and variability in real-world conditions—and underscores the need for lightweight, adaptive, and embedded solutions. Furthermore, the work identifies promising directions for future research, including the development of efficient edge-compatible models, integration of multimodal data, and incorporation of privacy-preserving methods, aiming to support scalable, context-aware safety systems in emerging urban mobility ecosystems.

Keywords: Safety, Monitoring, BLE, Kalman filtering

INTRODUCTION

Motorcycle-related accidents are a major contributor to road traffic fatalities worldwide. Wearing helmets significantly reduces the risk of severe injuries and fatalities, yet compliance remains low in many regions. Helmets serve as a critical safety device, mitigating head injuries and saving lives in the event of accidents. Despite strict helmet laws in many countries, enforcement remains challenging, particularly in densely populated or rural areas where manual monitoring is difficult to sustain.

The detection of inappropriate helmet use, such as wearing non-standard helmets or improperly fastened helmets, is equally critical. These issues compromise the protective benefits of helmets, underscoring the need for reliable detection systems. Traditional manual monitoring is labor-intensive and prone to human error, necessitating the adoption of automated systems. Such systems not only enhance enforcement efficiency but also act as a deterrent, promoting safer riding practices. Moreover, real-time detection of helmet usage can provide actionable data for policymakers to identify high-risk areas and devise targeted interventions.

Numerous technologies and methodologies have been developed in recent years to automate helmet detection, leveraging advances in computer vision, artificial intelligence, and embedded systems. Image processing techniques have laid the groundwork for helmet detection by identifying colour, shape, and texture features. Machine learning and deep learning approaches have further revolutionized this domain by enabling high-accuracy detection under varying conditions, such as different lighting, occlusions, and diverse helmet designs. These advancements have paved the way for scalable, real-time systems capable of integration with existing traffic monitoring infrastructure.

This review explores the technological advancements in this domain, focusing on their technical underpinnings and real-world applications. It presents a comprehensive overview of existing technologies, emphasizing their underlying principles, advantages, limitations, and potential future directions.

TECHNOLOGIES APPLIED IN SAFETY HELMET DETECTION

In alignment with the objectives of this study and in closer relation to its specific focus, the monitoring of proper motorcycle helmet usage has been approached through a variety of methodologies (Table 1). Several systems have been developed for helmet detection, employing diverse technologies such as YOLO-based Convolutional Neural Networks (CNNs) (Jia et al., 2021; Peña Cáceres et al., 2022), traditional machine learning algorithms (Dahiya et al., 2016; Siebert & Lin, 2020; Silva et al., 2013), and Internet of Things (IoT) frameworks (Jesudoss et al., 2019). YOLO-based techniques offer notable advantages, including high detection speed and the capacity for multi-object recognition. However, these methods face challenges when dealing with occluded objects and exhibit significant dependency on the quality and representativeness of the training dataset (Krishna et al., 2021).

In prior implementations of such methods, the camera and observer are typically positioned several meters away from the motorcycle, capturing and processing images from an external vantage point (Jia et al., 2021; Peña Cáceres et al., 2022). Conversely, in our context, the integration of a camera into a motorcycle platform imposes practical constraints on achieving comparable image quality due to the proximity and dynamic positioning. Similarly, machine learning-based approaches cited in the literature often rely on fixed external stations for both data collection and processing, thus encountering comparable limitations when applied to our scenario (Dasgupta et al., 2019; Siebert & Lin, 2020; Silva et al., 2013). Most of these studies are oriented toward detecting helmet usage in fixed environments, such as specific streets or public areas. In contrast, helmet detection in the context of motorcycle use necessitates continuous monitoring throughout the journey, thereby requiring real-time data acquisition and processing capabilities.

Moreover, the mobile nature of motorcycle introduces additional challenges that are not commonly addressed in traditional helmet detection systems. These include varying lighting conditions, rapid changes in background scenery, and the presence of vibrations or movement in the captured footage.

Given these constraints, the development of an effective helmet detection system for motorcycle calls for a departure from conventional static surveillance paradigms. Instead, it necessitates the design of integrated, onboard sensing and processing solutions that can function autonomously during transit. This shift also opens up opportunities for user-centric applications, such as real-time alerts or usage feedback, and could contribute to broader efforts in promoting safety compliance in micromobility ecosystems. Consequently, our work aims to bridge this gap by exploring novel strategies for real-time, embedded helmet detection tailored specifically to the dynamic and resource-constrained environment of motorcycle operation.

Table 1: Main technologies related with safety helmet detection.

Function	Technologies	Author
Helmet detection	YOLOv5	(Jia et al., 2021)
Helmet detection	YOLOv4	(Peña Cáceres et al., 2022)
Helmet use	Deep learning	(Siebert & Lin, 2020)
Helmet detection	Machine Learning	(Almeida et al., 2013)
Behaviour in helmet use	CCTV	(Satiennam et al., 2020)
Helmet on multiple riders	CNN	(Dasgupta et al., 2019)
Helmet for crash prevention	IoT – Led Alarm	(Rasli et al., 2013)
Helmet for alcohol detection	IoT sensors	(Jesudoss et al., 2019)
Helmet in e-scooters	AoA and BLE Beacons	(Fernández-Madrigal et al., 2024)
Detection of Personal protection Equipment at workplace	BLE-beacons	(Gómez-de-Gabriel et al., 2023)

CONCLUSION

The review and analysis of existing helmet detection systems reveal a predominant focus on motorcycle use in static surveillance contexts, where cameras are externally positioned and data processing is performed on fixed infrastructures. While these approaches have demonstrated effectiveness in monitoring helmet usage in controlled environments, their design assumptions and technological constraints limit their applicability in dynamic, mobile contexts.

Our analysis underscores a clear gap in the current state of the art regarding real-time, onboard helmet detection. Motorcycles, require continuous monitoring across an entire trip. This introduces unique challenges, including camera placement limitations, variable lighting conditions, and restricted processing resources. Moreover, the physical integration of sensors and computational units into compact, low-power platforms calls for lightweight, adaptive algorithms capable of functioning under these constraints without compromising detection reliability.

Consequently, there is a pressing need for novel detection frameworks that move beyond fixed surveillance paradigms and support real-time, embedded deployment. Such frameworks should not only detect helmet usage with high accuracy under diverse real-world conditions but also contribute to a more proactive and user-aware approach to safety compliance. The insights derived from this analysis inform the design choices of our proposed solution, which aims to address these limitations by leveraging efficient deep learning models and context-aware processing mechanisms suited to the operational characteristics of motorcycle.

FUTURE RESEARCH

Building on the limitations identified in current helmet detection approaches, several avenues for future research can be proposed.

First, there is a need to develop lightweight deep learning architectures specifically optimized for edge devices. These models must strike a balance between computational efficiency and detection accuracy, enabling real-time inference on the limited hardware available in motorcycles without requiring external processing infrastructure.

Second, future studies should explore robust data augmentation and domain adaptation techniques to improve model performance under varying environmental conditions. The dynamic nature of motorcycle trips—characterized by fluctuating lighting, diverse urban backdrops, and motion-induced artefacts—demands detection models that are resilient to non-ideal input data. Transfer learning from large, diverse datasets and the use of synthetic data generation may play key roles in enhancing model generalization.

Another promising direction involves the integration of multimodal sensor data—such as accelerometers, gyroscopes, or GPS—with visual inputs. Combining contextual cues with image-based detection could increase reliability and reduce false positives. Furthermore, incorporating temporal analysis across video frames might help improve detection continuity and robustness.

Finally, future work should also address user privacy and ethical concerns in deploying on board helmet monitoring systems. Investigating privacy-preserving methods, such as federated learning or anonymized image processing, will be crucial to ensuring user trust and regulatory compliance. Additionally, longitudinal studies could evaluate the behavioural impact of such monitoring systems on helmet usage over time, contributing to broader safety policy development in urban mobility contexts.

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