HELMETTRACK AI: CNN-BASED MULTI TASKING HELMET DETECTION ON MOVING MOTORCYCLE

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ABSTRACT

Helmet Track AI is an advanced deep learning-based system designed to enhance road safety by automatically detecting helmet usage among motorcyclists in real-time traffic environments. The rapid increase in two-wheeler usage has significantly contributed to road accidents, particularly due to non-compliance with helmet regulations. To address this issue, the proposed system employs Convolutional Neural Networks (CNNs) integrated with Multi-Task Learning (MTL) to simultaneously perform motorcyclist detection and helmet classification. Unlike traditional systems that process detection and classification separately, this unified approach reduces computational redundancy and improves inference speed. The system is trained on diverse real-world datasets, enabling it to perform effectively under varying lighting conditions, weather scenarios, camera angles, and motion blur. It utilizes real-time video streams captured through surveillance cameras and processes them using advanced computer vision techniques for accurate detection. The integration of YOLO-based object detection further enhances performance by enabling fast and efficient localization of riders and helmets. Experimental results indicate that HelmetTrack AI achieves high precision, recall, and accuracy compared to conventional models. Additionally, the system supports edge deployment, making it suitable for smart city applications and automated traffic law enforcement. By providing real-time monitoring, violation detection, and data storage capabilities, the system contributes to improved compliance and reduced accident rates. Overall, HelmetTrack AI offers a scalable, efficient, and intelligent solution for modern traffic surveillance systems.

Keywords: Helmet Detection, CNN, Multi-Task Learning, Computer Vision, YOLO, Traffic Safety, Deep Learning, Smart Surveillance

I. INTRODUCTION

Road transportation plays a vital role in modern society, contributing significantly to economic growth and mobility. However, the increasing number of vehicles, especially motorcycles, has led to a rise in road accidents and fatalities [1]. Motorcyclists are highly vulnerable due to the absence of protective structures, making helmet usage essential for safety [2]. Studies indicate that wearing helmets can reduce fatal injuries by a substantial margin [3]. Despite strict traffic regulations, helmet compliance remains inconsistent due to inadequate monitoring and enforcement [4]. Traditional surveillance systems rely heavily on manual observation, which is time-consuming and prone to human error [5]. With the growing vehicle density in urban areas, manual enforcement is becoming increasingly inefficient [6]. This has created a need for automated and intelligent traffic monitoring systems [7]. Advances in Artificial Intelligence (AI) and Computer Vision have enabled the development of automated detection systems capable of analyzing real-time video data [8]. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in image classification and object detection tasks [9]. CNNs can extract complex spatial features from images, making them suitable for traffic surveillance applications [10]. Furthermore, object detection algorithms such as YOLO provide real-time performance, which is crucial for monitoring fast-moving vehicles [11]. The integration of these technologies has opened new possibilities for intelligent traffic management systems [12]. However, many existing systems perform detection and classification as separate tasks, leading to increased computational complexity [13]. This separation reduces efficiency and limits real-time applicability [14].

To overcome these limitations, HelmetTrack AI introduces a CNN-based multi-task learning framework that simultaneously performs motorcyclist detection and helmet classification [15]. Multi-Task Learning (MTL) enables the sharing of features across related tasks, reducing redundancy and improving performance [16]. This unified approach enhances both accuracy and speed, making it suitable for real-time applications [17]. The system is trained on diverse datasets to ensure robustness under different environmental conditions such as lighting variations, weather changes, and occlusions [18]. It also addresses challenges such as motion blur and crowded traffic scenarios [19]. The use of YOLO further improves detection efficiency by performing classification and localization in a single step [20]. The proposed system supports deployment on edge devices, enabling real-time processing without reliance on cloud infrastructure [21]. This reduces latency and enhances system responsiveness [22]. Additionally, the system can be integrated with automated enforcement mechanisms such as fine generation and violation recording [23]. By leveraging AI-driven automation, HelmetTrack AI contributes to smart city initiatives and intelligent transportation systems [24]. It enhances road safety by ensuring compliance with helmet regulations and reducing accident risks [25]. The system also provides valuable data for traffic analysis and policy-making [26]. With its scalable architecture and high accuracy, HelmetTrack AI represents a significant advancement in automated traffic monitoring solutions [27]. It addresses the limitations of traditional systems while offering improved efficiency and reliability [28]. Therefore, the proposed system serves as a practical and effective solution for modern traffic surveillance challenges [29]. Its implementation can significantly improve road safety and enforcement mechanisms in urban environments [30].

II. LITERATURE SURVEY

Several researchers have explored helmet detection systems using deep learning and computer vision techniques. Early approaches relied on traditional image processing methods such as edge detection and color segmentation, which lacked robustness under varying conditions [1]. Later, Convolutional Neural Networks (CNNs) were introduced to improve classification accuracy [2]. Sanjay et al. proposed a CNN-based helmet classification model that achieved good accuracy but lacked localization capability [3]. Abhiram and Dhanush utilized YOLO for real-time helmet detection, improving speed but facing challenges in low-light environments [4]. Varsha et al. developed a two-stage model combining Faster R-CNN for detection and CNN for classification, which increased accuracy but also computational complexity [5].

Ruthvik Reddy and Suvikram integrated helmet detection with number plate recognition, enabling automated enforcement but requiring high processing power [6]. Bhavani and Pranavi proposed a vision-based system combining image processing and deep learning, which performed well in controlled conditions but struggled with generalization [7]. Kailash introduced preprocessing techniques to improve detection under varying illumination, enhancing daytime accuracy but not nighttime performance [8]. Ragunath incorporated contextual features such as posture and motion patterns, improving detection reliability at the cost of increased computation [9]. These studies highlight the trade-off between accuracy and efficiency in helmet detection systems [10]. Many existing approaches rely on separate pipelines for detection and classification, leading to redundancy and increased latency [11]. Additionally, real-world challenges such as occlusion, motion blur, and crowded traffic conditions affect system performance [12]. Edge deployment remains a significant challenge due to hardware limitations [13]. Therefore, there is a need for efficient models that balance accuracy, speed, and resource utilization [14].

Recent advancements focus on integrating detection and classification tasks into a unified framework using multi-task learning [15]. Multi-task learning allows models to share features across tasks, reducing redundancy and improving efficiency [16]. YOLO-based architectures have gained popularity due to their ability to perform real-time detection [17]. Studies show that single-stage detectors outperform two-stage models in terms of speed [18]. However, accuracy can still be affected by environmental variations [19]. Researchers have explored data augmentation techniques to improve model generalization [20]. Transfer learning has also been used to enhance performance by leveraging pre-trained models [21]. Edge computing solutions have been proposed to enable real-time processing on low-power devices [22]. Lightweight CNN architectures are being developed to reduce computational requirements [23]. Despite these advancements, challenges such as small object detection and occlusion remain [24]. Recent works emphasize the importance of combining detection, classification, and tracking in a single framework [25]. This approach improves overall system performance and reduces latency [26]. HelmetTrack AI builds upon these advancements by integrating CNN and multi-task learning into a unified architecture [27]. It addresses the limitations of existing systems by improving both accuracy and efficiency [28]. The system is designed for real-time deployment in diverse environments [29]. Thus, it represents a significant improvement over traditional helmet detection approaches [30].

III. PROPOSED SYSTEM

The proposed system, HelmetTrack AI, is a CNN-based multi-task learning framework designed to detect motorcyclists and identify helmet usage simultaneously in real-time traffic environments. Unlike traditional systems that use separate models for detection and classification, this system integrates both tasks into a single unified architecture. The system captures real-time video input from surveillance cameras and processes it using advanced computer vision techniques. The input frames are preprocessed to remove noise and normalize image quality. A CNN backbone extracts spatial features from the images, which are then shared across multiple tasks. The multi-task learning module performs motorcyclist detection using bounding boxes while simultaneously classifying whether the rider is wearing a helmet or not. This shared learning approach reduces computational redundancy and improves efficiency.

Fig.1 Architecture

The system leverages YOLO-based object detection for fast and accurate localization of objects within video frames. It is trained on diverse datasets containing real-world traffic scenarios to ensure robustness under different conditions such as lighting variations, weather changes, and occlusions. The model is optimized for real-time performance and can be deployed on edge devices such as embedded systems and CCTV cameras. Once a violation is detected, the system records the event, stores the image, and can generate alerts for enforcement purposes. The proposed system aims to enhance road safety by ensuring helmet compliance and reducing accident risks. It also supports scalability, making it suitable for smart city applications and intelligent traffic monitoring systems.

III. SYSTEM DESIGN

The HelmetTrack AI system is designed using a three-tier architecture consisting of the presentation layer, application layer, and data layer. The presentation layer provides a user-friendly interface through a web application developed using Flask. It allows administrators to log in, monitor real-time detection, upload videos, and view violation records. This layer ensures smooth interaction between users and the system while maintaining security through authentication and session management. The application layer is the core processing unit where all computations take place. It uses YOLO and CNN models to detect motorcyclists and classify helmet usage. The system processes video frames, extracts features, and applies decision-making logic to identify violations. This layer ensures efficient real-time detection and minimizes false positives through spatial verification of detected objects.

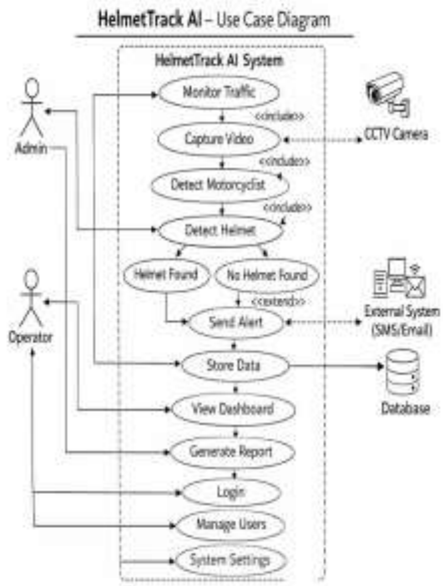

Fig.2 use case diagram

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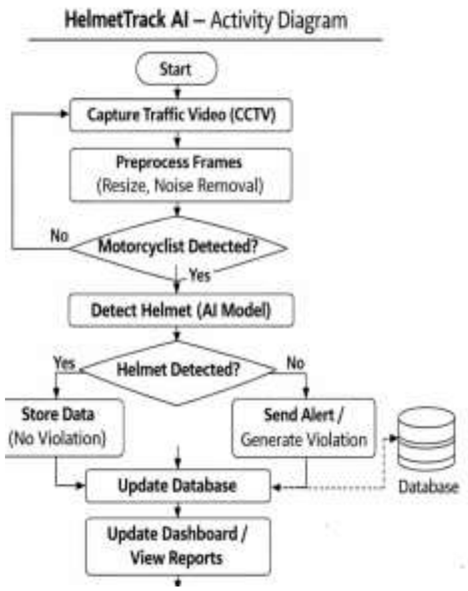


Fig.3 Activity diagram

The data layer is responsible for storing and managing all system data, including user information, violation records, and system logs. It uses a MySQL database to maintain structured data and ensure quick retrieval when needed. The system also stores images and videos in organized directories for easy access and analysis. Additional components such as session management and environment configuration enhance system security and performance. The modular design ensures scalability, allowing new features such as number plate recognition and analytics to be integrated بسهولة. The overall architecture improves system reliability, efficiency, and maintainability, making it suitable for large-scale deployment in traffic monitoring applications.

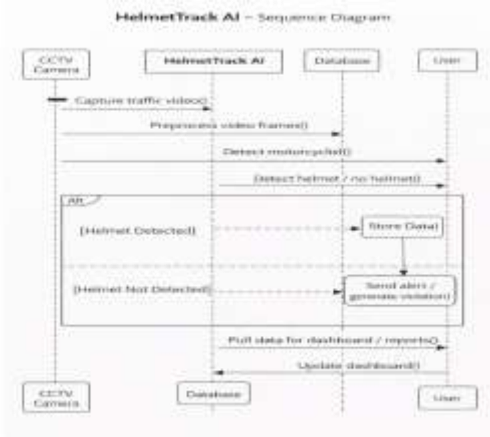
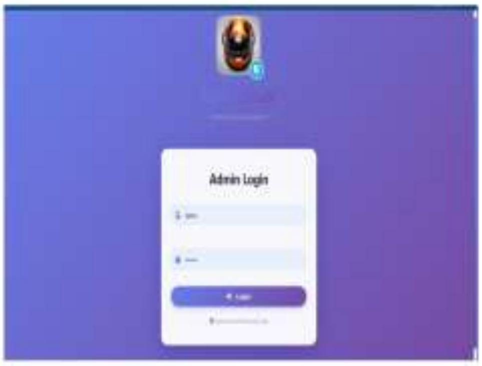
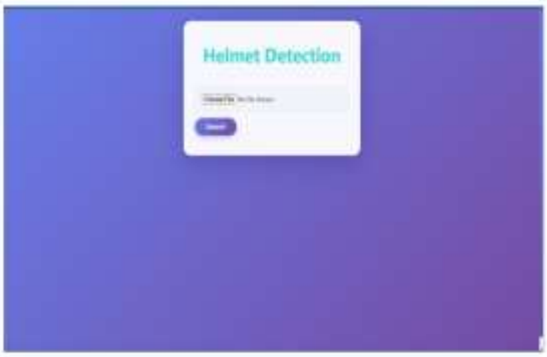


Fig.4 Sequence diagram

V. RESULTS





No Helmet violations

VI. CONCLUSION

HelmetTrack AI presents an intelligent and efficient solution for automated helmet detection in real-time traffic environments. The system addresses the critical issue of road safety by ensuring compliance with helmet regulations among motorcyclists. By leveraging Convolutional Neural Networks and Multi-Task Learning, the system performs simultaneous detection and classification, reducing computational redundancy and improving performance. The integration of YOLO-based object detection enhances real-time capabilities, making the system suitable for deployment in dynamic traffic conditions. Unlike traditional systems that rely on manual monitoring or separate processing pipelines, HelmetTrack AI provides a unified and scalable approach.

The system demonstrates high accuracy and robustness under varying environmental conditions, including lighting changes, weather variations, and occlusion scenarios. Its ability to operate on edge devices further enhances its practicality by enabling low-latency processing without dependence on cloud infrastructure. Additionally, the system supports automated violation detection, data storage, and alert generation, making it highly useful for traffic law enforcement and smart city applications. By reducing human intervention and improving monitoring efficiency, HelmetTrack AI contributes significantly to accident prevention and public safety. Future enhancements may include integration with number plate recognition systems, predictive analytics, and advanced tracking mechanisms. Overall, the proposed system offers a reliable, scalable, and cost-effective solution for modern traffic surveillance, paving the way for safer roads and improved compliance with safety regulations.

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