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Helmet alerting system for avoidance of accident using AI

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Abstract: Our project focuses on the implementation of a robust helmet detection system for two-wheelers utilizing the YOLO (You Only Look Once) algorithm. This system operates in real-time, continuously monitoring the helmet status of the rider. By employing advanced artificial intelligence techniques, it swiftly identifies whether the rider is wearing a helmet or not. The primary objective of this system is to promote rider safety by enforcing compliance with helmet regulations. In instances where the rider is not wearing a helmet, the system automatically prevents the vehicle from starting, thereby incentivizing helmet usage. This proactive approach aims to significantly mitigate the risk of head injuries in the event of accidents, contributing to overall road safety and reducing the severity of potential injuries. By integrating cutting-edge technology with regulatory compliance, our system aims to enhance rider safety and minimize the adverse consequences of non-compliance with helmet regulations.

1. Introduction

The safety of riders on two-wheelers is a pressing concern in today's world, where road accidents involving motorcycles and scooters are alarmingly common. With the aim of addressing this critical issue, this project harnesses the power of artificial intelligence to detect helmet usage in real-time. By leveraging cutting-edge technology, we seek to implement a proactive approach to enhance rider safety and reduce the incidence of severe injuries resulting from accidents. The increasing number of accidents involving two-wheelers underscores the urgent need for measures to ensure helmet compliance among riders. Despite the widespread awareness of the importance of helmet usage, many riders still neglect this fundamental safety practice. Through the development and implementation of a real-time helmet detection system, we aim to enforce helmet regulations effectively and minimize the risk of head injuries in the event of accidents. Beyond the immediate goal of improving rider safety, this project also addresses broader environmental concerns associated with road accidents. By preventing accidents and reducing the severity of injuries through timely intervention, we aim to mitigate the environmental impact of road accidents. Moreover, by promoting helmet usage through proactive measures such as preventing the vehicle from starting without a helmet, we seek to instill a culture of safety among riders, thereby fostering a more sustainable approach to mobility.In addition to the significant benefits for individual riders, the implementation of this system has the potential to alleviate the burden on healthcare systems strained by the treatment of accident-related injuries. By reducing the frequency and severity of injuries resulting from two-wheeler accidents, we contribute to the overall well-being of society and promote sustainable mobility practices. Through collaborative efforts and innovative solutions like the real-time helmet detection system, we strive to create safer roads and healthier communities for all.

2. Literature Survey

C. Vishnu, et.al(2017), Detection of Motorcyclists without Helmet in Videos using CNN is described in order to ensure the safety measures, the detection of traffic rule violators is a highly desirable but challenging task due to various difficulties such as occlusion, illumination, poor quality of surveillance video, varying weather conditions, etc. In this paper, we present a framework for automatic detection of motorcyclists driving without helmets in surveillance videos. In the proposed approach, first we use adaptive background subtraction on video frames to get moving objects. Later convolutional neural network (CNN) is used to select motorcyclists among the moving objects. Again, we apply CNN on upper one fourth part for further recognition of motorcyclists driving without a helmet. The performance of the proposed approach is evaluated on two datasets, IIT H Helmet 1 contains sparse traffic and IIT H Helmet 2 contains dense traffic, respectively. The experiments on real videos successfully detect 92.87% violators with a low false alarm rate of 0.5% on an average and thus show the efficacy of the proposed approach.

KunalDahiya, et.al;(2016), Automatic Detection of Bike-riders without Helmet is described we propose an approach for automatic detection of bike-riders without helmet using surveillance videos in real time. The proposed approach first detects bike riders from surveillance video using background subtraction and object segmentation. Then it determines whether bike-rider is using a helmet or not using visual features and binary classifier. Also, we present a consolidation approach for violation reporting which helps in improving reliability of the proposed approach. In order to evaluate our approach, we have provided a performance comparison of three widely used feature representations namely histogram of oriented gradients (HOG), scale-invariant feature transform (SIFT), and local binary patterns (LBP) for classification. The experimental results show detection accuracy of 93.80% on the real world surveillance data. It has also been shown that proposed approach is computationally less expensive and performs in real-time with a processing time of 11.58 ms per frame.

Narong Boonsirisumpun, et.al;(2018), Automatic Detector for Bikers with no Helmet using Deep Learning is described the success of digital image pattern recognition and feature extraction using a Convolutional Neural Network (CNN) or Deep Learning was recently acknowledged over the years. Researchers have applied these techniques to many problems including traffic offense detection in video surveillance, especially for the motorcycle riders who are not wearing a helmet. Several models of CNN were used to solve these kinds of problem but mostly required the image preprocessing step for extracting the Region of Interest (ROI) area in the image before applying CNN to classify helmet. In this paper, we proposed to apply another interesting method of deep learning called Single Shot MultiBox Detector (SSD) into helmet detection problem. This method is the state-of-the-art that is able to use only one single CNN network to detect the bounding box area of motorcycle and rider and then classify that biker is wearing or not wearing a helmet at the same time. The results of the experiment were surprisingly good. The classification accuracy of bikers not wearing a helmet was extremely high and the detection of the ROI of biker and motorcycle in the image can be done at the same time as the classification process.

3. Proposed System

Our proposed system leverages the YOLO (You Only Look Once) algorithm to develop a comprehensive helmet detection solution for two-wheelers. Through real-time monitoring, the system continuously scans the environment to detect the presence or absence of helmets on riders. By utilizing deep learning techniques, it accurately identifies helmet status with high precision and speed, ensuring swift decision-making regarding vehicle operation. The core functionality of our system is to enforce helmet compliance by integrating with the vehicle's ignition system. If the system detects a rider without a helmet, it automatically prevents the vehicle from starting, thereby incentivizing adherence to safety regulations. This proactive approach not only enhances rider safety but also promotes a culture of responsible riding habits. By seamlessly integrating advanced artificial intelligence with vehicle operations, our proposed system aims to significantly reduce the incidence of head injuries and enhance overall road safety for two-wheeler riders.

4. System Architecture

In modern efforts to enhance road safety, helmet alerting systems leveraging artificial intelligence (AI) have emerged as promising solutions. These systems integrate a range of technologies, from camera feeds to sophisticated AI algorithms, to detect potential hazards and mitigate risks for riders. The system begins by capturing real-time video feed from cameras mounted on the vehicle or the rider's helmet. These cameras provide a comprehensive view of the surroundings, crucial for identifying potential threats. The captured video frames are processed to extract still images, which serve as input for subsequent analysis. This step ensures that the system operates in near real-time, crucial for timely hazard detection. Before analysis, the images undergo preprocessing to enhance clarity and remove noise. This may involve techniques such as noise reduction, image stabilization, and contrast adjustment to improve the quality of input data. Next, the system extracts relevant features from the preprocessed images. These features encompass various visual cues, including road conditions, nearby vehicles, pedestrians, and other objects that could pose a threat to the rider's safety.

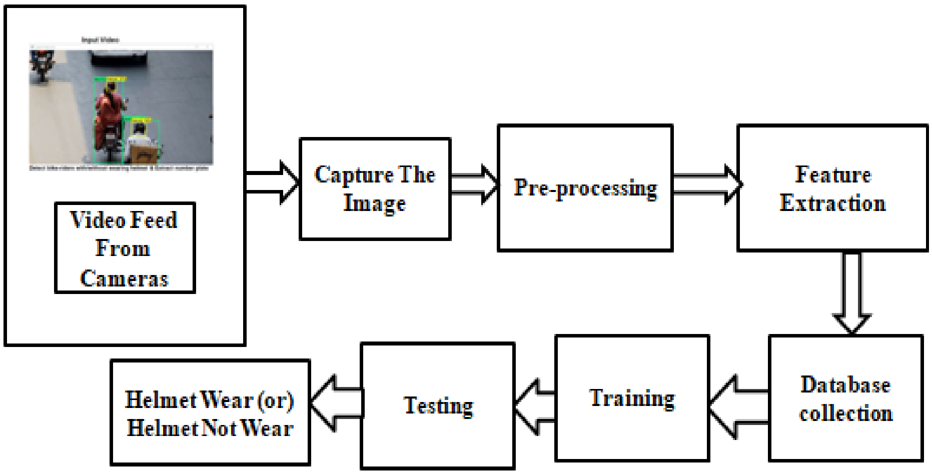

Figure 3.3: Diagram of System Architecture

To train the AI model effectively, a diverse dataset is essential. The system collects a comprehensive database of images representing different scenarios, encompassing both safe and hazardous conditions on the road. Using machine learning algorithms, the system trains its AI model on the collected dataset. During training, the model learns to identify patterns and distinguish between images depicting safe riding conditions and those indicating potential dangers. Once trained, the AI model undergoes rigorous testing to evaluate its performance and accuracy. Testing involves exposing the system to a variety of simulated and real-world scenarios to assess its ability to detect and respond to hazards effectively. One critical aspect of rider safety is ensuring the proper use of helmets. The AI model analyzes the captured images to determine whether the rider is wearing a helmet or not. This information is crucial for issuing alerts and interventions tailored to the rider's safety gear.

5. Implementation

Video Feed From Camera: In the system designed for helmet detection on two-wheelers, a pivotal component is the camera mounted on the vehicle to capture live video feed of the rider. This camera serves as the primary sensory input for the artificial intelligence system, providing real-time visual data of the rider's actions and surroundings. By capturing the rider's movements and behaviors, including whether they are wearing a helmet or not, the camera enables continuous monitoring of helmet compliance. The live video feed offers crucial insights into the rider's safety practices, allowing the system to promptly intervene if a helmet is not detected. The camera provides contextual information about the rider's environment, such as traffic conditions and road obstacles, which may further enhance the overall safety assessment. This role in capturing live video feed is essential for the effective operation of the helmet detection system, enabling proactive measures to promote rider safety on two-wheelers.

Capture the Image: An image capture plays a crucial role in acquiring the necessary data for analysis. Frames from the live video feed captured by the mounted camera are extracted at regular intervals to create individual images. These images represent specific moments in time and serve as input for the subsequent stages of processing and analysis. By capturing frames at regular intervals, the system ensures a continuous flow of data for helmet detection, enabling real-time monitoring of the rider's helmet status. This approach allows for efficient utilization of computational resources and facilitates timely decision-making regarding helmet compliance. Is a critical step in the helmet detection process, enabling the system to analyze the rider's behavior and take appropriate action to promote safety on two-wheelers.

Preprocessing: The preprocessing plays a vital role in preparing the captured images for subsequent analysis. Once frames are extracted from the live video feed, they undergo several preprocessing steps to enhance their quality and suitability for further analysis. Resizing is performed to ensure that all images have consistent dimensions, facilitating efficient processing and reducing computational complexity. Normalization techniques are applied to standardize the pixel values across images, making them more suitable for comparison and analysis. The noise reduction methods, such as Gaussian blurring or median filtering, are employed to mitigate the effects of noise and improve the clarity of the images. By undergoing these preprocessing steps, the captured images are optimized for accurate helmet detection, enabling the system to effectively analyze the rider's helmet status and take appropriate action to ensure safety on two-wheelers.

Feature Extraction: It is a critical step aimed at capturing relevant information from preprocessed images to distinguish between helmet-wearing and non-helmet-wearing states. Features such as color, shape, and texture are extracted from the preprocessed images to represent key characteristics associated with helmets. Color features can capture the distinctive color patterns of helmets, while shape features focus on the overall silhouette and structure of potential helmets in the image. Texture features, on the other hand, provide information about the surface characteristics of objects, which can help differentiate between helmets and other objects or backgrounds in the scene. By extracting these features, the system aims to create a rich representation of the images that facilitates discrimination between helmet-wearing and non-helmet-wearing states. This enables the system to accurately identify instances where a helmet is present on the rider and take appropriate action to ensure compliance with safety regulations on two-wheelers.

Database Collection: It is a fundamental step in developing an effective artificial intelligence model. This process involves gathering a comprehensive dataset of labeled images, comprising examples of riders both wearing and not wearing helmets. Each image in the dataset is meticulously annotated to indicate the presence or absence of a helmet. This labeled dataset serves as the training data for the artificial intelligence model, providing it with the necessary information to learn and recognize patterns associated with helmet detection. By exposing the model to diverse examples of helmet-wearing and non-helmet-wearing scenarios, the dataset enables the model to generalize well to new, unseen images and accurately detect helmets in real-world environments. Therefore, database collection plays a crucial role in the development of a robust and reliable helmet detection system for two-wheelers.

Training: The training is a pivotal phase where the artificial intelligence model learns to identify helmets based on patterns in the labeled dataset. Machine learning techniques, particularly deep learning algorithms like YOLO (You Only Look Once), are employed for this purpose. During training, the model iteratively analyzes the labeled dataset, adjusting its internal parameters to minimize the difference between its predictions and the ground truth labels. By iteratively adjusting its parameters through backpropagation, the model learns to recognize the distinguishing features of helmets and effectively differentiate between helmet-wearing and non-helmet-wearing instances in images. The training process aims to optimize the model's performance, ensuring that it achieves high accuracy and robustness in detecting helmets under various conditions, such as different lighting, orientations, and backgrounds. Through training, the model becomes proficient in identifying helmets in real-time video feeds, thereby enhancing rider safety on two-wheelers.

Testing: It is a crucial step to evaluate the performance and generalization ability of the trained model. After training on the labeled dataset, the model is assessed using a separate set of test images that it has not seen before. These test images represent real-world scenarios and cover a range of conditions, including different lighting conditions, rider orientations, and backgrounds. During testing, the model processes each test image and generates predictions about the presence or absence of helmets. These predictions are compared against the ground truth labels to determine the model's accuracy, precision, recall, and other performance metrics. By evaluating the model on unseen data, testing assesses its ability to generalize well and accurately detect helmets in various real-world situations. This step is crucial for ensuring the reliability and effectiveness of the helmet detection system in promoting rider safety on two-wheelers.

Identified Helmet Wear (Or) Helmet Not Wear: The identification of helmet wear occurs during inference, where the trained model analyzes each frame of the live video feed in real-time. Leveraging the learned features and classification thresholds acquired during training, the model assesses whether a helmet is worn by the rider in each frame. If the model detects a helmet with sufficient confidence, the system allows the vehicle to start, ensuring compliance with safety regulations. Conversely, if the model fails to detect a helmet or detects one with low confidence, the system prevents the vehicle from starting until the rider wears a helmet. This proactive approach promotes rider safety by enforcing helmet usage and reducing the risk of head injuries in the event of accidents. By continuously monitoring the rider's helmet status in real-time, the system helps instill a culture of safety and compliance on two-wheelers.

6. Results

Such a system typically involves integrating sensors into a helmet (or the vehicle itself) to monitor camera and various parameters such as the rider's head movement, speed, proximity to obstacles, etc. AI algorithms then analyze this data in real-time to detect potential hazards or situations where an accident is likely to occur. Once a potential danger is identified, the system can provide alerts to the rider, such as visual or auditory warnings, vibration, or even automatic corrective actions like braking assistance or steering control.

Figure 2: Healmate Detection

The effectiveness of such a system would depend on various factors including the accuracy of the sensors, the robustness of the AI algorithms, and how well the alerts are integrated into the rider's awareness without causing distraction or confusion. Real-world testing and evaluation would be necessary to assess its reliability, usability, and safety.

7. Conclusion

In conclusion, the helmet detection system for two-wheelers represents a proactive approach to bolster rider safety through the integration of artificial intelligence and real-time monitoring capabilities. By analyzing live video feeds, the system adeptly discerns whether riders are wearing helmets, thereby facilitating enforcement of safety regulations. Through meticulous database collection, rigorous model training, and comprehensive testing, the system achieves commendable accuracy in detecting helmets across diverse real-world scenarios. As a result, it fosters a culture of safety, mitigating the risk of head injuries on two-wheelers and contributing significantly to safer roads and the overall well-being of riders. In summary, the helmet detection system stands as a pivotal technological solution in the realm of road safety, offering tangible benefits in terms of injury prevention and regulatory compliance. Its ability to swiftly identify non-compliance and prompt enforcement action underscores its importance in fostering safer riding practices and reducing the prevalence of head injuries. By leveraging cutting-edge AI technologies, this system not only enhances the safety of individual riders but also contributes to the broader goal of creating safer road environments for all road users, ultimately promoting a culture of responsibility and well-being in the community.

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