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A REVIEW ON HELMET DETECTION USING MACHINE LEARNING

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***Abstract* - The continual motorisation of traffic has led to an increase in road accidents across the globe. The government is trying hard to make people follow driving rules to reduce accidents and fatal deaths, especially in India. In our country, the motorcycle is the most commonly used vehicle. As a recommendation, a system for automatically detecting helmet wear is mandatory for road safety, where a significant number of people have died in the death of not wearing a helmet. This project's main aim is to automatically detect bike riders without helmets using CCTV videos. As a result, a machine learning-based algorithm is used to generate a unique object detection model that can specify motorcycle riders. The first step is to use the background subtraction technique to identify the bike riders. Then it detects whether the rider is wearing a helmet or not. If the person who is riding the motorcycle without a helmet is detected, then the number plate is extracted from the video frame. Then, with the help of an Optical character recogniser, the number plate is recognised.**

***Keywords-* CCTV, Motorcycle, Machine Learning**

I. INTRODUCTION

All over the world, around 1.35 million lives are lost each year, 50 million people are getting injured due to road accidents, according to a report titled "The Global Status Report on Road Safety 2018" released by World Health Organisation. It is very hard to imagine that this burden is unevenly borne by motorcyclists, cyclists and pedestrians. This report noted that a comprehensive action plan has to be set up in order to save lives. The worrying fact is that India ranks number one as far as road crash deaths are concerned. Rapid urbanisation, avoiding helmets, seat belts and other safety measures while driving are some of the reasons behind this trend, according to analysis done by experts.

In 2015 India signed the Brasilia Declaration on Road Safety, where India committed to reduce road crash deaths to 50 percent by 2020. Policy makers first have to acknowledge the problems that persist in India before halving road crash deaths. When a two-wheeler meets with an accident, due of sudden deceleration, the rider is thrown away from the vehicle. If head strikes any object, motion of the head becomes zero, but with its own mass brain continues to be in motion until the object hits inner part of the skull. Sometimes this type of head injury may be fatal in nature. In such times helmet acts as life savior. Helmet reduces the chances of skull getting decelerated, hence sets the motion of the head to almost zero. Cushion inside the helmet absorbs the impact of collision and as time passes head comes to a halt. It also spreads the impact to a larger area, thus safeguarding the head from severe injuries.

Helmet detection using machine learning is a crucial application in enhancing safety across various domains like traffic and construction. By employing object detection algorithms, particularly deep learning models such as YOLO (You Only Look Once) and CNNs (Convolutional Neural Networks), systems can automatically identify if individuals are wearing helmets in images or video streams. These models are trained on large datasets of helmeted and non-helmeted individuals to accurately classify and locate helmets in real-time. The technology contributes significantly to monitoring safety regulations, reducing accidents, and potentially automating enforcement processes.

II. LITERATURE SURVEY

Deep Learning Dominance: Deep learning models, particularly CNNS and the YOLO family of algorithms (YOLOv3, YOLOv4, YOLOv5, YOLOv7, YOLOv8), are the most prevalent and effective approaches for helmet detection. These models demonstrate high accuracy, precision, recall, and MAP (mean Average Precision) in identifying the presence or absence of helmets [1]. Many studies emphasise the real-time detection capabilities of models like YOLO, making them suitable for live video surveillance in traffic monitoring and construction sites [2].

The performance of helmet detection systems heavily relies on the quality and size of the training datasets. Several publicly available datasets like the "Bikes Helmets Dataset," "Hard Hat Dataset," and "SHEL5K" are utilised. These datasets contain images with annotations for helmeted and non-helmeted individuals, and sometimes additional classes like heads and persons. Data augmentation techniques are often employed to enhance the robustness and generalisation of the models.

Two-Stage vs. One-Stage Detectors: Object detection algorithms are broadly categorised into two-stage (e.g., Faster R-CNN) and one-stage (e.g., YOLO, SSD) detectors. One-stage detectors are generally faster, making them more suitable for real-time applications, while two-stage detectors can sometimes achieve higher accuracy but with increased computational cost. Ensuring the use of safety helmets in hazardous work environments like mining. Challenges and Future Directions: Research continues to focus on improving accuracy in complex scenarios (e.g., varying lighting, occlusions, different helmet types), reducing computational complexity for deployment on edge devices, and enhancing the robustness of the systems [3-4]. Lightweight models and attention mechanisms are being explored to address these challenges. Combining helmet detection with number plate recognition is also a growing area of interest for comprehensive traffic violation management.

III. METHODOLOGY

In this research work, a Non-Helmet Rider detection system is built, which attempts to satisfy the automation of detecting the traffic violation of not wearing a helmet and extracting the vehicles' license plate numbers. The main principle involved is Object Detection using Deep Learning at three levels. The objects detected are person, motorcycle/moped at first level using YOLOv2, helmet at second level using YOLOv3, and License plate at the last level using YOLOv2. Then the license plate registration number is extracted using OCR (Optical Character Recognition). Methodology of Non-Helmet Rider Detection System. All these techniques are subject to predefined conditions and constraints, especially the license plate number extraction part. Since this work takes video as its input, the speed of execution is crucial. We have used above said methodologies to build a holistic system for both helmet detection and license plate number extraction.

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3.1 DATASET

A proper and large dataset is required for all classification research during the training and the testing phase. uploading the dataset called 'dataset.txt' after uploading the dataset.

3.2. Upload dataset

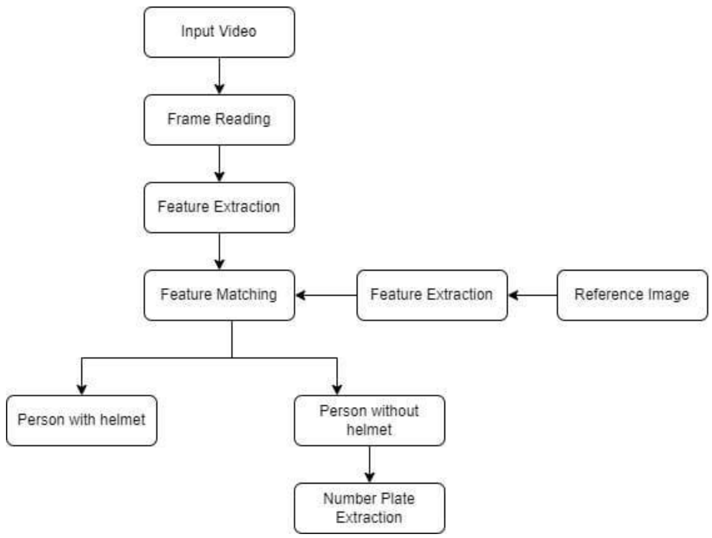

Figure 1: Methodology of Non-Helmet Rider Detection System

3.3 Proposed model

They proposed a methodology for feature extraction using LBP-based hybrid descriptor, HOG, and Hough transform descriptors. Whereas Xinhua Jiang et al. incorporated grey level co-occurrence matrix along with LBP for feature extraction. YOLOv2 and the COCO dataset can be employed to detect different types of objects and classify them accordingly. The intended objects are motorcycles, motorcyclists, pedestrians and workers. Helmet and tyre colour exhibits different characteristics, which can be exploited to detect motorbikes. proposed a method to identify two-wheeler accidents using a microcontroller and accelerometer. Most of the time, pedestrians are the real victims for road accidents; their safety is essential. Jie Li et al. They proposed a method to classify pedestrians using SVM based on the histogram of oriented gradient features (HOG). The last step involves helmet detection. Colour-based and circle Hough transform is used to detect helmets, and HOG descriptors can also be used for helmet detection. Colour feature recognition is another option. deployed colour space transformation and colour feature discrimination for detecting the helmet. GLCM statistical features and Back-Propagation artificial neural network are used to detect helmets more effectively. The helmet detection system involves the following steps such as collection of datasets, moving object detection, background subtraction, object classification using neural networks and extraction of license plate number if the rider is not wearing a helmet. Rattapoom Waranusast et al. used a KNN classifier for moving object extraction and classification. Here, the head is classified as wearing a helmet or not based on various features obtained from the segmented head region. Moving objects can be detected using adaptive background subtraction.

ViBe background modelling algorithm can also be applied to detect moving objects. A Canny edge detection algorithm is used to get segmented moving objects.

3.4 Existing Model

The Existing system monitors the traffic violations primarily through CCTV recordings, where the traffic police have to look into the frame where the traffic violation is happening, zoom into the license plate in case rider is not wearing helmet. But this requires lot of manpower and time as the traffic violations frequently and the number of people using motorcycles is increasing day-by-day. What if there is a system, which would automatically look for traffic violation of not wearing helmet while riding motorcycle/moped and if so, would automatically extract the vehicles' license plate number. Recent research have successfully done this work based on CNN, R-CNN, LBP, HoG, HaaR features,etc. But these works are limited with respect to efficiency, accuracy or the speed with which object detection and classification is done. In this research work, a Non-Helmet Rider detection system is built which attempts to satisfy the automation of detecting the traffic violation of not wearing helmet and extracting the vehicles' license plate number. The main principle involved is Object Detection using Deep Learning at three levels.More importantly it acts as a mechanical barrier between head and object to which the rider came into contact. Injuries can be minimized if a good quality full helmet is used. Traffic rules are there to bring a sense of discipline, so that the risk of deaths and injuries can be minimized significantly. However strict adherence to these laws is absent in reality. Hence efficient and feasible techniques have to be created to overcome these problems. Manual surveillance of traffic using CCTV is an existing methodology.

3.5 MODULES

To implement the above technique, we are following or implemented module below. The first image will be uploaded to the application, and using YOLOV2, we will check whether the image or video contains a person with a motorbike or not. if the YOLO model detects both a person and a motorbike, then we will proceed to step 2.

1) In this module, we will use the YOLOV3 model to detect whether an object wears a helmet or not. If he wears a helmet, then the application will stop hearing itself. If the rider does not wear a helmet, then the application proceeds to step 3
2) In this module, we will extract number plate data using the Python Tesseract OCR API. OCR will take the input image and then extract the vehicle number from it.

IV. RESULT

4.1 Key Performance Metrics

1. **Accuracy:** Often reported in the range of 90% to 98% in various studies, indicating a high ability to correctly classify helmeted and non-helmeted individuals.
2. **Mean Average Precision (MAP):** A crucial metric for object detection tasks, with values frequently ranging from 85% to 95% and even higher in some optimised models. This signifies the model's precision and recall across different classes and intersection over union (IoU) thresholds.
3. **Precision**: Measures the proportion of correctly identified helmets out of all detected helmets. High precision indicates fewer false positives.

4. **Recall**: Measures the proportion of actual helmets that were correctly identified by the model. High recall indicates fewer false negatives.
5. **F1-score**: The harmonic mean of precision and recall, providing a balanced measure of the model's performance.
6. **Frames Per Second (FPS):** Important for real-time applications, with some models achieving 30+ FPS, allowing for timely analysis of video streams.
7. **Factors Influencing Results:**
8. **Dataset Quality and Size:** Models trained on large, diverse, and well-annotated datasets generally exhibit better performance and generalization.
9. **Model Architecture:** Different models (e.g., YOLOv3, YOLOv5, Faster R-CNN) have varying strengths in terms of speed and accuracy. Newer, optimized architectures often show improved results.
10. **Training Techniques**: Transfer learning, data augmentation, and appropriate hyperparameter tuning can significantly impact the final performance.

    Environmental Conditions: Lighting, occlusion, and camera angle can pose challenges and affect detection accuracy.
11. **Overall:**

    Current machine learning models for helmet detection achieve high accuracy and real-time capabilities, making them suitable for various safety-critical applications. Ongoing research continues to focus on improving robustness, efficiency, and performance in challenging real-world scenarios.

V. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

A Non-Helmet Rider Detection system is developed where a video file is taken as input. If the motorcycle rider in the video footage is not wearing a helmet while riding the motorcycle, and then here we are uploading an image to identify license plate number of that motorcycle is extracted from the image and displayed. Object detection principle with YOLO architecture is used for motorcycle, person, helmet and license plate detection. OCR is used for license plate number extraction if the rider is not wearing a helmet. Not only are the characters extracted, but also the frame from which it is also extracted, so that they can be used for other purposes. All the objectives of the project are achieved satisfactorily.

5.2 Future Scope

Developing models that perform reliably under diverse and challenging conditions (varying lighting, weather, occlusions, different helmet types, and fast-moving objects).Improving the detection of partially visible helmets or helmets worn improperly.Utilising more sophisticated deep learning architectures and training methodologies.

5.2.1 Integration with Other Safety Systems:

Combining helmet detection with number plate recognition for automated challan generation and traffic law enforcement. Integrating with rider identification systems for personalized safety monitoring and alerts

Synergising with vehicle telematics to provide comprehensive safety analytics.

5.2.2 Real-time Edge Deployment:

Developing lightweight and efficient models suitable for deployment on edge devices (e.g., smart cameras, embedded systems) for real-time processing without relying on cloud infrastructure. Optimising models for low-power consumption and cost-effectiveness.

5.2.3 Expansion to Diverse Applications:

Extending beyond traffic safety to construction sites, industrial environments, sports activities, and other scenarios where head protection is crucial. Detecting other types of safety gear (e.g., vests, goggles) for comprehensive safety compliance monitoring.

5.2.4 Advanced Analytics and Insights:

Analysing helmet usage patterns over time and across different locations to identify high-risk areas and inform safety interventions. Providing data-driven insights for policy making and infrastructure planning related to safety.

5.2.5 Human-Computer Interaction:

Developing systems that provide feedback or alerts to individuals not wearing helmets in real-time. Integrating with smart helmets to enhance safety features and communication.

5.2.6 Privacy and Ethical Considerations:

Addressing privacy concerns related to surveillance and data collection through anonymisation techniques and robust data governance frameworks. Ensuring fairness and avoiding biases in detection models across different demographic groups.

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