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HELMET VIOLATION DETECTION AND NUMBER PLATE EXTRACTION USING DEEP LEARNING

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Abstract

The abstract outlines a proposal for a system designed to detect helmeted and non-helmeted motorcyclists, which is crucial for ensuring the safety of motorcycle riders on the road. Wearing a helmet is essential for protecting the head of the rider in case of an accident, and failure to do so can lead to fatal injuries. Currently, most traffic and safety violations are identified by analyzing surveillance footage captured by cameras. The paper presents an innovative approach using deep learning algorithms for automatically detecting helmeted and non-helmeted motorcyclists. The YOLOv4 model, an improved version of YOLO used for object detection, is utilized to identify motorcycle riders in the videos. The proposed model is evaluated on traffic videos, and its results are promising compared to other convolutional neural network (CNN)-based approaches. In addition to detecting whether a rider is wearing a helmet, the algorithm aims to detect the number plate of the vehicle and recognize its registered number. If the rider is found to be violating the helmet-wearing rule, a notification containing the time of the violation will be sent to the relevant party. This system has the potential to improve road safety by enforcing the mandatory use of helmets and identifying violators in real-time.

Keywords: YOLOv4, Object Detection, Convolutional Neural Network, Helmet Detection.

Introduction

The high number of traffic fatalities in industrialized and middle-income nations is due, in part, to the failure of motorcycle riders to wear helmets. Active law enforcement can promote compliance, but this requires a large number of police officers, which can lead to traffic congestion and safety issues. The goal is to improve helmet conformity by autonomous helmet violation detection using computer vision and machine learning technologies to tackle this issue..

Motorcycles are a common mode of transportation in almost every nation, but they carry a higher risk of danger due to their lower level of safety. Head injuries have been the leading cause of death in recent cases. Therefore, it is highly recommended that riders wear helmets to reduce risk. In recent years, the automatic system's significance in traffic control has grown to increase the efficiency of the traffic flow system, lower labor costs, and reduce accident causes.

In underdeveloped nations like India, where two-wheelers are a common and widely used mode of transportation, it is illegal to ride a bike without a helmet. However, many riders disregard this law and operate their vehicles without safety gear. As a result, the number of fatalities has risen yearly.

To solve this problem, cutting-edge technology has been developed to detect helmet use while driving. As it can quickly issue infraction citations and identify drivers who are not wearing helmets, this technology is crucial for ensuring public safety. Established video surveillance methods, however, are passive and heavily rely on human interaction, rendering them useless because there are people whose performance degrades over time.

Using the existing infrastructure of security camera systems installed in public spaces in many nations is a cost-effective way to find traffic law violators. However, this system requires automation to reliably track these abuses in real-time and with little human influence. Therefore,

automation of this system is urgently required to catch offenders.

Automating the system would also let the administration issue helmet infringement tickets more rapidly and efficiently.

Related work

This chapter examines various research publications on helmet detection systems in order to provide a greater understanding of the project. This section documents the substantial literature reviews conducted by the earlier scholars.

Rattapoom Waranusast et al.[1] suggested a real-time motorcycle safety helmet recognition system. The system classified heads using procedures that mainly consisted of head extraction and classification while using a moving object identification strategy. The categorization method is based on the features gleaned from the head regions, while the extraction method is based on vertical and horizontal projection profiling techniques. According to experimental results, the approaches correctly identified helmet use in both lanes at a rate of 74%.

The identification of moving vehicles using the CNN model for helmet and no helmet classification, The author Matthew N. Dailey et al. [2] has used image recognition to identify the license number plate. After the full analysis, we conclude that the AdaDelta model gives 87.10% accuracy of validity and 93.11% accuracy of the evaluation. Although we also observe that there are mistakes where a motorcyclist wears a cap when the front rider wears a helmet and the second person does not wear a helmet..

The Feature extraction for measuring traffic density from the video and image inputs. Grayscale frames are subjected to background subtraction during pre-processing/moving object detection in order to discriminate between moving and static objects. Although there is consolidated alarm generation, continuous frame correlation is not taken into consideration. Consolidate local results in order to decrease false alarms. Singh et al. [3] demonstrated impressive classification performance for their proposed system, achieving detection rates of 98.88% for bike riders and 93.80% for violators based on their experimental results. These findings provide strong support for the effectiveness of their approach. The drawback in this situation is that machine training will take longer. Accuracy cannot be your goal.

Two grouping systems, CNN and YOLO (You Only Look Once), have been proposed. The method was divided into three steps: first, the identification of motorcycles, second, the monitoring of motorcycles and third, the classification of helmets. From these proposed methods by Felix Wilhelm Siebert at. [4], we infer that the precision is 95.3% and the computational time for the identification of motorcycles is 0.059 seconds per frame. However, multiple motorcycles can be mistakenly assigned to the same track or the same motorcycle can be mistakenly assigned to a different track.

"Dasgupta and colleagues [5] proposed an approach to identify helmetless motorcycle riders in traffic surveillance videos." YOLOv3 architecture is used for the detection of persons and motorcycles. On the second stage for helmet detection, lightweight CNN architecture has been proposed.

Researchers have been working to find a solution to the problem of helmet identification in surveillance footage for a long time. Rattapoom Waranusast et al. [1] suggested a system for motorcyclists that would recognise safety helmets in real-time. The evolution of this tactic was only beginning. The system used a moving object recognition technique. The most typical methods used to categorize the heads were head extraction and categorization. The vertical and horizontal projection profiling approaches made up the extraction process. On the other hand, the categorization strategy was founded on the characteristics of the head regions.

Mohan et al. [2] used vehicle counting and trajectory prediction in their model. This article's main concern was how to tell bike riders from from other people. The background removal method was used to extract moving objects from traffic records using Object Classification using a Convolutional Neural Network, a sophisticated adaptive Gaussian mixture model. A CNN model was created using these pictures to distinguish between motorbike riders and non-riders by tracking the movement of other objects..

Madhuchhanda Dasgupta et al. [3] suggested a method to identify all motorcycle riders who are not wearing helmets from traffic surveillance footage. Motorcycles and humans are both identified using the YOLOv3 architecture. Yolov3 was a huge improvement over version 2 in many ways. The second stage of helmet detection has also been suggested for a compact CNN model. The lightweight CNN design for non-GPU computers is influenced by YOLO-LITE. The model excels in identifying helmets in different settings

he advancement of deep learning technology has resulted in a new approach to object identification that relies on convolutional neural networks. This shift has significantly improved the speed and accuracy of the process.

Sr. No.	Author Name	Methodology	Findings
1	Rattapoom Waranusast	Real-time motorcycle safety helmet recognition system. Head extraction and classification, moving object identification strategy.	Identified helmet use at a rate of 74%.
2	Matthew N. Dailey	Image recognition to identify license number plate using AdaDelta model.	Achieved 87.10% accuracy of validity and 93.11% accuracy of evaluation.
3	Singh et al.	Feature extraction for measuring traffic density from video and image inputs. Achieved detection rates of 98.88% and 93.80%.	Effective approach, but machine training will take longer.
4	Felix Wilhelm Siebert	Two grouping systems proposed: CNN and YOLO. Identification of motorcycles, monitoring of motorcycles, classification of helmets.	Achieved 95.3% precision and computational time of 0.059 seconds per frame.
5	Dasgupta et al.	Used YOLOv3 for detection of persons and motorcycles. Proposed lightweight CNN for helmet detection.	Identified helmetless motorcycle riders in traffic surveillance videos.

According to the analysis above, the focus on number plate detection using OCR is insufficient. To send notifications, it is crucial to extract the vehicle registration number from the image, and OCR can enhance the system's reliability in reading this information. Additionally, the system records the time of the rule violation for added clarity.

Proposed Framework

The present investigation employs YOLOv4 to perform an image classification test on images depicting motorcycle riders wearing helmets as well as those without helmets. Additionally, we utilize our deep learning image detection technique to identify an individual riding a motorcycle without a helmet from a video clip.The integration of elements that categorize and identify photographs and videos is necessary for system functionality. Manually extracting features is nearly impossible. Hence,

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CNN became a crucial technique for achieving high accuracy in image categorization a few years ago. Due to its ability to learn the entire scene and extract features using a feature map, CNN has been proven to perform better than other detection and classification algorithms.

For its initial training, CNN needs a lot of data and top-notch computer technology. Nonetheless, these sources also call for the proper setting. A limited amount of data may also overfit or underfit the data, depending on the type of learning used. Transfer learning is therefore applied on Yolov4-large Darknet. Also, a CNN model that was trained using the video dataset Yolov4:

Despite the precision of single-stage detectors such as the YOLO shown in Figure 1, there are also two-stage detectors available, including R-CNN, Fast R-CNN, and Faster R-CNN. While they may be slower, they do provide high levels of accuracy. When considering the essential components of a contemporary one-stage object detector, it is important to keep the following factors in mind.

Backbone: ResNet, DenseNet, VGG, and other models are examples of feature extractors. They will initially receive pre-training on datasets for image categorization like ImageNet. They are then adjusted on the detection dataset after that. These networks prove helpful in the later stages of the object recognition network because they provide varied degrees of characteristics with stronger interpretations as the network becomes deeper (has more layers).

Neck: Between the backbone and the head, there are some more layers. These layers are used to extract different feature maps that were constructed in earlier phases. It is possible to use the neck section from FPN, PANet, or Bi-FPN

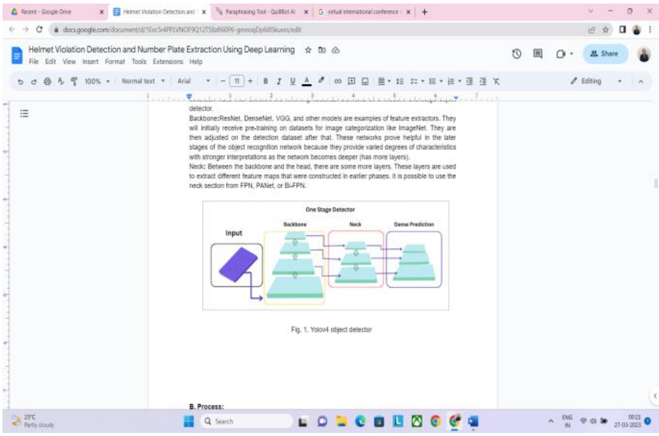


Fig. 1. Yolov4 object detector

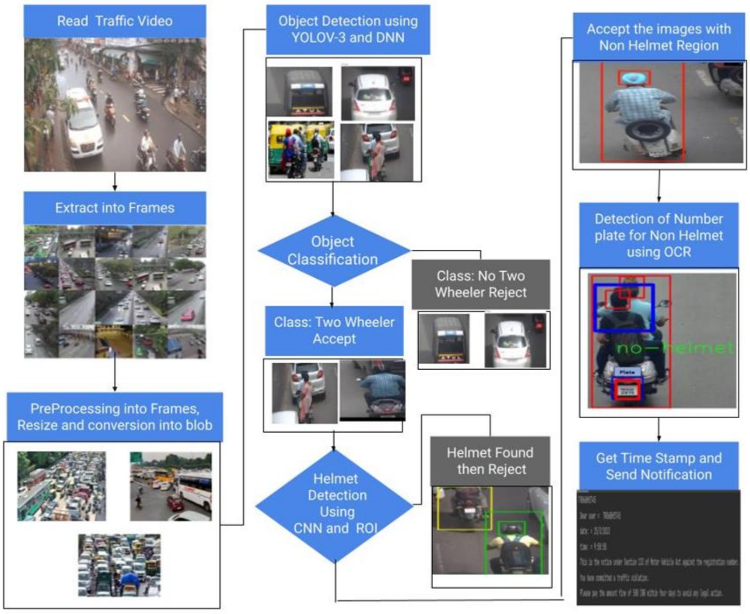
Yolov4 is divided into a N by N cell grid. The grid's cells are tasked with making predictions about certain bouncing boxes. The square shape is shown as a bounding box. An article item is entirely covered by that square shape. It provides a certainty score as well. The certainty score is highly important for indicating the bounding box that contains a particular object. The model is used to change the size and location of an image. A picture can be altered in terms of scale and orientation using the model. The high-scoring areas of the image are examined as detections. A single neural network is used to process the entire image each time. The probability for a given region is then projected, and similarly sized bounding boxes are projected for a given region. Based on the estimated probability, weights are assigned to the bounding boxes. The steps in this technique are as follows:

1. Begin by entering an image.
2. Resizing of images.
3. Create N by N grids from the image.
4. Apply weights to the frame that represents the bounding box of each cell.
5. Determine the confidence score for every cell and select the cell with the highest score for detection.
6. Print the boundary box when an output picture is detected.
7. Show the final image

System Architecture

Traditional neural networks have been replaced by deep neural networks. These are multi-layer neural networks with several nodes in each layer. Cutting-edge developments in the fields of computer vision and natural language interpretation are made possible by the application of deep learning. Deep neural networks need training data to outperform conventional machine learning methods. Nonetheless, a tremendous amount of data is needed. Because of this, we were interested in seeing how well this approach would work with scant training data.

The YOLOv3 model receives input from the annotated images to train for the custom classes in this system. The weights produced during training are used to load the model. An image is then given as input after that. The two training classes are recognised by the model. This tells us details about the motorcycle-riding individual. If the rider is not wearing a helmet, we may easily obtain the rider's other class details.



Fid.2 System Architecture

Dataset:

The dataset came from unique sources. The dataset is taken from run time video frames. The dataset is categorized between two classes- people with helmets and people without helmets. Fig.3. Represents the images of riders with and without helmets from the dataset.

Training:

The Yolov4 methodology that has been suggested may recognise and group motorcyclists into different classes. The head portion of the upper one-fourth of the detected rider is cropped and used as a parameter in the model for helmet detection. The input layer receives an image and feeds it through several convolutional layers, each of which modifies the image in a different way before passing it on to the following layer. These layers serve as a filter, removing characteristics that set the target object apart from other objects.

On a computer with a graphics processing unit, the experiments are carried out (GPU). The test platform consists of an Intel i7 11th generation Processor and 16GB of Memory. It is possible to programme with Python 3.7. Both Tensorflow, developed by Google, and OpenCV 3.0 are used for the computer vision library. his is a fully open-source machine learning platform that offers a versatile ecosystem of tools, libraries, and community resources. It enables researchers to push the boundaries of machine learning and developers to quickly and easily develop and launch ML-driven applications.

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Algorithm:

To detect two-wheelers and four-wheelers in a traffic video file, the first step is to load the file and extract its frames. Next, two models are initialized – a machine learning classification model like the random forest or support vector machine, and a deep learning object detection model like YOLO. These models will be used to identify two-wheelers and four-wheelers in each frame, it will be passed through the classification model to determine whether it contains a two-wheeler or a four-wheeler. If the frame contains a two-wheeler, it will be passed through the object detection model to detect if the riders is wearing a helmet. If the helmet is not detected, an Optical character Recognition (OCR) model will be used to read the number plate of the two-wheeler and send a notification to the concerned authority. These steps will be repeated for all frames in the video to ensure all two-wheelers are detected and reported.

Here is an algorithm with notation for the given task:

Input:

- Traffic video file

Output:

- Helmet detection notifications

Algorithm:

Step 1. Load the traffic video file video = load_video("traffic.mp4")
Step 2. Extract the frames from the video frames = extract_frames(video)
Step 3. Initialize a classification model and a deep learning object detection model clf = initialize_classification_model() detector = initialize_object_detection_model()
Step 4. for each frame in frames:

- vehicle_type = clf.predict(frame)
- if vehicle_type == "two-wheeler": helmet_detected = detector.detect_helmet(frame)
- if not helmet_detected: number_plate = ocr.read_number_plate(frame)
- send_notification(number_plate)

End if
End for loop

Result

In this section, the final results of the proposed model are demonstrated including phase wise outputs and figures. The model has been tested on different traffic scenarios which are showed in this section. In order to test the model, motorbike riders were captured on a traffic video. Internet images of motorbike riders are frequently utilised for testing. to evaluate the system's algorithm for resilience. As shown in Figure 3, we evaluated the system using motorcycle riders wearing and without wearing helmets. As seen in the graphic, the suggested system can also tell whether a biker is wearing a helmet, cap, hood, scarf, etc..

Fig.3. The proposed method for detecting helmeted and non-helmeted motorcyclists.

In order to generate a report and penalize for non-helmeted motorcyclists, the system recognized their license plates, as shown in Fig. 4. And in Fig. 5, a warning message is created for riders who are not wearing helmets.

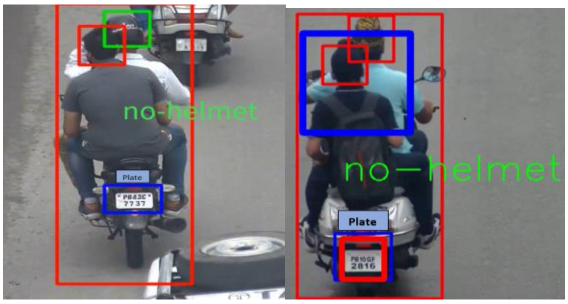

Fig. 4. Number Plate detected for non-helmeted motorcyclists.

Fig.5. Message generated after number plate extraction for a particular rider who is not wearing a helmet.

Conclusion

The objective of the Helmet and Number Plate Detection and Recognition project is to detect whether or not a motorcyclist is wearing a helmet, and if not, to identify the number plate and generate a report with associated fines. Our proposed solution aims to automate the identification of helmetless riders and impose fines accordingly. To accomplish this, we have developed a real-time monitoring system that utilizes computer vision technology to detect riders without helmets. This system is capable of processing a sequence of images, and it addresses various challenges related to helmet detection, such as low lighting and poor video quality. Our approach involves adapting contextual information subtraction, which remains consistent across different conditions. Additionally, we have integrated deep learning techniques to enhance the system's accuracy by enabling it to automatically learn and recognize distinguishing characteristics.

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