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DETECTION OF HELMETLESS BIKE RIDERS USING DEEP LEARNING

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ABSTRACT

Motorcycles are more likely than four-wheelers to be involved in deadly accidents. When a driver is involved in a high-speed accident while not wearing a helmet, the consequences are more dangerous. It's extremely dangerous and can result in fatalities. As a result, wearing a helmet can lower the incidence of accidents and potentially save lives. Two-wheelers are the most popular way of transportation nowadays. Although it is generally recommended that bike riders wear helmets, many riders fail to do so, resulting in accidents and deaths around the world. To combat this issue, most countries have legislation requiring two-wheeler riders to wear helmets.

A major section of the police force, in addition to the law, discourages this behaviour by issuing a traffic infraction citation. This method is currently manual and time consuming. The suggested technology will address this issue by automating the process of detecting cyclists who are not wearing helmets while riding.To detect riders who are not wearing helmets, the system uses deep learning and image processing algorithms. The system detects moving objects in the scene using a video of traffic on public highways as input. To determine whether the moving object is a two-wheeler, a machine learning classifier is deployed. If the cyclist is not wearing a helmet, the licence plate is used as the output.

Keywords *- YOLOv5, Helmet, Motorcycles, RasNET50*

1. INTRODUCTION

In practically every nation, two-wheelers are a fairly common form of transportation. Due to the importance of wearing a helmet, governments have made it illegal to ride a bike without one and have implemented manual enforcement methods to apprehend offenders. The current video surveillance-based solutions, however, are passive and heavily reliant on human labour. Automation of this procedure will greatly minimise the requirement for human resources while ensuring reliable and effective monitoring of these breaches. As a result, using the current infrastructure to detect offenders is a cost-effective solution. One of the main applications of computer vision in engineering in recent years has been intelligent monitoring. The foreground and background can only be separated using conventional picture recognition techniques like the Gaussian mixture model. Although it can be used for particular recognition tasks, mobile cameras are not ideal for this strategy, and it is significantly more challenging to determine which category the foreground belongs to. Researchers employ HOG, a hand-designed feature extractor, to extract contour features in the study of pedestrian recognition.

A classifier like SVM is then used to recognise pedestrians based on the collected features. The hand-designed feature extractor has limited generalisation capabilities and imprecise characteristics, making it challenging to use in actual engineering. Ross Girshick suggested R-CNN in 2014. The algorithm's implementation is broken down into several steps: Feature computation using CNNs (Convolutional Neural Networks), region suggestions extraction, and bounding-box regression. However, pre-fetching the region suggestions is necessary and will use up a lot of disc space. The CNN network must simultaneously calculate each proposed region, therefore a high number of overlapping regions will result in a waste of computational power. Fast-RCNN put forth a fix for ROI pooling layers and multi-task loss layers as a result of these drawbacks. Faster-RCNN used a method of adding additional RPN branch networks to integrate region proposals extraction into deep networks.

2. LITERATURE SURVEY

2.1. Machine Vision Techniques for Detecting Motorcycle Safety Helmets:

This study describes a system that identifies motorcycle riders and assesses whether or not they are wearing safety helmets. Using the K-Nearest Neighbour / (KNN) classifier, the system collects moving items and classifies them as a motorcycle or other moving objects based on information collected from their region properties. Following that, projection profiling is used to count and segment the heads of the riders on the identified motorcycle. The system uses KNN to determine whether the head is wearing a helmet or not, based on features extracted from four regions of the segmented head region. The average correct identification rate for the near lane, distant lane, and both lanes in the experiment was 84 percent, 68 percent, and 74 percent, respectively.

2.2. Motorcycle Detection and Tracking System with Occlusion Segmentation:

In areas where traffic checks are not conducted, bicyclists do not wear helmets. The motorist has a tendency to wear a helmet only where they expect to be checked; they do not wear a helmet when no checking is expected. By passing the ignition switch, the vehicle can be turned on or stolen. In large countries like India, testing the alcohol concentration of each individual rider's blood is very difficult. Due to the lack of Bluetooth speakers in prior helmets, accidents have occurred as a result of phone calls.

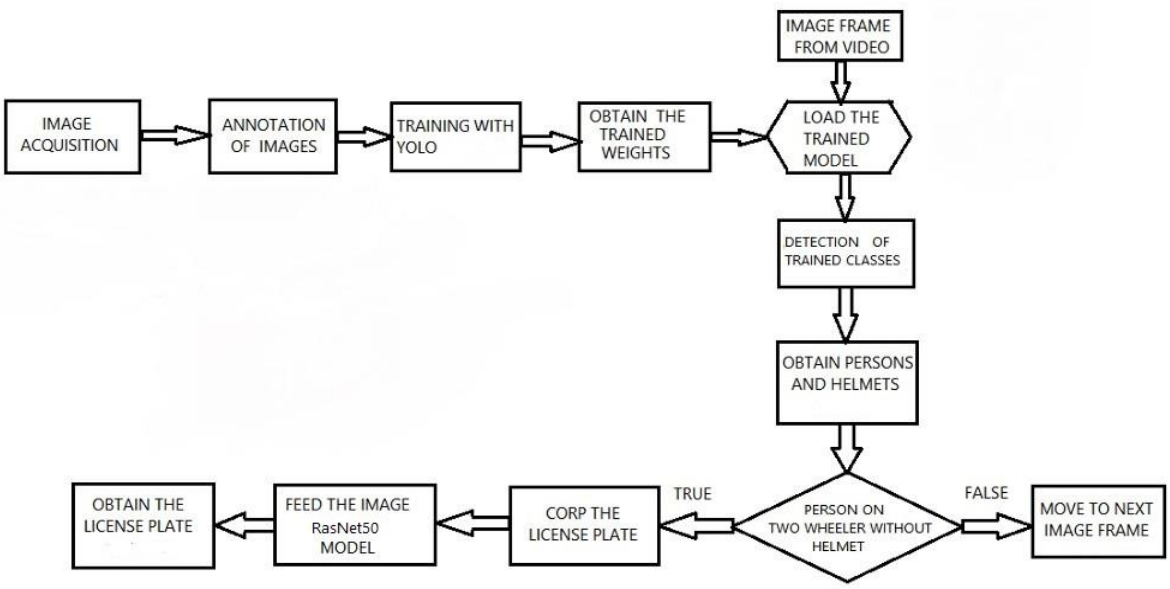
2.3. Automatic detection of motorcyclists without the helmet:

Motorcyclists without helmets are automatically detected by a system that classifies public highways. This necessitates the use of a hybrid system. This study proposes a descriptor for feature extraction based on Local Binary Patterns, Histograms of Oriented Gradients, and the Hough Transform descriptors to describe and illustrate an automatic approach for motorcycle recognition. Camera-captured traffic photos were used. The best classification result was an accuracy rate of 0.9767, and the best helmet detection result was an accuracy rate of 0.9423.

2.4 Automatic Detection of Bike-riders without Helmet using Surveillance Videos in Real-time:

In this research, we offer a method for detecting bike riders without helmets in real time using surveillance videos. Using background subtraction and object segmentation, the proposed method first recognises bike riders in surveillance video. Then, using visual cues and a binary classifier, it assesses if the bikerider is wearing a helmet or not. We also provide a consolidation strategy for violation reporting, which helps to improve the suggested approach's reliability.

To assess our technique, we compared the effectiveness of three widely used feature representations for classification: histogram of oriented gradients (HOG), scaleinvariant feature transform (SIFT), and local binary patterns (LBP).



3. METHODOLOGY

Accuracy and speed are required for real-time helmet detection. As a result, the CNN-based YOLO (You Only Look Once) paradigm was chosen. YOLO is a real-time object detection technology that is state-of-the-art. YOLOv5 is a major advance over prior YOLO versions in terms of speed and accuracy. In contrast to systems like R-CNN, which require thousands of network evaluations for a single image, it provides predictions with just one. This makes it a thousand times quicker than R-CNN and a hundred times faster than Fast R-CNN.

Object identification is the art of finding instances of a specific class in an image or video, such as animals, humans, and others. Using pretrained object detection models, the Pre-Existing Object Detection API makes it simple to detect objects. However, these models detect a number of objects that are of no interest to us, necessitating the use of a custom object detector to discover the required classes.

Five objects must be recognised in order to accomplish helmet detection and number plate recognition and extraction. Helmet, No Helmet, Motorbike, Person (seated on the bike), and License Plate are the objects. It is necessary to develop a specific object identification model capable of detecting these items. A Dataset is a collection of photographs that contain the objects of the classes to be discovered. The custom model is then trained using this dataset. The model can then be used to detect these custom objects after it has been trained.

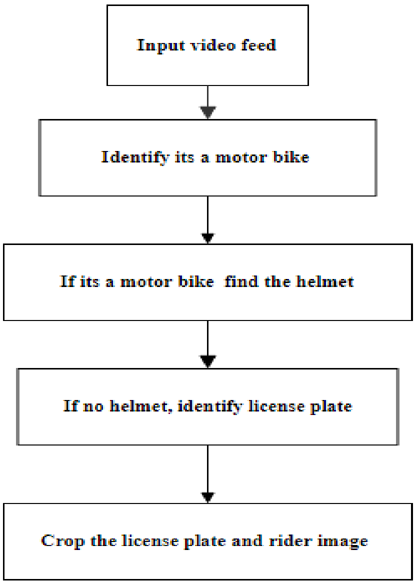
All of the collected images with their annotations are fed into the training system. With the support of ground truth for the required classes, the model extracts the features of each class from each image. We utilise a deep learning, convolutional neural network-based classifier to extract the characteristics and store them so that we can recognise them in other photographs. The detection of the pretrained class is required when an image is presented to this trained model. A few photographs are shown as examples to demonstrate the custom trained model's detecting capacity.

3.1 Helmet Detection

The annotated photos are fed into the YOLOv5 model, which is used to train for bespoke classes. The model is loaded with the weights obtained after training. After that, an image is provided as input. All five training classes are detected by the model. This provides us with information on the person who is riding a motorcycle. We can simply collect the rider's other class information if the person is not wearing a helmet. The licence plate can be extracted using rasnet50 model.

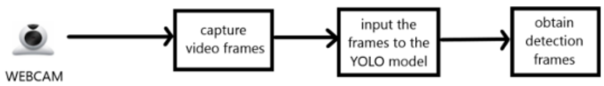
3.2 License Plate Extraction

The corresponding person class is detected after the helmetless rider is detected. Rasnet50 accomplishes this by determining if the coordinates of the no helmet class are contained within the person class or not. Similarly, the methods for detecting the linked motorcycle and licence plate are the same. After locating the licence plate's location, it is cropped and saved as a new image.



3.3 Real time implementation using webcam

The camera will be utilised as an input device to receive picture frames in real time for object detection. Because we're utilising the YOLOv5-tiny model, we can get up to 220 frames per second.



4. RESULT

The model was trained on 7,000 photos on classes for 40,000 iterations on small YOLOv5. The detections of all object classes were achieved with great precision, and the mean average precision attained a constant maximum value of 87%, therefore the training was terminated after 40,000 iterations.

The pictures show a few samples of the input image and the output object detector.

The License plate is extracted from the Object detector output by the algorithm. The License plate extraction code only extracts licence plates from motorcycles with a rider who is not wearing a helmet and discards licence plates from motorcycles with a helmeted rider.

5. CONCLUSION

The YOLO object detection is ideally suited for real-time processing, as seen by the findings above, and was able to reliably identify and locate all of the object classes. The planned end-to-end model was successfully constructed and contains all of the necessary features for automation and monitoring deployment. To extract the number plates, certain algorithms are used that take into account various scenarios, such as many motorcyclists without helmets, and are designed to handle the majority of the situations. Our project's libraries and software are all open source, making it extremely adaptable & cost-effective The initiative was created primarily to address the issue of inefficient traffic management. As a result, we may conclude that if used by traffic manageing departments, it would make their job easier and more efficient.

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