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Helmet Detection using ML & IoT

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Abstract— This paper is about detecting motorbike riders without a helmet with the assistance of machine learning and IoT. Motorcycle accidents are increasing day by day in many countries. The helmet is that the primary safety equipment of Bike riders, however many drivers don't use it. The primary objective of a helmet is to protect the driver's or pillion rider head just in case of an accident or fall from bike.

We came up with an approach that first collected a dataset of the time-image of road traffic where we've got differing kinds of photos like with helmet, without a helmet and also the rider is wearing a helmet and another person not wearing a helmet so differentiates the 2 wheelers from other vehicles on road. It then checks whether the rider and pillion rider is wearing a helmet or not using an open-source computer vision and machine-learning software called OpenCV. If anybody of the riders is found not wearing the helmet, their vehicle number plate is processed using optical character recognition (OCR).

Key words—Helmet Detection; Machine Learning; OpenCV; OCR.

1. INTRODUCTION

In the larger part of nations, the two-wheeler is a mainstream method for transport. It is because of the low price and low maintenance cost as contrasted and another vehicle. In any case, there is less security and high danger engaged with engine bicycles. It is profoundly alluring for bike riders to utilize a protective cap to scale back the danger. In any case, the high risk and less safety is involved with bikes. In the past 10 years, it was noticed an growth in the number of bike mishaps.

With regards to insights given by transport service around 28 bike riders kick the bucket every day on Indian streets in 2016 on account of not wearing head protectors. Additionally, it is demonstrated that one among six bicycle riders kicked the bucket because of not wearing a head protector. To downsize the included danger, it is profoundly attractive for bicycle riders to utilize a protective cap.

There are existing strategies that use particular sensors in the ergonomics of the motorbike to check the presence of a head protector. However, it is difficult to persuade each client to the establishment of sensors on the bicycles. [1-3].

As of now, all significant urban communities previously sent huge video observation organizations to keep a vigilance on a wide assortment of street dangers. In this way utilizing such previously existing framework will be a cost-effective arrangement, anyway, these frameworks require an enormous number of people whose presence isn't supportable for significant stretches of time.

Ongoing investigations have demonstrated that human reconnaissance is inadequate, and not exact as the hour of observing recordings builds, human mistakes likewise increments and it is a repetitive cycle. Mechanization of this repetitive process is far required for solid and hearty observing of these infringements just as it likewise decreases the prerequisite of HR required. Be that as it may, to embrace such programmed arrangements certain moves should be addressed.

2. Related work & problems to be addressed

2.1) significant measure of data

Gathering in a restricted time might be a testing task. As such applications include errands like information assortment, highlight extraction, characterization, and following, in which a significant and prominent measure of data should be handled quickly in a brief span to accomplish our objective of continuous execution [1] [2].

2.2) Different situations:

In genuine situations, the dynamic articles ordinarily block each other because of which basic item may just be incompletely noticeable. Recognizable proof and isolation get hard for these somewhat noticeable articles [3].

2.3) Direction of vehicle movement:

As vehicles are 3-dimensional items they generally have various appearances from the changed point of vision or survivable. Notably, the exactness of classifiers relies upon highlights we utilized which thus relies totally upon point somewhat. The best model is to consider the appearance of a bicycle rider from the front view and side view.

2.4) Temporal Changes in Conditions:

Over time, there are numerous adjustments in climate conditions like light, shadows, fog, and so on there could be minute or prompt changes which expands trouble of undertakings like foundation displaying of pictures.

2.5) Quality of Video:

Generally, The CCTV cameras catch low goal recordings and are affected by conditions, for example, low light, terrible climate, fog. Because of such restrictions, undertakings, for example, distinguishing proof, grouping, and the following turn out to be much more troublesome.

As supported in [1], effective structures for observation application have helpful properties like continuous execution, adjusting, dynamic to abrupt changes, and unsurprising. Remembering all difficulties and wanted impacts, we proposed a technique for programmed discovery of bicycle riders without cap utilizing information from existing surveillance cameras, which works progressively mounted on streets. C. Chiu et al. expressed a way to deal with identify protective caps in reconnaissance recordings.

This cycle crops the moving item and afterward distinguishes bikes and heads utilizing likelihood. This framework couldn't deal with minute varieties on account of commotion and brightening impacts. [4] In [2] two stages were utilized for head protector recognition. In the principal stage, moving articles were resolved where a cross-line was determined. It at that point orders if it is a motorbike.

In the subsequent advance, a procedure was utilized to improve productivity. An SVM classifier was utilized to arrange moving items into two classes. Three characterization families were utilized viz. mathematical, intermittent, and tree-based. Recordings were caught at 25 fps and the picture size was 1280x720 to beat conditions, for example, low light, awful climate J. Chiverton et al. utilized edge histogram highlights to distinguish bike drivers. This technique performed well regardless of whether there's low light in reconnaissance recordings because of the utilization of edge histograms close to the head.

In any case, as the edge histograms utilized round hough changes to analyze and arrange caps, it prompts a ton of misclassification among motorcyclists with a Helmet as items like head protectors were ordered while the distinctive Helmet was not classified. [5]

3. LITERATURE SURVEY

3.1 Paper-1

This paper, they implemented the advanced deep learning model motorcyclist using CNN. They used an advanced deep learning method YOLOv2 which combines both object detection and classification of objects with in a single architecture. YOLOv2 implements two different stages successively in order to improve the helmet detection accuracy. At the first stage, the YOLOv2 detects different objects in the given input test image. Then it crops image and cropped images of detected persons in image are provided as input to the second YOLOv2 stage which was previously trained on our predefined dataset of persons wearing helmet images. The proposed approach involved several steps like person detection from input images.

It detects classes in given image and segregate them such as a person, car, motorbike, etc., in addition to other classes that are predefined in the dataset. We utilize a person detection class after segregating of all other classes in order to identify helmeted motorcycle rider. All other segregated classes from the primary YOLOv2 model will be discarded to reduce the lag in the architecture. Intermediate processing is implemented where all the other classes except person are removed. Also, the detected person’s bounding box is cropped automatically and that image is stored for further analysis and process. Helmet detection is third step for this step, again used YOLOv2 model which is trained with predefined dataset of helmeted images of Motorcyclists.

The cropped images of the detected person that are obtained in second stage are provided as input here to the YOLOv2 model. This paper successfully decreases the number of helmets being undetected. The helmets are detected accurately in crowded areas and also in the images with a single motorcyclist. In order to increase the helmet detection accuracy used two-stage of YOLOv2 models. The algorithm can successfully distinguish between cap and helmet despite both having the same features. The algorithm has many negatives it requires large datasets and the weather conditions may affect the accuracy of the detection i.e the effect of weather conditions is not addressed in the paper.

3.2PAPER-2

This paper proposed a architecture for the automatic detection of Bike riders driving without helmets which is observed from surveillance videos. In this proposed approach, adaptive background subtraction is implemented on video frames to get proper images from moving objects that are observed in surveillance video.

Later convolutional neural network (CNN) is utilized to select two wheelers among other moving objects. The steps involved are Background Modelling and Moving Object Detection, CNN for Object Classification and detection, Recognition of Motorcyclists from Moving Objects, Recognition of Motorcyclists without Helmet.

This paper addressed issues like illumination effects and the occlusion of objects. The background modeling and moving object detection are very accurate. Adaptive background subtraction which may rise invariant various challenges such as illumination, poor quality of the video is clearly discussed in the paper.

The experiments on real time surveillance videos successfully detected 92.87% bike riders without helmet with a low false rate of 0.5% on average and thus shows how efficient is the proposed approach yet the helmets are not classified as objects in this paper.

3.3 PAPER-3

This paper is completely based on the safety of workers in industrial areas where the wearing of helmets is mandatory. It used the Faster R-CNN algorithm to inspect the wearing of a safety helmet. The experimental outputs show that compared with the Faster R-CNN algorithm, the mean average precision of the Improved Faster R-CNN is improved and the real-time automatic detection of the wearing of safety helmets is realized.

This paper used techniques of Used R-CNN which is more accurate than CNN. All, images are normalized before being input into the feature extraction framework which improves the accuracy of classification of the helmet in traffic. By applying this method to the on-side operation of substations, the interference of light, distance, and other factors can be overcome and the wearing situation of multiple people can be identified at the same time.

The accuracy obtained by this method is up to 94.3%. In addition to this, all positives a few drawbacks involved in this paper also. Not addressed scenario at different backgrounds like a large crowd, large gatherings, and more blockings in background. In order to train the system with the pictures, we need vast data set of different backgrounds and different conditions of weather lighting and object blocking. They implemented R CNN which is advanced than CNN which will increase the accuracy of detecting riders with helmets and without helmets but, still the detection speed is slow.

3.4 PAPER-4

This paper proposes motorcycle riders are detected using the YOLOv3 model which is an incremental version of the YOLO model. In the second stage, a CNN based architecture has been utilized for helmet detection of motorcycle riders. The steps involved are Motorcycle rider detection using CNN where implemented YOLO3. The second stage is Helmet detection using CNN. Then, the proposed lightweight convolutional neural network detects the wearing of a helmet or no helmet for all motorcycle riders. In this proposed architecture they used YOLO3 which is advanced CNN used that of YOLO 2.

This architecture performs comparably well with other CNN based helmet detection. The accuracy of results and detection of the rider without a helmet is up to 96.23 which is almost perfect results for the project. This paper discussed the children also as the heads of children is very small and sometimes children are in their parent's hands so this paper also worked on detecting the heads of small children and highlights of the fact that children security on two-wheelers.

This paper has few drawbacks like not addressed the problems risen by the complex scenarios of bad weather for detection of helmetless motorcyclists not addressed. They have not discussed the low video quality, less clarity of video, and resolution of video which may affect the detection of moving objects in input video. The main drawback is they not discussed the Classification of helmet-like objects (cap, monkey caps, Turbans).

4. PROPOSED FRAMEWORK

The proposed work mainly involves two main steps: i) The deep neural network which is employed for identification of single and multiple riders on a motorcycle using the YOLOv3 model and ii) We implemented another deep neural network in this which is implemented for motorcycle rider's helmet detection. For these two steps, traffic surveillance video is the main input to the YOLO3 model, and the individual video frames are obtained by cropping images and taking screenshots from input videos are utilized as the input to the CNN to detect motorcycle riders and pillion riders with or without a helmet.

4.1 Motorcycle riders detection using CNN

A convolutional neural network (CNN) is a variety of feed-forward neural network that implements the back propagation algorithm. It trains it high-level features from the primary data like images. The current accomplishment of convolutional neural networks is in their ability to extract inter-dependent information from the input images i.e centralization of the pixels which are highly sensitive compared to other pixels. The convolutional neural network training consists of different convolution layers, relu layers max-pooling layers, fully connected layers, and a loss function (e.g. SVM/Softmax) on the last (fully-connected) layer these layers are liable for the detection, classification, and evaluating of objects in images. In the preliminary layers we obtain the edge information of the input images familiar to some of the algorithms but, In the penultimate layers, we start obtaining texture and ridge information which helps us in evaluating sensitive information useful for the classification of objects in images into different classes based on their sizes and category(moving or not).

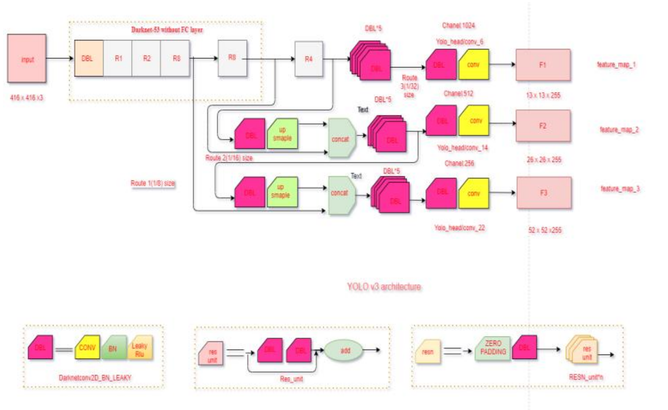

Fig 1 Architecture of YOLO

4.2 Helmet detection using CNN

The proposed CNN architecture is able to detect and classify helmet in images. The top portion of the identified motorcycle rider mainly the head portion is cropped and forwarded as input for the proposed CNN architecture of helmet detection. This proposed network involves in five convolutional layers.

The primary layer takes the cropped input image and passes the image through successive five convolutional layers where each layer converts the image using specific functions, algorithms and sends to the consecutive layers step by step. These layers act as filters to extract features with sufficient discriminating attributes to differentiate targeted object from other objects.

After successfully passing through five convolutional layers, two fully connected layers are further added. Depending on the extracted properties from the layers, softmax classifier which classifies the object to distinguish into different classes with probability distribution as a Helmet or other objects like cap. The CNN predicts bounding boxes along with class probabilities [4] for accurate prediction of helmet. In the detection process the input image is divided into an N × N grids. This grid is responsible for object detection of any kind of objects falls into that grid's cell. Each bounding box consists of 4 measures: px, py, w, h where (px, py) coordinates represent the center of the box relative to the bounds of the grid cell. The width (w) and height (h) are predicted relative to the whole input image.

One bounding box is allotted per object based on highest Intersection over Union (IOU) which represents a fraction between 0 and 1. IOU = AreaofIntersection/AreaofUnion (1) Area of Intersection is the overlaying area between predicted bounding box of object and the ground truth.

Area of Union is the total area of both predicted bounding box and ground truth. The IOU value is predefined as threshold for object detection and it is predefined as IOU threshold = 0.5 which means that a detection with a IOU greater than 0.5 is a truly positive but practically, IOU should be near to 1 to show the perfect matching. In the proposed network to add non-linearity, Rectified Linear Unit (ReLU) activation function is used after each convolutional layer, followed by additional max-pooling layers that are added after convolutional layers for dimension reduction of the feature maps.

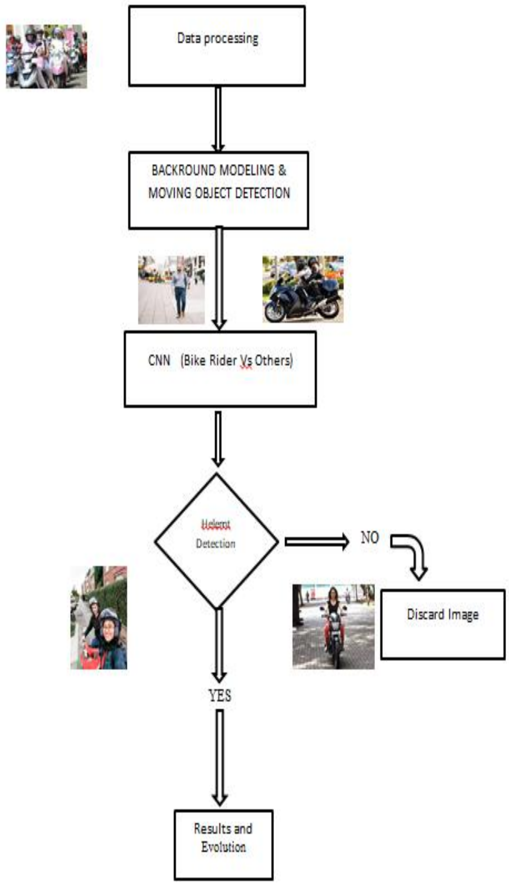

Fig 2 Flow chart of implemented method

Fig.3 Detection of the Helmet

Fig.4 Detection of Without Helmet

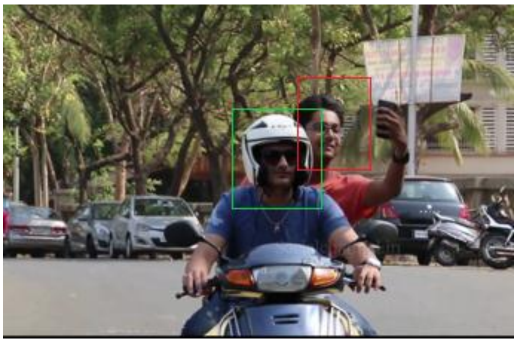

Fig.5 Detection of combined riders with & without Helmet

5. Results and Discussion

The experiments are implemented on non-GPU computer. The experimental platform is Intel core i7 7th generation 4.7 GHz CPU with 16 GB RAM. To implement this proposed model, we opted Python 3.6 as programming language, OpenCV 3.0 as computer vision library, a neural network framework Darknet and various libraries have been used in evolving the accurate results of proposed method. For detection of motorcycle riders, one hour traffic video is recorded using surveillance cameras. Pre uploaded internet images of motorcyclists are also taken for testing purpose to train the model. Altogether among 180 motorcyclists, 174 motorcyclists are successfully identified in the classification of motorcycle riders that shows accuracy of 96.23% which is acceptable in comparison with other existing methods. Helmet dataset is made by considering internet motor-cyclists images and real-time traffic helmet images that are obtained from the cropping the images from video. The recording taken for this purpose is a 45 minutes video. The total frame of first 25 minutes video is used for training the network. Another 10 minutes video is used to validation of the network and remaining 10 minutes video is used for testing purpose of the network. YOLOv3 architecture is used for detection and differentiation of person and motorcycle from others. On the second stage for helmet detection, lightweight CNN architecture has been proposed. The lightweight CNN architecture for non-GPU computer inspired from YOLO-LITE [3]. Due to smaller input image size for helmet detection, less data passes through the network which increases the speed of the network. As batch normalization is not essential for a small network, therefore no intermediate calculation is required for it at each layer of the network. Hence, there is no additional time loss in the feed-forward process.

Technique	Accuracy(%)	Performance of detecting Helmet(%)	Performance of detecting NoHelmet(%)
YOLO3	96.23	99.28	99.21
YOLO2	94.12	98.88	98.91
RCNN	94	91.81	91.78
HOG SVM	92.8	81.84	81.84

Table 1 PERFORMANCE (%) OF THE CLASSIFICATION OF 'HELMET AND NO HELMET' DIFFERENT TECHNIQUES

The above table shows the difference between different techniques used before to detection of helmets, and the accuracy of detection of the helmet. The highest accuracy is observed in the YOLO3 model which was implemented for this project and other methods show their respective accuracies and prove that YOLO3 is produced the best outputs. YOLO3 showed better results in detection of a helmet that is up to 99.28% of the provided images and also effectively detects no helmet also up to 99.21% accurately which increases the reliability of the YOLO3 to the detection of a helmet in this project.

Technique	Low false rate
YOLO3	0.001 – 0.1
YOLO2	0.001
RCNN	0.001
HOG SVM	<0.5

TABLE 2 LOW FALSE RATE OF DIFFERENT TECHNUQUES

The Table 2 shows the Low false rate of different Techniques and shows that the YOLO3 has less low false rate than other techniques which increases the accuracy of detecting riders wearing a helmet and not wearing the helmet.

6. Conclusion and Future work

The software of the helmet detection has been thoroughly tested and implemented we have very good exercise in high level language and have realized the ingenuity and patience with this job has to be done. In our project we provided the YOLO based Helmet detection and also made a detailed study about CNN.

We used jupyter notebook to implement the program and we successfully implemented the program. Our project was tested successfully tested in python. We also made study of applications and future scope of the project.

Our project can be linked with the traffic cameras and with some modifications it can be used to detect helmets in the real time system. Further more we can merge the algorithm of automated license plate detection and make a system which generates challans for those who don't wear helmets.

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