Identifying Bikers Without Helmets and Triple Riding Automatically

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Abstract. Enforcing traffic laws in a densely populated nation like India is challenging. However, many motorcyclists continue to put their lives in danger by without wearing protective headgear. The traffic police have an extremely time-consuming job in keeping tabs on all the cars on the road. CCTVs are commonplace in several of the more populous places. There is already the technology in place to make motorcycle riders' tracking and monitoring more streamlined. This study proposes a technique for identifying triple riding, helmetless motorcyclists and retrieving the vehicle identification number of any motorbike driven by an unprotected rider. The YOLO (You Look Only Once) approach is used to identify the triple riding, biker's helmet and the bike's licence plate. Modeled on the COCO dataset, YOLO has the ability to identify 80 different classes. YOLO learned its stuff using inputs like helmet images and licence plate data. This technique yields excellent outcomes. Identifying triple riding, helmets and licence plates is done with great precision.

Keywords: Bikers · Traffic Laws · YOLO · Helmet Detection · Number Plate Detection · License plate

1 Introduction

In India, motorbikes are widely employed as a mode of transportation. When riding a motorbike, the only real safety precaution is to wear a helmet. Many individuals in India disregard the law requiring them to wear helmets when riding motorcycles. Accidents occur often because people disregard this guideline. According to the 2018 WHO Global Report on Road Safety, India has the highest number of road accident fatalities among all 199 nations, followed by China and the United States. The Union Ministry of Road

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Transport and Highways (MORTH) found that 2,384 people in India lost their lives in vehicle collisions in 2018 due to head injuries that may have been prevented by wearing a helmet [1]. A total of 33% more people lost their lives this year than in the previous year. Not donning a helmet was a factor in the 6212 reported injuries.

Another poll [2] conducted by Exide life insurance firm found that 74% of pillion riders in India's main cities did not wear helmets. They weren't wearing them because they weren't required, because they were too expensive, because they were too hot, etc. According to research conducted by the Transport and Road Safety Commissioner, non-helmet use is a major contributor to fatalities among motorcyclists. The Indian government has been pushing for helmet legislation for some years. For the time being, motorcycle riders are manually monitored by police. Continuous checks of the CCTV feeds allow for the rapid identification and punishment of lawbreakers. Constant monitoring is crucial for CCTV surveillance, which may be a time-consuming and error-prone process when performed by humans. In this work, we explore ways to automatically retrieve licence plates from motorbikes whose riders aren't wearing helmets, as well as to track the whereabouts of motorcycles whose riders aren't wearing helmets.

2 Literature Survey

Multiple methods have been used for quite some time to identify headgear. There is a wide selection of methods and techniques to choose from in vision systems. CNN, Image recognition algorithms, image analysis, etc. are only few of the methods utilised for helmet recognition. Evidence from studies shows that object identification methods function effectively in videos. YOLO, SSD, and Accelerated R-CNN are the most commonly prevalent methods for detecting objects. When contrasted to a YOLO image identification method, SSD and Faster R-CNN are noticeably slower. In this study, we describe a YOLO-based method for identifying helmets and licence plates.

3 Proposed Methodology

There are two components to the procedure outlined above. Firstly, bikers are checked for triple riding and helmets. Secondly, spotting unprotected motorcyclists by their licence plates. There is an identical implementation of the YOLOv4 Darknet model for detecting objects in both sections. Pictures are used as input for both frameworks, and both still and moving examples are used for assessment.

3.1 Exploration

Figure 1 shows a conceptual representation of the working model. The YOLOv4 CNN-based helmet identification algorithm is fed photographs to identify helmets and number plates. Pictures of bikers without helmets are extracted after helmet recognition has been conducted. The registration plate classification method is then fed with these photos. Furthermore, a YOLOv4-trained model for identifying license plates has been developed. Registration plates are read, then clipped and stored.

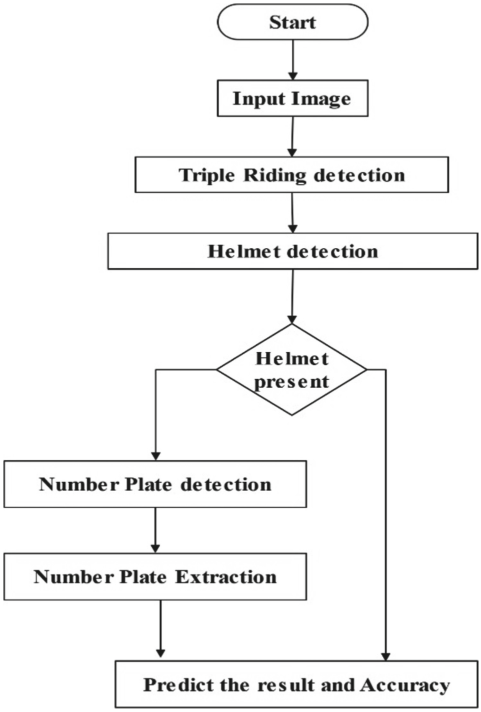

Fig. 1. Process flow of suggested approach

3.2 Suggested System

The YOLOv4 model is employed for Object Recognition in the suggested method. When compared to its predecessor, the YOLOv3 iterative algorithm, YOLOv4 represents a significant improvement. The Object Recognition CNN serves as the foundation for YOLO. All of the source image is processed by a single neural network (NN) and then segmented using the SxS panel in YOLO. Thus, each panel cell can only make a single prediction about a given category or kind of item. Protective gear and license plate designate a certain category. Each panel then makes a classification and box prediction. The class's rectangular boundaries are denoted by "rectangular shaped boxes." Where the thing is located is shown. Different rectangular shaped boxes are predicted by the model, but only the highest-scoring ones are considered true detection. The name YOLO comes from the fact that YOLO only has to query the NN once to make a prediction.

3.3 A System for Identifying Drivers' License Plates and Safety Helmets

The newest version of YOLO, v4, is used for both helmet and registration platerecognition. The process of developing the algorithm is the same for both. Initial input consisted of the photographs themselves. Separate sets of pictures were created for the training and testing phases. The settings for model development in YOLOv4 are stored in an admin panel. Learned rate, CNN architecture, and predicted class are just few of the settings you may tweak in the admin panel. Only motorcyclists who are not protecting their heads with helmets will have their licence plates checked. As a result, two separate algorithms, one for helmet identification and a second for licence plate recognition, are generated. After identifying helmets, the photos of bikers without helmets are extracted; from there, licence plate recognition is performed. Precision is used to measure the efficacy of the system. After 200 repetitions, it is computed. The YOLO frequency repetition at which observations are most accurate is chosen.

Helmet Recognition and Registration Number Recognition Training in YOLO requires the following setup settings which was tabulated in below Table 2 (Table 1) (Table 3 and Table 4).

Table 1. Represents various survey papers implementation results and methods.

Research	Method	Disadvantages
S. Kadam et al. (2021) [3]	YOLO	Accuracy is low
B. Srilekha et al. (2022) [4].	YOLO	The primary research flaw is its dependence on a high-quality input video or picture
D. S. S. Sarma et al. (2021) [5].	ML	The technology's ability to analyse data quickly means that it may be challenging to identify every item in the picture
P. Sathe et al. (2022) [6].	YOLO	Securitycameras will have a hard time getting decent video
F. A. Khan et al. (2020) [7].	DL & MV	Accuracy is low
M. I. Hossain et al. (2021) [8].	DL	The platform's performance may potentially suffer in dim lighting
Y. Kulkarni et al. (2018) [9].	CNN	Only 3 parameters were considered for assessment
S. Maheswaran et al. (2022) [10].	YOLO	Only one parameter was considered for performance evaluation
D. Manocha et al. (2019) [11].	OpenCV & OCR	Only two parameters were considered for performance evaluation
S. Shanmugam et al. (2021) [12].	DL	Not an fully automated system
PremmaranG etal. (20220 [13].	ML	Class imbalance was not considered for dataset
R. S. Charran et al. (2022) [14].	YOLO	Not an fully automated system
R. Ferdian et al. (2022) [15].	DL	A high-quality input source is not being recorded

Table 2. Configuration settings

Batch	Subdivisions	Steps	Classes	Filters	width	Height	Class-1	Class-2
64	24	2800, 4200	2	20	500	500	With helmet	Without helmet
64	24	2800, 4200	2	20	500	500	With Number plate	Without Number plate
64	24	2800, 4200	2	20	500	500	With Triple Riding	Without Triple Riding

Table 3. Validation via Recognition on Sample Pictures

S. No	Category	Limit	Accuracy
1	Helmet Recognition	0.7	85.77%
2	Licence plate Recognition	0.7	77.33%
3	Tripe Riding	0.7	67.11%

Table 4. represents performance comparisons by time taken, precision and recall.

Performance	Time taken to identify	Precision (%)	Recall (%)
Existing	0.008s	86.28	86.53
Proposed	0.003 s	88.12	87.21

4 Results and Discussion

To get the helmet recognition dataset, see [12] on kaggle. Descriptions on 764 photos made up the database. In addition to the database, one hundred more photos were collected through web scraping and labelled. All of the notes were written in PAscal VOC format. Description includes the rectangular grid boxes and other data for each picture. To facilitate YOLO training, the descriptions were changed to the appropriate format. Several of the descriptions and photos in the collection were flawed. After reducing the database, we settled on 760 photos with descriptions for the training phase. In the case of licence plate recognition, the dataset included 684 photos with corresponding descriptions. Train and test data sets were created. There were a total of 608 photos in the training dataset for helmet identification, but there were only 152 in the testing dataset. There were 548 photos in the training set and 136 in the testing set for licence plate recognition. Google Colaboratory was used for all the investigations. It's a Python development and ML platform hosted in the cloud. Google's cloud platform supports

Intel Xeon processors running at 3.3 GHz, NVIDIA K80 GPUs with 4 cores, 18 GB of RAM, and 35 GB of storage capacity.

The best Mean Average Precision (MAP) for detecting helmets is at repetition 2000, with a threshold of 0.5 IOU. Three bikers' helmets have been detected in Fig. 2. Posterior distribution and recognition of the helmet inside the rectangular frame are shown. The best MAP for identifying licence plates is 67.25 percent at 2000 iterations, using a 0.5 IOU criterion. We find that YOLOv4 outperforms [10] by a wide margin. In contrast to YOLO's completely linked layers, the [10] makes use of pooling layers of variable sizes. YOLOv4 outperforms the [10] in terms of speed and efficiency. On the MSCOCO database, YOLOv4 has the best MAP. When it comes to testing object recognition techniques, the COCO database is by far the most often used option.

Fig. 2. Three motorcyclists were checked for helmets.

Fig. 3. Two bikers' helmets were scanned and found to be present.

Fig. 4. One bikers' helmets were checked for helmets

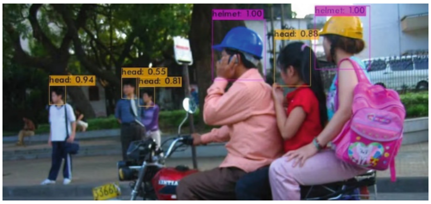

Fig. 5. Testing Triple riding images

The findings are shown in Fig. 2, 3, 4 and 5. The recognition of helmets worn by bikers is shown in Figs. 2 and 3. Figure 4 demonstrates that a motorbike without a helmet is being used to test out the registration plate recognition system. Figure 5 demonstrates testing triple riding images. Table 3 displays a tabulation of the identification categories and their corresponding efficiency. Interpretations on the photographs are shown in the Table 3. To demonstrate, in Fig. 2, the system successfully identified all three bikers. The model's predictions for the various courses are spot on. Two bikers are seen in Fig. 3. The framework describes the biker from a considerable distance and with a high degree of precision. The photos are captured with a high degree of precision. The quicker transfer rate is a result of the picture only having to be sent via the network once. After being seen, the licence plates are removed. Observations are stored in a json file. The file's rectanglar frame coordinates are used to selectively trim and retrieve the licence plate. When the model detects an object, it will only display its rectangular frame if the associated class probability is more than 70%. Below the 0.7 cutoff, any further identification is ignored. Table 3 represents the accuracy of the model (Fig. 6).

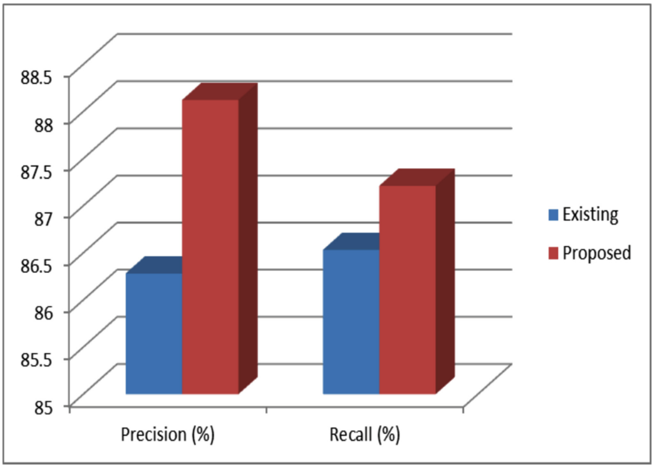

Fig. 6. Precision and recall of existing and proposed

5 Conclusion

This study demonstrates how licence plate identification may be used to identify bikers, both with and without helmets. The overall average accuracy for helmet identification is 85.77%, while for licence plate recognition it is 77.33% and for triple riding it is 67.11%. For both helmet and licence plate recognition, the model relies on the CNN-based YOLOv4. The detection performance of YOLOv4 is acceptable, and it provides decent precision. The licence plate of the biker who wasn't protecting his or her head was retrieved. Growing the dataset will help the algorithm become more accurate. In order to improve the recognition rate, it is recommended that more photos from a variety of settings be contributed to the collection. Inaccuracy in number plate identification may be attributed to the fact that the data source used for the task includes both bicycle and automobile licence plates. Adding additional photos of motorcycle licence plates may improve the reliability of licence plate recognition. Maximum benefits may be achieved by using and comparing several alternative techniques.

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