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Third Eye: A Comprehensive Solution for Road Safety

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Abstract

Factors such as reckless and careless driving have led to a rapid increase in two-wheeler accidents, leading to an increased fatality rate. As per a recent United Nations survey, lives of at least four in ten motorcyclists who die in road accidents could have been saved by wearing proper head safety gear. It becomes utmost clear to impose strict helmet regulations. However, the limited presence of traffic police personnel makes it impossible to pursue legal action against every violator. Thus, automating this process of handling violations is highly desirable. We propose a system that will monitor live feeds from inputs such as traffic surveillance systems, vehicle dashcams, and traffic personnel bodycams to detect the offense. The system in discussion will be lightweight and optimized to work efficiently on existing commodity hardware. Suppose the motorcyclist is not wearing a helmet. In that case, the system will record the offense by capturing the license plate information along with snapshots of the vehicle, location and timestamp of the offense.

Keywords: Machine Learning, YOLO, Object Detection, Automated Helmet Detection, ALPR, OCR.

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Introduction

In India, the use of two-wheeler vehicles is more than the use of any other vehicle due to varied factors such as affordability, compact size, convenience of parking, etc. A rampant increase in 2-wheeler accidents, resulting in increased accident fatality, has been observed. Helmets absorb most of the impact during a crash or fall, rather than your head and brain, which could be fatal. Studies have shown that wearing a helmet lowers the rate of fatalities in motorcycle accidents by more than 70%. Not wearing a helmet is a traffic violation and a highly overlooked safety risk. Limitations such as limited traffic personnel, etc., result in poor helmet regulation. The proposed system helps overcome the limitations by automating this process. If the motorcyclists are not wearing a helmet, it will record the offense and will make it easier for the traffic police to take speedy, legal action against such violators. The wearing of helmets by bike riders will definitely be enforced if law enforcement effectively reports the violators by taking quick legal action. RTO can implement this technology on existing surveillance systems to automatically file "challans" against violators in real-time.

The system in discussion is divided into two parts: detecting the violation and storing the vehicle information using ANPR and OCR techniques. The detection model is built using YoloV3 algorithm.[1-4]

Related Work

In their research, Yonten Jamtsho *et al.*[5] focused on the identification of motorcycle license plates for riders who were not wearing helmets. For video stream detection, one CNN network was employed. A central tracking approach was implemented to recognize and avoid situations where false-positive detections can occur. 98.52% of the obtained license plate information was correct. It was successful to get rid of false positives using a horizontal line. Additionally, the dataset received from Naresuan University in Phitsanulok, Thailand, was the only one used, which revealed a research need.

In their work, K. Han *et al.*[6] employed YOLO v5 to detect helmet wear while incorporating transfer learning and targeted data augmentation. The major goal was to automatically determine if workers were wearing helmets on construction sites.

The specific study by P. Doungmala *et al.*[7] employed a novel strategy for helmet detection in which they combined two algorithms to achieve their desired judgment rates. When detecting helmets with and without helmets, Haar-like properties are employed. In contrast, half-helmets and no helmets are employed when using the Circle Hough Transform. High detection rates and few false positives are produced when tested on photos. In this work, the technique for detecting moving objects was effectively investigated.

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The focus of the study by F. Wu *et al.*[8] is the usage of Densenet for the model parameters. A YOLO- Densebackbone convolutional neural network has been developed by them. It addresses some significant problems, like poor image resolution.

Dr. V.P. Balpande *et al.*[9] In this paper, they use computer vision techniques, like image processing algorithms and machine learning, to detect if motorcyclists wear headgear or not and recognize license plates from surveillance images or videos. For object detection, they are using YOLO. For object classification, they are using SVM (support vector machine).

B. Yogameena *et al.*[10] They use deep learning techniques for analyzing helmets worn by bike riders. In this paper, they are using deep learning techniques like Convolutional Neural Networks (CNNs) and image processing algorithms to analyze helmet wear by motorcycle riders from images or videos captured by surveillance cameras. This paper also discusses the use of popular deep learning frameworks, data collection and annotation techniques, and evaluation metrics for assessing the system's performance.

Methodology

Objective

To develop a smart system, referred to as "Third Eye" by the authors. A lightweight, optimized system capable of detecting motorcyclists not wearing helmets and recognizing the vehicle license plate for further legal action.

Modules

- Input Module: This module captures the input feed and propagates it further for the next steps. Video can be a direct live feed or a recorded input video as discussed earlier.
- Frame Separation and Bike Detection Module: This module receives the data from the input module as a continuous stream which is broken down into individual frames, and bikes are detected in each frame, respectively. The bike detection module works on the individual images.
- Helmet Detection Module: The portion of the bike detected is received, and the helmet detection works on it to generate results. The frame is sent to the number plate recognition system if no helmet is detected in the frame.
- Number Plate Recognition Module: The license plate recognition module detects the number plate and recognizes the registration numbers using OCR. The images along with the detected numbers, are sent to the storage system.
- Storage Module: This module stores the image as proof along with the system-recognised numbers for further legal action. System overview is shown in Figure 1.

Data Annotation

We used LabelImg tool to manually label/annotate the images used in training the model.

Flowchart depicting the working

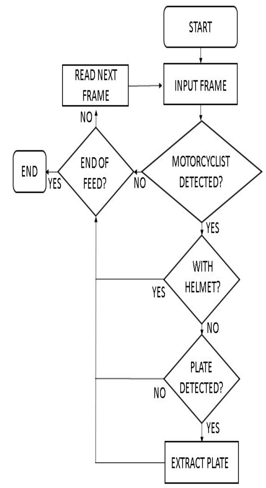

Figure 1: Execution Flow

Implementation

Dataset and Data Annotation

A dataset of motorcyclists with clear number plate captures is not available. We created a custom dataset manually consisting of real-time recorded videos and photographs collected from various motorcycle hotspots in Mumbai. Manually labeled the dataset of over 1000+ images of bike riders with and without helmets using the LabelIMG tool. LabelIMG is an annotation tool for images. It saves images as XML files for labeled images. It is often used to draw visual boxes around objects.

Divided the dataset samples randomly into training set and validation set categories using the general 80:20 split ratio (80% for training and 20% for testing).

Training

Trained the model on Google Colab using Tensor K80 GPU and 12GB RAM. Python 3.10.6 was the programming language used. AP with average IOU of every class is shown in Table 1.

YOLOv3 object detection includes Darknet-53, (Figure 2) which is a convolutional neural network.[1-3] Its predecessor, Darknet-19, included the use of residual connections and additional layers.[2]

Table 1: AP with average IOU of every class

Epochs	*Rider*	*Helmet*	*Plate*	*Avg IOU*
1000	97.77	97.08	98.17	71.58
2000	96.80	97.57	98.53	73.12
3000	96.48	98.43	98.16	74.12
4000	97.29	98.17	98.39	74.59
5000	96.58	98.15	98.24	74.5
6000	97.09	97.96	98.21	74.53
7000	96.95	97.93	98.4	74.72
8000	96	97.48	98.41	74.62

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
	Convolutional	32	1 × 1	
1×	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
	Convolutional	64	1 × 1	
2×	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
	Convolutional	128	1 × 1	
8×	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
	Convolutional	256	1 × 1	
8×	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
	Convolutional	512	1 × 1	
4×	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Figure 2: Darknet-53

Results And Discussion

We have chosen a sample set of 200 motorcyclists to determine system accuracy. Motorcyclists with helmets are 90, and those without helmets are 110 (Table 2). F1-score determines accuracy of our system. See Table 3 for system accuracy metrics. Figures 1 to 5, depict the helmet and license plate detection phase. Figure 6 depicts the OCR output on detected license plate. See Table 4 for OCR model accuracy.

Confusion Matrix

Table 2: Confusion matrix

	With Helmet	*Without helmet*
With helmet	88	2
Without helmet	3	107

Evaluation Metrics

Table 3: Evaluation metrics

	Precision (%)	*Recall (%)*	*F1-Score (%)*
With helmet	96.70	97.78	97.24
Without helmet	98.17	97.27	97.72
Weighted avg	97.51	97.5	97.504

Results

Figure 3: Detection of bike rider with helmet

Figure 4: Detection of bike rider with helmet

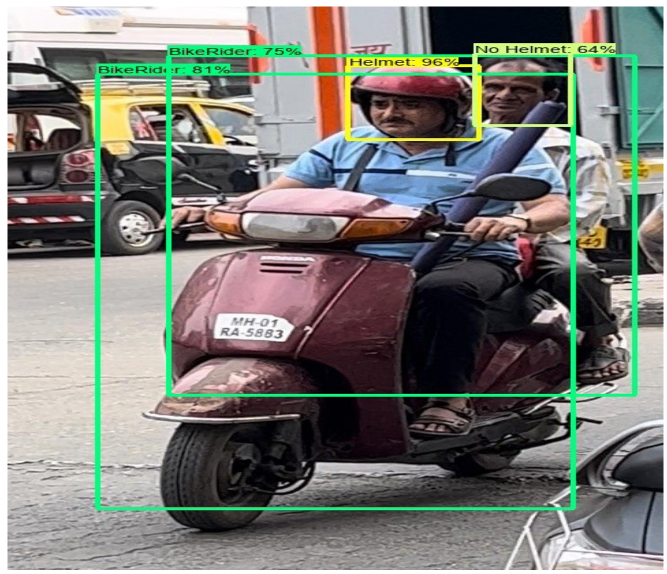

Figure 5: Detection of bike rider with helmet and pillion rider without helmet

Figure 6: OCR output on cropped license plate

Table 4: OCR output of 5 LP taken randomly

Observed	*Predicted*	*Correctness*
MH47 AM5753	MH47 AM5753	100%
MH02 BW2588	MH02 8W258B	80%
GJ03 LK0563	GJ03 LK0563	100%
TN24 AU0597	TN24 AU0597	100%
TN07 CM1347	TN07 CM13A7	90%

Conclusion

The initial phase included the completion of vehicle and helmet detection. The next stage was finding the license plates of riders who weren't wearing helmets. We successfully trained and tested our model on a tailored dataset of video recordings taken from Mumbai's streets under various illumination conditions to account for both daytime and nighttime traffic activity. Additionally, we trained the Yolov3 model using a customized dataset of more than 1000 photographs.

Future Scope

The future enhancements to this system would preferably be to accelerate and make the detection process more rampant. Another enhancement would be to detect other traffic law infractions like over-speeding, running red lights, etc.

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