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A REAL TIME DETECTION OF LICENSE PLATE FOR NON-HELMETED MOTOR CYCLIST USING YOLOv5

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Abstract
In the current situation, we come across various problems in traffic regulations in India which can be solved with different ideas. Riding motorcycles/mopeds without wearing a helmet is a traffic violation that has resulted in an increase in the number of accidents and deaths in India. The existing system monitors traffic violations primarily through CCTV recordings, where the traffic police have to look into the frame where the traffic violation is happening and zoom into the license plate in case the rider is not wearing a helmet. But this requires a lot of manpower and time as traffic violations frequently and the number of people using motorcycles is increasing day by day. What if there is a system that would automatically look for traffic violations of not wearing a helmet while riding a motorcycle/moped and if so, would automatically detect the vehicle's license plate number? This project presents the real-time detection of license plates for non-helmeted motorcyclists using the real-time object detector YOLO (You Only Look Once). In this proposed approach, a single convolution neural network was deployed to automatically detect the license plate of a non-helmeted motorcyclist from the video stream. Recent research has successfully done this work based on CNN, R-CNN, LBP, HoG, HaaR features, etc. However, these works are limited with respect to efficiency, accuracy, or the speed with which object detection and classification are done. In this project work, a Non-Helmet Rider detection system is built which attempts to satisfy the automation of detecting the traffic violation of not wearing helmets and detecting the vehicles' license plate numbers. The main principle involved is Object Detection using Deep Learning at three levels. The objects detected are a person, a motorcycle/moped at the first level, and a helmet at the second level using YOLOv5. All these techniques are subjected to predefined conditions and constraints, especially the license plate number detection part. Since this work takes video as its input, the speed of execution is crucial. We have used above said methodologies to build a holistic system for both helmet detection and license plate number detection.

Keywords: YOLO, Deep Learning, Helmet, neural network, Classification, license plate.

I. Introduction

Since the Internal Combustion Engines have become efficient and affordable, the two-wheeler motorcycles are the most preferred use of transportation methods in developing nations. However, the risks associated with driving a motorcycle are comparatively higher than other modes of transportation. Helmets are considered as one of the simple yet remarkable solutions in reducing the severity of head injuries and fatality rates of the riders. This problem could be overcome over time by penalizing the riders without helmets by identifying them using their vehicle's license plate. Even though the Government has mandated the use of helmets for both the rider and the pillion rider, it is not feasible to monitor the roads 24x7 by employing traffic police personnel for checking the compliance status. This project aims to address this issue, by employing Object Detection Algorithms to the video sourced from the traffic surveillance cameras to effectively classify the riders without a helmet and capture their vehicle's license plate and extract the Alphanumeric characters so that we could use this information to identify and penalize the riders without a helmet.

Convolution Neural Networks (CNN) is one of the most computationally efficient Deep Learning algorithms used for image recognition. You Only Look Once (YOLO) is one such algorithm that can recognize objects from images, videos, or streaming services in real-time. Since in this project we aim to detect the helmets using a video source it is important to consider that the algorithm is fast enough to detect objects in higher Frames Per Second (FPS). The YOLO algorithm is incredibly efficient in that it detects objects at 45FPS making it the suitable algorithm for this application. There have been few kinds of research that previously used algorithms YoloV3. But, for this project, we will be using the YoloV4- Dark net and YoloV5s algorithm which are comparatively newer and has never been tried before for this application. Followed by Helmet detection, the License Plate detection will be performed using SSDMobileNetV2 FPN lite which is a lightweight CNN. Extraction of Characters from the license plate will be performed using EasyOCR. The data collected from various sources will be manually annotated and trained on both the algorithms and compared to find out the suitable model for this application.

1.1 Assumptions

1. Only 2 persons are riding on the bike (Standard protocol allows only 2 persons to ride on a motorcycle.
2. The Design of the License plate and the Alphanumeric characters present on that are set according to the Government standards.
3. The model will be trained with Indian motorcycle License plate images for demonstration.

1.2 Methodology

In this study, a Non-Helmet Rider noticing system is built which attempts to satisfy the automation of detecting the traffic violation of not wearing a helmet and detecting the vehicles' license plate number. The main concept involved in Object Detection using Deep Learning at three steps. The objects detected are person, motorcycle at first step using YOLOv2, detecting helmet at a second step using YOLOv3, recognizing license plate at the last step using YOLOv2. Then the license plate registration number is takeout using OCR (Optical Character Recognition). All these techniques are put through to prearrange conditions and constraints, especially the license plate number extraction part. Seeing that this work takes video as its input, the speed of execution is crucial. We have used above said procedure to build a holistic system for both helmet and license plate number extraction.

1.3 Scope of the Proposed Work

In this study, we are detecting whether a two-wheeler rider wearing a helmet or not if he is not wearing a helmet then we are extracting the number plate of that two-wheeler. To extract the number plate we have the YOLO CNN model with some train and test images and if you want to add some other images then send those images to us so we can include those images in the YOLO model with annotation to extract the number plate of those new images.

II. Literature Survey

2.1 Helmet Detection

Vakani *et al.* (2020) in these study motorcyclists without helmets are recognized, and the picture of the license plate is recorded as an image, according to the research. The investigation is limited by the fact that no characters from the license plate are recognized. This approach creates duplication, and it is not possible to digitally save the pictures of the license plate and utilize them for future research.

The Histogram of Oriented Gradient (HOG) and Circular Hough Transform (CHT) are some of the widely used feature extraction techniques in the object detection domain Ranchman Jibril *et al.* (2021). CHT is utilized in the detection of circular objects. HOG feature extraction and classification using KNN are the two components of the classification module. Pre-processing of the recorded frames, computing the gradient and then calculating the HOG value in each cell, normalizing each block, and calculating the feature is all part of the HOG feature extraction process. In pre-processing, all frames in the footage are transformed to grayscale, contrary to previous studies. In each cell, the HOG is calculated by matching the Gradient Direction and Magnitude. The article ended with a discussion of the future potential for identifying license plate characters, which is now being incorporated into my project. In the following part, we'll look at how a lightweight Neural Network model called MobileNet may be used to identify helmets and license plates.

2.2 License Plate Detection

Using the K-NN algorithm for extracting the alphanumeric character from the license plate is discussed in this research Dari *et al (2021*). The data utilised in this study for training and testing was collected in broad daylight. The Mobile Net version that was utilised in this study is unclear. To determine which model works better for this purpose, this model must be evaluated to other image recognition algorithms. Rajkumar, Mahindra (2020) discusses the effective two-step approach for helmet recognition and Licence plate detection is restricted to the recognition of those objects and does not include alphanumeric character recognition from the licence plate. Enhanced Key Frame Identification (KFI) and Background Separation are the two-step methods presented in this study. From the input data, the KFI is utilised to extract a set of optimum frames. The Candidate KFI employs Feature Vector Generation and improved Key frame Clustering. A Discrete Wavelet Packet Transformation (DWPT) approach is utilised to distinguish the foreground and background pictures in the background separation technique. The input video is transformed to frame sequences, and the frames are identified using Key Frame Identification. Once the best frames have been found using this approach, DWPT is used to separate the background picture from the licence plate. The licence plate is isolated from the remainder of the image in the resulting frames, which are then post-processed. Valencia *et al*. (2020) research discusses various technologies utilised in ITS are discussed in this study.

III. System Analysis

3.1 Problems with Existing System

Existing system monitors the traffic violations primarily through CCTV recordings, where the traffic police have to look into the frame where the traffic violation is happening, zoom into the license plate in case rider is not wearing helmet. But this requires lot of manpower and time as the traffic violations frequently and the number of people using motorcycles is increasing dayboy-day. What if there is a system, which would automatically look for traffic violation of not wearing helmet while riding motorcycle/moped and if so, would automatically extract the vehicles' license plate number. The License plate extraction code extracts only from the motor bikes which has a rider who is not wearing helmet and discards the License plate of the motor bikes whose rider has helmet. The OCR model is able to detect and recognize the License plates present in an image with an accuracy up to 85 percent. In recent years, many researchers have solved the problem of license plate detection for vehicles. License plate detection is one of the crucial steps in the Automatic Number Plate Recognition (ANPR) since the accurate detection of license plate hampers the accuracy of segmentation and the recognition stages. One of the distinguishing features used in license plate detection is its geometric shape with the known aspect ratio. In and, a vertical Sober operator was applied to detect the vertical edges followed by plate verification using width to height aspect ratio. The boundary-based approach is more sensitive to unwanted edges. Some license plates have different colors to differentiate the ownership of the vehicles. Shi et al. proposed an HSI (hue, saturation, intensity) model for license plate detection since these color models are insensitive to different illumination. Similarly, many researchers have also proposed a method that involves the detection of motorcyclists, followed by checking whether the motorcyclist wears a helmet or not. For detection of moving objects, the authors in have proposed a background subtraction method to extract the moving object and classify them by extracting features using Local Binary Pattern (LBP) . After getting the motorbike, the 1/5 of the image from the top was cropped to get the helmet section and classified it using HOG, Hough Transform and LBP descriptors. In and, the authors have also proposed a background subtraction to detect the object followed by connectedcomponent labeling to segment the object. In, the object is classified as a motorcycle or another object using a kNN classifier whereas in, visual length, visual width and pixel ratio as proposed by Chiu et al. to find the motorcycles. Wen et al. proposed a circular arc detection method based on the modified Hough transform for the detection of a helmet in the ATMs. With the advancement in the computer vision technology, a CNN based LP extraction fornon-helmeted biker was proposed in. In their approach, they have used two YOLOv2 model for the detection of a motorcyclist and helmet. Hirota et al. also proposed a CNN based classification of a helmeted and non-helmeted motorcyclist but, different colors of helmet hampered the detection accuracy.

3.2 Proposed System

A system to detect moving objects using a KNN classifier over the motorcyclist's head to classify helmet. These models were proposed based on statistical information of images and had a limitation to the level of accuracy that could be achieved. With the evolution of neural networks and deep learning models there was further improvement in the accuracy of classification. Introduced a convolution neural network (CNN) based method for object classification and detection. Use a CNN for classification of helmeted and non-helmeted riders. Although they use CNN, their helmet detection accuracy is poor with limitations to helmet color and multiple riders on a single motorcyclist. For real-time helmet detection, there is a need for accuracy and speed. Hence a DNN based model You Only Look Once (YOLO) was chosen. YOLO is a state-of-the-art, real-time object detection system. YOLOv3 is extremely fast and accurate and is a huge improvement over the previous YOLO versions In the primary stage, we identify a bicycle rider in the video outline. In the subsequent stage, we find the leader of the bicycle rider and recognize the number plate and furthermore distinguish whether the rider is utilizing a head protector or not. So as to decrease bogus forecasts, we merge the outcomes from successive casings for conclusive expectation. The square graph shows the different strides of proposed system, for example, foundation subtraction, include extraction, object order utilizing test outlines. As helmet is important just in the event of moving bicycle riders, so preparing full casingbecomes computational overhead which doesn't increase the value of discovery rate. So as to continue further, we apply foundation subtraction on dim scale outlines, with an aim to recognize moving and static items. Next, we present advances associated with foundation displaying.

3.3 Proposed System Architecture

For detecting helmet and recognizing license plate. The whole process consists of five steps. For detection of the helmet, we first insert the photo of the motorcyclist and in the next step, we process the video and remove the background. The third step involves the segmentation of two-wheelers. Next step the system detects persons without a helmet. In the last step, we detect the license plate

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and display the license plate number from the image.

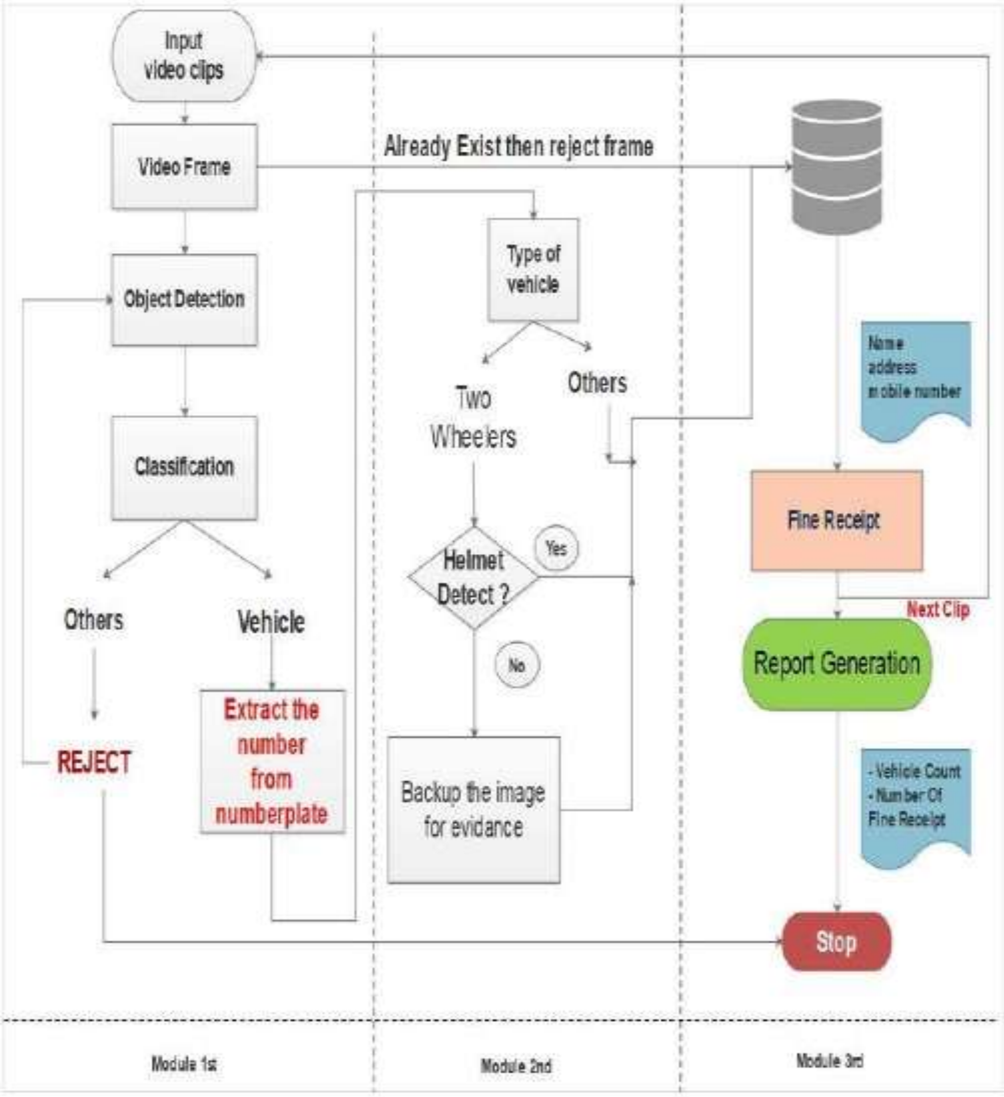

Fig 1: Proposed System Architecture

A system to detect moving objects using a KNN classifier over the motorcyclist's head to classify helmet. These models were proposed based on statistical information of images and had a limitation to the level of accuracy that could be achieved. With the evolution of neural networks and deep learning models there was further improvement in the accuracy of classification. Introduced a convolution neural network (CNN) based method for object classification and detection. Use a CNN for classification of helmeted and non-helmeted riders. Although they use CNN, their helmet detection accuracy is poor with limitations to helmet color and multiple riders on a single motorcyclist. For real-time helmet detection, there is a need for accuracy and speed. Hence a DNN based model You Only Look Once (YOLO) was chosen. YOLO is a state-of-the-art, real-time object detection system. YOLOv3 is extremely fast and accurate and is a huge improvement over the previous YOLO versions. In the primary stage, we identify a bicycle rider in the video outline. In the subsequent stage, we find the leader of the bicycle rider and recognize the number plate and furthermore distinguish whether the rider is utilizing a head protector or not. So as to decrease bogus forecasts, we merge the outcomes from successive casings for conclusive expectation. The square graph shows the different strides of proposed system, for example, foundation subtraction, include extraction, object order utilizing test outlines. As helmet is important just in the event of moving bicycle riders, so preparing full casing becomes computational overhead which doesn't increase the value of discovery rate. So as to continue further, we apply foundation subtraction on dim scale outlines, with an aim to recognizemoving and static items. Next, we present advances associated with foundation displaying.

IV. Project Implementation

The implementation part of this project is carried out in 3 different parts. The first part consists of the Detection of Helmeted and non-helmeted motorcyclists from a video source using the YoloV5. The second part follows a similar procedure, but the data would be trained with the YoloV5s algorithm. The third part involves annotating the License plate images and using the SSD MobileNetV2 FPN Lite algorithm for detection.

4.1 Helmet Detection using YoloV5

For implementation, PyCharm has been used with a runtime set to use GPU for acceleration. The YoloV5 model that is needed to be implemented is cloned from the repository5. For custom object detection for YoloV4, 3 significant files are to be created and modified. The first one is a custom configuration file where we can set custom filters and batch sizes for the neural networks. The batch contributes to the number of images processed per iteration. The batch number will be set as 64. Further, the smaller number of batches can be created using subdivision and this count will be set to 16. The maximum number of batches (max_batch) sets the number of iterations for the darknet Yolo. 2000 iterations for a single class are ideal for this application. Since we have 2 classes (Helmeted riders and non-helmeted riders)2000*2 = 4000 will be set as max_batch. The second file will be the object data file. The object data file contains the information regarding the number of classes, paths associated with the training, test and validation folders that contain both the images and corresponding annotations. The third file will be the object names file which contributes to setting the name of the classes that are to be detected from the video. 'With Helmet', 'Without Helmet' is set in this file. Darknet algorithm is developed to take full advantage of CUDA and CUDNN architectures which are needed to run the models with the help of GPU. Hence CUDA and CUDNN are enabled in code for this purpose. The data is present in .zip format in Google Drive, these contents are unzipped to corresponding folders created in the colab. Training and Test files in .txt format contain the list of names of the data in corresponding folders. This is generated by invoking the process file in the model. Then the model training will be initiated. The Mean Average Precision (mAP) and the loss function calculation are carried out by the darknet detector for every 100 epochs. The threshold value is set to 0.5 to not include detections with a confidence score below 50%.

4.2 License plate detection

The License plate detection is carried out by importing TensorFlow 2 Machine learning library. The pre-trained models (trained on COCO Dataset) is obtained from the TensorFlow GitHub repository6. However, the model needs to be custom-trained using the License plate dataset. The previously trained and saved checkpoints will be removed for this purpose. The label map creation will be done. The label map is a .txt file that contains information about the number of classes to be detected and the corresponding name. Since we only detect the license plate, the number of classes will be 1. The TensorFlow record file (TF record) file for both the training and the test data will be created. The images and annotations cannot be separately processed by TensorFlow.

Fig 2: Helmet detection snapshot from video using YoloV5

Hence both the images and annotations will be converted to binary files which can be processed by the Tensor Flow algorithm. The pipeline configuration file will be updated with the label map, test and train records paths. With these ideal conditions, training for the model would be initiated.

Fig 3 :Licensed Plate Detection

V. RESULTS

The initial objective is to train the model to 10,000 Epochs. But due to hardware limitations such as free GPU availability time in Google Colab, longer training time, the trainingwas later limited to 3000 Epochs. The metrics displayed below are for the same.

Metrics	Score
Precision(Test Data)	51.06%
Total Detection Time	900ms
Total Layers with Weights	232

Table 1:YOLO V5 Metrics

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video 1/1 (24/31) /content/gdrive/MyDrive/yolov5/video.mp4: 384x640 5 With Helmets, Done. (0.010s)
video 1/1 (25/31) /content/gdrive/MyDrive/yolov5/video.mp4: 384x640 5 With Helmets, 1 Without Helmet, Done. (0.010s)
video 1/1 (26/31) /content/gdrive/MyDrive/yolov5/video.mp4: 384x640 5 With Helmets, 1 Without Helmet, Done. (0.010s)
video 1/1 (27/31) /content/gdrive/MyDrive/yolov5/video.mp4: 384x640 2 With Helmets, 1 Without Helmet, Done. (0.010s)
video 1/1 (28/31) /content/gdrive/MyDrive/yolov5/video.mp4: 384x640 1 With Helmet, Done. (0.010s)
video 1/1 (29/31) /content/gdrive/MyDrive/yolov5/video.mp4: 384x640 1 With Helmet, Done. (0.010s)
video 1/1 (30/31) /content/gdrive/MyDrive/yolov5/video.mp4: 384x640 1 With Helmet, Done. (0.010s)
video 1/1 (31/31) /content/gdrive/MyDrive/yolov5/video.mp4: 384x640 2 With Helmets, Done. (0.010s)
Results saved to runs/detect/exp3
```

Fig 4: Glimpse of model performance during detection from video

Video resolution impacts the Frames processed per second and the detection time. The video resolution processed in this study is 384*640, where the original video stream resolution is 960*540.As we could see from the figure 15 that the precision shows an upward trend, which signifiesincreasing the number of iterations of training could improve the precision factor. The loss shows a downward trend till the training are carried out, which signifies that increasing the number of iterations of training could still decrease the loss factor.

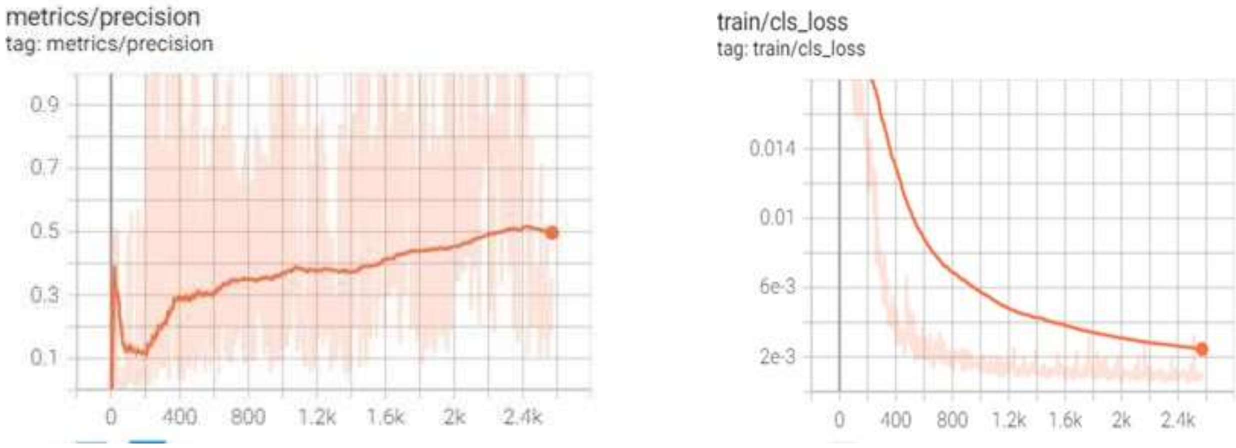

Fig 5: Precision and Loss Graph

As we could see from the above metrics, the precision of both the YOLO models has been found to be low. However, the confidence score was found to be better for real-time detections. The metrics are always dependent on various factors such as the quality of the data, optimization of the model parameters, increasing the number of iterations of learning until it overfits the model. This research is limited by Hardware (GPU). Even though the model uses free GPU from Google Colab, it is limited by usage as Colab doesn't allow longer training times using their GPU. By having access to better GPU and longer usage limits, the training could have been improved for (6000 Epochs for YoloV4 and 10,000 Epochs for YoloV5s) which improves can improve the precision of the model. The error in extracting the alphanumeric character in thefinal step can be avoided by mandating standardized license plate character fonts across the region.

Fahad *et al.* (2020) has performed the study with YoloV3-tiny and was able to achieve anmAP of 81%. Meghal *et al.* (2020) have 91% accuracy with lightweight MobileNet CNN. However, in both these experiments, better hardware is used and longer training times are achieved. For comparing the results with previous studies, this research has to be further continued with dedicated, high-performance GPU for a longer training period. It is not possible to conclude that the one Yolo model performed better than the other in general terms as they are different in architecture, framework and object detecting techniques as discussed previously. Butfor this particular application, even though the Yolov4-darknet algorithm has

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higher precision than YoloV5s, due to higher detection time (which is crucial for traffic surveillance) easier prototyping and deployment, YoloV5s is a better model for implementing this system asprecision can always be improved through other techniques

Fig 6: Rider without helmet

Fig 7: License plate number

Fig 8: Pillion rider without helmet

Fig 9: Rider with helmet

VI. CONCLUSION AND FUTURE ENHANCEMENTS

From the results shown above it is evident that the YOLO object detection is well suited for real time processing and was able to accurately classify and localize all the object classes. The proposed end-to-end model was developed successfully and has all the capabilities to be automated and deployed for monitoring. For extracting the number plates some techniques are employed by considering different cases such as multiple riders without helmets and designed to handle most of the cases. All the libraries and software used in our project are open source and hence is very flexible and cost efficient. The project was mainly built to solve the problem of non-efficient traffic management. Hence at the end of it we can say that if deployed by any traffic management departments, it would make their job easier and more efficient. This solution can be commercially implemented after training the model with lots of real surveillance camera images and training till better precision is reached. The limitation of the proposed work is that the helmet and license plate detection work in two different flows. The system can be improved by combining both detections to work as a single process flow. The logic to detect only the license plate of non-helmeted riders should be included. This research excluded this scenario due to computational limitations. By addressing these limitations, an efficient system for helmet compliance can be developed. In the future we will extract the license plate number using the OCR and also UI will be design to easily use the project.

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