Traffic Rules Violation Detection System

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***Abstract*—In the world of new developing technologies, traffic violations have become a critical problem for most developing countries. As the population grows, the number of vehicles on the roads also increases rapidly and traffic violations also increase exponentially. The world is rapidly urbanizing. It has led to a multi fold increase in the number of vehicles driving on city roads that causes traffic violations more critical these days. This causes serious destruction property and more accidents that can threaten lives people. Solve the alarming problem and prevent it unpredictable consequences, detection of traffic violations systems are needed. Therefore, managing traffic violations has become a tedious task. Although there are several automated technologies to manage traffic violations, due to uneven lighting conditions, the variety of license plate formats makes it very challenging to manage these conditions. So, the solution to this problem is to develop a system that is linked to several parameters such as traffic signal detection, speed estimation to find out how often the driver violates the traffic rules. This system detects violations of traffic signs, which can be combined with speed estimation to control speeding and this information is sent to a database where the relevant authorities can take necessary action against violators.**

In this paper, we present a method that can automatically detect bike-riders without helmets using surveillance videos. The system first uses object segmentation and background subtraction to identify bike riders, and it then determines if they are using a helmet or not. In addition, we introduce a consolidation approach that can improve the accuracy of the proposed system for violation reporting. We tested the three feature representations of this method by comparing their performance. The results of the evaluation revealed that the detection accuracy of the system was 93.80 percent. The proposed method is significantly less expensive and can perform in real-time with an average processing time of 11.58 milliseconds.

KeyWords:-Data Collection, Python Open CV, Object Detection,Tensorflow.

I. INTRODUCTION

Traffic violations are now a major problem in 4,444 mostly emerging countries in today's changing world. The number of motorcycles on the road and the number of traffic violations are increasing rapidly. Monitoring traffic has always been the difficulty and risk of investigating violations. Although handling traffic is automated, this makes an extremely difficult challenge. Different plate sizes, rotations, and illumination are not consistent conditions when the captures images. Two-wheelers are very popular means of transport in almost all countries. However, with less protection, the risk of is high. To reduce the risks involved, cyclists are advised to wear a helmet. Seeing the effectiveness of helmets, the government made cycling without a helmet a punishable offense and resorted to manual tactics to catch offenders. However, existing video surveillance methods are passive and require significant human assistance[1].

In general, such a system is impractical due to human intervention, and its effectiveness drops over long periods of time. Automating this process is highly desirable for 4044 reliable and robust monitoring of these violations, as it can also significantly reduce the number of human resources 4044 required. Many countries also use systems that include surveillance cameras in public places. Therefore, a solution to detect violators using existing infrastructure is also cost effective[2]:

1) Real-time implementation: Processing large amounts of information in a limited time is a difficult task. Therefore, applications involve tasks such as segmentation, feature extraction, classification and detection, where a large amount of information has to be processed in a short period of time to achieve the execution goal in real time.

2) Occlusion: In real-world scenarios, dynamic objects often occlude each other, so the object of interest is only partially visible. For these partially visible objects, segmentation and classification become difficult.

3) Direction of movement: 3D objects generally look different when viewed from different angles. It is well known that the accuracy of a classifier depends on the features used, which in turn depend to some extent on the angle. A reasonable example is to consider the appearance of a cyclist seen from the front and from the side.

4) Temporary environmental changes: Over time, there are many changes in environmental conditions, such as light, shade, etc. Subtle or immediate changes can occur, adding to the complexity of tasks such as background modeling.

5) Video quality: Usually CCTV cameras capture low resolution video.

Due to these limitations, tasks such as segmentation, classification, and detection become more difficult. As mentioned in, a successful monitoring application framework must have useful properties such as real-time performance, fine-tuning, robustness to sudden changes, and predictability. With these challenges and desired functionality in mind, we propose a method to automatically detect helmetless cyclists using real-time mined feeds from existing safety cameras[2].

Considering the ever increasing traffic, it is clear that it is still difficult for the to detect everyone these situations, and it is also difficult to control road traffic, because it requires more people power[3]. This problem can also lead to dangerous situations such as accidents and traffic violations. Therefore, this research paper proposes an automated system to keep these violations under development control a computer vision system detects violations caused by vehicles and identifies the license plate of the vehicle being processed to send a notification to the host. In general, Computer Vision is about how systems obtain advanced capabilities from input images or video. This article discusses the process of locating and identifying a vehicle registration number. neurons for visual image analysis. This project is built on TensorFlow and depends on several libraries to perform the required operations[4].

II. Literature Survey

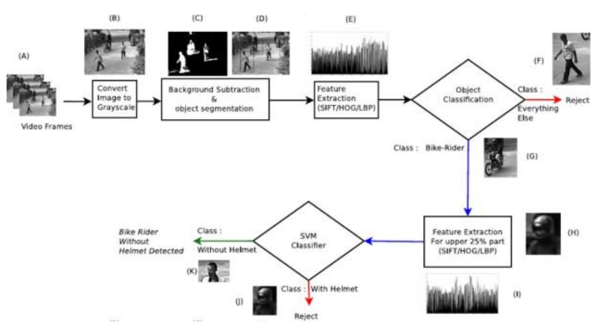
In the current system, the traffic is checked by a police officer and photographed, then the image of the vehicle violating the traffic rules is sent to the official website based on the license plate number. This process is time-consuming and some vehicles may slip away when taking photos, because it is difficult to direct traffic and photograph vehicles violating traffic rules at the same time[5].

III. Existing System

The automatic detection of cyclists without a helmet belongs to the large category of anomaly detection in video surveillance. As described in, effective automatic surveillance systems typically involve the following tasks: modeling the environment, detecting, tracking, and classifying moving objects. A method is proposed to Chiverton which uses the geometry of the helmet and the variation of the lighting on different parts of the helmet[6]. It uses arc detection method based on Hough transform. The main limitation of this approach is that it tries to detect helmets in the full frame, which is computationally expensive and often confuses other helmet-like objects. He also ensures that helmets are only for cyclists. In Chen et al. An effective monitoring method is proposed. Proposed method to detect cyclists without helmets[7]. A) input frame sequence, B) sample frame, C) foreground mask of sample frame, D) bounding box around foreground object, E) sample object characteristics of D, F) classification of object as non-cyclist, G) Object is classified as cyclist, H) a partial head of a cyclist, I) of H, J) a cyclist classified as ”with helmet” and, K) a cyclist classified as ”without a helmet”. An example characteristic of the cyclist class. Vehicles in city traffic. It uses a Gaussian mixture model and a leading blob refinement strategy to extract the foreground. It uses a Kalman filter to track vehicles and uses majority voting to improve classification. In [8], Duan et al. A robust method for real-time vehicle detection from a single camera is proposed. To speed up calculations, it uses an IMAP processor (Integrated Memory Array Processor). However, this is not an efficient solution due to the need for dedicated hardware. In Silva et al. A method is proposed which starts with the detection of cyclists. It then finds the head of the cyclist by applying the Hough transform and classifies it as a head or a helmet. However, the Hough transform used to locate the cyclist's head is computationally expensive[8]. The same is done only on the static images in the experiments. Generally speaking, the existing works discussed above suffer from two major limitations. First, the proposed methods are either computationally expensive or passive in nature, unsuitable for real-time performance. Second, the correlations between frames are not used enough for final decision making, because the results of consecutive frames can be combined to create more reliable violation alerts. The proposed method overcomes the aforementioned limitations by providing an efficient solution suitable for real-time applications[9].

IV. Proposed System

This section presents the proposed method for the real-time detection of cyclists without a current helmet in two stages. First, we detect cyclists in the video images. In the second step, we find the cyclist's head and detect if the cyclist is wearing a helmet. To reduce prediction errors, we merge the results of consecutive frames for the final prediction. The block shows the different steps of the proposed framework, such as background subtraction, feature extraction, object classification using sampling frames[10]. Since the helmet is only relevant to the moving cyclist, processing the full image becomes a computational overhead that adds no value to the detection rate. To take this a step further, we apply background subtraction to the grayscale frames, with the aim of distinguishing between moving and static objects. Next, we introduce the steps involved in background modeling[11,12].



V. METHODOLOGY

A. Image Processing

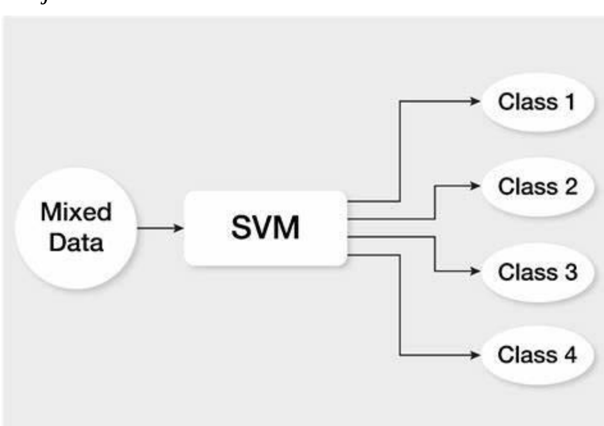
- Grayscale and Blur :- Before processes the input material, it is very necessary for to achieve the best precision, and the video is blurred and grayscale processed using the Gaussian blur method. To remove noise and achieve the best accuracy, a gray scale is used.

- Background subtraction Background subtraction Subtracts the background subtraction from the reference image using the current image, the result will be the desired area of the object . Equation (1) shows the method. distance(i) = saturate(–frame1(i) frame2(i)–).

- Binary Threshold:- To remove noise and other disturbances from the input video, a binarization method is used. Holes and noise are removed during this process. Equation (2) shows how a binary threshold of is handled. dist(x,y) = MaxVal if frame(x, y) ¿ threshold other

- Dilation and contours Dilation and contours When we get a threshold we fill it and we dilate the hole, compute the image reshape the image better based on contour.

B. Object Detection



Regions with CNN features. Three phase approach:- A. Our uses the Support Machine Provider (SVM). Objects can be extracted from images B. Using a convolutional neural network (CNN), we were able to extract features from each region photo. C. Classify and each region using SVM[13].

C. Object Classification

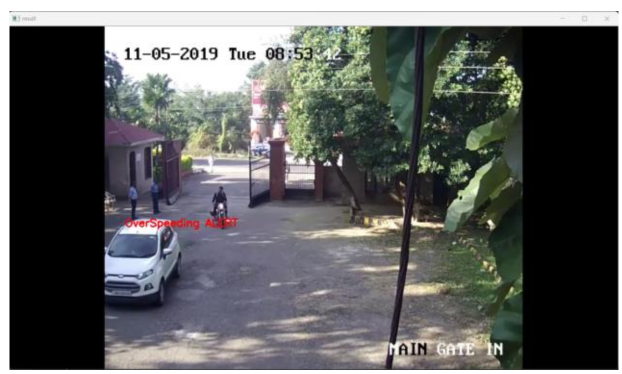
After the pre-processing method, the moving object is obtained from the image. The vehicle classification model classifies moving objects into four classes - 4-wheel, 2-wheel, 3- wheel without transport[13].

VI. DATASET USED

As there are no public datasets available for this purpose, we collected our own data from the monitoring system of Hyderabad Institute of Technology, India. Here we collected 2 hours of surveillance data at a frame rate of 30 fps. We use the first hour of video to train the model and test it. The training video contains 42 bikes, 13 cars and 40 people. While the test video contains 63 bikes, 25 cars and 66 people[15].

VII. RESULT

When the signal failure detection system is enabled on the input video collected remotely from the CCTV, the inputs are preprocessed and after presentation of the pre-determined line system output: Wherever has a violation of road traffic rules, the system maintains a CCTV camera photos, from which useless images are then read, providing functionality for the vehicles in the photos that require RCNN. RCNN is used to judge whether vehicle in the photo is illegal. Finally, when vehicles violate the traffic rules, the system cuts the image of the violating vehicles into an image almost the same as the photo[16,17].



VIII. CONCLUSION

In this paper, we propose a framework for real-time detection of helmetless bicycle traffic offenders. The proposed framework will also help traffic police to detect such violators under strange environmental conditions (i.e. hot sun, etc.). The experimental results show that the accuracies of cyclist detection and violation detection are 98.88 percent and 93.80 percent respectively[17]. The average frame processing time is 11.58 ms, suitable for real-time use. The proposed framework also automatically adapts to the new scene, if necessary, with minor adjustments. This framework can be extended to track and report license plates of offenders[18].

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