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ijircce@gmail.com



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# Detection of Red-Light Runners in Traffic

**K. Mohan Krishna, M. Dakshayani, N. Bhagya Sri, Sk. Akheel Uz Zama**

Associate Professor, Dept. of CSE, Vasireddy Venkatadri Institute of Technology, Nambur, A.P., India

Student, Dept. of CSE, Vasireddy Venkatadri Institute of Technology, Nambur, A.P., India

Student, Dept. of CSE, Vasireddy Venkatadri Institute of Technology, Nambur, A.P., India

Student, Dept. of CSE, Vasireddy Venkatadri Institute of Technology, Nambur, A.P., India

**ABSTRACT:**The unprecedented increase in the number of vehicles has led to an increased number of road accidents. Detecting and catching traffic violators has become a necessity for authorities all over the world in order to reduce the chances of accidents and ensure road safety. Red light violations and speeding are the major causes of road collisions. The offenders tend to violate traffic rules if they know that they can get away with it without getting caught. SSD, an object detection algorithm is used to detect the violated vehicles from the input video provided. As the system is highly capable of detecting violated vehicles when compared to the normal human eyes, it makes the work of officers more efficient. In this project, the input video is obtained by employing a camera in junction-like regions. Then the input video gets processed to make a comparison between the outputs of three different neural networks by applying SSD as the base for detecting the violated vehicles from the input videos provided. Based on the output obtained, the system can achieve up to 100% accuracy on all feature extractors for red-light runner (RLR) and 92.1% accuracy for overspeeding with the consideration of the best set-up.

**KEYWORDS:**computer vision; deep learning; Convolutional Neural Networks (CNN); Single Shot Detector (SSD); vehicle detection, openalpr

## I. INTRODUCTION

Through this project, we tried to develop a system that will detect the vehicles which do not follow the traffic rules by having a video as an input. The offenders tend to violate traffic rules if they know that they can get away with it without getting caught. As this system detects the violators faster than the human eyes, it makes the responsibilities of traffic officers more effective and also makes the drivers feel more responsible as an individual to follow traffic rules and regulations. An automatic traffic red light violation detection system was implemented which may play a big role in transportation management in smart cities. Existing systems of red-light violation detection have some issues with the input videos as the video may contain different levels of variability such as the depth of view, video capture perspective, and location. Approaches that are based on deep learning generated outstanding performance in various computer vision tasks like object detection.

## II. RELATED WORK


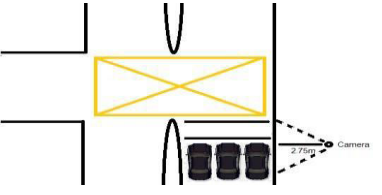
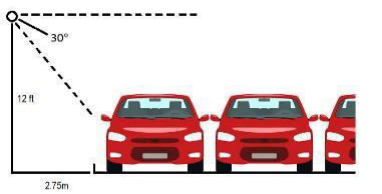
Existing solutions in the field of object detection that make use of CNN (Convolutional neural networks) are reviewed for this literature. In addition to that, two types of methods are introduced for vehicle detection: feature-based methods and CNN-based methods. CNN-based methods are more versatile when compared to the Feature-based methods in the field of computer vision. That is why over the years many researchers have chosen CNN methods over feature-based methods.

## III. METHODOLOGY

### A. Input

Table I indicates how the input data is obtained. The input is given in the form of a video captured by a camera at an intersection point or otherwise called a junction at a Seaside in Pasay City. As there are no officers at that intersection point, the system developed will play a major role in traffic management.

TABLE I. SUMMARY OF INPUT INFORMATION

<b>Resolution</b>	640 x 352
<b>FPS</b>	24 fps
<b>Set-up Location</b>	Intersection at Seaside Avenue
<b>Camera Angle and Elevation</b>	Tilted down 30 degrees Elevated 12 feet high
<b>Image of Location</b>	
<b>Camera Top View</b>	
<b>Camera Set-Up</b>	

**B. Process**

An image containing ground truth boxes is sent to the SSD object detection algorithm where the image is passed into VGG16(Visual Geometry Group) which outputs feature maps. And these feature maps are passed to a series of convolutional filters. Then thousands of predictions will be generated as the output above which Non-Max Suppression is applied to output the bounding box surrounding the object. MobileNet, Inception V2, and ResNet 50; these three feature-based methods are compared.

**C. Bounding Boxes**

An imaginary rectangle drawn around a given object is called as a bounding box and it serves as the region of interest. To draw a bounding box around an object in the given image, we make use of a function called selectROI() function in OpenCV. The image on which the bounding box is to be drawn using the selectROI() function is read using imread() function. The selectROI() function is used on the input image by passing it as the parameter to the selectROI() function to select the region of interest by drawing a bounding box around the required object. The output of convolutional filters on an image is termed as a bounding box. Different bounding boxes have different aspect ratios.

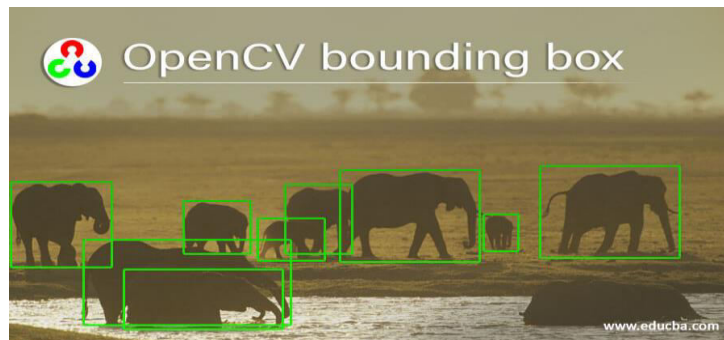


Fig 1: Bounding Box

#### D. Non-Maxima Suppression

NMS (Non-Maxima Suppression) is a method that is used in eliminating multiple bounding boxes at the time of object predictions. In a way, it is used as a filter to choose the best bounding box out of all having high confidence.

As shown in figure 3, during prediction, non-maxima suppression is used to filter the multiple boxes per object that may appear

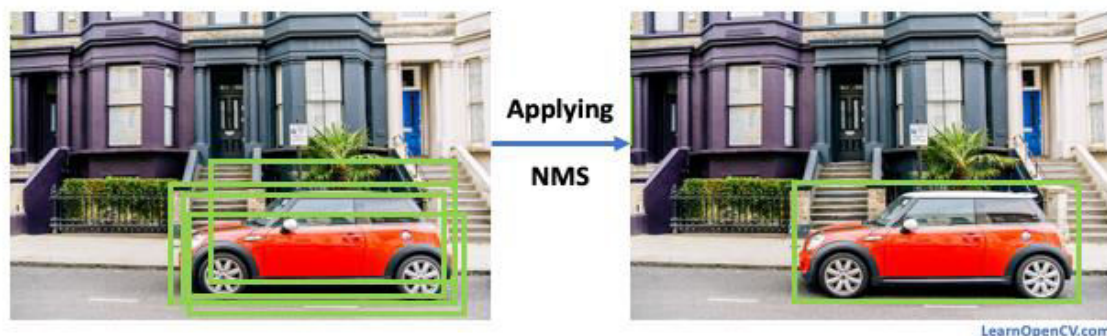


Fig 1.1: NMS

#### E. Red Light Runners Detection

The main components of this system: Detecting red-light runners are: estimating violation lines, object detectors, and object tracker. Each of them is demonstrated below:

##### Estimating violation line:

Specifying the area for which the vehicles are considered as the violators when crossed is impossible and it plays a major role in the construction of red-light violation detection. Such specifications cannot be achieved due to the presence of different variability levels in the input video provided. An alternative approach to such specifications is to have direct assumptions so that we can break down the complexity of the problem. So, we considered two assumptions when the input is provided: first and foremost is to represent the region as any vertical area inside the input video provided which exceeds a certain threshold horizontal line, which can be considered as the violation line, which divides the road into zones of regular and violating. At last, the main aim of the system eventually becomes to find out the vertical location of this horizontal line. The second assumption is the existence of a crosswalk between the regular zone and the violated zone is mandatory so that one can have a clear understanding of the vertical area and an idea to find out where the violated line must be placed in the video. In order to obtain clear info and an indication of the approximate vertical location of the violation line, within the surroundings of the traffic light. The assumptions made above are shown in the following figure.

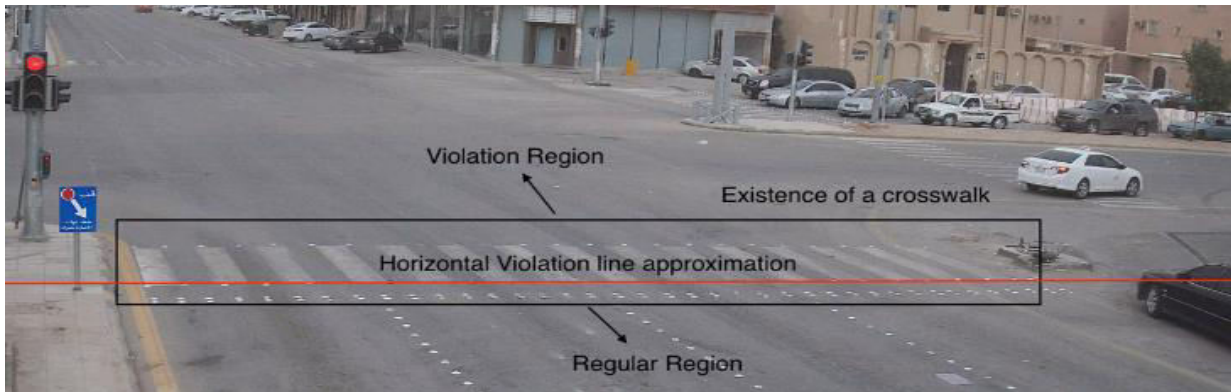


Fig 1.2: Violation line

It was important to get clear info about the crosswalk components. To achieve them, we have to go through a series of steps: Convert the above input image into a greyscale image. Now, Convert the greyscale image to a binary image on the basis of experimental threshold values.



fig 1.3: Binary image

To limit the level of noise in the above-binarized image, perform a series of erosion and dilation operations.

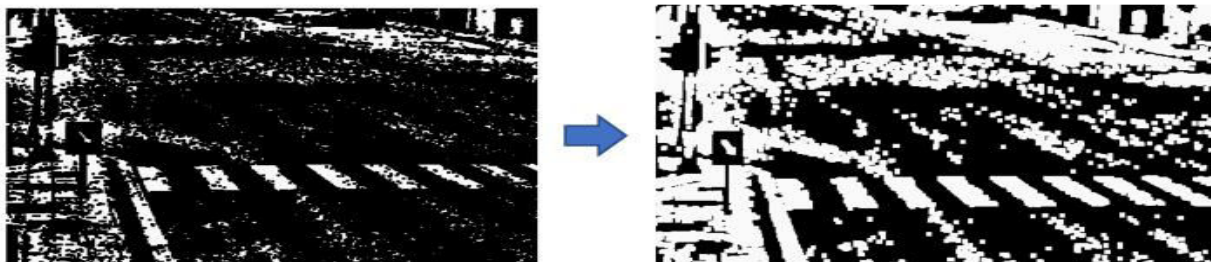


Fig 1.4: Result of operations on binary image

Now, we are able to detect contours from the above-binarized image.



Fig 1.5: detecting contours

Filtering is applied to the above image to reduce the randomness of the contours.



Fig 1.6: Result of Filtering

Only have the contours with approximating points,



Fig 1.7: Contours with approximating points

Bounding boxes are drawn to each contour for better understanding and visualization.

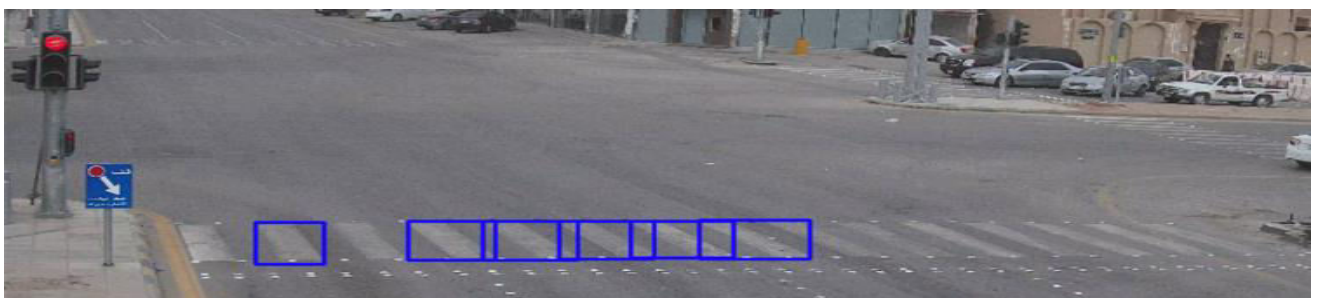


fig 1.8: Bounding boxes

we tried to find out the contour which is nearest to the traffic light, so that we can draw the violation line in the vertical area.

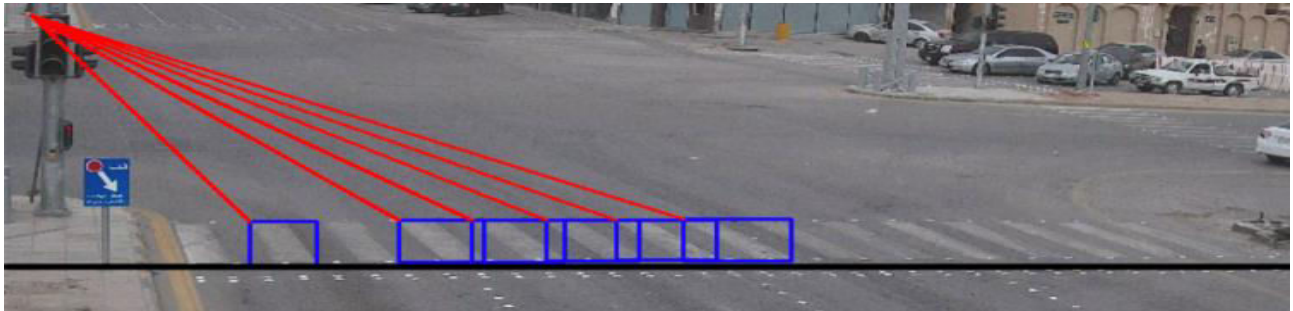


Fig 1.9: final bounding boxes

**Vehicle detector:**

Detection is done for every five frames using SSD pretrained model. The results of detection are processed in a series of steps: filtering and then applying Non-Max Suppression to select the best bounding box with a high confidence rate. A vehicle is considered a violated vehicle when it crosses the violation line and at the time the state of the traffic light is red.

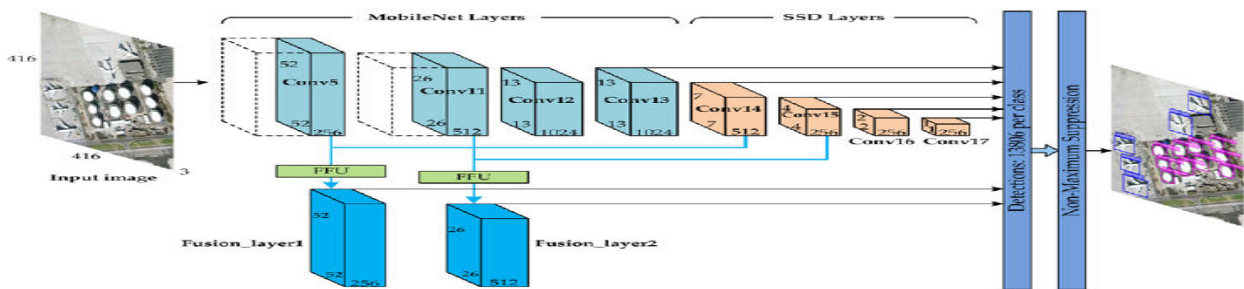


Fig 2: SSD architecture

**Vehicle tracker:**

Having the exact locations of detected vehicles is a very difficult task. Only tracking the vehicles in the first frame is of no use, as the incoming and outgoing vehicles keep on changing. To address the issue, we need to have a bridge between vehicle tracking and vehicle detection. We will track the vehicles in each frame but the vehicle detection task occurs only for every five frames. At the same time, for each bounding box detected, IoU is calculated and will have a comparison with the IoU of the current tracking bounding box. If there is a match with a high percentage then it is the same box in the list that is to be tracked. If there is no match, then the vehicle detected is a new incoming one. Therefore, the tracking list must be updated. The tracker is removed when the vehicle detected is an outgoing one. The final conclusion is to update the tracking list for every iteration.

**F. Over Speeding Detection**

To calculate the distance traveled by the tracked vehicle per second, we require the pixel per meter(ppm). To calculate the speed of the vehicle we require the distance traveled in seconds. We manually estimated these values for the road in the input video to determine ppm. So the values vary from one input video to other. Let us come to the part of how we calculated ppm. First of all, the width of the road must be known in meters. One can make use of the Google search engine for this purpose. Now we have the width of the road digitally as well as in real-world also. For mapping the distances in both the worlds, we determined ppm.

Calculation of ppm is as shown below:

$$ppm = \frac{\text{distance of the road in pixels}}{\text{distance of the road in meters}}$$

From our video processing,  $d_{\text{pixels}}$  represent the distance traveled by the vehicle in one frame in terms of pixels. To determine speed, we first required to convert  $d_{\text{pixels}}$  to  $d_{\text{meters}}$ . At last, the speed of the vehicle can be calculated as

$$\text{speed} = (d_{\text{meters}} * \text{framespersecond} * 3.6).$$

Distance traveled by vehicle in one frame is represented using  $d_{\text{meters}}$ . fps is already calculated in the processing stage.



Fig 2.1: Detecting overspeeding vehicles

#### IV. RESULTS AND DISCUSSION

The output of the system is represented in the following figure:



Fig 3: Result of the code

OpenALPR is used here to detect license plates and then extract the license plate number. It uses Tesseract OCR and opencv internally for the above mentioned task.

TABLE II. SUMMARY OF THE RESULTS OF THREE FEATURE BASED EXTRACTORS

Feature Extractor	Average Deviation	Average Error%
MobileNet	10.46	7.90%
Inception V2	10.02	9.00%
ResNet 50	9.85	9.03%



## V.CONCLUSION AND RECOMMENDATION

Through this paper, we tried to study the role of Deep Learning neural network techniques in the field of object detection where the object is a vehicle. We make use of the SSD object detection algorithm for the above-mentioned purpose. The method we proposed shows high performance and accuracy compared to the existing systems in detecting violations. The SSD algorithm processes the input video and detects the red light violators along with the speed of the vehicles with better performance and accuracy. This system does not concern about the traffic lights instead depends on the estimator line for bringing the problem to a technical level. In general, the SSD algorithm is trained on datasets which is typically the COCO dataset used here. After the completion of vehicle detection from the input video using the SSD algorithm, we will check whether the vehicle is a red light violator or not. It is also considered that the SSD algorithm with varying feature extractors stands best for detecting traffic violations.

Clarifying the questions regarding what are the parameters considered for detecting red-light violators, the system developed achieves 100% accuracy on RLR violations whereas the speed of the vehicle is determined with 93.04% accuracy bounding to the conditions that all the prerequisites are satisfied. Using Mobilenet we can achieve a faster model whereas by using ResNet we can achieve a model with better accuracy. The choice of which network to be used depends on the person. If the person wants a faster model then the person can go with Mobilenet. If the person wants a model with better accuracy then the person can go with ResNet, the feature extractor. For extracting the license plate number, we make use of OpenALPR API which internally requires Tesseract OCR and OpenCV. It first detects the license plate of the violated vehicle and then extracts the digits of the license plate.

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