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# Vehicle and Pedestrian Video-Tracking with Classification Based on Deep Convolutional Neural Network

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**ABSTRACT**: This method is used to track the vehicles, to count the number of vehicles and pedestrians through the surveillance camera in the traffic signals. This algorithm is divided into two parts, The first one is classification algorithm, which is based on convolutional neural networks, which is implemented using the method called YOLO (You Look Only Once). Then the second part is Proposed algorithm which is used for tracking the vehicles and also for measuring its performance. The tracking process is much better than the manual counts in the video sequences. So the number of accidents can be lowered by using this classification and proposed algorithms.

**KEYWORDS**: CNN based Object identification, Object segmentation, YOLO algorithm, Tracking algorithm, Performance evaluation, Optimization, Convolutional Neural Network, Vehicle and pedestrian tracking.

#### **I.INTRODUCTION**

Several methods have been implemented for counting the number of vehicle and pedestrian during previous years. There are different methods have been used and some are used for commercial purposes,here CNN method is used for object detection and classification of vehicles. comparing to other algorithms CNN has given the outstanding results not only in the computer field but also in the speech recognition and other natural language processing field.Here we proposed an algorithm for tracking vehicles and pedestrians in video sequences. object detection plays a major role in analyzing the traffic flow and accidents in the some of the over populated metropolitan traffic areas.

The factors like lighting various and weather conditions affects the recognition process of the vehicles.for that we introduce the existing literature on object detection along with CNNs.It describes various video object detection and classification methods.It also includes some older methods which is based on video tracking, vehicle classifications.

The convolutional networks have the capability to perform the tasks for both vehicle tracking and video object detection. The object tracking algorithms can be classified into five steps, it is also called five steps taxonomy, they are, Division of objects, clustering, extraction, cost computation and optimization.

#### **II.R**ELATED WORK

Deep convolutional neural networks for pedestrian detection

Pedestrian detection is a popular research topic due to its paramount importance for a number of applications, especially in the fields of automotive, surveillance and robotics. Despite the significant improvements, pedestrian detection is still an open challenge that calls for more and more accurate algorithms. In the last few years, deep learning and in particular convolutional neural networks emerged as the state of the art in terms of accuracy for a number of computer vision tasks such as image classification, object detection and segmentation, often outperforming the previous gold standards by a large margin. In this paper, we propose a pedestrian detection system based on deep learning, adapting a general-purpose convolutional network to the task at hand. By thoroughly analyzing and optimizing each step of the detection pipeline we propose an architecture that outperforms traditional methods, achieving a task accuracy close to that of state-of-the-art approaches, while requiring a low computational time. Finally, we tested the system on an NVIDIA Jetson TK1, a 192-core platform that is envisioned to be a forerunner computational brain of future p r o g r a m m e d s e l f - d r i v i n g c a r s . Ten Years of Pedestrian Detection, What Have We Learned?

Paper-by-paper results make it easy to miss the forest for the trees. We analyse the remarkable progress of the last decade by discussing the main ideas explored in the 40+ detectors currently present in the Caltech pedestrian detection benchmark. We observe that there exist three families of approaches, all currently reaching similar detection quality. Based on our analysis, we study the complementarity of the most promising ideas by combining multiple published

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strategies. This new decision forest detector achieves the current best known performance on the challenging Caltech-USA dataset.

ImageNet Classification with Deep Convolutional Neural Networks

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0%, respectively, which is considerably better than the previous state-of the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully connected layers with a final 1000-way softmax. To make training faster, we used nonsaturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully connected layers we employed a recently developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

Preliminary studies On The Taxonomy Of Object's Tracking Algorithms In Video Sequences

Different techniques for tracking objects in controlled environments using video cameras have been proposed. These state of the art algorithms are focused especially on how to find a better segmentation of the tracking object and also on how to make this segmentation stable through time, regardless of temporal changes on the morphology of the object. Unlike any of that, this article reviews the state of the art, focusing on algorithms for segmentation of the scene and of tracking objects, then addresses the previous steps in the creation of a binary image that segments the objects and convert them into useful data, found frame by frame to be used afterwards for tracking. The intention is to classify the methods of temporal matching between the binary images which are the outcome of the segmentation of foreground and background into general groups, in order to give an organized starting point to the advances made regarding the tracking of moving objects with fixed cameras and to be able to adapt faster to the implementation of tracking on the new advances in specific techniques in the field of the proposed taxonomy.

A comprehensive review of background subtraction algorithms evaluated with synthetic and real videos

Background subtraction (BS) is a crucial step in many computer vision systems, as it is first applied to detect moving objects within a video stream. Many algorithms have been designed to segment the foreground objects from the background of a sequence. In this article, we propose to use the BMC (Background Models Challenge) dataset, and to compare the 29 methods implemented in the BGSLibrary. From this large set of various BG methods, we have conducted a relevant experimental analysis to evaluate both their robustness and their practical performance in terms of processor/memory requirements.

#### **III.PROPOSED ALGORITHM**

We propose an algorithm to provide a video tracking solution for vehicular and pedestrian tracking in video sequences, the algorithm follows an organized taxonomy based on, the algorithms for counting vehicles and pedestrians worked mostly from the segmentation of the scene in a foreground and background (FG-BG) to then analyze a binary threshold using contours or blob detection,

#### ADVANTAGES OF PROPOSED SYSTEM

We make special detail in the tracking algorithm following a well differentiated taxonomy that works for both FG-BG and object detection estimations.

### **IV.ALGORITHM DESCRIPTION**

Convolutional Layer (CONV)

The convolutional layer is calculated using equation 1. The Gaussian distribution's standard deviation used is calculated using equation 2. Equation 3 is an expanded form of equation 1 that shows the row and column (i, j) indices of the C1 feature map.

where I is the input image, k is the kernel filter, and b is the bias denotes the convolution, and i, j are row and column indices of the feature map.

defdetect\_image(image, yolo, all\_classes):
pimage = process\_image(image)

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start = time.time()

boxes, classes, scores = yolo.predict(pimage, image.shape) end = time.time() print('time: {0:.2f}s'.format(end - start))

while True: res, frame = camera.read()

if not res: break image = detect\_image(frame, yolo, all\_classes) cv2.imshow("detection", image) # Save the video frame by frame vout.write(image) if cv2.waitKey(110) & 0xff == 27:

breakvout.release() camera.release()

## V.SIMULATION RESULTS

💭 jupyter	Q	l Log	gout
Files Running Clusters			
elect items to perform actions on them.	Upto	id New •	- 3
0 - M / Desktop / vehicle / vehicle	Name 🌢 🛛 Last Modifie	f Files	size
۵	seconds a	p	
🗐 🗅 data	23 days a	p	
🗎 🖸 model	23 days a	jo	
C videos	23 days a	p	
C weights	23 days a	jo	
🗧 🖉 testing.ipynb	19 days a	jo 35	50 ke
🔲 🖉 training ipynb	23 days a	p 88	318



Fig. 2. Calculating distance between each vehicles

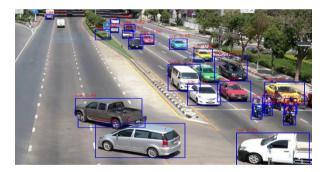
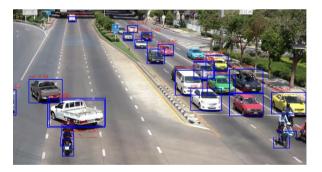
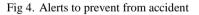


Fig.3 Precaution to prevent accident

Fig.1.Start by clicking the testing.ipynb





## VI.CONCLUSION AND FUTURE WORK

Vehicle detection and classification have great influence on the advances in the field of transport system. This vision task help in preventing accidents by tracking the vehicle and assist in preventing the pedestrians from the road side accidents. It is helpful in many ways, detecting and classifying vehicles is a most difficult tasks. There are two main approaches in this project, they are vehicle detection and classification. In this object detection and classification have more accurate and faster than the other methods. These neural networks will produce high results and helps in most cases. This allows us to broaden the understanding of appropriate space of citizens identifying their needs and opportunities in metropolitan areas.

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