

Feature Extraction in Vehicle ID & Classification using Deep Learning & Image Processing

Pragati Narbolikar Department of Artificial Intelligence and Data Science

Sharnbasva University Kalaburagi, India

pragatinarbolikar04@gmail.com

Laxmi Math

Department of Artificial Intelligence and Data Science

Faculty of engineering and technology (Co-ed) Sharnbasva University

Kalaburagi, India laxmi.math@gmail.com

Abstract- Intelligent transportation systems have acknowledged the ration of attention in the last decades. In this area vehicle classification and localization is the important task. In this task the important challenge is to discriminate the features of different vehicles. Further, vehicle classification and detection is a bigger problem to identify and locate because different variety of vehicles don't follow the lane discipline. In this project, to identify and locate, we have created a convolution neural network from scratch to classify and detect objects using a modern convolution neural network based on fast regions. In this project we have considered three types of vehicles like bus, car and bike for classification and detection. Our approach is to use the entire image as input and create a bounding box with a probability estimations of the feature classes as a output. The results of the project have shown that the projected system can considerably improved the accuracy of the detection.

Keywords: CNN , FASTER R-CNN

I.INTRODUCTION

Vehicles detection and counting are done a non-intrusive sensor method is video infrared, magnetic, radar, ultrasonic, acoustic, and video imaging sensors and intrusive sensor sensors the include pneumatic road tube, piezo-electric sensor, magnetic sensor, and inductive loop . Non intrusive technology has advantages over intrusive technology which requires closing of traffic lanes and put construction workers in harm's way, stop traffic or a lane closure and non-intrusive sensors are above the roadway surface and don't typically require a stop in traffic or lane closure. Both types of the sensors have advantages and as well as disadvantages. But the accuracy from video or digital counting manually is very high as compared to other technology. However the image processing is time consuming and requires some automation to save the time for image count and classification. In current era of Matlab , Python type programming language has much addition of image processing and time saving for vehicle detection, counting and classification. The paper states about way to image process, type of filter used and proposed technique

are able to detect, count and classify the image accurately Drones, also known as unmanned aerial vehicles, are quickly becoming a widely used and very effective technology for monitoring infrastructure and the environment. Particularly, there is a lot of interest in the employment of UAVs in the field of road traffic monitoring (RTM). In the above-mentioned deployments, UAVs are in charge of looking for, gathering, and sending vehicle information from on-board video sensors in real time for traffic regulation purposes. Since the introduction of convolution neural networks and other deep learning techniques, object identification and recognition have displayed a noticeable improvement in accuracy. This opens the door for the broad use of UAVs for data collection and analysis across a variety of technical domains. The accuracy of categorization and object identification has significantly increased as a result of developments in deep learning, particularly convolution neural network (CNN) applications. There were several suggested CNN architectures and algorithms, including YOLO and its variants, R-CNN and its variants, and R-CNN, which is a region-based CNN. To overcome the limitation of R-CNN, selective search of region, Faster R-CNN was introduced.

People can easily identify and analyze things in the images. Man's visual system is fast and precise, and can perform complex tasks, such as identifying many things and identifying obstacles with sensible thoughts. But in computer vision object recognition is one of the major challenges because, we should not focus only on the classification of different images, we should also identify the location of things accurately in individual image. This bustle is called an object detection [1]. Object detection can provide valued information about the clear meaning of images and videos and is associated with numerous claims such as image classification [2], [3], human behavior analysis [4] and facial recognition [5]. In recent year's deep neural networks (DNN) have become a [6] powerful machine learning model. DNN have the important differences with respect to traditional classification approaches. First they are profound architectures that have the ability to learn more complex models than surface models [7]. This Expressiveness and robust training algorithms have powerful representations of objects without the need for a

manual design. However, large differences in types, poses, occlusions and lighting conditions make it tough to detect objects. Therefore, it attracts so much attention from researchers in this field [8], [9]. In this article, we show that algorithmic modification, which computes a deep network performance map, leads to a sophisticated and effective solution.

II. LITERATURE SURVEY

In paper [1], Dikbayir et.al discussed about two most popular algorithms Faster R-CNN and YOLO. The aim of Faster R-CNN (region based convolutional neural network) is to create a certain number of regions with a selective search method and search through the regions instead of searching through the whole picture and find the right object. The YOLO algorithm aims to offer a structure suitable for real-time processing by taking the picture completely convolutional rather than a regional-based approach. In this paper, firstly; Munich Vehicle Data Set was used, because it includes images of different vehicle types over 100m, and high- resolution images obtained from the “Google Earth” application and DJI drone images were also included in the set to expand the data set.

In paper [2], Ammar, A. et.al assessed the performance of three cutting-edge CNN algorithms, including the most well-known region-based technique, Faster R-CNN, and the fastest detection algorithms, YOLOv3 and YOLOv4. Faster R-CNN is a deep convolutional network that simulates an end-to-end network to the user and is used for item detection. The network can accurately and rapidly predict the locations of different objects. YOLO, an acronym for You Only Look Once, processes the image using a Fully Convolutional Neural Network that predicts the bounding boxes and their corresponding class probabilities, based on the global context of the image. The model was successfully validated on two datasets (Stanford & PSU). Future work includes Extending our results to the newly released EfficientDet detector and to much larger datasets of aerial images.

In paper [3], Lu, J. et.al performed research and compared all the versions of YOLO. By combining three open-source aerial picture datasets, the method creates an aerial image dataset appropriate for YOLO training. The VEDAI (Vehicle Detection in Aerial Imagery) dataset is made by Sebastien Razakarivony and Frederic Jurie of University of Caen, whose original material is from public Utah AGRC database. COWC (Cars Overhead with Context) dataset was designed by T. Nathan Mundhenk and others of Lawrence Livermore National Laboratory, whose original materials are from six opensource websites. DOTA (Dataset for Object detection in Aerial images) is an aerial image dataset made by researchers from Wuhan university.

Future work includes integration of more public aerial image datasets to increase the number and diversity of training samples, at the same time, optimize the YOLO algorithm to further improve the detection accuracy.

In paper [4], Liao et.al presented an experimental study to evaluate the performances of several state-of-the art deep learning-based detection approaches on vehicle detection from aerial imagery using deep learning techniques such as Faster R-CNN, R-FCN, and SSD. As a benchmark, the VEDAI dataset is utilised. Two different aerial picture sizes are included in the VEDAI dataset: VEDAI 512 and VEDAI 1024 (1024×1024 and 512×512 pixels, respectively). VEDAI dataset 1024 consists of 1250 instances in total, and 1164 images are remaining after we removed the scarce categories mentioned above.

In paper [5], Valappil et.al proposed a procedure which includes the Kanade-Lucas optical flow method for detecting moving objects, the construction of connected graphs to separate items, convolutional neural networks (CNN), and support vector machines (SVM) to determine the outcome of the classification. The classifier eliminates the possibility of any additional (moving) items being present and being identified as cars. On both fixed and moving aerial films, the approach is evaluated. The capacity of CNN to extract features and subsequently apply the effectiveness of SVM for binary classification. The future scope is Development of multi-class classification applied to deep learning approaches in situation where various categories of vehicles are being detected.

III. EXISTING SYSTEM AND PROPOSED SYSTEM

Existing System: IR sensor placing on eye for fatigue detection the problem with the system is, it is having user aiding complex with placing sensor over the eye directly.

Disadvantages

- Sensors are costly
- Not accurate

Proposed System:we proposed a road safety situation and threat analysis framework and algorithms based on driver behaviors and vehicle dynamics. In current environment modelling, obstacles are detected and tracked in future situation assessment; Here we use the position and size of obstacles at a current time ,To anticipate future road conditions using vehicle dynamics equations, we can employ mathematical models that incorporate factors like vehicle speed, acceleration, position, and external elements such as road conditions and traffic flow.For lidar data, we distinguish the object types, namely, static or moving objects, by estimating object speed. Here, a fusion algorithm is proposed to detect and track obstacles. We have proposed the

following three features in our paper

- Driver Assistance system with camera
- Vehicle external vehicle availability detection
- Human detection-based attention

Advantages

Less expensive

Give more accuracy

Avoids accidents

IV. PROPOSED SYSTEM

The following components make up the proposed system:

A] Datasets used - we have taken CCTV footage of any highway. It consists of annotated images with classes of objects.

B] Preprocessing - This module converts image into gray color and removes the noise from the image.

C] Image segmentation : In numerous road traffic video surveillance systems, motion detection within a video sequence predominantly relies on background subtraction techniques. The basic concept is to determine a model of background corresponding to the static regions of video sequence by training them. In our scenario, the camera remains fixed, implying that the background model encompasses stationary elements within the scene such as the road, trees, and road signs. This model is then compared to the observed image to isolate mobile elements within a foreground mask. The foreground mask contains the moving objects. Among these methods, we have used here is Mixture of Gaussian Model . Taking into consideration the multi-modal aspect, propose a method based on modelling with a mixture of N Gaussian for each pixel with $2 \leq N \leq 5$. For $n = \{1, \dots, N\}$, each element of Gaussian mixture is represented by an average μ_n , standard deviation σ_n and a weight α_n (). Noise can infiltrate the foreground mask during the segmentation process, resulting in some level of interference. To remove the noisy and blurry image, morphological operations, such as opening and closing, are applied.

D] Feature Extraction

Feature extraction refers to the process of converting raw data into numerical features that can be processed while preserving the information in the original data set. This leads to better results than applying machine learning directly to the raw data.

E] Framework used - Faster R-CNN: Faster R-CNN is the most accurate version of region-based convolutional neural networks. Faster R-CNN is a two-stage network, region proposal network is used for generating the region proposals and these proposals are used for detection of objects. In Faster R-CNN the use of the selective search algorithm is discarded and is replaced with Region Proposal Network (RPN). RPN provides the probable regions in the image and proposes the ones most likely to contain objects. RPN has learnable parameters which make it more efficient than the previous versions of region-based convolutional neural networks. Faster R-CNN is very accurate and also fast in processing therefore can be extended to soft real-time applications.

SYSTEM ARCHITECTURE

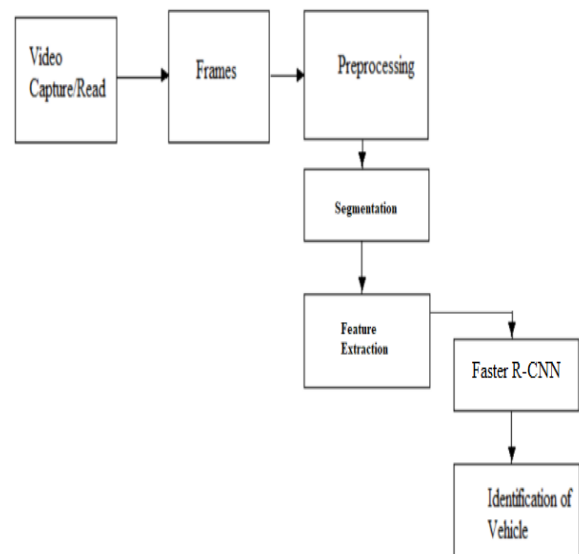


Figure 1 : System Architecture

The above system architecture, captures the video, converts to frames and applies preprocessing then the binary classification stage is completed with support vector machine, where extracted features from CNN layers form the input. The interest regions built during connectivity graph undergo final step in Faster R-CNN used for classification.

V. RESULTS

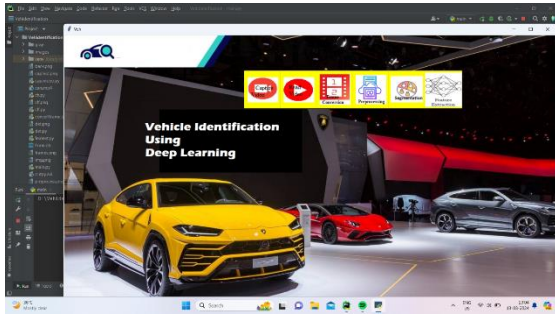


Figure 2 . **MAIN SCREEN**

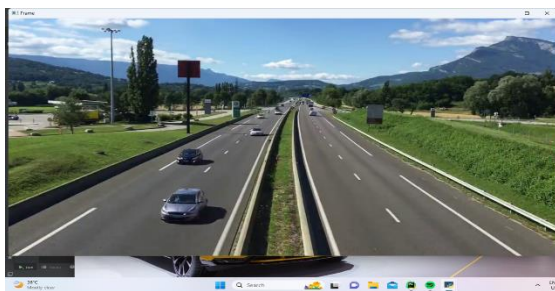


Figure 3: **REAL VIDEO**

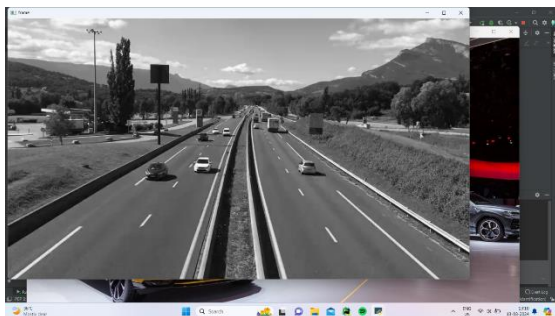


Figure 4 : **PREPROCESSING**

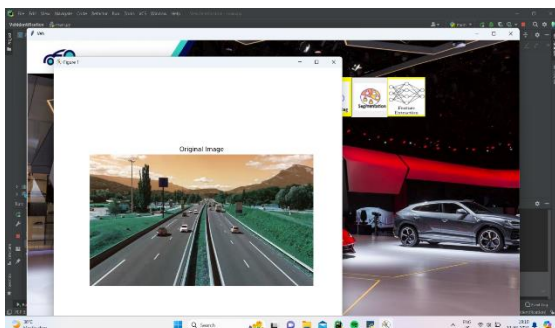


Figure 5 : **ORIGINAL IMAGE**

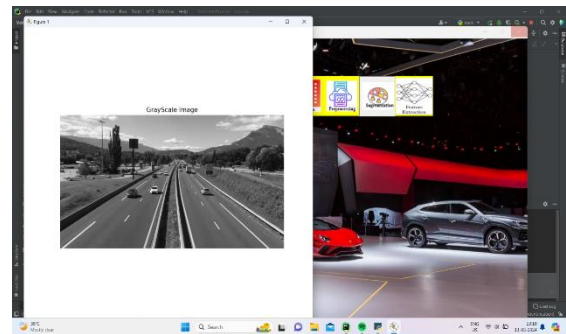


Figure 6 : **GRAY-SCALE**

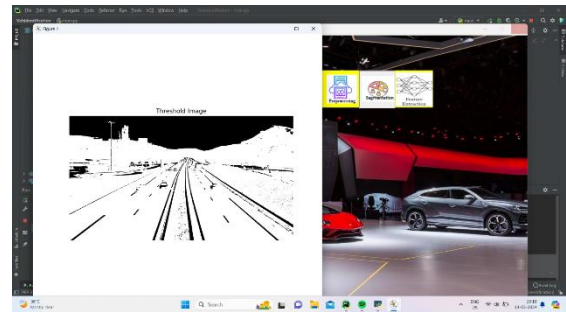


Figure -7 **THRESHOLD IMAGE**

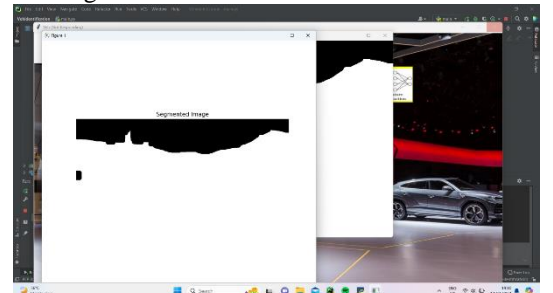


Figure 8: **SEGMENTED IMAGE**

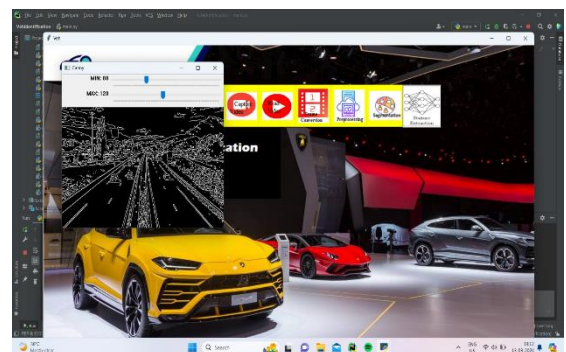


Figure 9 : **FEATURE EXTRACTION**

VI. CONCLUSION

We have developed a completely innovative convolutional neural network, that is simple but accurate and efficient. In object detection framework the convolutional features gathered from our system is better than state-of-art image classification network. Our method achieves accuracy by exchanging the flexibility characteristics with a faster R-CNN, both during training and during testing.

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