ADVANCED TRAFFIC SIGN AND LANE DETECTION FOR AUTONOMOUS CARS

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Abstract

Automobiles that drive themselves are called "Autonomous Vehicles" or "Self-Driving Cars". This car has the ability to sense around the environment. Without a human driver, an autonomous vehicle functions similarly to a conventional vehicle. In order to carry out their automated functions, autonomous vehicles depend on sensors, actuators, machine learning algorithms and software. Safety is an important aspect while driving, and ensuring safety and reducing accidents on the road is the primary concern for autonomous vehicles. Accidents takes place due to lack of response time to instant traffic events on the road. So, real-time monitoring and guidance to traffic is crucial for reducing accidents caused by delayed responses to sudden traffic events. This involves the use of Traffic Sign recognition and Road Lane detection. This study proposes a machine learning algorithm. Python is utilized for both, using the OpenCV standard file and the Hough Transformation technique. VGGNet is used for image recognition. With these resources we can train the shape models using a supervised learning algorithm and conduct detection in a manner that support vehicles in identifying road lanes and traffic signs. The method used in this, divides the video into a series of frames and generates image-features for each of them which are used to recognize the lanes and traffic signs on the road.

Keywords: Self-driving cars, OpenCV, Hough transformation technique**,** VGGNet, Traffic Sign recognition, Road Lane detection.

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1. SCOPE

Advanced traffic sign and lane detection for autonomous is used to provide accurate and reliable information to autonomous cars driving system to ensure safe and efficient navigation. Advanced traffic sign detection technology enables the vehicle to identify and interpret traffic signs such as speed limit signs, stop signs, yield signs and other regulatory signs on the boards. Lane detection technology enables the vehicle to identify and track lanes on the road, including lane boundaries, markings and other features that define the lanes.

2. INTRODUCTION

Safety is the most crucial aspect that many people consider around the world while driving. The issue of driver negligence has become increasingly severe due to the number of vehicles on the road, leading to a common traffic problem. More than 10 million deaths have been reported as a result of road traffic accidents with approximately 98% of them caused by human error. Consequently, the development of advanced systems for traffic sign recognition or detection and lane detection in autonomous vehicles is very useful. By leveraging these technologies, real-time information about the road environment can be provided, allowing to react quickly and safely to changing traffic conditions. Autonomous vehicles are those that can operate themselves utilizing combination of technologies without the need for a human driver. The creation of software tasks is crucial for autonomous vehicles as the software architecture connects the hardware components with the software program. Detecting lanes and traffic signs are two vital responsibilities of autonomous vehicles and many accidents may be traced back to failures in these areas. In this study, we present a new method for traffic sign recognition and road lane detection. This system enables better information for various users and make drive in a safe mode. For traffic sign identification, we utilize VGG16(VGGNet), a convolutional neural network architecture imported from TensorFlow Keras for image recognition and road lane identification can be done using Hough line transformation. Various colour-based edge detection algorithms available in python are used to determine the correct lane for the vehicle to travel on the road. In this paper we use machine learning models for traffic sign recognition and road lane detection.

3. RELATED WORK

"Using a Multilayer Proposal Network and a Lightweight Network to Identify Traffic Signs Rapidly University of Toronto, Department of Electrical and Computer Engineering"

Eyesight traffic sign detection is a crucial component of any intelligent transportation system. Yet, obstacles in driving conditions and the diminutive size of road signs in photographs of traffic scenes continue to limit the effectiveness of deep learning-based methods to this problem. The inferential slowness of current state-of-the- art methods for traffic-sign identification is a significant limitation. The issue of sluggish inference speed was first addressed by deploying a simple network with a small and effective design. To boost the performance on minor road signs identification, a noise removal module is employed to combine lower-level features extracted with a broader feature map. It is hoped that the upgraded area proposal network can provide ideas rapidly and reliably. The studies use the University of China's 100K dataset and the German Highway Thorough and Systematic Good Indicator dataset, respectively, to evaluate the effectiveness of the enhanced modules and to compare them to current state-of-the-art approaches for traffic sign recognition. The proposed solution outperforms government methods on the Tianjin 100K dataset while simultaneously being faster and easier to implement.

“Lightweight, energy-efficient and flexible convolutional neural network (Esp. netv2)”

Here, we present ESPNetv2, a convolutional neural network that is lightweight, power-efficient and can be used to represent both visual and sequential data. Learning representations from a large field while using fewer floating-point operations per second (FLOPs) and parameters. Our network is tested on four distinct scenarios: First, we have language modelling, then object identification, then semantic segmentation, and finally object categorization. The results of our experiments depend on two tasks—image categorization on the Resnet and language understanding on the Penn Tree banking dataset—show that our strategy outperforms the current gold standard. Our network achieves 4-5% better performance than Espinet with 2-4% fewer Flip - flop on the PASCAL VOC and Cityscapes datasets. ESPNetv2 outperforms YOLOv2 by 4.4% on MS-COCO object identification while using 6 less FLOPs. Our results demonstrate that ESPNetv2 significantly outperforms other efficient approaches, such as Shuffle Nets and Mobile Nets in terms of power consumption.

"Small-footprint deep network for identifying traffic signs"

In the realm of computer vision, larger neural networks have shown to be quite effective, being used for tasks such as road signs identification. Yet, network architecture must be compact and accurate in recognizing traffic sign systems, since they are commonly used in contexts with limited resources. In this study, we offer two unique lightweight networks that have the potential to boost identification accuracy while using fewer trainable parameters. The term "knowledge distillation" refers to the process of condensing the information found in a training sample into a simpler form. To further improve the teaching network's traffic-sign identification capabilities, we implement a new module that uses 2 data streams with dense connectivity. It facilitates portability across mobile platforms. We also remove superfluous nodes from the student network, resulting in condensed model with accuracy by using regularization scaling factor values tending towards 0 to detect irrelevant nodes. When evaluated on the Hydraulic fracturing general dataset, our trainer network achieved an accuracy of 93.16 percent. Our teacher network is used to educate a student network, which is then used to train just on GTSRB and BTSC road signs datasets. As this is the case despite having 99.61 percent points and 99.13 percent accurate on the data sets, respectively, our student model only needs 0.8 million variables. The findings from the experiments demonstrate the potential use of our lightweight networks for the deployment of convolutional neural networks (CNNs) on portable embedded devices.

4. METHODOLOGY

The two important stages of this advanced system are traffic sign recognition and road lane detection. At first, we use VGG16(Visual Geometry Group) for image recognition. First phase consists of traffic sign recognition and some feature extraction methods are used to get target image. This system phase consists of video frames input, pre-processing, lane detection, traffic sign recognition, object recognition, decision making, control and final output. The first video source input is taken from the positioned camera looking in the rear-view mirror, then every video frame picture compress with discrete wavelet transform approach. With this approach the distance-based signal quantification is measured between zero line and certain places on the wavelets and the distances are recorded as coefficients in the records. The average coefficients from neighbouring images are used to generate a streamlined representation of the wave or signal. This whole procedure is repeated and again, till the waves get smaller. The procedure has a name called decomposition. The signboards in traffic are segmented based on colour pixels. The symbol board is identified by measuring the pixel intensity of colours like red, white and black as well as other board colours. Each picture is scanned to determine its brightness value and the vicinity of that value is then located. After segmented image is pre-processed, then converting the image into grayscale in which we use gaussian filters, a useful tool for smoothing and enhancing grayscale images by reducing noise and preserving important features. After this, processing to identify road boundaries or lane identification by using edge data. We use Canny edge detection method, a popular edge detection technique used in computer vision (OpenCV) and image processing to detect edges in an image. This picture is transformed into binary representation so that it is easy for image classification from the dataset and reduced processing time is another benefit. Then classification is done using a model-matching technique.

In second phase, it detects the edges of the road using canny edge detection method. This method involves steps like video frames input, grayscale conversion (black-and-white), canny edge detection, Hough line transformation. First, the video input frame is captured from camera. As the video frames contains RGB colour space format, it is difficult to process the image because processing a three-channel colourful picture, processing a channel image is much quicker, so it is converted to grayscale. As erroneous edges detection might lead to the creation of noise, it is necessary to smooth the picture using a Gaussian filter. After that, we use a technique called canny edge detection, to find edges with significant intensity changes by computing the gradient in all directions of the blurred picture. Lastly, the Hough line transformation is used to find straight lines that returns the lines' ends as its output.

5. RESULTS

Get the data you have collected ready to be analysed. The ML model is used for detection of road lanes and traffic signs.

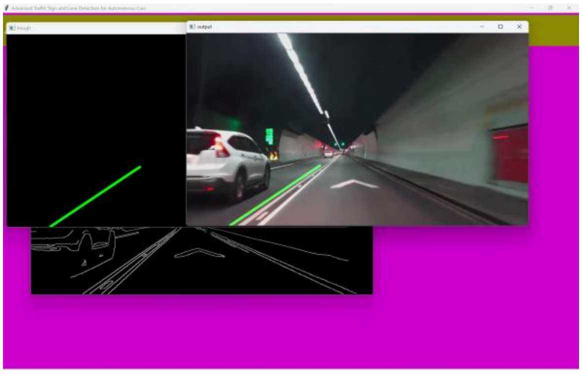

Figure 1 Displaying Lane Detection

In the figure 1, despite the absence of traffic lights, the green line on the screen is used for lane recognition and the same line can be seen in the black story window called Hough line and the light skinned canny edge detection window.

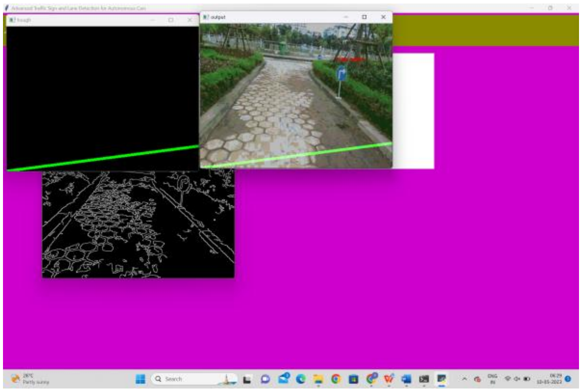

Figure 2 Displaying Traffic Sign Detection

In the figure 2, the traffic sign is recognized and it is labelled with red colour. The green line on the screen is used for width of the pedestrian walk and the same line can be seen in the black story window called Hough line and the light skinned canny edge detection window.

6. CONCLUSION

In this paper, we proposed the approach using Machine Learning which effectively recognizes traffic signs and road lanes. The proposed technique uses video frames that contains raw RGB images to do image analysis for identifying road lanes and traffic sign. Therefore, the proposed technique is well suitable for autonomous cars in terms of safety and avoidance of accidents to sudden traffic events.

7. REFERENCES

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