

Traffic Sign Detection using Clara and Yolo in Python

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Abstract— Research in the field of self-driving and autonomous vehicles is continuously growing. Many researchers are working to make self-driving cars more secure. Researchers work diligently to make cars as safe as possible to minimize fatal injuries on our roads. In about 30 percent of these incidents, there is a central factor: speed. For several decades, speeding has been a widely discussed subject for major automotive companies. The purpose of the project is to contribute to this research by implementing a driving simulator for a device that can understand speed limit signs and make decisions that make the driver more comfortable and safer to drive. The CARLA Learning to Act (CARLA), an open-source autonomous test simulator consisting primarily of two modules, the CARLA simulator and the Python API module, is used as a simulator in this analysis. The algorithm You Look Just Once (YOLO) is used to classifying road signs. Yolo sees the whole picture during training and testing, encoding contextual information about the groups of objects and their appearances instead of a sliding window over several places in an image. This feature makes it extremely easy to analyze an image. Several utilities may be used to identify the speed signs of a road. There are two applications for this project: a request for a notice warning the driver that the vehicle's speed is above the maximum allowed speed of that traffic, and a request for a rule to reduce the vehicle's speed when the traffic limit is reached.

Keywords—Self-driving simulator, object detection, traffic sign detection, Convolutional Neural Network, Fast Convolutional Neural Network, Bounding Boxed, CARLA, YOLO

I. INTRODUCTION

Every year, traffic accidents in India are a significant cause of death, injury and property damage. These 464,674 road accidents resulted in 148,707 traffic-related deaths in India. The road safety in India in 2015 reported an accident rate of 0.8 per 1000 vehicles and a fatality rate of 11.35 per 100,000. The exact number of fatal incidents is difficult to measure because of

speed, but the probability of being involved in one of them is greatly affected. The higher the speed, the less reaction time the drivers have and the harder it is to avoid an accident. There are two ways to fix this. The first approach is to raise awareness of road users' responsibilities, and the second way is by making cars safer and speeding. While theoretical awareness sessions are strongly encouraged, men will likely fight and make mistakes on the road. Therefore, governments and researchers have to develop safer cars, in which maximum speed can be regulated according to reasonable lane speed.

Autonomous driving vehicles have become popular in the research community over the last few years. An autonomous car is capable of detecting and navigating its surroundings without human interference. For an autonomous vehicle, one of the essential aspects is 'vision,' which involves identifying and detecting road signs. Due to obstacles such as occlusion, shifting lighting conditions, camera angle and other variables that occur in natural scenes, traffic sign detection is a challenging activity. Another difficulty to deal with is many signs in a single view.

In 2016, Joseph Redmon et al. introduced a new approach to object detection. The You Only Look Once (Yolo) method. Yolo is a consistently built architecture that detects frames with a not-so-complicated pipeline as a regression problem, which allows the device incredibly quick. It executes 45 frames per second in real-time and processes real-time video streaming with less than 25 milliseconds of latency. It makes more localization errors than other systems, but false-positive errors are less likely to be expected in the rear. ACC has the potential to learn fully general representations of artifacts that transcend many other methods of detection, such as neural networks and sequential cameras.

The CARLA Simulator will be used in this project. The reasons why the CARLA Simulator will be used in this project are because it has a broad user/study community linked to it, it has a roadmap² scheduled for December 2019, it is known to all the autonomously driving research groups, and researchers from the University of Barcelona have it built. CARLA presents realistic city plans (including houses, vehicles, footpaths...) and a wide variety of environmental factors that show similarities to the real world. This high degree of similarity helps a real car to replicate the unit that this project introduces.

II. RELATED WORK

The first research was published in 1984 on automatic traffic sign detection under [1]. Various researchers tried to create an effective TSDR method. The entire TSDR system can be sorted into several stages: preprocessing, identification, reconnaissance and recognition. The visual quality of the images was improved during the preprocessing phase. A variety of color and form-based methods reduce test images' effects on the environment [2–4]. This project aims to determine and classify known traffic signs after a thorough search in the picture for candidates. Different color and shape-dependent methods are used to detect ROI. The color detection methods most known and renowned are the HSI/HSV Transformation [7,8], the Growing Region[9], the Color Indexation [10], and the YCbCr transformation of color space [11]. Since color information is not accurate through lighting and weather changes, the form-based algorithm is implemented. Hough transformation [12], similarity detection [13], distance transformation matching [14], and hair-like edges [15] are the common formal approaches.

Methods more recent, such as the R-CNN, use the proposed Range of Interest (ROIs) methods to set possible boundary boxes and then run a classification system for each of these suggested boxes. However, in instances, using an image classifier thousands of times means creating detections on a neural network with thousands of evaluations. This takes many computational resources, prevents generalization and can introduce a delay in the microprocessing and convert the whole system into a pseudo-real-time system. After post-processing, this would refine the many boundary boxes, detect and rescan duplicate boxes depending on the number of objects in the scene. After 2013, CNN's began to become the standard for tasks for object detecting. Some examples of CNNs for these over feats, which uses a scalable sliding window and a greedy method of combining to generate bounding boxes and ratings, and R-CNN, implement a two-step procedure system for the proposal of an area and regression issue within the proposed areas. It is costly in both time and memory, and the processing of it takes about 47 seconds for a test picture. Via sharing of computation and the substitution of neural search with selective search Network [16], and Faster R-CNN [17] achieve greater precision and higher latencies overall than making a sequential area pipeline.

YOLO offers ideas and objects classification by treating the overall problem as regression. The alternative is the problem. This contributes to a much lower latency at the expense of any precision. On the Test Set for PASCAL VOC 2012, YOLO can achieve 63.4 percent mAP at 22 ms latency. Yolo is a single framework that defines the regression problem with a not too complicated pipeline that allows the regression problem. The system is speedy: images run on 45 frames per second in real-time, and video streaming is processed in real-time with a delay of under 25 milliseconds. It creates more localization compared to other detection systems.

III. LITERATURE SURVEY

They discussed the basic chronology leading to autonomous car production. This paper explores the historical context, recent patterns and innovations, and semi-autonomous cars' predictable future for public use [18].

Furthermore, the unified object detection model YOLO was developed. It can be educated directly on the full images in them. YOLO is not trained on a set of detection rules but instead trained on a set of non-negative output losses to detect scenes [19].

They proposed a method that effectively detects and monitors one or more moving objects in a variable context simultaneously. The algorithm's key benefit was that it did not rely on any previous environmental information [20].

They expressed the importance of deep learning applications in image classification, object detection and face identification. Experimental evidence shows that deep learning technology is an efficient method to move from the human-made function that relies on the drive of experience to the learning that relies on the data drive. Extensive data is the foundation of deep learning performance, large data, and the rocket's fuel for deep learning [21].

The degenerative model fed by the degraded image has been educated. The results showed that the model enhanced the overall classifications of objects. The model trained with reduced data has higher generalization ability, more significant potential, and more robustness [22].

A method for improving YOLO v2's network structure and obtained the YOLO-R network model. In pedestrian identification, they have achieved successful outcomes [23].

A barrier algorithm combines YOLO and light field camera, which would categorize objects into various categories and mark them in the input image [24].

A process for identifying and detecting welding joints used on the production line of automobile door panels by using the

YOLO algorithm. It was suggested that a detector for detecting the position of joints in solder [25].

A deep fusion practical method for detecting objects in remote sensing images with high resolution. This method consisted of three main steps: the generation of candidate regions, the fine-tuning extraction of in-depth features, and the deep feature classification of SVM [26].

They suggested a single layer multilayer perceptron network YOLO for object detection. YOLO can predict boundaries, thanks to its ability to detect object boundaries [27].

They proposed YOLO v1 neural object detection network by modified loss function and added spatial pyramid pooling layer and initial module with coevolutionary kernels [28].

YEAR	METHOD	CONCLUSIONS AND RESULTS
2015 [18]	Summary of Autonomous Cars	This paper explores the basic chronology of autonomous car creation. Autonomous vehicles have evolved from simple robotic cars to guided vehicles with a highly efficient and realistic vision. Ernst Dickmanns' Mercedes-Benz vision established led the autonomous van, and his team changed the autonomous car approach.
2016 [19]	YOLO for Object Detection	YOLO implemented a single unified regression go image architecture for bounding boxes in contrast with object detection techniques that came before YOLO, such as R-CNN, and finding class probabilities for each box. YOLO worked much quicker and offered more precision as well. Also, it could accurately predict artwork.
2017 [20]	Feature Extraction Techniques for Object Detection	This paper's proposed algorithm senses and monitors one or more moving objects in a variable context simultaneously. The experimental results show that the use of two object dimension features and their intensity distribution solved the data association problem very efficiently during monitoring.
2017 [21]	R-CNN, Fast R-CNN, Faster-R-CNN	The paper shows some primary methods and approaches for object detection like R-CNN, SPP-net, Fast R-CNN, Faster-R-CNN. All these object detection techniques are compared, and experimental data shows that Faster-R-CNN performs better than others.
2018 [22]	YOLO Network, Image Restoration	The experiment demonstrated that the model trained with standard sets has no adequate capacity for generalization for the degraded images and has low robustness. The model was then trained using degraded images that resulted in enhanced average accuracy. In the general degenerative model, the average quality of degraded images was demonstrated to be higher relative to the regular model.
2018 [23]	YOLO-R and YOLO v2	The YOLO algorithm's network structure has been strengthened. A new YOLO-R network structure has been

		proposed that will allow the network to better extract fine-grained feature details by adding pass-through layers to the original YOLO network. The number of detection frames reached 25 frames/s, effectively fulfilling the real-time output criterion.
2018 [24]	YOLO, Light Field Camera	The pictures of the typical barriers were labeled and used for YOLO training. To remove the uninquiring barrier, the object filter is applied. Different types of scenes are seen to illustrate the efficacy of this obstacle detection algorithm, including pedestrians, tables, books and so on.
2019 [25]	Modified YOLO	The YOLO algorithm, proposed in real-time, accurately identifies the location of the solder joints. This improves the productivity of the production line and is critical for the versatility and real-time welding of car door panels.
2019 [26]	SVM, Fusion Based Deep Learning Approach	A deep learning technique focused on fusion features to detect artifacts in high-resolution remote sensing images. The process consists of three main steps: the generation of candidates, the deep extraction of functionality, and the SVM classification's deep-fine-tuning.
2019 [27]	YOLO, Boundary Prediction Algorithms	In the prediction of boundaries, the YOLO algorithm accesses the entire image. It also predicts fewer false positives in the background. Compared to other classification algorithms, this algorithm is much more efficient and easy to use in real-time.
2020 [28]	Modified YOLO v1	A modified YOLOv1 model is being used for object detection. There have been significant changes in the new architecture of the neural network. A significant improvement will be made to the YOLOv1 network loss feature. The revamped model has exceeded the marginal proportional model.

Table 1. Literature Survey

IV. PROPOSED SYSTEM

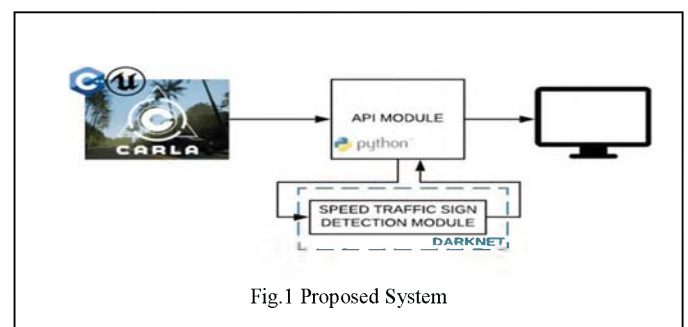


Fig.1 Proposed System

The figure above shows the project's succession pipeline and the key agents, i.e., Model detection and CARLA simulation. Yolo object detection model is built on top of the neural network model of open source darknet. After altering

some of the CARLA simulator sources, the learned Yolo model will detect the maximum allowable road speed and make those decisions accordingly.

A. Yolo Detection Module

Yolo is a real-time object detection system that is remarkably fast and reliable compared to other detectors. The next move was to shape our network to detect our custom images, the speed signs for CARLA. To do that, we have used the smaller Yolo 3 version model, i.e., the latest and fastest upgrade. Yolo is a regression-based real-time object detection method that predicts classes and boundary boxes in one run of the whole image algorithm. Instead of 22 deep Convolution Neural Network (CNN) layers, the smaller version has 16 layers, and the whole third version has 75 layers, followed by two entirely linked layers. The GoogLeNet image classification model inspires YOLO network architecture.

B. Network Modification

Yolo is a real-time object detection system that is remarkably fast and reliable compared to other detectors. The next move was to shape our network to detect our custom images, the speed signs for CARLA. To do that, we have used the smaller Yolo 3 version model, i.e., the latest and fastest upgrade. Yolo is a regression-based real-time object detection method that predicts classes and boundary boxes in one run of the whole image algorithm. Instead of 22 deep Convolution Neural Network (CNN) layers, the smaller version has 16 layers, and the whole third version has 75 layers, followed by two entirely linked layers. The GoogLeNet image classification model inspires YOLO network architecture.

Training Network Configuration			
batch	64	exposure	1.5
subdivisions	16	hue	0.1
width	608	flip	0
height	608	learning_rate	0.001
channels	3	burn_in	1000
momentum	0.9	max_batches	6000
decay	0.0005	policy	steps
angle	0	steps	4800, 5400
saturation	1.5	scales	0.1, 0.1

Fig. 2. Values of the network

C. Carla Simulator

CARLA is an Unreal Engine-based open-source simulator for autonomous driving research with modular APIs that enables users to change and control certain aspects of the simulation. This simulation is conducted on realistic urban layouts that allow users to obtain environmental feedback and make appropriate decisions. Regarding the speed signs in the CARLA 0.8.2 version, in both cases, there are only three different types of road signs: 30km/h, 60km/h and 90km/h.

Based on a C++ engine, this simulator can be monitored with an external client script that can control most aspects of the simulation. A PyGame Graphical User Interface (GUI) is included in the Python API module provided by researchers to manually control their vehicle. Also, some sensors, including RGB or Depth Map 'Light Imaging Detection and Range Systems' (LIDAR), are connected to the car to collect information on the environment and retrieve these measurements to make some decisions when driving.

For this project, a camera was mounted to the front of the vehicle to imitate the driver's point of view. Every five frames, this camera gets the RGB information of the scene. It saves it, allowing it to be ready for the model evaluation and the overwriting of the previous picture saved.



Fig. 3. Scenes recorded by the hood Camera Attached to Camera

The function to run the learned Yolo model on CARLA will be introduced and detect if the speed sign is on the scene and, in that case, recognize it. In this function, every five frames, the previously saved image of the current scene is read and evaluated by the model. The output file is then generated indicating whether a speed traffic sign that is signposted and the location is found is then sent to the rendering feature, which imprints on top of the display the maximum permissible speed of the road and remains embedded until a new speed limit signal has been detected.

It is tested when the current speed of the vehicle reaches the speed limit. If the vehicle speed is below the detected speed, the monitor will alert you to the necessary details. On the other hand, if the vehicle's current speed is more significant than that detected, the warning message at the bottom of the screen will appear.

V. CONCLUSION

While several project studies on the identification mechanism of speed traffic signs have previously been carried out with very satisfactory results, none have been implemented into CARLA. The Yolo-based approach to traffic sign detection in the Clara Stimulator was proposed in this paper. A real-time CNN was equipped to carry out this project to detect and recognize CARLA speed signals. After every five frames, the vehicle was attached to an RGB camera sensor, which obtained the environmental data. Implications for speed traffic research, in particular, indicate the field of recognition and the applications which can be applied to help drivers simplify and make driving safer. This project's success is promising and has implications for more progress on self-driving research.

Acknowledgment

First of all, we would like to thank our project guide Prof. Mohandas V. Pawar, for giving us the courage, guidance and suggestions for doing this major project. We also express our gratitude towards Dr. Rajneesh Kaur Sachdeo, HOD CSE and Dr. Kishore Ravande, Principle MITSOE sir for their support and guidance. We are thankful to MIT School of Engineering-MIT ADT University, Pune, for providing all resources and valuable information required about data mining techniques for our project. The process of analyzing and doing research on the valuable inputs helped us to explore knowledge, was a continuous source of inspiration and a unique experience.

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