Autonomous Driving System with Road Sign Recognition using Convolutional Neural Networks

Vaibhav Swaminathan, Shrey Arora, Ravi Bansal, Rajalakshmi R* School of Computing Science and Engineering Vellore Institute of Technology, Chennai, Tamilnadu, India vaibhav.swaminathan2014@vit.ac.in, rajalakshmi.r@vit.ac.in

Abstract— According to statistics, most road accidents take place due to lack of response time to instant traffic events. With the self-driving cars, this problem can be addressed by implementing automated systems to detect these traffic events. To design such recognition system in self-driving automated cars, it is important to monitor and manoeuvre through realtime traffic events. This involves correctly identifying the traffic signs that can be faced by an automated vehicle, classifying them, and responding to them. In this paper, an attempt is made to design such system, by applying image recognition to capture traffic signs, classify them correctly using Convolutional Neural Network, and respond to it in realtime through an Arduino controlled autonomous car. To study the performance of this road sign recognition system, various experiments were conducted using Belgium Traffic Signs dataset and an accuracy of 83.7% has been achieved by this approach.

Keywords— Convolutional Neural Networks, Self-driving car, Road Sign Recognition System

I. INTRODUCTION

Traffic signs provide the link for an autonomous car to perceive the road ahead and take informed decisions. An added benefit of traffic signs is that, they are placed well in advance, therefore giving the system adequate time to process the traffic event about to take place (Example: road under construction, dead end, slippery road, traffic signal etc) and then corresponding action may be performed. By recognizing road signs, we can ensure that an autonomous car can accurately manoeuvre these traffic events and thus ensure safe driving of the car.

There have been rapid advancements in the field of Machine Learning and Artificial Intelligence recently. Meanwhile, the automotive industry is witnessing a boom and more companies are focusing on technologies such as driverless cars, hybrid-powered cars etc. It would be useful, if the Machine Learning algorithms are applied in automotive industries for social benefit. According to statistics, most driving accidents occur due to human error. In order to make the driving process safer, an attempt is made to design a self-driving car with a road sign recognition system that

updates itself in every drive. As the road sign recognition is an important issue that needs to be addressed every time a car is on a drive, the proposed system incorporates machine learning to help the system learn better on every drive iteration and thus increase the system's prediction accuracy.

Although there are many such systems existing already, a majority of them focus only on road sign detection. While detecting traffic signs, colour and geometric patterns are the most basic characteristics commonly used for screening. So as to make the traffic signs easier to be noticed while driving, most of the warnings and restrictions on traffic signs choose to use the eye-catching red colour as a design feature. Therefore, in [1], this is used as a preliminary screening feature. A commonly used color space is the HSI color space because the color is independent of a channel and less affected compared to the R, G, B on the brightness change. Convolutional neural networks are now a widely researched topic, with its main use case lying in pattern recognition. Both Aris [1] and Shuo [2] proposed a system for road sign detection. While Aris [1] used HOG and PHOG, Shuo [2] implemented a CNN-ELM approach for prediction. Yujun [3] focussed on analysing the depth of deep neural networks using Adaboost. Chirstian [4] employed a 3-layer convolution followed by a fullyconnected layer to detect road signs and classified the driving style. These systems did not focus on the decision making approach of an autonomous car to these prediction. Another advantage of this system is its easy integration method into a car's default system. This can be achieved by connecting a microcontroller to the car's motor drivers and supplying them with response signals from the control station. By this proposed approach, fore through our system, we have successfully improved the time from detection of road sign to time of decision, thus achieving quick response of car to events such as road signs, road curvature and thus, preventing accidents.

In our system, we propose a hardware integration using Arduino connected to a self-car model to perform real-time response to the traffic signs. In addition,

distance of oncoming road sign from the car camera is calculated. Lastly, a lane following algorithm was applied to detect curves on the road ahead and respond to them. For implementing this recognition, we have used Belgium Traffic Signs Dataset and studied the performance of the system. It is shown by experimental results that, an accuracy of 83.7% can be achieved with this approach.

The paper is organized as follows. The existing works and the limitations are presented in Section II. The proposed approach is discussed in Section III. Results and discussions are briefed in Section IV followed by Conclusion in Section V.

II. RELATED WORKS

There are several existing systems proposed to perform road sign detection. Aris [1] focussed primarily on road signs detection using Histogram of Oriented Gradient (HOG) and Pyramid Histogram of Gradient (PHOG) on a Support Vector Machine (SVM), with the Indonesian database of traffic signs. Shuo [2] used CNN-ELM model to perform traffic sign recognition on German traffic sign recognition benchmark dataset. Yujun [3] applied an ensemble classification algorithm for convolutional neural networks. They have used the US traffic database as the test dataset. Christian [4] also used CNN with 3 convolution and pooling connected layers, and one fully connected layer and they used a private test dataset.

Support Vector Machines have been proposed in numerous works for road sign classification. Safat [5] used kernel based supervised SVM with K-means algorithm for classification. They used their own data that were captured using the camera on the Malaysian roads. In [6], a Histogram of Gradient with SVM was used for traffic sign recognition. Auranuch [6] suggested a multi-layer perceptron for recognition purpose.

Several algebraic approaches have also been used in the task of road sign recognition. Abdul Rahim [7] focused on finding contours in the image followed by the detection of ellipse and rectangle in the image. These images are then given as input to a multi-layer perceptron for recognition. Ruben [8] employed edge detection using Laplacian of Gaussan filter (LOG). Later, a Region of Interest (ROI) was computed and the shapes within this region were compared with an existing database to perform road sign recognition.

In all the above approaches, an integrated solution that involves real time data and the swift response is not suggested. In this paper, a hardware based integrated approach is proposed in which the traffic sign is detected by applying a deep learning approach and a prototype for real time decision making for self-driving car has been developed.

III. METHODOLOGY

For safe driving and to avoid accidents, it is important to detect the traffic signs on the road and to take the decisions in real time. The purpose of this work is to build a system that autonomously maneuvers itself on a track by recognizing road signs. In order to do this it should be able to record the road ahead in real time, and accurately identify the road signs and take corresponding response within the stipulated time. The summary of the proposed work is presented below with the fine details in the following sections. The first phase involves obtaining data about the track in front of the car using the car's environment through a mounted camera. This is followed by relaying the obtained information to the control station using wireless technology. In the second phase, CNN is used to recognize the road signs by calculating distance of road sign from the car and relaying the corresponding signal back to the car. The last phase involves maneuvering the car by altering its speed, direction based on the road sign detected.

The overall system is aimed at enabling an autonomous car to detect, recognize road signs, detect lane path ahead and calculate the distance to the road sign so as to take appropriate decision to stop / turn / continue driving. The proposed system consists of the following phases viz., Road Sign Recognition, Distance Calculation to Road Sign, Lane Following Control and Autonomous Driving on Assigned Track. In Phase 1, the input is taken from the camera module on the self-driving car of the track ahead. This feed is streamed to the control station where it is received frame-byframe and converted from RGB mode to gray scale. The frames of the track are given as input to the CNN and the output prediction of the road sign is then fed as signal to Raspberry Pi using local LAN. Phase 2 applies the Triangle Similarity law to calculate the distance from the camera to the road sign. Phase 3 includes performing training of the neural network by navigating the car over the assigned track. Once trained, the car is set on the track and automatically maneuvers itself in response to the track's curvature. Phase 4 finally integrates all the above functionalities using Raspberry Pi, Arduino Uno. Raspberry Pi is used to relay the signal and Arduino Uno, to control the self-driving car. This signal is then sent to Arduino, which controls the driver motors of the self-driving car. On receiving the signal, the Arduino relays the signal (forward, backward, left, right) to the driver motors attached to the four wheels on the selfdriving car.

A. Road Sign Recognition

For road sign detection, Google's MobileNet architecture was used. The GoogLeNet model was implemented using TensorFlow which was run on Anaconda 5.1. The MobileNet architecture consisted of a 3x3 convolution layer followed by a fully connected layer and a single convolution

layer. This was connected to a softmax layer for classification. The advantage of using TensorFlow with Anaconda is the ease of installation since most frequently used data science Python libraries are available within the Anaconda framework. Another advantage with TensorFlow, was the ability to visualize network graphs and view metrics using TensorBoard. For potential use in commercial vehicles, a library like TensorFlow would be beneficial due to its low computation time. For our work, we have used Belgium Traffic signs dataset consisting of 5 classes of roadsigns that include: stop, left turn, right turn, men at work, and school.

B. Distance Calculating Module

In phase 2, the system is made to be capable of calculating the distance of on road objects from the vehicle to maintain a safer distance as well as help in assisting the lane control system to take proper decisions. As more number of cameras would increase the weight as well as the cost to the model, the distance calculation with monocular vision was preferred.

In order to determine the distance from our camera to a known object or marker, we utilized triangle similarity. If an object with a known width W is placed some distance D from our camera. We take a picture of our object using our camera and then measure the apparent width in pixels P. This allows us to derive the perceived focal length F of our camera:

$$F = (P \times D) / W \tag{1}$$

As we continue to move the camera both closer and farther away from the object/marker, we can apply the triangle similarity to determine the distance of the object to the camera:

$$D' = (W \times F) / P$$
 (2)

C. Lane Following Control

In phase 3, the live streamed lane image is given to the processor, post which the image is converted to a black and white format for easier edge detection. Further, a Gaussian filter is applied to smooth out the edges found on the images. After this processing of the image, the extraction of edges is done for detection of the lane to be followed. These two lines are marked on the left and the right lane and an imaginary line is created as an average of these two lines. Further, the distance shift of this line from the center of the image is calculated. This calculated shift helps the processor to take the steering decision while keeping the vehicle in its lane. Although this method was successful in some occasions, the main drawback was the bulk of processing to be performed due to which it increased the computation time, and thereby, the response time.

In order to overcome, machine learning algorithm is used. The initial training phase included manually navigating the car around the track. This helps the car learn the features of the road and the manual inputs (left, right, forward, backward) given in response to these features. A multi-layer perceptron is created using OpenCV module

having input layer as the collected images and output layer as the navigational inputs given to the vehicle controller unit. This neural network is trained on the basis of the collected track data. The network consist of three layers in which 38,400 nodes are present in the initial input layer, later the middle layer consist of 32 nodes which further gives the output to the required 4 nodes depicted as the output.

D. Autonomous Driving on Assigned Track

In order to ensure that the car responds to real-time traffic events, it was integrated with all the above three phases using a Raspberry Pi microprocessor and Arduino Uno microontroller. After training our self-car on the assigned track, it was run on a test track with different lanes and road signs. The Raspberry Pi module acts as a router for connectivity for relaying frames to the control station. The Arduino is interfaced with the motor drivers to ensure that the car responds to the track and road sign. Figure 1 shows the self-driving car prototype made using this proposed design.



Figure 1: Prototype of autonomous car

IV. RESULTS AND DISCUSSION

To study the performance of the algorithm, different experiments were conducted. For all the experiments, Belgium traffic sign data set has been considered. The task is to classify among the five classes viz., left turn, right turnm men at work, speed limit 20, stop. We have considered a total of 385 images, in which 259 were used for training and kept aside for 126 images were testing. MobileNet_v1_1.0_224 of GoogleNet was used and trained on 259 images of road signs from Belgium Traffic Signs -Training for the following 5 classes (left turn, right turn, men at work, speed limit 20, stop). The test set consisted of 126 images of 'Belgium Traffic Signs - Testing with a test set accuracy of 83.7%. (Figure 2).



Figure 2:Performance of the proposed system

After doing several test runs, the distance calculating algorithm achieves a minimum detection distance of 19cm and a maximum of 61cm. This metric must be considered in scale to the overall length of the car. The time duration between detection of the sign and response of the car is 0.3 second. The performance of the proposed work is compared with other existing works and summarized in Table 1. As observed from Table 1, with the proposed approach, an accuracy of 83.7% has been achieved, which is a significant improvement. The proposed system has the advantage of accurate detection and providing fast response for the detected event.

Table 1: Comparative Analysis

Method	Accuracy
ACNN4 [1]	72.1%
PHOG + SVM [2]	82.01%
CNN-ElM Model [3]	82.4%
MobileNet CNN	83.7%

V. CONCLUSION

In this paper, we have broadened the boundaries of autonomous driving by successfully detecting, recognizing road signs, followed by calculating the distance of from the car to the said road sign. In addition, a lane following approach has also been devised to maneuver the car within the lanes of the road. With these results, such use cases may be developed as devices that could be attached to the car and make an autonomous car more intelligent at recognising and responding to real-time traffic events.

In future, we hope to seek out a larger dataset so as to train our system to recognize lesser-known traffic signs that are used in other parts of the world. Another aspect that could be improved is the ability of the system to recognise road signs at high speeds (>100 km/hr). This would mean to substantially decrease the prediction time. We would also like to increase the maximum distance of recognition, so as to give the car sufficient time to take a real-time decision.

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