

ENHANCING VEHICLE CONTROL USING A COMBINED SIGN BOARD APPROACH

CS492 PROJECT

A Report submitted to

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in partial fulfilment of the requirements for the award of the degree of

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We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

This is to certify that this report entitled "**ENHANCING VEHICLE CONTROL USING A COMBINED SIGN BOARD APPROACH**" is a bonafide record of the project work done by Mr. Albyn Babu (MUT15CS008), Mr. Mathews Ignatius (MUT15CS044), Mr. Roshin Jojo (MUT15CS052) and Mr. Sreehari Rajeev (MUT15CS055) of Muthoot Institute of Technology and Science, Varikoli for the award of the degree of Bachelor of Technology in Computer Science and Engineering under my supervision and guidance. The content of the report, in full or parts have not been submitted to any other Institute or University for the award of any other degree or diploma.

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Abstract

In today's world, the rash driving has contributed to a hundreds of deaths. One of the factors that boost is the negligence of road signs. Another matter in concern is about the migrants from other states who are unfamiliar with the local languages of the state they work. This introduces a hurdle for them to work in the field of driving. As a special case the school zones are given more attention by building an automatic speed reduction system. Distraction to the thought for a minute leads a blank state causing accidents and later to death. To resolve the barrier of language unfamiliarity we have introduced a Linguistic Assistance feature that help to understand the local sign scripts in use but which is available in few. An alert to drivers during a drive and a sophisticated electronic hardware to control speed would address the problem of getting distracted there by offering an automatic safety precaution. Well defined dataset of the road sign images are been considered here as training set. For the deliberation of aging, multiple appearance of sign and blurring of sign boards a ConvNet YOLOV3 is been used to get trained and to deliver the more expected meets. This will fill in as an extra to present a well defined ADAS (Advanced driver-assistance systems). Developing a prototype that is a real view of the system adds onto merit of the project.

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List of Abbreviations

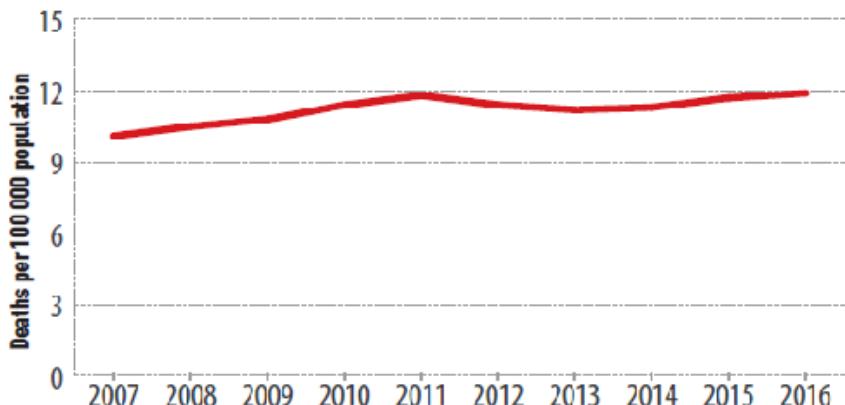
ADAS	Advanced Driver Assistance Systems
BO	Battery Operation
C-CNN	Convolutional Neural Network
CAD	Computer Aided Drawing
CNN	Convolutional Neural Network
ConvNet	Convolutional Network
CPU	Control Processing Unit
CUDA	Compute Unified Device Architecture
DC	Direct Current
DFD	Data Flow Diagram
FC	Fully Connected
GIMP	GNU Image Manipulation Program
GND	Ground
GPIO	General Purpose Input/Output
GPU	Graphical Processing Unit
GTSRB	German Traffic Sign Recognition Benchmark
HCNN	Hierarchical Convolutional Neural Network
HDMI	High Definition Multimedia Interface
HPC	High Performance Computer
HSV	Hue, Saturation, Value
IC	Integrated Circuit
IoT	Internet of Things
IoU	Intersection over Union
mAP	Mean Average Precision
MLP	Multilayer Perception
MPP	Max Pooling Positions
NLP	Natural Language Processing
NOOBS	New Out-Of-Box Software
OS	Operating System
OTG	On-The-Go

PC	Personal Computer
PWM	Pulse Width Modulation
R-CNN	Region Convolutional Neural Network
RGB	Red, Green, Blue
ROC	Receiver Operating Characteristic
RPi	Raspberry Pi
RPM	Revolutions Per Minute
SD	Secure Digital
SoC	System on a Chip
SVM	Support Vector Machine
TSDR	Traffic Sign Detection and Recognition
TSR	Traffic Sign Recognition
TV	Television
UML	Unified Modeling Language
USB	Universal Serial Bus
VCC	Voltage Collector to Collector
WHO	World Health Organization
YCbCr	Y: Luminance; Cb: Chrominance-Blue; and Cr: Chrominance-Red
YOLO	You Only Look Once

Chapter 1

Introduction

In the recent past the accident rates has increased drastically due to rash driving and over speed. Drivers are usually in a mind perspective to give less importance to road signs which results in increased road accidents. As a quick fix to this an automatic traffic sign recognition system that enhances the vehicular system could help.



Source: Ministry of Road Transport and Highways, Road Accidents in India 2016

Figure 1.1: Trending accident rates in India

Focusing from traditional methods one could notice the role played by the standard computer vision methodologies to detect and classify traffic signs. Studies in this field indicate that even though these methods are considerable they are high time-consuming manual works. Traffic signs are an integral part of our road infrastructure. They provide critical information, sometimes compelling recommendations, for road users, which in turn requires them to adjust their driving behavior to make sure they adhere with whatever road regulation currently enforced. For the smooth running of advanced driver assistance system linguistic assistance feature is also added which contributes the drivers with local scripts acquaintance found in signboards. An adequate

alertness combined with the automatic system helps the driver to indicate the found speed limits found on the journey.

Without much information of the useful signs, accidents rates get higher as drivers would not be given critical feed-back on how fast they could safely go, or informed about road works, sharp turn, or school crossings ahead. As per the latest statistic road accidents kill over a lakh a year. Around 1.3M from the total die on roads each year without road signs uncleanness. Naturally, autonomous vehicles must also abide by road legislation and therefore recognize and understand traffic signs.

The Figure 1.1 depicts the trending rates of accident from recent years. Sign board from a local regional language again creates an obstacle their way. Speed limits shown neglected where on the other side causes severe causalities. What happens in the mentioned is again traffic rule violation happens due to the recognition problem in their visual aspect. In all means of these negligence and as well as unfamiliarity is an accident and that leads to severe injury and might to death. Even if there are enormous number of methods deployed to help in situations like this, there are no measures taken in account to prevent this. Another alarming status that we have found out is given below Figure 1.2.



Figure 1.2: A simple statistic of accident rates

It's very sad to see that the negligence and rash driving itself has caused the life of these much people. This data will give a rough idea about what is happening in our country.



Figure 1.3: Reasons for accidents

The statistics has clearly showed that out of all the accidental deaths the major share is from vehicle accidents that too is because of the negligence of road signs and rash driving. According to the accident statistics report in India it is said that there is one road accident happening every 4 minutes in India which is not at all a good report.

According to the World Health Organizations Report, India occupies a top position in terms of vehicle accidents. Over confidence, carelessness, over speed and negligence of traffic sign trigger all the accidents. So thinking about a system which can overcome all these problems make our project relevant. A system where in which automatic detection of sign boards and controlling of the vehicle is made possible. It reduces the human effort to recognize the sign board and control the vehicle which will eventually led to the decrease in the accident rates. This paper gives an overview of the proposed method and tries to recognize the traffic sign boards along with linguistic features and an electronic support system that controls the speed and produces alerts when required.

Chapter 2

Literature Survey Report

2.1 Traffic Sign Recognition Using CNN [1]

Authors: Kaoutar Sefrioui Boujema, Afaf Bouhoute, Karim Boubouh and Ismail Berrada; 2017

2.1.1 Summary

Traffic sign recognition (TSR) represents an important feature of advanced driver assistance systems, contributing to the safety of the drivers, pedestrians and vehicles as well. Developing TSR systems requires the use of computer vision techniques, which could be considered fundamental in the field of pattern recognition in general. Recently the number of road vehicles has increased enormously thanks to the technological achievements in the motor industry and very precisely the availability of low rates. With this remarkable growth, the number of accidents is as well in an infinite raise year after year, due to different causes, in which the ignorance of traffic signs is considered as a major cause of these lasts. This paper presented an analytical study of two effective and efficient road sign detection and recognition approaches. The experimental results achieved after testing both of the methods on the German Traffic Sign Detection & Recognition datasets, conclude that the Fast R-CNN is so much faster than the C-CNN method, also it is invariant to illumination changes (as long as this type of images is available in the training dataset). On the other hand, even though the C-CNN approach is slow and sensitive to weather conditions, it is invariant to scale and viewing angle.

2.2 Robust Chinese Traffic Sign Detection and Recognition Using Deep CNN [2]

Authors: Rongqiang Qian, Bailing Zhang, Yong Yue, Zhao Wang and Frans Coenen; 2015

2.2.1 Summary

Detection and recognition of traffic sign, including various road signs and text, play an important role in autonomous driving, mapping/navigation and traffic safety. In this paper, we proposed a traffic sign detection and recognition system by applying deep convolutional neural network (CNN), which demonstrates high performance with regard to detection rate and recognition accuracy. Acquisition of the information from various traffic signs is crucial in many applications, such as autonomous driving, mapping and navigation. It is also important in intelligent transportation systems. Generally, a traffic sign recognition system involves two related issues: traffic sign detection and traffic sign classification. The former aims to accurately localize the traffic signs in an image, while the later intends to identify the labels of detected object into specific categories/subcategories. Generally, traffic signs are designed with regular shapes and attractive color to be easily noticed. The most widely used traffic signs can be classified into three subcategories, namely, prohibitory type, including circle, red rim, white or red inner; mandatory type, including circle, blue rim, blue inner; and danger type, including triangular, black rim, yellow inner. In this paper, a multi-task CNN based road traffic information acquisition method is proposed. Aiming to detect and recognize not only traffic signs, but also digits, English letters and Chinese characters. The whole procedure includes two stages. For any input image, firstly, a set of candidate regions are proposed by using colour space thresholding. Secondly, multi-task CNN is used to determine the similarity and reject false samples in detection task. Simultaneously, the detail categories of the true samples are obtained by classification task. The approach is evaluated on several popular datasets, achieving comparative results.

2.3 A Road Sign Detection and the Recognition for Driver Assistance Systems [3]

Authors: Amol Jayant Kale and Prof. R.C.Mahajan; 2015

2.3.1 Summary

Automatic traffic sign detection and recognition, as an important task of Advanced Driver Assistance Systems, has been of great interest in recent years. The road signs are typically placed either on a roadside or above the roads. They provide important information regarding to guiding, warning, or regulating the behaviors to drivers in order to make driving safer and easier. The main purpose of driving assistance systems is to collect significant information for drivers in order to reduce their effort in safe driving. Drivers have to pay attention to various conditions, including vehicle speed and orientation, the distance between vehicles, passing cars, and potential dangerous or unusual events ahead. If driver assistance system can collect such information a prior, it will greatly reduce the burden of driving for drivers and make driving safer and easier. Traffic sign detection has a direct impact on the safety of driver, and damages can be easily produced due to

their ignorance. Automatic systems developed to assist the driver, based on detection and recognition of signs can consequently correct the most unsafe driving behavior. In this paper the reliable approach of the recognition and detection of the road sign has been discussed. Image detection has been implemented on real life road sign image. Robust method of color segmentation is employed in the YCbCr color space. The experimental results show that the image detection method is accurate.

2.4 Traffic Sign Detection A new approach and recognition using CNN [4]

Authors: Prashengit Dhar, Md. Zainal Abedin, Tonoy Biswas and Anish Datta; 2017

2.4.1 Summary

Traffic Sign Recognition (TSR) system is a component of Driving Assistance System (ADAS). The TSR system assists the drivers in safe driving as road signs provide important information of the road. This research focuses to design and develop a TSR system by using color cues and Convolution Neural Network (CNN) as both features extractor and classifier for Bangladeshi traffic signs. In the first step, after image acquisition, some pre-processing task is performed. Then the image is segmented using color information of HSV color model. After that, morphological closing is executed to fine the segmented image. Consequently, after filtering the image by using region properties and shape signature, the desired region is cropped. Finally, the extracted sign area is classified by means of automatic features extraction with deep CNN. The experimental results illustrate that the proposed algorithm shows comparable performance with good recognition accuracy. Vision oriented traffic TSR is an significant field to do research that continuously attracts the researchs community of the industry . Since Traffic sign helps to interpret the state of the road, regulate the traffic and also helps in warning and guiding pedestrians and drivers. This paper represents a new efficient traffic sign detection and recognition algorithm towards the design of TSR system in the domain of Bangladesh. Segmentation is done using color information and CNN is used as a classifier. As a classification tool it is a well-accepted technique as it shows invariance to affine transformation of the image. It uses convolution layer which perform most key role in features selection. CNN allow networks to have fewer weights and they have a very effective tool named as convolutions for image processing. The proposed system is for red rim triangular Bangladeshi traffic sign. The system is tested for four types of sign.

2.5 A Smart Traffic Sign Recognition System [5]

Authors: Adnan Shaout, Nevrus Kaja, Selim Awad; 2015

2.5.1 Summary

With recent developments in automotive industry it has become a standard for every new automotive project to require vision as an integral part of it. One of the most common vision applications in automotive industry is traffic sign recognition system (TSR). This paper addresses some of the advantages and drawbacks that computer vision has in assisting Advanced Driver Assist Systems (ADAS) and proposes a new method for real time traffic sign recognition (TSR) system which combines intelligent algorithms with classical image recognition algorithms. In order to design a TSR with the new requirements as stated they first studied its feasibility and created in this section a proof of concept design. The new contribution that is presented in this design application is the intelligence aspect. Through using machine learning algorithms such as neural networks, support vector machines or decision trees we are able to train the system to “learn” the traffic signs that it detects and eventually get better at it. The paper presented an implementation for the new proposed method for real time traffic sign recognition (TSR) system which combined intelligent algorithms with classical image recognition algorithms. The proposed method have shown that using machine learning, and intelligent systems algorithms is suitable for automotive vision and ADAS systems. This provides a better approach in traffic sign recognition systems than the traditional template base methods.

2.6 An Automatic Traffic Sign Detection and Recognition System based on Color segmentation, Shape matching [6]

Authors: Safat B. Wali, Mohammad A. Hannan, Aini Hussain, and Salina A. Samad; 2015

2.6.1 Summary

The main objective of this study is to develop an efficient TSDR system which contains an enriched dataset of Malaysian traffic signs. The developed technique is invariant in variable lighting, rotation, translation, and viewing angle and has a low computational time with low false positive rate. The development of the system has three working stages: image preprocessing, detection, and recognition. The system demonstration using a RGB colour segmentation and shape matching followed by support vector machine (SVM) classifier led to promising results with respect to the accuracy of 95.71%, false positive rate (0.9%), and processing time (0.43s). The area under the receiver operating characteristic (ROC) curves was introduced to statistically evaluate the recognition performance. The accuracy of the developed system is relatively high and the computational time is relatively low which will be helpful for classifying traffic signs especially on high ways around Malaysia. The low false positive rate will increase the system stability and reliability on real-time application. In the image acquisition stage, the images were captured by an on board camera under different weather conditions and the image preprocessing was done by using RGB colour segmentation. The recognition process is done by SVM with bagged kernel which is used

for the first time for traffic sign classification. The recognition performance is evaluated by using ROC curve analysis. The simulation results are compared with the existing methods showing the correctness of the implementation.

2.7 Hierarchical CNN for Traffic Sign Recognition [7]

Authors: Xuehong Mao, Samer Hijazi, Ral Casas, Piyush Kaul, Rishi Kumar, and Chris Rowen; 2016

2.7.1 Summary

The Convolutional Neural Network (CNN) is a breakthrough technique in object classification and pattern recognition. It has enabled computers to achieve performance superior to humans in specialized image recognition tasks. Prior art CNNs learn object features by stacking multiple convolutional or non-linear layers in sequence on top of a classifier. The Convolutional Neural Network (CNN) is a deep learning approach that stacks several convolutional, subsampling and non-linear activation layers in sequence. Recently, the CNN has become a breakthrough technique in the field of artificial intelligence for object classification and pattern recognition applications such as handwritten digit recognition , object classification, speech recognition, and face identification. Meanwhile, Advanced Driver Assistant Systems (ADAS) have received tremendous interest from both industry and academia. To improve driving safety, a vehicle needs to be able to see and understand its surroundings. Reliable detection and classification of objects such as pedestrians, vehicles, roads and traffic signs are highly demanded in ADAS. This work proposes a novel CNN algorithm and applies it to the problem of traffic sign recognition (TSR). In this paper, we proposed a hierarchical CNN for traffic sign recognition, and demonstrated its superior performance to the best reported results with the GTSRB. The benefit of the proposed HCNN is two-fold. First, the hierarchical CNN is able to solve a difficult problem by partitioning it into multiple easier sub-problems and distributing the effort of solving these sub-problems according to their difficulty. In this paper, we have used a secondary member classifier that is of equal size and architecture for all families. Alternatively, the size and architecture of each member classifier could be tailored to the size of each corresponding family. The second benefit of our approach comes from the use of an unsupervised CNN to learn the hierarchy of classes because the HCNN perceives the CNN-oriented families better than the human defined families. As part of the future work, HCNN will be applied to other applications and investigate recursive multi-level classification.

2.8 Traffic Sign Recognition with CNN Based on Max Pooling [8]

Authors: Rongqiang Qian, Yong Yue, Frans Coenen and Bailing Zhang; 2016

2.8.1 Summary

Recognition of traffic signs is very important in many applications such as in self-driving car/-driverless car, traffic mapping and traffic surveillance. Recently, deep learning models demonstrated prominent representation capacity, and achieved outstanding performance in traffic sign recognition. In this paper, we propose a traffic sign recognition system by applying convolutional neural network (CNN). In comparison with previous methods which usually use CNN as feature extractor and multilayer perception (MLP) as classifier, we proposed max pooling positions (MPPs) as an effective discriminative feature to predict category labels. Through extensive experiments, MPPs demonstrates the ideal characteristics of small inter-class variance and large intra-class variance. Moreover, with the German Traffic Sign Recognition Benchmark(GTSRB),outstanding performance-based on Color segmentation, Shape matching has been achieved by using MPPs. The acquisition of information from real-world traffic system is a key component in many applications, such as selfdriving car/driverless car, traffic mapping and traffic surveillance. With the advent of some publicly available benchmark datasets such as the German Traffic Sign Recognition Benchmark (GTSRB), a number of outstanding results for recognition of European traffic signs have been reported in the literature. Recently, the development of deep learning has attracted much attention in computer vision research as more and more promising results are published on a range of different vision tasks. Among the deep learning models, the convolutional neural networks (CNN) have acquired unique noteworthiness for their repeatedly confirmed superiorities. Convolutional neural networks have powerful representational learning capabilities, with a number of desirable properties such as the translation invariance and spatially local connections. A pre-trained CNN model can be efficiently exploited as a generic feature extractor for different vision tasks. In this paper, a novel traffic sign recognition system is proposed, with main contributions including: (i) a CNN model to learn a compact yet discriminative feature representation; (ii) a novel method to perform recognition based on MPPs; (iii) a novel method to improve classification performance and speed using MPPs. By introducing MPPs for recognition, accuracy rate is significantly improved. Extensive experiments have been performed, yielding promising results.

Chapter 3

Comparison of Existing Techniques

Methods	Variable lighting	Blurring and fading	Multiple appearance of sign	Damaged sign	Partial obscured sign	Fast algorithm for Real-time	Motion Blur effect	Rotation, translation, scaling	Noisy background	Viewing angle
MSER based HOG + Decision tree	√	√	√			√				
Gradient Orientation + Karhunen-Loeve transform	√	√	√						√	√
Genetic Algorithm + Probabilistic NN	√	√				√			√	
adaptive shape analysis+ Probabilistic NN	√					√			√	
YCbCr + Image Normalization+NN	√	√				√			√	
SVM	√	√				√		√		√
Haar like features + SVM			√		√		√			√
Hough based SVM	√				√	√		√	√	√
CIE XYZ transform in LCH spacing + FOSTS Model	√	√	√						√	
HSI Transform + Fuzzy shape recognizer				√		√		√		√
Gabor Filter + Joint Transform Correlation			√		√			√		√
SIFT matching + SVM	√								√	
AdaBoost + CHT	√	√	√			√				
3D re-construction method				√	√	√				

Table 3.1: Comparison of existing methods for TSR

Chapter 4

Proposed Work

4.1 Problem Statement

Rash driving and negligence to road traffic signs leads to deaths of many. Another matter in concern is about the migrants from other states who are unfamiliar with the local languages of the state they work. Negligence to traffic signs are a key factor to accidents and unfamiliarity to local scripts in traffic boards. Carelessness to speed limits and school zone boards are another factor to hike in number. This system act as a complementary along with the driver for assistance

4.2 Objectives

The main objectives of the proposed project are:

1. To develop a system that recognizes Traffic Sign Boards
2. A system that could recognize local language sign board
3. An assistance to autonomous driving

4.3 Proposed Solution

A system that could detect and recognize any traffic signs seen in the road is the primary objective that will be implemented using with the help of machine learning.

We are creating a dataset by collecting local sign board written in local languages. As the dataset is available by online we will retrieve it directly whereas sign boards containing local scripts is in few. Augmenting and manipulating collected dataset to over needs will resolve this problem and change accordingly to our view. On field work will help for collecting more signs on the same category.

Labelling the dataset will produce output annotation files that contains required data for further processing. The annotation file will contain labelling boundaries of the traffic sign available

and seen in the image in consideration in the labelling software. An open source labelling tool, LabelImg has menu driven tools to produce model specific annotating tools that helps to generate the proper annotation file. It may contain information about the bounding boxes, its axes co-ordinates and center co-ordinates.

Then we are training it with YoloV3 model that will produce an output weight file that will enable us to continue the project with testing and implementation of the system. The training phase may include the feeding of the labelled images towards the deep learning algorithm that will eventually creates the weight file for the model that is required. The maximum the dataset we get to train, that maximum will be the accuracy of the system. Around thousand images will have to be collected for attaining proper output weight file that will have enough information to recognize any future testings.

A language recognition facility is also been incorporated that will recognize local scripts in traffic signs and will be greatly useful.

The weight file generated will be then used for the testing. The 75% of the dataset collected were only used for training and thus we would use the rest 25% of the dataset for testing purposes. The percentage of accuracy that we should get must meet atleast above 96% to finalize the software implementation phase.

The model that was used for the testing is the key thing for the implementation. The model weight file will be taken to reside in the server system which is a HPC that has GPU capabilities.

A prototype that have image capturing feature will be set up to capture and store the image as in the client vehicle. The captured image will be fetched by the server for the processing. The processed output will be transferred back to the client vehicle to control it by itself. Better follow ups and future plans may help it be used for the autonomous vehicles and the TSR systems later.

4.4 Scope of the Project

The proposed solution will serve as an add-on to the existing Advanced Driver Assistance System and an extra to the Autonomous Vehicles. Detecting and recognizing traffic signs are crucial to all vehicles and hence this could be implemented in vehicles to prevent accidents due to negligence and carelessness to the traffic and warning signs provided. Alerting driver about the speed limits and slow speed zones along with danger priority stop symbols will surely assist the driver on his drive.

Chapter 5

Methodology

5.1 Background and Algorithms

The Dataset collection was the primary objective for the entire project flow. In field data collection was in-feasible and hence the entire dataset images were collected from online sources. In total we had 900 images that contain and not contain any traffic sign boards. The dataset collection was completed by augmenting and manipulating the downloaded dataset. GIMP and Adobe Photoshop were used for the same.

Background study were done by reading the literature survey papers mention in the Literature Survey chapter. Background studies on CNN, available frameworks on the field of Deep Learning, Algorithms used in deep learning were all done.

5.1.1 Deep Learning

Deep learning is a class of machine learning algorithms that use multiple layers to progressively extract higher level features from raw input. For example, in image processing, lower layers may identify edges, while higher layer may identify human-meaningful items such as digits/letters or faces.

Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on artificial neural networks. Learning can be supervised, semi-supervised or unsupervised.

Deep learning architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolutional neural networks have been applied to fields including computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases superior to human experts.

Neural networks were inspired by information processing and distributed communication nodes in biological systems. ANNs have various differences from biological brains. Specifically, neural

networks tend to be static and symbolic, while the biological brain of most living organisms is dynamic (plastic) and analog.

5.1.2 Convolutional Neural Network

Convolutional Neural Network or Conv-net or CNN is such an Artificial Neural Network used in deep learning. CNNs specifically are inspired by the biological visual cortex. The cortex has small regions of cells that are sensitive to the specific areas of the visual field. This idea was expanded by a captivating experiment done by Hubel and Wiesel in 1962. In this experiment, the researchers showed that some individual neurons in the brain activated or fired only in the presence of edges of a particular orientation like vertical or horizontal edges. For example, some neurons fired when exposed to vertical sides and some when shown a horizontal edge. Hubel and Wiesel found that all of these neurons were well ordered in a columnar fashion and that together they were able to produce visual perception. This idea of specialized components inside of a system having specific tasks is one that machines use as well and one that we can also find back in CNNs.

Convolutional Neural Networks may be mentioned as one of the major milestone in the advancement pathway of computing and visual recognition. There are enormous number of applications that could be found in every field of engineering. In image Detection and Recognition, help for Self Driving cars, Image Classification etc.

Convolutional Neural Network(CNN) is an artificial neural network that has some type of specialization for being able to pick out or detect patterns. This pattern detection is what makes CNNs so useful for image analysis. CNNs have layers called convolutional layers along with it pooling layers, normalization layers, fully connected layers. CNNs can, and usually do, have other, non-convolutional layers as well, but the basis of a CNN is the convolutional layers.

5.1.3 YOLOV3

There are a few different algorithms for object detection and they can be split into two groups:

- Algorithms based on classification they work in two stages. In the first step, we're selecting from the image interesting regions. Then we're classifying those regions using convolutional neural networks. This solution could be very slow because we have to run prediction for every selected region. Most known example of this type of algorithms is the Region-based convolutional neural network (RCNN) and their cousins Fast-RCNN and Faster-RCNN.
- Algorithms based on regression instead of selecting interesting parts of an image, we're predicting classes and bounding boxes for the whole image in one run of the algorithm. Most known example of this type of algorithms is YOLO (You only look once) commonly used for real-time object detection.

You only look once, or YOLO, is one of the faster object detection algorithms out there. It is a very good choice when you need real-time detection, without loss of too much accuracy. YOLO v3

uses a variant of Darknet, which originally has 53 layer network trained on Imagenet. For the task of detection, 53 more layers are stacked onto it, giving us a 106 layer fully convolutional underlying architecture for YOLO v3. Here is how the architecture of YOLO now looks like.

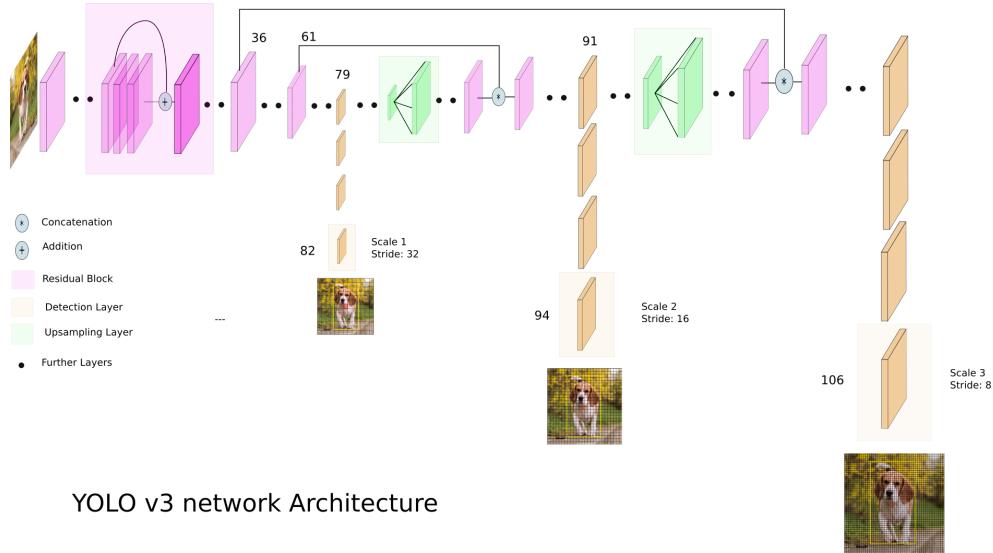


Figure 5.1: Architecture of YOLO

Instead, independent logistic classifiers are used and binary cross-entropy loss is used. Because there may be overlapping labels for multilabel classification such as if the YOLOv3 is moved to other more complex domain such as Open Images Dataset. In YOLOv3, a much deeper network Darknet-53 is used, that is 53 convolutional layers.

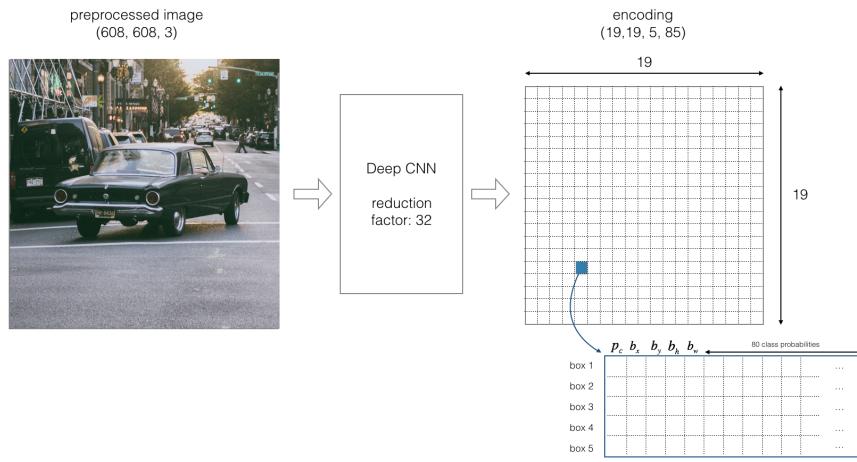


Figure 5.2: Bounding Boxes

Our task is to predict a class of an object and the bounding box specifying object location. Each bounding box can be described using four descriptors : center of a bounding box (bx by), width (bw), height (bh), value c is corresponding to a class of an object. We've got also one more

predicted value pc which is a probability that there is an object in the bounding box.

Instead of searching for interested regions on our image that could contain some object we are splitting our image into cells, typically its 1919 grid. Each cell will be responsible for predicting 5 bounding boxes (in case there's more than one object in this cell). This will give us 1805 bounding boxes for an image. Majority of those cells and boxes won't have an object inside and this is the reason why we need to predict pc . In the next step, we're removing boxes with low object probability and bounding boxes with the highest shared area in the process called non-max suppression.

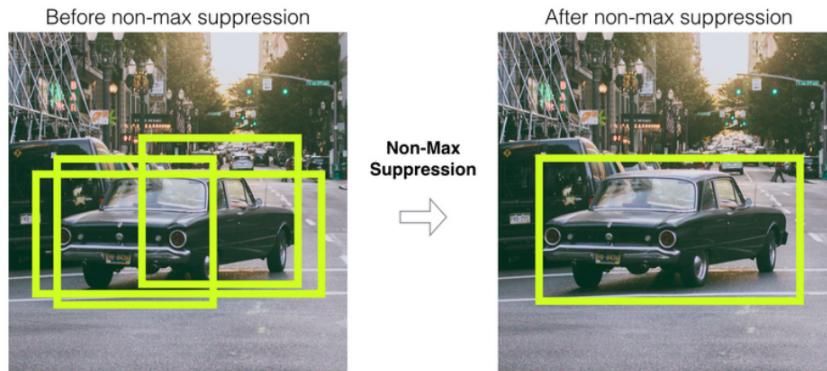


Figure 5.3: Non-Max Suppression

The above figure shows the image before and after the Non-Max Suppression. The image to the left has a number of bounding boxes visible over the image whereas the right figure shows how Non-max Suppression helps to find the best bounding box by calculating the probability of each bounding boxes.

5.1.4 General Algorithm

1. Collect Dataset
2. Prepare Dataset as Ready-to-feed to Training module
3. Repeat until minimum loss acquired
 - (a) Train the dataset using YOLOV3 algorithm in Darknet Framework
4. Test the accuracy
5. If accuracy less than expected
 - (a) Add more dataset
 - (b) Then go to step 3
6. Else

- (a) Make the prototype
 - (b) In the prototype
 - i. Client Capture Image
 - ii. Server fetch the image captured
 - iii. Process and recognize the traffic sign if exists
 - iv. Return the result recognized to the prototype
 - v. Execute the motor control code using the returned result from server
 - (c) end
7. end

5.1.5 General Flowchart

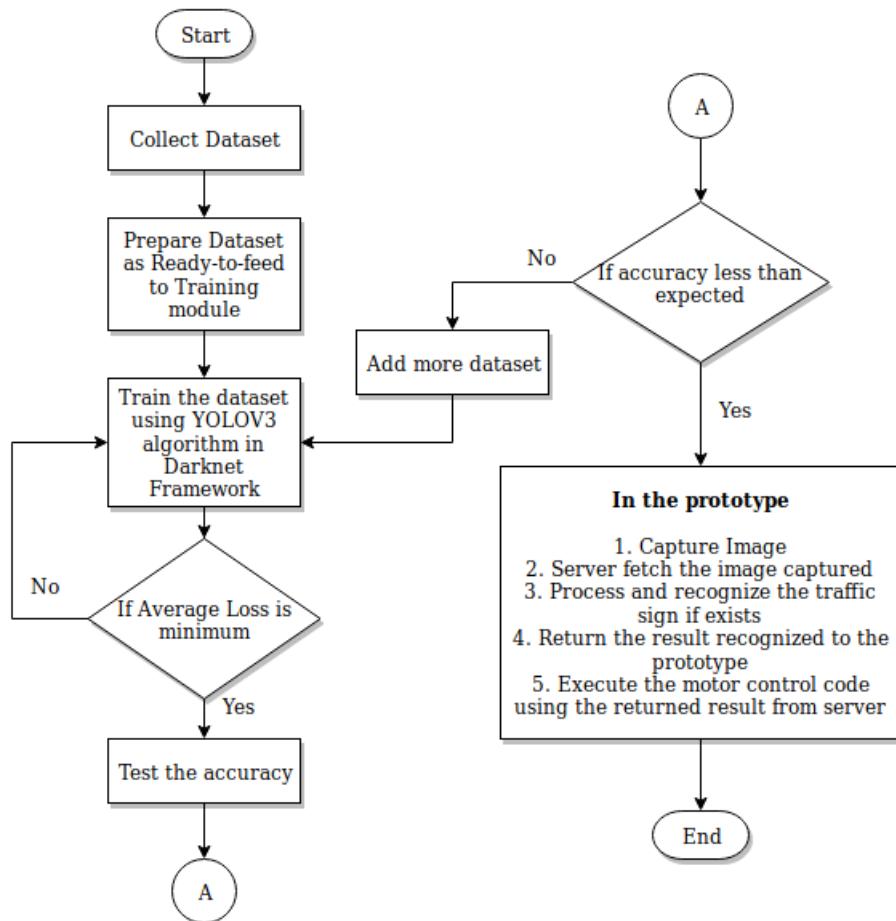


Figure 5.4: General Flowchart

5.2 Project Design

5.2.1 Data Flow Diagram

Level 0

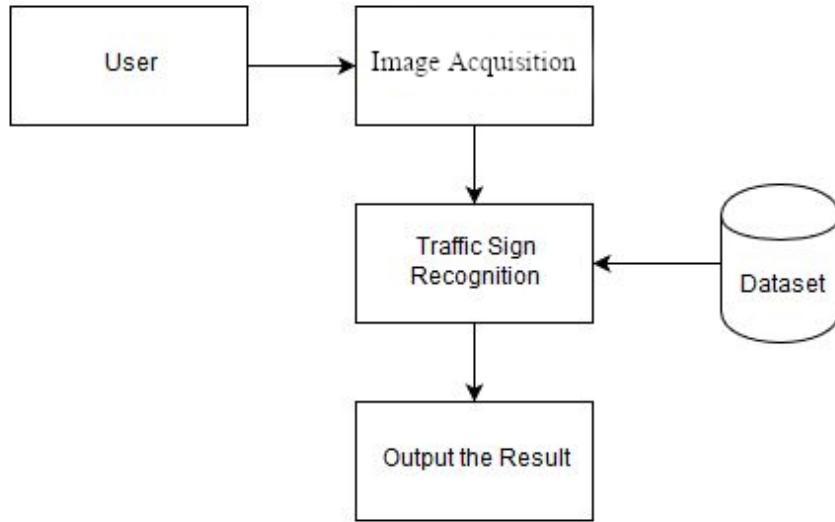


Figure 5.5: ‘Level 0’ Data Flow Diagram

This is the Data flow of our project. Here there is a user or the dash cam who giving the image as the input. And the image then passed to the image acquisition phase, where the image will be cropped for analysis as the traffic sign portion has to be taken. Then there the image is processed and make the digital image representation.

Next stage is that it will pass through a portion where the image will be then recognized or the traffic sign will be recognized. And at the end the recognized output will be send out to the display screen.

Level 1

The inner traffic sign recognition portion will have the three layers, namely the Convolutional Layer, the Pooling layer and the Fully connected layer.

Convolutional Layer is the core building block of the entire CNN. Convolution is the first layer to extract features from an input image. Convolution preserves the relationship between pixels by learning image features using small squares of input data. It is a mathematical operation that takes two inputs such as image matrix and a filter or kernel.

Pooling layers section would reduce the number of parameters when the images are too large. Spatial pooling also called subsampling or downsampling which reduces the dimensionality of each

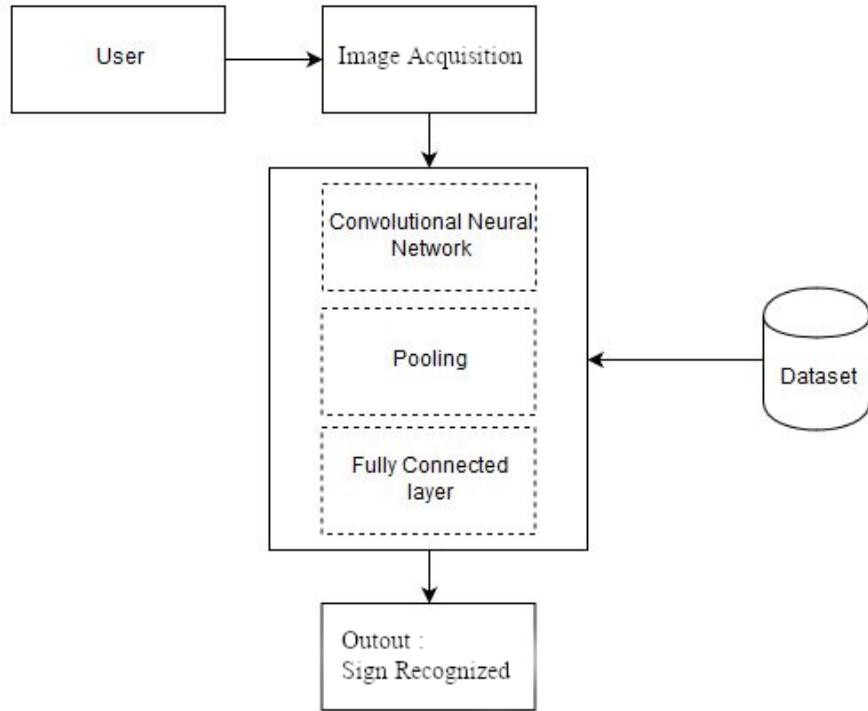


Figure 5.6: ‘Level 1’ Data Flow Diagram

map but retains the important information.

The layer we call as FC layer, we flattened our matrix into vector and feed it into a fully connected layer like neural network.

5.2.2 Activity Diagram

Activity diagram is another important diagram in UML to describe the dynamic aspects of the system. Activity diagram is basically a flowchart to represent the flow from one activity to another activity. The activity can be described as an operation of the system. The control flow is drawn from one operation to another. This flow can be sequential, branched, or concurrent. Activity diagrams deal with all type of flow control by using different elements such as fork, join, etc. Activity is a particular operation of the system. Activity diagrams are not only used for visualizing the dynamic nature of a system, but they are also used to construct the executable system by using forward and reverse engineering techniques.

The basic usage of activity diagram is similar to other four UML diagrams. The specific usage is to model the control flow from one activity to another. This control flow does not include messages. Activity diagram is suitable for modeling the activity flow of the system. An application can have multiple systems. Activity diagram also captures these systems and describes the flow from one system to another. This specific usage is not available in other diagrams. These systems can be database, external queues, or any other system.

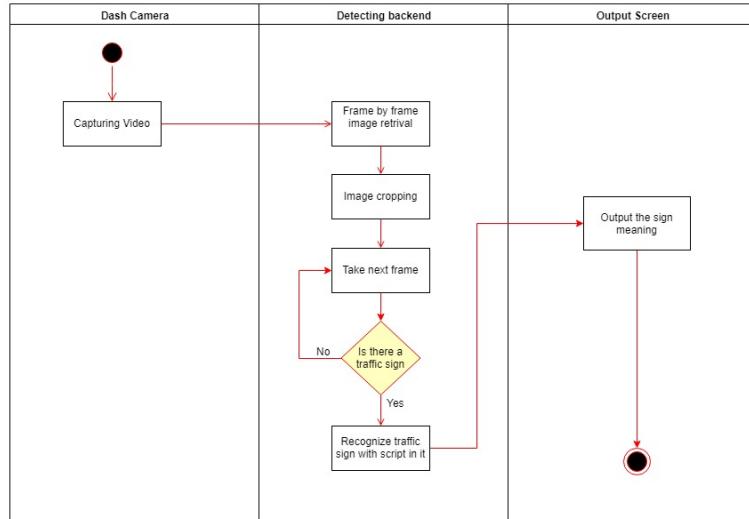


Figure 5.7: Activity Diagram

The activity diagram indicates what all are the activities we are done through this entire process. First of all we are capturing a video of the sign boards in different angles. Then the image will be retrieved by cutting the video frame by frame. Then the image will be cropped and if there is any traffic sign occurs then it will get recognized and give the output as what signal is that.

5.2.3 Usecase Diagram

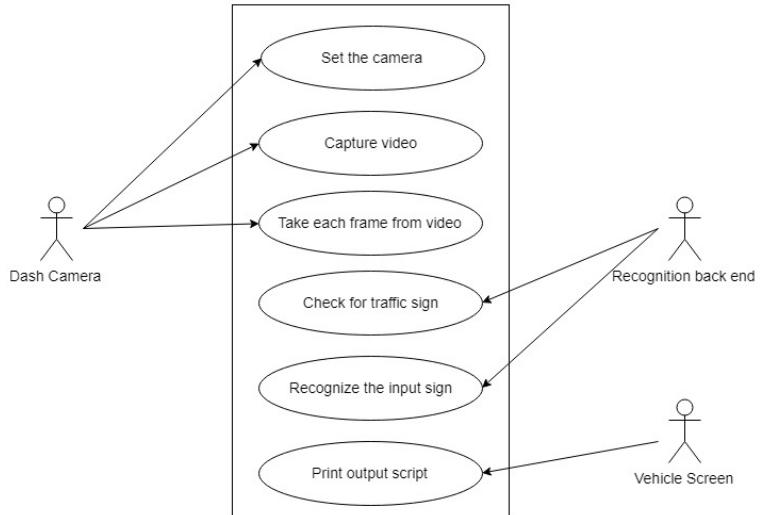


Figure 5.8: Usecase Diagram

A use case diagram is a dynamic or behavior diagram in UML. Use case diagrams model the

functionality of a system using actors and use cases. Use cases are a set of actions, services, and functions that the system needs to perform. In this context, a “system” is something being developed or operated, such as a web site. The “actors” are people or entities operating under defined roles within the system.

Use case diagrams are valuable for visualizing the functional requirements of a system that will translate into design choices and development priorities. They also help identify any internal or external factors that may influence the system and should be taken into consideration. They provide a good high level analysis from outside the system. Use case diagrams specify how the system interacts with actors without worrying about the details of how that functionality is implemented.

This is the usecase diagram and there are the users and the activities which they are involved. Here the users are Dash Camera, Recognition Back End and Vehicle screen.

The dash camera has the permission to set the camera and capture the video of the sign board in different angles and to take the image by cut the video frame by frame. Then the recognition back end has the permission to check that whether there is any traffic sign is there in the current frame. And the final user is that the vehicle screen, and it has the task to print the output that indicates which traffic sign is that in the vehicle screen.

Chapter 6

Software and Hardware Requirements

6.1 Software Requirements

1. Darknet Framework

Darknet is an open source neural network framework written in C and CUDA. It is fast, easy to install, and supports CPU and GPU computation

2. Yolo V3 Algorithm

You only look once (YOLO) is a state-of-the-art, real-time object detection system. YOLOv3 is extremely fast and accurate. In mAP measured at .5 IOU YOLOv3 is on par with Focal Loss but about 4x faster. Moreover, you can easily tradeoff between speed and accuracy simply by changing the size of the model, no retraining required.

3. Linux or Windows OS

For Linux based systems the generated darknet file will be executed by `./darknet` while in the Windows based system we could execute it as `darknet.exe`.

4. Python 2.7 or above

Python is a popular programming language. It is used for web development (server-side), software development, mathematics, system scripting. Python works on different platforms (Windows, Mac, Linux, Raspberry Pi, etc).

5. Raspbian OS

Raspbian is a free operating system based on Debian optimized for the Raspberry Pi hardware. An operating system is the set of basic programs and utilities that make your Raspberry Pi run.

6. LabelImg

LabelImg is a graphical image annotation tool and label object bounding boxes in images. labelImg is an excellent tool which makes the face annotation boxes.

7. OpenCV

OpenCV is a library of programming functions mainly aimed at real-time computer vision. The library is cross-platform and free for use under the open-source BSD license. OpenCV supports the deep learning frameworks Darknet, TensorFlow, Torch/PyTorch and Caffe.

8. NVIDIA CUDA Toolkit

The NVIDIA CUDA Toolkit provides a development environment for creating high performance GPU-accelerated applications. With the CUDA Toolkit, you can develop, optimize and deploy your applications on GPU-accelerated embedded systems, desktop workstations, enterprise data centers, cloud-based platforms and HPC supercomputers. The toolkit includes GPU-accelerated libraries, debugging and optimization tools, a C/C++ compiler and a runtime library to deploy your application.

6.2 Hardware Requirements

1. Graphical Processing Unit(GPU)

A graphics processing unit (GPU) is a specialized electronic circuit designed to rapidly manipulate and alter memory to accelerate the creation of images in a frame buffer intended for output to a display device. GPUs are used in embedded systems, mobile phones, personal computers, workstations, and game consoles.

2. Raspberry Pi 3 Model B

The Raspberry Pi hardware has evolved through several versions that feature variations in memory capacity and peripheral-device support. The Ethernet adapter is internally connected to an additional USB port. In Model A, A+, and the Pi Zero, the USB port is connected directly to the system on a chip (SoC). On the Pi 1 Model B+ and later models the USB/Ethernet chip contains a five-port USB hub, of which four ports are available, while the Pi 1 Model B only provides two. On the Pi Zero, the USB port is also connected directly to the SoC, but it uses a micro USB (OTG) port.

3. L293D Motor Driver

L293D is a dual H-bridge motor driver integrated circuit (IC). Motor drivers act as current amplifiers since they take a low-current control signal and provide a higher-current signal. This higher current signal is used to drive the motors.

4. BO Motors

Dual shaft DC motor with gear box which gives good torque and rpm at lower voltages. This motor can run at approximately 200rpm when driven by a Dual Li-Ion cell battery at 6 V and approximately at 300 rpm when driven by a 9V Li-Ion cell.

Chapter 7

Implementation

The implementation includes all the steps that are required for the completion of the project. Standing at the design phase or the preliminary phase of the project team has collected a minimal amount of the datasets that are required.

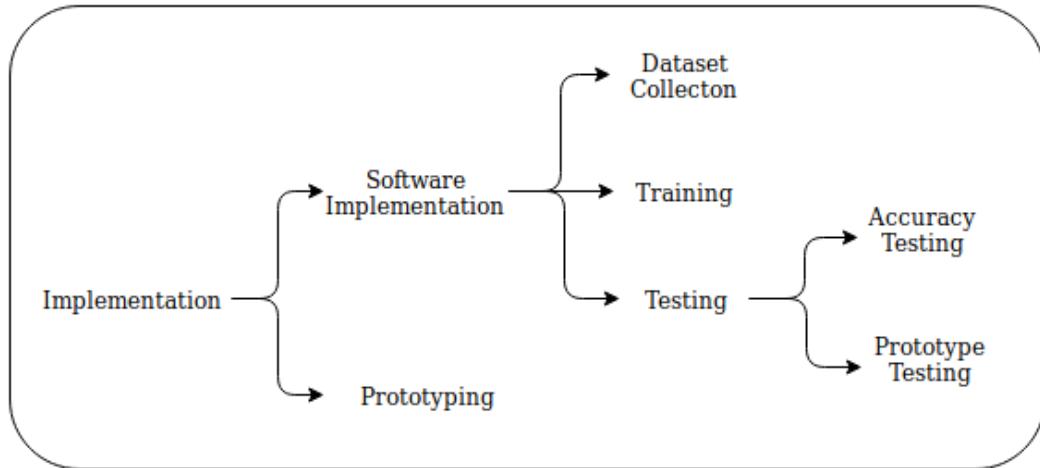


Figure 7.1: Implementation

The entire implementation phase could be divided into two phases namely, the software implementation and prototype implementation. Here in the software implementation the dataset is collected, manipulated, trained and tested. There were around thousand images collected to the dataset and same number of gray scale images were added from the collected ones. Augmenting were done to increase number of images in the set and manipulations like cropping were also done.

For training YOLO algorithm were used which has real-time operation to recognize classes or objects from the image. Above 90% were the accuracy of the system after first training. Later on new datasets were added and accuracy were increased.

Testing included two phases where the software part as well as the prototype were tested multiple time to get good outcome and accuracy. On board prototype testing from the beginning showed

great accuracy. Accuracy testing done to test whether all images fed are recognized successfully.

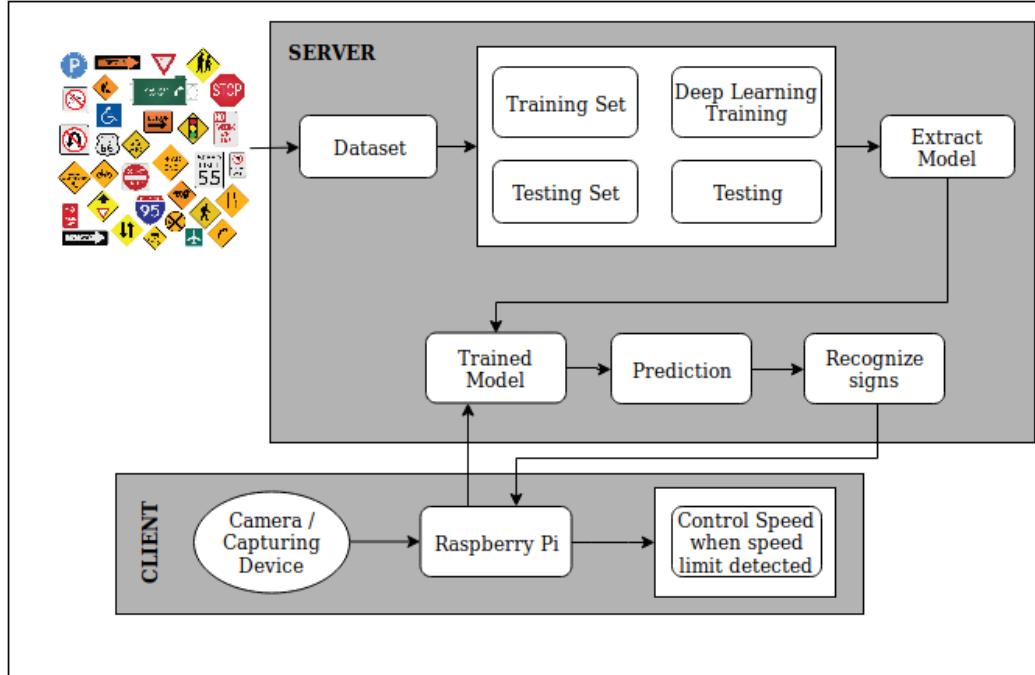


Figure 7.2: Basic architecture

7.1 Data Set Collection

The data set required for the work is basically a collection of images having traffic signs present in it. Online resources where there to collect huge amount of this data set.

The deep learning model that was used for the testing is the key thing for the implementation. Better follow ups and future plans may help it be used for the autonomous vehicles and the TSR systems later.

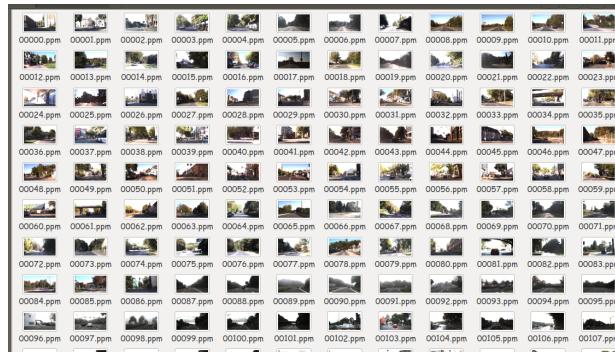


Figure 7.3: Dataset of Traffic Signs collected

The above is the set of collected dataset that contain the German Traffic Sign Boards. The

training phase will use 75% of the dataset and the rest 25% for testing purposes. The percentage that we should get must meet the threshold percentage set. In the Deep Learning side the data set after the conversion will be labeled using any of the tools that are available online or offline.

Dataset	
Type	No. of Images
Images Collected	900
Grayscale converted	900
Manually Manipulated	100
Augmented	50

Table 7.1: Dataset types and count

The above set of images were in .ppm format and which was not compatible for feeding for training and hence has to be converted to proper image format(.jpg). “ImageMagick”, an open source software available for Ubuntu were used to convert .ppm images to .jpg images so easily through a simple single line command.

*\$ convert *.ppm %d.jpg*

The converted image was divided to training and testing set, where each of the image used in training was pre-labelled using LabelImg, an open source software for labelling. It produces .txt files that contain object-class, x, y, width and height respectively.

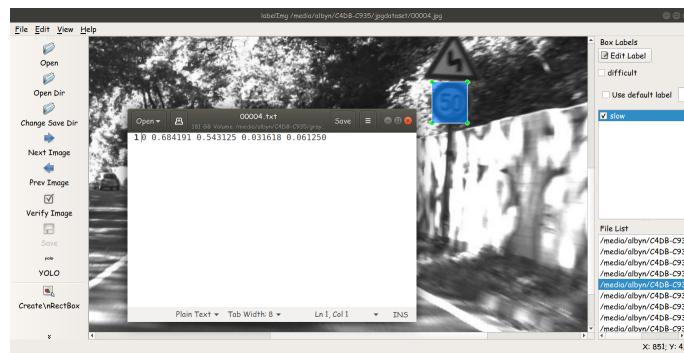


Figure 7.4: Labelling an image and its output .txt file

- object-class - integer object number from 0 to (classes-1)
- x_center y_center width height - float values relative to width and height of image, it can be equal from (0.0 to 1.0]
- $x = \text{absolute_x} / \text{image_width}$ or $\text{height} = \text{absolute_height} / \text{image_height}$
- x_center y_center - are center of rectangle

7.2 Traffic Sign Recognition

7.2.1 Training

The Traffic Sign Recognition module includes two sub parts that are training and testing. The dataset that were collected as mentioned earlier were separated randomly to training and testing set. The images along with its label information has been fed to the training. We had used the **Darknet**, deep learning framework with **Yolov3** model(algorithm) for training.

The darknet framework directory structure is given below.

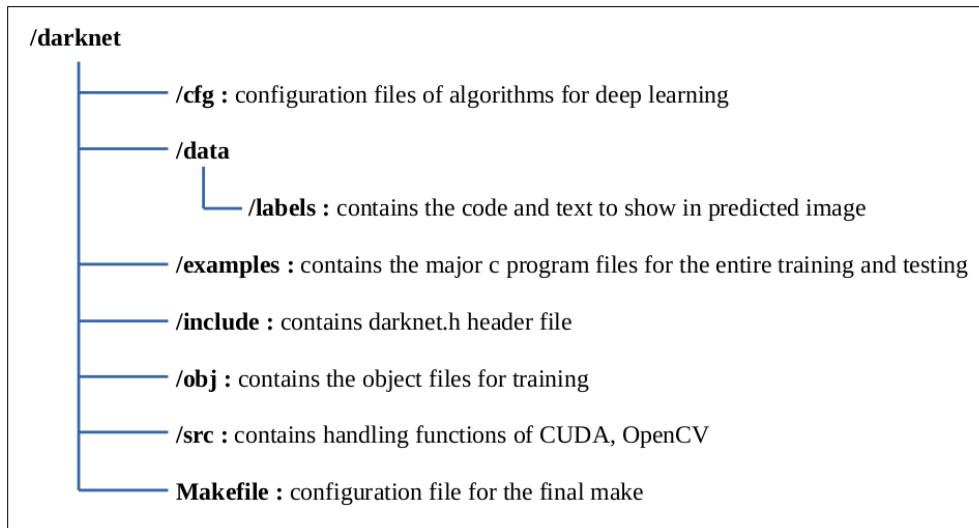


Figure 7.5: Directory structure of Darknet before make

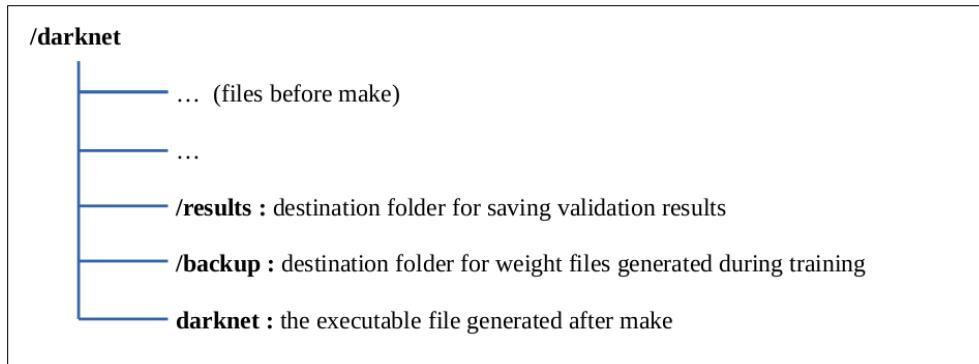


Figure 7.6: Directory structure of Darknet after make

The directory structure after the make is given in the Figure 4.5. An executable *darknet* file has been made along with a result and backup folder. The makefile is available in the directory where the specifications available for the system has to be mentioned.

GPU was set to 1 as the GPU was available for training and the processing. All are optional where we may work with or without all or any of it. The made file *darknet* is executable in all

```

1 GPU=1
2 CUDNN=0
3 OPENCV=0
4 OPENMP=0
5 DEBUG=0

```

Figure 7.7: Specifications in the makefile

OS an in Linux we may run it using `./darknet` (function) (arguments) and in windows `darknet.exe` (function) (arguments). The basic functions that are passed includes **detector train**, **detector train**, **detect**, **demo**, **etc** and the arguments are ***model configuration file***, ***weight file***, ***image to detect***. The executable `darknet` file assess the input got and immediately pass those arguments to the respective functions to process and generate the output.

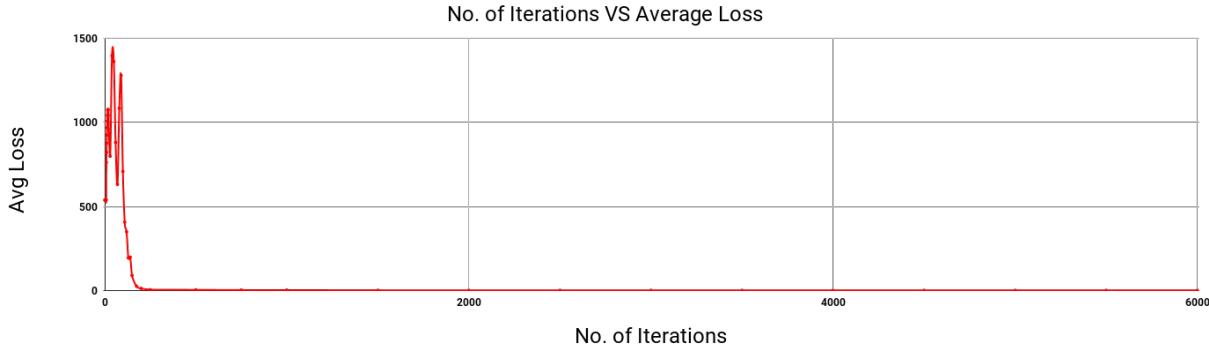


Figure 7.8: No. of iterations vs. Average Loss graph

The above graph shows the analysis of the No. of Iterations along with the Average Loss change. The number of iterations is selected according to the or dependent to the number of classes that we are selecting.

$$\text{max_batches} = \text{no. of classes} * 2000$$

Here we had three(3) classes and hence the ***max_batches*** was equal to 6000. And thus the system will iterate 6000 steps on the image with the training algorithm. At the point of 6000th iteration the Average Loss was 0.078951 from Average Loss of 1397.51 at the initial steps. Lower the loss higher the accuracy. There are cases where minimum average loss is seen in the mid or at intermediate iterations. In this case if the weight files are generated in between, we may use it as the final weight file.

After we make sure the original repo compiles in the system, lets make some minor modifications in order to store the intermediate weights. In the file `examples/detector.c`, change line135 from

```
if(i%10000 == 0 ||(i < 1000 && i%100 == 0))
```

```
to
if(i%1000 == 0 ||(i < 1000 && i%100 == 0))
```

The original repository saves the network weights after every 100 iterations till the first 1000 and then saves only after every 10000 iterations. In our case, since we are training with only a three class, we expect our training to converge much faster. So in order to monitor the progress closely, we save after every 100 iterations till we reach 1000 and then we save after every 1000 iterations. After the above changes are made, recompile darknet using the make command again.

```
[net]
# Testing
# batch=1
# subdivisions=1
# Training
batch=64
subdivisions=16
```

Figure 7.9: Training parameters

The batch parameter indicates the batch size used during training. Our training set contains a few hundred images, but it is not uncommon to train on million of images. The training process involves iteratively updating the weights of the neural network based on how many mistakes it is making on the training dataset. It is impractical (and unnecessary) to use all images in the training set at once to update the weights. So, a small subset of images is used in one iteration, and this subset is called the batch size. When the batch size is set to 64, it means 64 images are used in one iteration to update the parameters of the neural network.

Even though we may want to use a batch size of 64 for training our neural network, we may not have a GPU with enough memory to use a batch size of 64. Fortunately, Darknet allows us to specify a variable called subdivisions that lets you process a fraction of the batch size at one time on your GPU. We can start the training with subdivisions=1, and if we get an Out of memory error, increase the subdivisions parameter by multiples of 2(e.g. 2, 4, 8, 16) till the training proceeds successfully. The GPU will process batch/subdivision number of images at any time, but the full batch or iteration would be complete only after all the 64 (as set above) images are processed. During testing, both batch and subdivision are set to 1.

Other parameters that are included are the steps count and filters. Both step count and filters have dependency with the classes as well as the max_batches.

$$\begin{aligned} \text{steps} &= 80\%, 90\% \text{ of } \text{max_batches} \\ \text{filters} &= (\text{no. of classes} + 5) * 3 \end{aligned}$$

Training a yolo model requires the made darknet file, the configuration file, the basic weight file, here in this case **darknet53.conv.74** which is a pre-trained weights for the convolutional

layers and the **detector train** function. This will train the model and the output weight file will be generated after the training. The number of iterations the training has to be done depends on the number of object classes that we have to recognize. 3 classes selected required 6000 iterations and steps 80% and 90% of the iterations selected.

```

teammars@jarvis:~/Desktop/btech-main_project$ ./darknet detector train data/obj/data.cfg/yolov3.voc.cfg darknet53.conv.74
yolov1.cfg          yolov2.cfg          yolov2-tiny.cfg      yolov2-voc.cfg      yolov3.cfg          yolov3-spp.cfg      yolov3-voc.cfg
yolov1-tiny.cfg     yolov2-tiny.cfg     yolov2-voc.cfg      yolov3-openimages.cfg    yolov3-tiny.cfg
teammars@jarvis:~/Desktop/btech-main_project$ ./darknet detector train data/obj/data.cfg/yolov3.cfg darknet53.conv.74
yolov3.cfg          yolov3-openimages.cfg    yolov3-spp.cfg      yolov3-tiny.cfg      yolov3-voc.cfg
teammars@jarvis:~/Desktop/btech-main_project$ ./darknet detector train data/obj/data.cfg/yolov3.voc.cfg darknet53.conv.74
yolov3
layer      filters   ssize      input       output
1 conv     32 3 x 3 / 1 608 x 608 x 3 -> 608 x 608 x 32 0.639 BFLOPs
1 conv     64 3 x 3 / 2 608 x 608 x 32 -> 304 x 304 x 64 3.407 BFLOPs
2 conv     32 1 x 1 / 1 304 x 304 x 64 -> 304 x 304 x 32 0.379 BFLOPs
3 conv     64 3 x 3 / 1 304 x 304 x 32 -> 304 x 304 x 64 3.407 BFLOPs
4 res      1          304 x 304 x 64 -> 304 x 304 x 64 0.379 BFLOPs
5 conv     128 3 x 3 / 2 304 x 304 x 64 -> 152 x 152 x 128 3.407 BFLOPs
6 conv     64 1 x 1 / 1 152 x 152 x 128 -> 152 x 152 x 64 3.407 BFLOPs
7 conv     128 3 x 3 / 1 152 x 152 x 64 -> 152 x 152 x 128 3.407 BFLOPs
8 res      5          152 x 152 x 128 -> 152 x 152 x 128 3.407 BFLOPs
9 conv     64 1 x 1 / 1 152 x 152 x 128 -> 152 x 152 x 64 3.407 BFLOPs
10 conv    128 3 x 3 / 1 152 x 152 x 64 -> 152 x 152 x 128 3.407 BFLOPs
11 res     8          152 x 152 x 128 -> 152 x 152 x 128 3.407 BFLOPs
12 conv    256 3 x 3 / 2 152 x 152 x 128 -> 76 x 76 x 256 3.407 BFLOPs
13 conv    128 1 x 1 / 1 76 x 76 x 256 -> 76 x 76 x 128 0.379 BFLOPs
14 conv    256 3 x 3 / 1 76 x 76 x 128 -> 76 x 76 x 256 3.407 BFLOPs
15 res     12         76 x 76 x 256 -> 76 x 76 x 256
16 conv    128 1 x 1 / 1 76 x 76 x 256 -> 76 x 76 x 128 0.379 BFLOPs
17 conv    256 3 x 3 / 1 76 x 76 x 128 -> 76 x 76 x 256 3.407 BFLOPs
18 res     15         76 x 76 x 256 -> 76 x 76 x 256
19 conv    128 1 x 1 / 1 76 x 76 x 256 -> 76 x 76 x 128 0.379 BFLOPs
20 conv    256 3 x 3 / 1 76 x 76 x 128 -> 76 x 76 x 256 3.407 BFLOPs
21 res     18         76 x 76 x 256 -> 76 x 76 x 256
22 conv    128 1 x 1 / 1 76 x 76 x 256 -> 76 x 76 x 128 0.379 BFLOPs
23 conv    256 3 x 3 / 1 76 x 76 x 128 -> 76 x 76 x 256 3.407 BFLOPs
24 res     21         76 x 76 x 256 -> 76 x 76 x 256
25 conv    128 1 x 1 / 1 76 x 76 x 256 -> 76 x 76 x 128 0.379 BFLOPs
26 conv    256 3 x 3 / 1 76 x 76 x 128 -> 76 x 76 x 256 3.407 BFLOPs
27 conv    256 1 x 1 / 1 76 x 76 x 256 -> 76 x 76 x 128 0.379 BFLOPs
28 conv    256 3 x 3 / 1 76 x 76 x 128 -> 76 x 76 x 256 3.407 BFLOPs
29 conv    256 3 x 3 / 1 76 x 76 x 256 -> 76 x 76 x 128 0.379 BFLOPs
30 res     27         76 x 76 x 128 -> 76 x 76 x 128
31 conv    128 1 x 1 / 1 76 x 76 x 128 -> 76 x 76 x 38 0.379 BFLOPs
32 conv    256 3 x 3 / 1 76 x 76 x 128 -> 76 x 76 x 256 3.407 BFLOPs
33 res     30         76 x 76 x 256 -> 76 x 76 x 128

```

Figure 7.10: Training started with the ./darknet file

```

teammars@jarvis:~/Desktop/btech-main_project$ ./darknet detector train data/obj/data.cfg/yolov3.voc.cfg darknet53.conv.74...done!
Learning Rate: 0.001, Momentum: 0.9, Decay: 0.0005
Resizing
384
Loaded: 0.000112 seconds
Region 82 Avg IOU: 0.001176, Class: 0.711371, Obj: 0.733969, No Obj: 0.543382, .SR: 0.000000, .75R: 0.000000, count: 1
Region 94 Avg IOU: -nan, Class: 0.061781, Obj: 0.049740, No Obj: 0.458740, .SR: -nan, .75R: -nan, count: 1
Region 106 Avg IOU: 0.001201, Class: 0.712343, Obj: 0.734563, No Obj: 0.544563, .SR: 0.000000, .75R: 0.000000, count: 2
Region 82 Avg IOU: 0.187192, Class: 0.802284, Obj: 0.394049, No Obj: 0.442892, .SR: 0.000000, .75R: 0.000000, count: 3
Region 94 Avg IOU: -nan, Class: 0.061, Obj: 0.453344, .SR: -nan, .75R: -nan, count: 0
Region 106 Avg IOU: 0.038189, Class: 0.979976, Obj: 0.982601, No Obj: 0.469926, .SR: 0.000000, .75R: 0.000000, count: 1
Region 106 Avg IOU: 0.001202, Class: 0.712343, Obj: 0.734563, No Obj: 0.544563, .SR: 0.000000, .75R: 0.000000, count: 2
Region 94 Avg IOU: -nan, Class: 0.061, Obj: 0.458873, .SR: -nan, .75R: -nan, count: 0
Region 106 Avg IOU: 0.047801, Class: 0.668785, Obj: 0.296812, No Obj: 0.465072, .SR: 0.000000, .75R: 0.000000, count: 3
Region 94 Avg IOU: -nan, Class: 0.061, Obj: 0.453382, .SR: -nan, .75R: -nan, count: 0
Region 106 Avg IOU: 0.001203, Class: 0.712343, Obj: 0.734563, No Obj: 0.544563, .SR: 0.000000, .75R: 0.000000, count: 2
Region 82 Avg IOU: 0.312572, Class: 0.838739, Obj: 0.278802, No Obj: 0.442657, .SR: 0.000000, .75R: 0.000000, count: 1
Region 94 Avg IOU: -nan, Class: 0.061, Obj: 0.459596, .SR: -nan, .75R: -nan, count: 0
Region 106 Avg IOU: 0.085654, Class: 0.791832, Obj: 0.098486, No Obj: 0.466439, .SR: 0.000000, .75R: 0.000000, count: 5
Region 82 Avg IOU: 0.291174, Class: 0.610244, Obj: 0.465507, No Obj: 0.544211, .SR: 0.000000, .75R: 0.000000, count: 1
Region 94 Avg IOU: -nan, Class: -nan, Obj: -nan, No Obj: 0.459851, .SR: -nan, .75R: -nan, count: 0

```

Figure 7.11: Pre-trained weight loaded and iterations started

Loading the weight file and training requires more time in normal system whereas in systems having more specifications it is much faster. The accuracy of the output directly depends on the optimal number of the iterations. The training graph goes in an exponential manner where there is a point at which the loss is the minimum. Even if the number of the iterations has not reached the number specified but the loss is increasing then the training has to be halt and the intermediate weight file with the minimum loss has to be taken for further processing.

The linguistic feature is the special addition that the idea brings up. NLP is the way through

which the local languages are processed and recognized. In here we are capturing the road signs that contain the local scripts and add those to the dataset that is taken for the phases of traffic sign recognition. The local scripts seen in the road signs are regenerated through image making tools and are captured from different viewing angles. As mentioned, weather and the condition of the sign board are also considered and holds a position.

```
./darknet detector train cfg/yolov3.cfg darknet53.conv.74
```

The above code when executed will fetch the pre-trained darknet53.conv.74 weight file, the configuration file of yolov3. And the generated weight file after the training will be stored in the /backup folder, which will be used later for detection or recognition.

7.2.2 Testing

The next phase is all about testing the trained model. It requires the finally generated weight file after the training, the configuration file of the model, the image path where the image to be tested resides. The weight file will be generated only after the completion of the entire max_batches that is given in the configuration file of the YOLO algorithm along with the step count, filters , subdivisions etc.

There are multiple ways through which we may make use of the detect function of the darknet. The image name and or path to the image could be explicitly given along with the detect code or we may run the detect command without the image name that results in dynamic fetching of image name from the user during execution and the other way by adding multiple images in a file to run it simultaneously.

```
./darknet detect cfg/yolov3.cfg backup/yolov3-final.weights image_path/image
```

In the above command we can see that the image name is explicitly given in the command to execute the recognition or the detection over the image. The image given is directly fetched for the processing.

```
./darknet detect cfg/yolov3.cfg backup/yolov3-final.weights
```

The above mentioned command will ask the user explicitly to enter the location and name of the image to recognize in the console. This will help in a way that it won't require to load the network all the time it detects.

```
./darknet demo cfg/yolov3.cfg backup/yolov3-final.weights
```

This will automatically access the webcam 0 associated with the system and in real-time will feed the video capturing to the recognizing module.

The test results will enable to stop us from further more training and ensuring that the model satisfies its use. The rest of the repositories and the files may be excluded from now in where we only use the weight file, configuration and the once made darknet executable file.

Input	Expected Output	Actual Output	Type of Test
Speed Limit 50	slow	slow	Software Side
STOP	stop	stop	Software Side
School Zone	slow	slow	Software Side
SIGN BOARDS (slow, stop, school)	recognize (slow, stop, school)	recognize (slow, stop, school)	Prototype Side

Table 7.2: Result Analysis

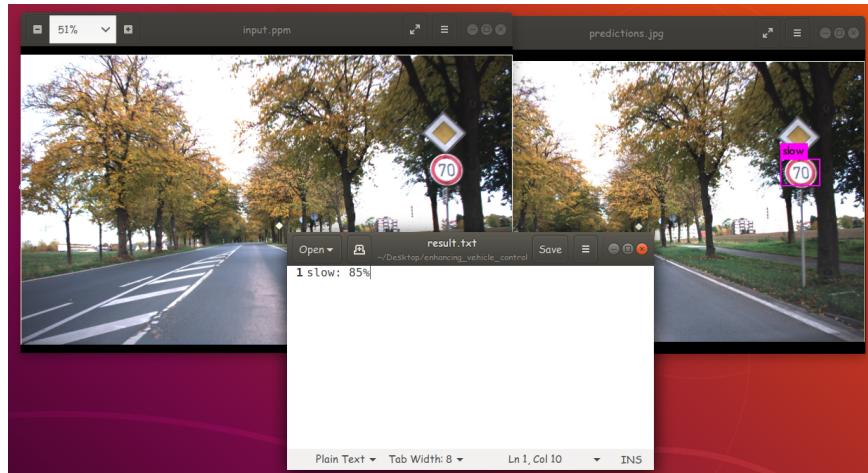


Figure 7.12: Traffic sign detected in Image

7.3 Sensor Detection and Alertness

The image processing approach is used, as the real time camera that is fixed to the vehicle, captures the image and are fed as the input for the entire process. The captured images are highly prone to damages because most of the sign boards are not maintained properly. The phase where the clarity of the image of the sign board is recreated will make it easy to detect the sign boards and to pass it over to further processes for the recognition.

The prediction of the traffic sign is required for the working electronic side to control the vehicle when required. The ultrasonic sensors connected to the Raspberry Pi will sense for the obstacles near the vehicle. The speed limit sign board and the zones specified have a role in controlling the vehicles speed. First step is to turn ON the PI to write the program in Python. After turning ON the Pi import GPIO file from library,

```
import RPi.GPIO as GPIO
```

This function enables us to program GPIO pins of the Raspberry Pi. When the recognized sign is a speed breaker to lower the speed than the vehicle's current speed then the Raspberry Pi controls the speed of the vehicle by controlling the rotations per minute thus give an alert to the driver.

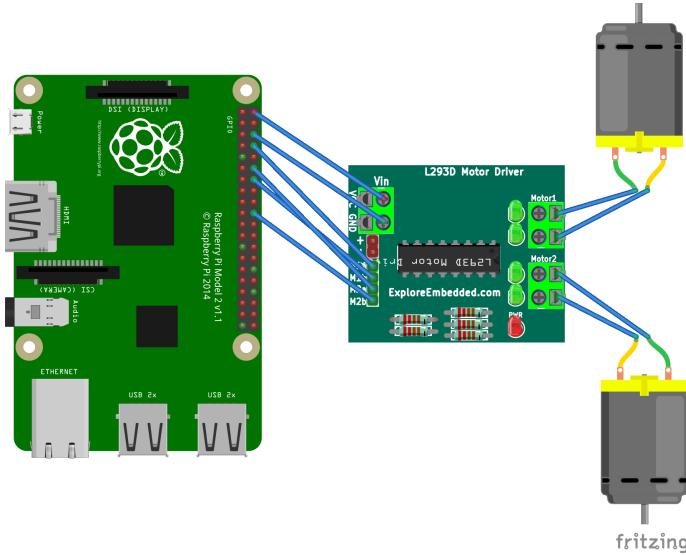


Figure 7.13: Raspberry Pi with L293D Motor Driver and BO Motors

The VCC(pin 4) and GND(pin 6) are directly given to enable the L293D Motor Diver, the Enable for Motor 1 and Enable for Motor 2 are shorted and connected to VCC(pin 2). This will enable signal passage to the motor connected to the motor driver. Motor 1 has A and B pins as well as Motor 2 has C and D pins. The A and C pins are connected to the PWM GPIO pins in the Raspberry Pi. This will help to control the speed with Pulse-Width Modulation. Pins 12 and 32 are PWM pins and the A and C of motor driver are connected to there. The pins B and D of motor driver are connected to GND pins of Raspberry Pi, i.e., pins 14 and 32

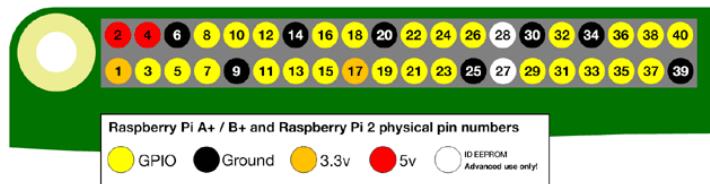


Figure 7.14: Pin layout of Raspberry Pi 3 Model B

When a slow or school sign id detected the result files that contains this result is read and if it is a slow sign or school sign then the pwm signal control the speed from 100% to 25%. And this continues to 10 seconds. When a stop sign is recognized then the pwm pin will stop the supply and this leads to stop the working of the motor. This again continues to 10 seconds.

7.4 Prototyping

Prototyping is the final phase for the work where the result is observed. A prototype is an early sample, model, or release of a product built to test a concept or process or to act as a thing to be

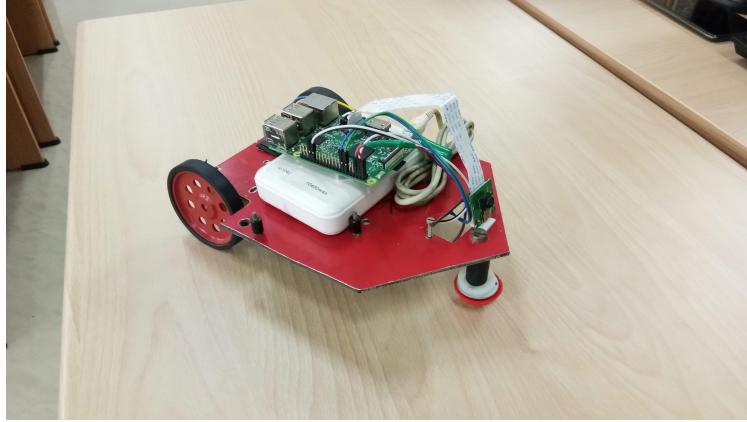


Figure 7.15: Prototype

replicated or learned from. Prototyping serves to provide specifications for a real, working system rather than a theoretical one

A Fibre model of car was made for prototyping. The model includes a Raspberry pi, Web cam, Motor, Ultrasonic sensor and the body. All these collectively become a prototype. During prototyping the image will get captured by the web cam and it will sent to the server. The server will process the image received from the web cam and sent back to Raspberry pi. Raspberry pi will check the result sent by the server and will work accordingly. The model also includes an Ultrasonic sensor which is used to check obstacles. It sends ultrasonic signals to check whether any obstacles is there or not by calculating the time taken to return the rays back.

7.4.1 Model

A Fibre model of car was made for prototyping. The model includes a Raspberry Pi, Web cam, Motor, Ultrasonic sensor and the body. A prototype is a preliminary model or mock-up of a product. Some prototypes are created to get a better idea of what the final look or feel of a product might be, while others help to prove the functionality of a design. For making prototype model we use 3D Printing. With a combination of low cost, high speed, and easy in-house operability, 3D printers are some of the most popular rapid prototyping tools today for engineering and design teams. 3D printers create three-dimensional parts directly from CAD models by building material layer by layer until a complete physical part is formed. As they require no tooling and minimal setup time for each new design, the cost of producing multiple iterations of a prototype on a 3D printer is negligible in comparison with traditional manufacturing processes.

7.4.2 Raspberry Pi

Raspberry Pi 3 model B was used in prototyping for pre-processing. The Raspberry Pi 3 Model B is a tiny credit card size computer. Just add a keyboard, mouse, display, power supply, micro SD card with installed Linux Distribution and you'll have a fully fledged computer that can run

applications from word processors and spreadsheets to games. The Raspberry Pi 3 Model B is the latest version of the Raspberry Pi computer.

The Pi isn't like your typical machine, in its cheapest form it doesn't have a case, and is simply a credit-card sized electronic board – of the type you might find inside a PC or laptop but much smaller. The Raspberry Pi is a very cheap computer that runs Linux, but it also provides a set of GPIO (general purpose input/output) pins that allow you to control electronic components for physical computing and explore the Internet of Things (IoT). One thing to bear in mind is that the Pi by itself is just a bare board. You'll also need a power supply, a monitor or TV, leads to connect to the monitor—typically HDMI, and a mouse and keyboard.

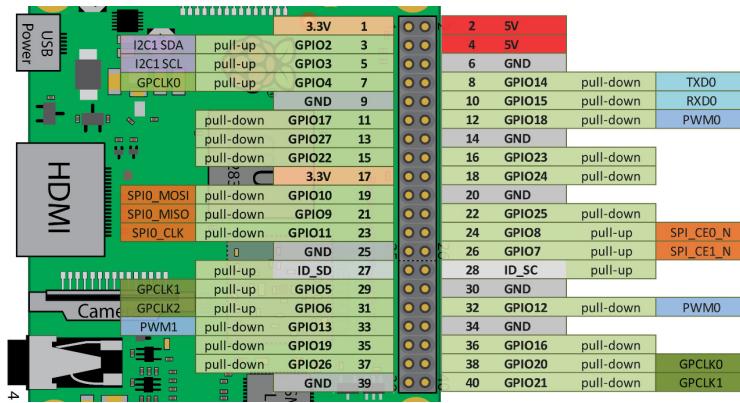


Figure 7.16: Raspberry Pi

Once you've plugged in all the cables, the easiest way for new users to get up and running on the Pi is to download the NOOBS (New Out-Of-Box Software) installer. Once the download is complete, follow the instructions here and here and it will walk you through how to install an OS on the Pi. The installer makes it simple to set up various operating systems, although a good choice for first time users is the official OS Raspbian.

7.4.3 Webcam

Webcam was used in our model for capturing the images of the traffic signals and signs. Webcam captures the image and sends the result to the server.

A webcam is a video camera that feeds or streams its image in real time to or through a computer to a computer network. Webcams come with software that needs to be installed on the computer to help users record video on or stream it from the Web. Webcams are capable of taking pictures as well as high-definition videos, although the video quality can be lower compared to other camera models. A webcam is an input device that captures digital images. These are transferred to the computer, which moves them to a server. From there, they can be transmitted to the hosting page. Laptops and desktops are often equipped with a webcam.

The features of a webcam are largely dependent on the software operating system of the computer as well as the computer processor being used. Webcams can have additional features



Figure 7.17: Pi Cam

such as motion sensing, image archiving, automation or even custom coding. Webcams are mostly used in videoconferencing and for security surveillance. Other uses include video broadcasting, social video recording and computer vision.

Chapter 8

Result and Discussion

8.1 Results

The model that we have created is supposed to give three basic outcomes. And we have obtained the following result. It detects the slow sign board and make the speed one by fourth of its original speed. Similarly it detects the school sign board and make the speed to 25 percent of the original speed. It also detects the stop sign board and make the vehicle stop. Time consuming process in our project are Image capturing by Raspberry Pi cam, Fetching the captured image by the GPU, Loading the network in the GPU, Recognizing the traffic sign, Transferring the result back to Raspberry Pi for further processing and controlling the motion of the vehicle using the obtained result.

From the time analysis we figured out that the overall processing of the proposed work will take approximately 5s in the system that we are using. The time may vary depending on the processing speed of the system. Higher processing speed may yield better result. The programmed delay given to the system is 10s. So after every 10s of change of state the vehicle will go back to running state.

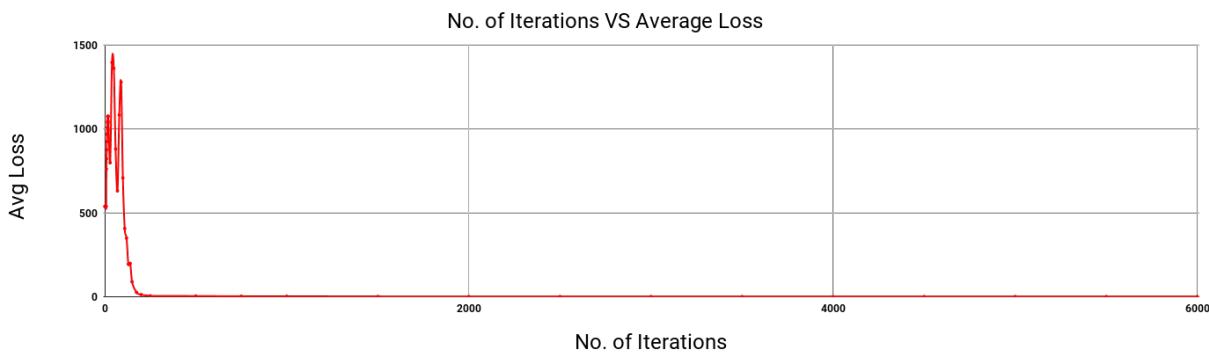


Figure 8.1: No. of iterations vs. Average Loss graph

The above graph shows the analysis of the No. of Iterations along with the Average Loss

change. The number of iterations is selected according to the or dependent to the number of classes that we are selecting.

In the testing phase, we test various images along with the images which are used for training. Some untrained images, blurred images and also we test the traffic sign board picture which is taken at night. When we are analyze the prediction percentage of the images which we are used for testing we got that, our system is much accurate. Only when testing the blurred images, at that time only we got the prediction percentage as 84%. And the rest of the images shows a prediction percentage more than 90%. Here is a graph (Fig 8.1) showing the image's prediction time and prediction percentage. From the graph we can see that the prediction is done in less than 0.5 seconds. We doesn't train the images which are blurred or traffic sign board pictures which are captured at the night time. But when we tested the images we got an output with prediction percentage which are greater than 80%, with lower prediction time.

Prediction Analysis

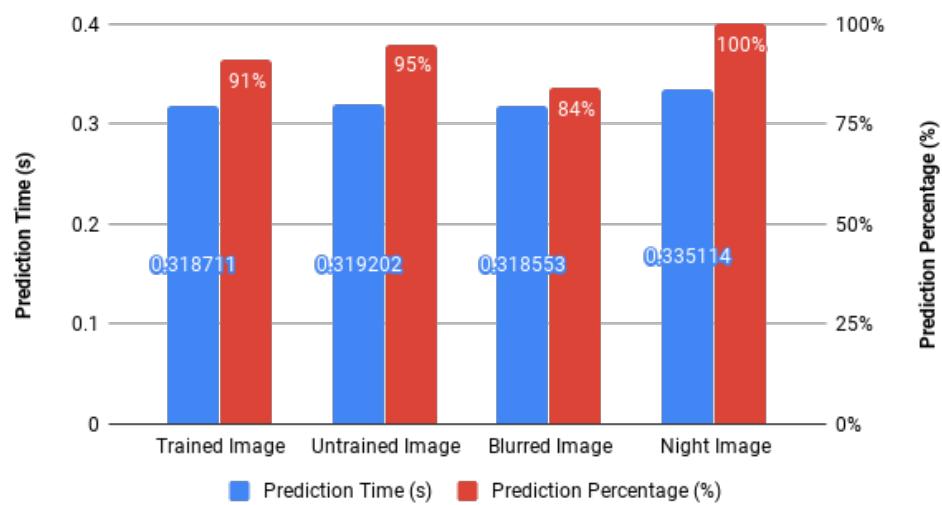


Figure 8.2: Prediction Analysis with Various Images

To check the relationship between the distance and accuracy, we test some images which contains traffic sign boards in different distances (Near, Medium, Far). From the analysis, we came to a conclusion that the distance of the traffic sign doesn't matter. In all the three cases we got a prediction percentage more 90%. We have taken 2 images for each of the categories. When we are looking at the graph(Fig 8.2) showing the relation between the distance and the prediction, we can see that it is doesn't matter that whether the sign board is near or far. In the graph it shows that when we are testing an image which contains a traffic sign board which is in a far distance and having a prediction percentage of 100% and with a prediction time which is less than 0.5 seconds.

The set of images were in .ppm format and which was not compatible for feeding for training

Dataset	
Type	No. of Images
Images Collected	900
Grayscale converted	900
Manually Manipulated	100
Augmented	50

Table 8.1: Dataset types and count

and hence has to be converted to proper image format(.jpg). “ImageMagick”, an open source software available for Ubuntu were used to convert .ppm images to .jpg images so easily through a simple single line command.

The above table shows the dataset used for the training purpose. There were 900 images in total that was collected. All images that were collected were converted to gray scale. Thus we had 1800 images in the training set. To include the language recognition we added 50 images augmented. This all together were inserted for the training purpose that finally got to output 96% accuracy.

8.1.1 Confusion Matrix

N = 200	Predicted Yes	Predicted No
Actually Yes	97	3
Actually No	2	98

Table 8.2: Confusion Matrix

The above **confusion matrix** clearly depicts the analysis about the accuracy of the system trained. From a number in total of 200 sample images taken it showed 97 True Positives output from 100 positive samples to predict. From 100 Negative sample images 98 were successfully not recognized. This simply states about the accuracy of the system developed.

In the graph we can see the analysis of the images that had traffic signs near to the capturing camera as well as to a medium distance and far from the camera connected to the device. Even if the distance increases or is near to the camera capturing the image the recognition part works well with good accuracy and in a finite good time.

For an image with prediction percentage above 70% it was recognized within 0.3 to 0.4 seconds. This surely assists the product that it is working at high accuracy and good output.

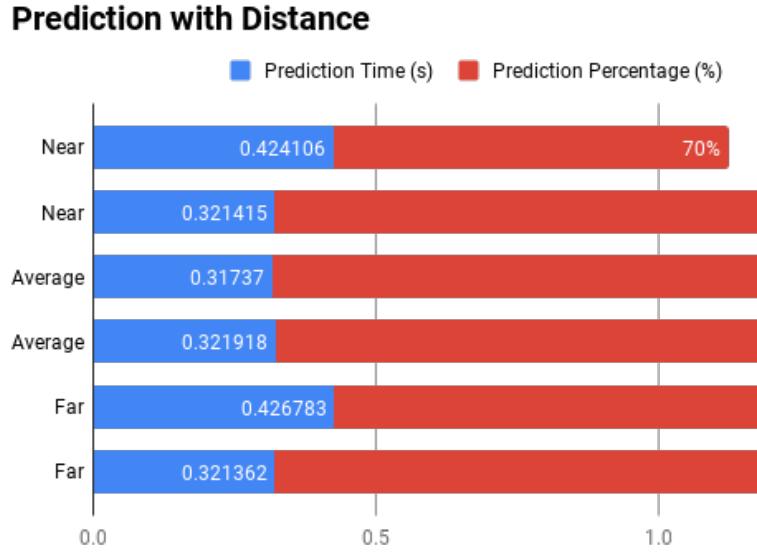


Figure 8.3: Prediction Analysis with Distance

8.1.2 Features and Outcome

The below enumerated are the most specialized features of the outcome of the project. This add on to the accuracy and efficiency of the system / project.

1. Variable lighting

Images capture under variable lighting like during night, day light all were recognized successfully. This helps the vehicle to use the system even in different time conditions as well as weather conditions.

2. Blurring and fading

As the traffic sign boards are not managed properly it obviously contain many damages as along with it, they may be faded and even the capturing results in getting blurred images. Even if the image is blurred it is also recognized.

3. Multiple appearance of sign

Images that contain multiple sign boards are also recognized properly. Around 100 of such images were added during the training phase. Even if the priority is not assigned now, it may be added later.

4. Damaged sign

Damaged sign boards seen throughout the road sides could be fairly detected and analyzed by the system. System shown medium positive response to the detection.

5. Viewing angle

The dataset chosen contain images of traffic sign boards that are tilted by different angle. This will help the system or enable the system to detect and recognize the signs even in different viewing angle.

6. Fast algorithm for Real-time

As mentioned in the background, YOLO algorithm is used for real-time operations and hence works perfectly for this system.

7. Rotation, Translation, Scaling

All types of image processing were done in the manipulated images fed as the dataset fed as input. This ensures that all images will be detected properly like which are rotated, translated and scales to down or up.

8.1.3 Language Recognition



Figure 8.4: An image with Keralite Traffic board detected and recognized

As stated in the objective, we implemented a short version of the linguistic feature enabled in the system. Keralite traffic sign boards that contain Malayalam language script is also recognized as seen in the above figure. A stop sign is been recognized here. The control over the vehicle will stop when such a board is seen. We trained a number of Malayalam Traffic Sign Boars along with other traffic sign boards that helped us to make this objective satisfactorily successful.

8.2 Discussions

The processing system is the main factor that regulates and boots the accuracy as well as the time criteria of the detection and recognition system. Information transfer after recognition consumes more time due to system specification limitation. The device that we were trying to communicate with were low specified system that took a good amount of time to process and recognize the sign board. Loading network also requires time which is a framework based limitation.

Weather conditions were not in consideration during the dataset collection, hence that reflects in the prediction. Later addition of such addition to the set of data images feed into the training phase will produce system that could recognize traffic sign during any weather conditions.

As seen in the Result part, the Keralite local language traffic sign board were recognized. The only limitation is that the Linguistic assistance is only supported for Keralite traffic sign boards. As said before addition of a verity of linguistic sign boards will surely make the system more perfect and that stands upto the complete objective.

Chapter 9

Conclusion

9.1 Conclusion

Traffic Sign Detection and Recognition (TSR) is an effective and simple method that could be implemented as the efficiency of the current system is not cent percent. The way that it works for all the technology that it relies upon is deep learning which already have much support in the field of computer science. The alarming increase in the accident rates can be reduced drastically using the proposed technique. Deep Learning methodology incorporates the working with the help of image processing technologies with the learning features of the machine. A sample prototype of the proposed model is developed which showcases the minimum functionality that we focuses on. The functionalities which were incorporated in the prototype model are recognition of stop sign board, Speed limit sign boards and school zone sign boards. On recognition the vehicle will reduce its speed or stop its motion based on the sign board. Moreover the model that we are here using is much faster than the models and hence will calculate the result much sooner in the real time.

9.2 Future Scope

The future scope of the system will be very high if the traffic condition will be Autonomous. This involves developing a model of autonomous driving that makes it possible to use human-controlled and autonomous vehicles with only minor modifications. This is important with regard to defining how the instruments of traffic management need to be developed in the future to enable them to handle autonomous vehicles in the transportation system. Of particular interest in this context is mixed traffic, in which normal and autonomously driving vehicles interact with each other. This will presumably be the normal state of affairs on roads for quite some time even after the introduction of autonomous vehicles; it is, therefore, of great practical significance to gain a good understanding of precisely this situation to predict and prevent any systemic effects that may occur.

Now a days most of the people are using google map as a reference while traveling .But it

seems that they find difficulty while using them because they cant able to find out correct traffic signals and signs while driving and since they are facing a huge difficulty. So if we could be able to add traffic signs and signals to Global positioning system, it will be a great advantage. So as a solution we can add the traffic sign boards that we had captured into google map so that people or users can easily find out .

By including many features to Map Apps in the recognition of Traffic Sign Boards on newly constructed road helps for easy navigation. Google Maps provides a route planner, allowing users to find available directions through driving, public transportation, walking, or biking. Google has stated that the speed and location information it collects to calculate traffic conditions is anonymous. Options available in each phone's settings allow users not to share information about their location with Google Maps. Google stated, "Once you disable or opt out of My Location, Maps will not continue to send radio information back to Google servers to determine your handset's approximate location. Just like google cars, when a new road has constructed then there may occur new traffic sign boards, so that once we link with any Map Apps the car that goes through that newly constructed road will recognize the new traffic sign board and which will includes in the Map App.

Keralite local language sign boards were included in the training sysytem. Incorporation of Natural Language Processing (NLP) to the system could improve it to handle all linguistic sign boards in future with a selection facility. We know that the migrants who comes to our places faces difficulty while driving for identifying traffic sign boards . Probably the could not able to understand the signs and sign board and hence accidents may occur. If this Linguistic assistance is added to our project it will help the outsiders to identify the sign boards and hence accident rate will decrease.

The increasing of the stabilization of the camera will improve the stability of capturing image for the Traffic Sign Recognition process. Here we used just a standard camera so that we faced many difficulties while handling our prototype.

Chapter 10

Publication Details

- “*Enhancing Vehicle Control Using A Combined Sign Board Approach*”, Albyn Babu ; Mathews Ignatius ; Roshin Jojo ; Sreehari Rajeev ; Sneha Sreedevi ; International Conference on IoT, Social, Mobile, Analytics and Cloud in Computational Vision and Bio-Engineering (ISMAC - CVB 2019), Date of Publication: 14 March 2019

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Appendices

Appendix A

Codes

Prototype Raspberry Pi code

```
1 import RPi.GPIO as GPIO
2 import time
3
4 GPIO.setmode(GPIO.BCM)
5
6 motorpin_1 = 18
7 motorpin_2 = 12
8
9 GPIO.setup(motorpin_1,GPIO.OUT)
10 GPIO.setup(motorpin_2,GPIO.OUT)
11
12 pwm1 = GPIO.PWM(motorpin_1,200)
13 pwm2 = GPIO.PWM(motorpin_2,200)
14
15 pwm1.start(0)
16 pwm2.start(0)
17
18 try:
19     while 1:
20         f = open("result.txt","r+")
21         str = f.read(4)
22
23         if str == "stop":
24             pwm1.ChangeDutyCycle(0)
25             pwm2.ChangeDutyCycle(0)
26             time.sleep(10)
27
28         elif str == "slow" or str == "scho":
29             pwm1.ChangeDutyCycle(25)
30             pwm2.ChangeDutyCycle(25)
31             time.sleep(10)
```

```

32         pwm1.ChangeDutyCycle(100)
33         pwm2.ChangeDutyCycle(100)
34         f.close()
35
36
37         f = open("result.txt", "r+")
38         f.write("mathews")
39         f.close()
40
41 except KeyboardInterrupt:
42     GPIO.cleanup()

```

Code Part A.1: Python Code to initiate the BO Motors and control them

Pi Cam Code

```

1 from picamera import PiCamera
2
3 camera = PiCamera()
4
5 camera.capture('/home/pi/Desktop/img.jpg')

```

Code Part A.2: Python code to enable and capture image through Pi Camera

Server side code

```

1 import os
2
3 while True:
4     os.system('sshpass -p mits ssh mits@10.90.16.49 < cmd1')
5     os.system('sshpass -p mits sftp mits@10.90.16.49 < cmd2')
6     os.system('./darknet detect cfg/yolov3.cfg backup/yolov3_final.weights data/img.
jpg > result.txt')
7     os.system('sshpass -p mits sftp mits@10.90.16.49 < cmd3')

```

Code Part A.3: Python code at server

cmd1

```

1 cd /home/pi/Desktop
2 python3 camera.py
3 bye

```

Code Part A.4: To enable Pi Cam and capture image

cmd2

```

1 lcd /home/mits/Desktop
2 cd /home/mits/Desktop

```

```
3 get img.jpg img.jpg  
4 bye
```

Code Part A.5: Fetch the captured image to server

cmd3

```
1 lcd /home/mits/Downloads  
2 cd /home/mits/Desktop  
3 put result.txt result.txt  
4 bye
```

Code Part A.6: Sends result to Pi

Appendix B

Literature Survey Papers

Paper 1

2016 IEEE Intelligent Vehicles Symposium (IV)
Gothenburg, Sweden, June 19-22, 2016

Hierarchical CNN for Traffic Sign Recognition

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and Chris Rowen, *Fellow, IEEE*

Abstract— The Convolutional Neural Network (CNN) is a breakthrough technique in object classification and pattern recognition. It has been applied to specialized image recognition tasks. Prior art CNNs learn object features by stacking multiple convolutional/non-linear layers in sequence on top of a classifier. In this work, we propose a hierarchical CNN (HCNN) which is inspired by a tree-in-a-tree human learning model [1]. For a given dataset, we introduce a CNN-oriented clustering algorithm to separate classes into K subsets, which are referred to as members of the same family. The algorithm consists of two parts: CNNs for family classification and K dedicated CNNs corresponding to each family for member classification. We evaluate this HCNN approach on the German Traffic Sign Recognition Benchmark (GTSRB) [6]. The results show that the proposed HCNN achieves a detection rate (CDR), which is superior to the best reported results (99.46%) achieved by a single network.

I. INTRODUCTION

The Convolutional Neural Network (CNN) is a deep learning approach that stacks several convolutional, subsampling and non-linear layers in sequence. Recently, the CNN has become a breakthrough technique in field of artificial intelligence for object classification and pattern recognition tasks such as handwritten digit recognition [1], speech recognition [2], image captioning [3], and face identification [4], [5]. Meanwhile, Advanced Driver Assistant Systems (ADAS) have received tremendous interest from both industry and academia. To improve driving safety, a vehicle needs to be able to see and understand its surroundings. In order to identify the presence of objects such as pedestrians, vehicles, roads and traffic signs, highly demanded in ADAS. This work proposes a novel CNN algorithm and applies it to the problem of traffic sign recognition (TSR).

The conventional multiclass CNN classification approach [1]-[5] treats all classes the same way: the output layer

generates a signal for each class and the strongest signal determines the class of the input object. With this “N-way” classifier strategy some classes are naturally more likely to be misclassified than others. For example, there are six subsets of traffic signs defined in Table I for the German Traffic Sign Recognition Benchmark (GTSRB) [6]. There is a strong likelihood of confusion between 30kmph and 80kmph speed limit signs since digits “3” and “8” are quite similar to each other. On the other hand, it is more difficult to distinguish between the first class “unknown” signs on the left of row (1) in Table I because it looks quite different from all other signs in Table I. The observation suggests a hierarchical approach to categorize objects into subsets, then to identify members in each set. This is a natural human learning behavior, which can also be directly applied to machine learning. It has two advantages: first, the hierarchical architecture enables more optimized resource allocation: the size of the network can be tailored to the size of the classification problem. Second, a smaller network with less classes to be identified is easier to learn than a larger network. Last tree-in-a-tree hierarchical learning approach is applied to learn the hierarchical structure of large multi-class objects [7], [8]. A hierarchical CNN architecture has been proposed in [9], which obtains a confusion matrix from a randomly sampled held-out set and then applies a spectral clustering algorithm to partition the classes into coarse categories.

In this paper, we propose a Hierarchical-CNN (HCNN) architecture for the GTSRB. Instead of using the human predefined subsets, we develop a CNN-oriented approach which clusters the GTSRB signs into new subsets, or families. The motivation of re-clustering signs by CNN is that the sign clustering is also learned, and thus the new clustering is demonstrated to improve the correct classification rate.

The rest of the paper is organized as follows: Section II is a brief introduction to the GTSRB, the dataset we used in our



Figure 1 Samples of the GTSRB dataset

Paper 2

2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)

Traffic Sign Recognition with Convolutional Neural Network Based on Max Pooling Positions

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Abstract—Recognition of traffic signs is very important in many applications such as in self-driving car/driverless car, traffic mapping and traffic surveillance. Recently, deep learning models demonstrated prominent representation capacity, and achieved outstanding performance in traffic sign recognition. In this paper, we propose a traffic sign recognition system by applying convolutional neural network (CNN). In comparison with previous methods which usually use CNN as feature extractor and multi-layer perceptron (MLP) as classifier, we proposed max pooling positions (MPPs) as an effective discriminative feature to predict category labels. Through extensive experiments, MPPs demonstrates the ideal characteristics of small inter-class variance and large intra-class variance. Moreover, with the German Traffic Sign Recognition Benchmark (GTSRB), outstanding performance has been achieved by using MPPs.

Keywords—Advanced Driver Assistance, traffic sign recognition, deep learning, convolutional neural networks, max pooling

I. INTRODUCTION

The acquisition of information from real-world traffic system is a key component in many applications, such as self-driving car/driverless car, traffic mapping and traffic surveillance. With the advent of some publicly available benchmark datasets such as the German Traffic Sign Recognition Benchmark (GTSRB) [1], a number of outstanding results for recognition of European traffic signs have been reported in the literature [2], [3], [4].

Recently, the development of deep learning has attracted much attention in computer vision research as more and more promising results are published on a range of different vision tasks. Among the deep learning models, the convolutional neural networks (CNN) have acquired unique noteworthiness for their repeatedly confirmed superiorities. Convolutional neural networks have powerful representational learning capabilities, with a number of desirable properties such as the translation invariance and spatially local connections. A pre-trained CNN model can be efficiently exploited as a generic feature extractor for different vision tasks.

Despite the excellent performance achieved by CNN, exploring, understanding and interpreting the internal working principle of CNN remains the most elusive problems to researchers. Some recent works visualize CNN models and

perform recognition tasks by activation of CNN [5], [6], [7], [8]. Inspired by these works, we propose a novel way for the recognition of the traffic sign recognition with CNN based on MPPs.

The main motivation of this paper is to present a novel scheme for traffic sign recognition. The main characteristics of our proposed system include:

- A CNN model to learn a compact yet discriminative feature representation.
- A novel method to perform classification based on MPPs.
- A novel method to improve classification performance and speed using MPPs.

The rest of this paper is organized as follows: Section 2 outlines some related research on traffic sign recognition and CNN applications; Section 3 provides a detailed description of the proposed system; Implementation details and experimental results will be provided in Section 4, followed by conclusion in Section 5.

II. RELATED WORKS

A. Traffic Sign Recognition

TSR has been an active area of research in computer vision community for many years. With many mature off-the-shelf techniques from machine learning, TSR can be generally treated as a pattern classification issue. Among the plenteous models, Support Vector Machine (SVM) demonstrates its excellent performance, which has been applied in [9], [10]. Boosting is another powerful method for traffic sign classification. A robust sign similarity measurement with SimBoost and fuzzy regression tree method was proposed in [11]. An ensemble of classifiers based on the Error-Correcting Output Code (ECOC) framework was introduced in [12], where the ECOC was designed through a forest of optimal tree structures that are embedded in the ECOC matrix.

As for any visual object classification, feature expression is the critical factor that affects system performance. How to design discriminative and representative features has been in the central stage of computer vision research. Due to the powerful representational learning capabilities of CNN, in recent works on traffic sign recognition, the dominant

Paper 3

Traffic sign recognition using convolutional neural networks

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Abstract—Traffic sign recognition (TSR) represents an important feature of advanced driver assistance systems, contributing to the safety of the drivers, pedestrians and vehicles as well. Developing TSR systems requires the use of computer vision techniques, which could be considered fundamental in the field of pattern recognition in general. Despite all the previous works and research that has been achieved, traffic sign detection and recognition still remain a very challenging problem, precisely if we want to provide a real time processing solution. In this paper, we present a comparative and analytical study of the two major approaches for traffic sign detection and recognition. The first approach is based on the color segmentation technique and convolutional neural networks (C-CNN), while the second one is based on the fast region-based convolutional neural networks approach (Fast R-CNN).

Keywords—traffic sign recognition; convolutional neural network; color segmentation; region proposal.

I. INTRODUCTION

Recently the number of road vehicles has increased enormously thanks to the technological achievements in the motor industry and very precisely the availability of low rates. With this remarkable growth, the number of accidents is as well in an infinite raise year after year, due to different causes, in which the ignorance of traffic signs is considered as a major cause of these lasts.

Developing automated traffic sign recognition systems helps assisting the driver in different ways in order to guarantee his/her safety, which preserves as well the safety of other drivers and pedestrians. These systems have one main goal: detecting and recognizing traffic signs during the driving process. With these functionalities the system can guide and alert the drivers to prevent danger. Even though it is possible to develop a system that can recognize traffic signs, it doesn't mean that any sign can be correctly recognized by the system due to some traffic environmental challenges, for example: lightning variations, bad illumination, weather changes and signs in a ruined condition.



Figure 1. Examples of traffic signs subjected to lightning variations & weather conditions (GTSRB).

Traffic signs (TS) are generally divided into three main categories according to their functions: regulatory signs to give notice of traffic laws or regulation, warning signs to give notice of a situation that might cause danger and finally guide signs to show information about route destinations, distances, ...etc. In each mentioned TS category, there are different subclasses with similar generic shape and appearance but different details. This suggests that traffic sign recognition should be carried out in two phases: the first phase consists of detecting traffic signs in a video sequence or image using image processing algorithms that are generally based on shape and color segmentation. The second one is normally related to recognition of the detected signs in the first step, by applying a classification algorithm. Various methods have been developed in this area on top of them, artificial neural networks.

In this paper, we present an analytical study and its experimental results comparing the two major approaches: color segmentation and convolutional neural network (C-CNN) approach and fast region proposal convolutional neural network (Fast R-CNN) approach. The C-CNN method consists of selecting a set of regions of interest (ROIs) by applying a color thresholding on the input image, thus reducing the search space. Then, a trained CNN is used to classify the ROI (whether it contains a traffic sign or not), followed by another CNN with the same architecture that is used to recognize the detected traffic signs. According to [28], the Fast R-CNN method employs several techniques to improve training and testing speed while also increasing detection accuracy, it trains the very deep VGG16 [47] network 9x faster than the regular R-CNN

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Traffic sign recognition using convolutional neural networks

Paper 4

2015 11th International Conference on Natural Computation (ICNC)

Robust Chinese Traffic Sign Detection and Recognition with Deep Convolutional Neural Network

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Abstract—Detection and recognition of traffic sign, including various road signs and text, play an important role in autonomous driving, mapping/navigation and traffic safety. In this paper, we proposed a traffic sign detection and recognition system by applying deep convolutional neural network (CNN), which demonstrates high performance with regard to detection rate and recognition accuracy. Compared with other published methods which are usually limited to a predefined set of traffic signs, our proposed system is more comprehensive as our target includes traffic signs, digits, English letters and Chinese characters. The system is based on a multi-task CNN trained to acquire effective features for the localization and classification of different traffic signs and texts. In addition to the public benchmarking datasets, the proposed approach has also been successfully evaluated on a field-captured Chinese traffic sign dataset, with performance confirming its robustness and suitability to real-world applications.

Keywords-component: traffic sign detection; traffic sign recognition; deep learning; convolutional neural networks; multi task CNN

I. INTRODUCTION

Acquisition of the information from various traffic signs is crucial in many applications, such as autonomous driving, mapping and navigation. It is also important in intelligent transportation systems. Generally, a traffic sign recognition system involves two related issues: traffic sign detection and traffic sign classification. The former aims to accurately localize the traffic signs in an image, while the latter intends to identify the labels of detected object into specific categories/subcategories. Though the topic has attracted research interests in computer vision community for many years [1], it is generally regarded as challenging due to various complexities, for example, diversified backgrounds of traffic sign images. On the other hand, Chinese traffic signs are much more complex compared with western countries due to the large number of Chinese characters. How to efficiently detect and recognize the traffic signs in China has virtually not been discussed.

With appropriate approaches of object detection for traffic signs from images, the mainstream traffic sign recognition is a two-stage procedure, namely, feature

extraction followed by classification. Many feature description algorithms have been proposed for traffic sign recognition, for example, circle detector [2], histogram of gradients, scale-invariant feature transform (SIFT) and Haar-wavelet [3]. However, these manually engineered features are separated with the classifier design, which means sub-optimal system performance as there is no joint optimization for the two modules.

Recently, the development of deep learning has attracted much attention in computer vision research as more and more promising results are published on a range of different vision tasks. Among the deep learning models, the convolutional neural networks (CNN) have acquired unique noteworthiness from their repeatedly confirmed superiorities. The CNN models have also been applied to traffic sign recognition, for instance, committee CNN [4], multi scale CNN [5], multi column CNN [6] and hinge-loss CNN [7].

The main characteristics of our proposed traffic sign recognition system include a multi-task CNN model to learn a compact yet discriminative feature representation, which simultaneously implement detection and classification, and a color-based region proposal for the improvement of the famous R-CNN model [8].

The rest of this paper is organized as follows. In section 2, some recent research on traffic sign detection, traffic sign recognition and CNN applications will be introduced. Then, the detail of our proposed multi-task CNN model will be presented in section 3, 4 and 5. Finally, experiments and some discussions are given in section 6 and 7, respectively.

II. RELATED WORK

Many works have been published in recent years for traffic signs detection and recognition. The classical approaches generally treated traffic sign detection and recognition differently, which is in sharp contrast with current deep learning methodology.

A. Traffic sign detection

Traffic sign detection is similar to other object detection tasks in computer vision, namely, identifying the image regions with bounding boxes that tightly contain a traffic

Paper 5

2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)
21 - 23 Dec 2017, Dhaka, Bangladesh

Traffic Sign Detection- A New Approach and Recognition Using Convolution Neural Network

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Abstract—Traffic Sign Recognition (TSR) system is a component of Driving Assistance System (ADAS). The TSR system assists the drivers in safe driving as road signs provide important information of the road. This research focuses to design and develop a TSR system by using color cues and Convolution Neural Network (CNN) as both features extractor and classifier for Bangladeshi traffic signs. In the first step, after image acquisition, some pre-processing task is performed. Then the image is segmented using color information of HSV color model. After that, morphological closing is executed to fine the segmented image. Consequently, after filtering the image by using region properties and shape signature, the desired region is cropped. Finally, the extracted sign area is classified by means of automatic features extraction with deep CNN. The experimental results illustrate that the proposed algorithm shows comparable performance with good recognition accuracy.

Keywords—Traffic Sign Recognition; HSV (Hue Saturation Value); Feature Extraction; Convolution Neural Network (CNN);

I. INTRODUCTION

Vision oriented traffic TSR is an significant field to do research that continuously attracts the research's community of the industry. Since Traffic sign helps to interpret the state of the road, regulate the traffic and also helps in warning and guiding pedestrians and drivers.

Recently road accidents are occurring frequently across the world. Leading cause of most accidents is the ignorance of the traffic sign. TSR system plays great potential in decline of road accidents by alerting driver in complex scenario and unconscious driver due to many psychological factors. Moreover, road sign provides information about state of the street to the drivers and pedestrians. Designing common TSR system is not conceivable option, because the structure, shape and colors of road signs are country specific. Many researches in this field have been explored for different countries. It is fact that no significant research works has not so far conducted to develop TSR system for Bangladesh road ways. Most of the traffic sign used in Bangladesh are triangular shape classified as warning sign. Non-triangular signs are seen very few. So, we emphasize our works on triangular traffic sign where the border color rim of these signs is red.

The TSR system is developed in three modules: detection, shape verification and recognition. Many algorithms had been proposed for traffic signs detection. Most of the methods used

color information for segmentation by using RGB, HSV, YIQ, YUV and L*a*b* color models [1][3] [6]. Soumen and Kaushik used YcbCr color model to detect road sign [4]. Traffic sign follows some well-defined shape signature such as triangle, circular, rectangle. To verify and classify shape, authors proposed algorithms based on distance to borders vectors, Fourier Descriptor (FD) and classifiers such as SVM, Adaboost. Recognition of traffic signs are implemented by using various feature descriptor(HOG, SURF, LBP, LSS) of the segmented blob and the state of art machine learning procedures such as SVM, extreme learning machine, K-d trees, random forest , artificial neural networks(ANN) and deep learning paradigm . Zumra and Imran used SIFT, SURF and BRISK features descriptor and nearest neighbor classifier (KNN) [1]. De La and Moreno proposed ANN as a classifier [7]. SVM was used for recognition module in [5, 9, 10]. Huang and Hsieh used Adaboost for the classification of traffic signs [6, 8]. The objective of our research is to design a TSR system by considering distinct color features of signs with automatic features extraction and classification by deep CNN.

Organization of this article is structured in a way that Section II describes the system outline, segmentation process is represented in Section III, Section IV is for recognition stage and at last conclusion and further research directions are outlined in Section V.

II. SYSTEM OVERVIEW

This section outlines the proposed system for Bangladesh traffic context. The system is designed and simulated for warning signs with triangular shaped and red border where the images are captured from road scenarios of Bangladesh under different illuminations. The algorithm of the system is revealed in Fig.1. In order to segment the sign area; the road image is binarized using hue and saturation color information of the signs. Then, morphological closing is applied to fill the gap and filter fickle noise. The region properties of every connected component are derived from the categorized image. Then, the labeled binary image is cleaned by applying area, aspect ratio limit parameters and shape properties to discard the non-interested component. Finally, recognition of the sign is implemented with deep learning methodology where features are extracted automatically without any crafted features descriptor.

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Traffic Sign Detection- A New Approach and Recognition Using Convolution Neural Network

Paper 6

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Dr. D. Y. Patil Institute of Engineering and Technology, Pune, India 30 Oct - 01 Nov, 2015

A Road Sign Detection and the Recognition for Driver Assistance Systems

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Abstract—This paper explores the effective approach of road sign detection and recognition for Driver Assistance Systems (DAS). In today's world road conditions drastically improved as compared with past decade. Express highways equipped with increased lane size made up with cement concrete. Obviously speed of the vehicle increased. So on driver point of view there might be chances of neglecting mandatory road sign while driving. This paper illustrates proposed system to help driver about the road sign detection to avoid road accidents. The automatic road-signs recognition is an important part of Driver Assisting Systems which helps driver to increase safety and driving comfort. In this paper an efficient approach for the detection and recognition of the road sign in the road and acquiring the traffic scene images from a moving vehicle is present. In this paper the road sign recognition system is to be divided into two parts, the first part is detection stage which is used to detect the signs from a whole image, and the second part is classification stage that classifies the detected sign in the first part into one of the reference signs which are presents in the dataset. In the detection module segments the input image in a YCBCR colour space, and then it detects road signs by using the shape filtering method. The classification module present determines the type of detected road signs by using an artificial neural network (ANN). The extensive experimentation has shown that the proposed system approach is robust enough to detect and the recognize road signs under varying lighting, rotation and translation conditions.

Index Terms—Driver Assistance System (DAS), Masking, Road Sign Recognition (RSR), Segmentation, Cropped Image, Classification, Principle Component Analysis (PCA).

I. INTRODUCTION

Automatic traffic sign detection and recognition, as an important task of Advanced Driver Assistance Systems, has been of great interest in recent years. The road signs are typically placed either on a roadside or above the roads. They provide important information regarding to guiding, warning, or regulating the behaviors to drivers in order to make driving safer and easier [1]-[2].

The main purpose of driving assistance systems is to collect significant information for drivers in order to reduce their effort in safe driving. Drivers have to pay attention to various conditions, including vehicle speed and orientation, the distance between vehicles, passing cars, and potential dangerous or unusual events ahead. If driver assistance system

can collect such information a prior, it will greatly reduce the burden of driving for drivers and make driving safer and easier.

Driving information mentioned above could be detected by many kinds of devices, such as infrared rays, ultrasonic waves, microwaves, radar, and a computer vision system. These devices can be utilized to extract various kinds of data from the driving environments [3].

Road signs are designed to attract a driver's attention with particular colors and simple geometric shapes. However, the difficulty in recognizing road signs is largely due to the following reasons:

(1) *The colors of road signs, particularly red, may fade after long exposure to the sun.*

(2) *Air pollution and weather conditions (e.g., rain, fog, shadows, and clouds) may decrease the visibility of road signs.*

(3) *Outdoor lighting conditions varying from day to night may affect the colors of road signs.*

(4) *Obstacles, such as vehicles, pedestrians, and other road signs, may partially occlude road signs.*

Traffic sign detection has a direct impact on the safety of driver, and damages can be easily produced due to their ignorance. Automatic systems developed to assist the driver, based on detection and recognition of signs can consequently correct the most unsafe driving behaviors [4]-[5].

To identify the signs, the most part of researchers divide the task in a three sequential stages: Detection, Segmentation and Classification. The approaches of identifying the signs can be classified into three main classes: geometrical methods which are based on the geometric shape to detect signs, colorimetric methods which are based on the color in the detection phase and there are also methods that combine learning with the methods in the previous two classes. Detection and recognition of traffic signs has long been in the center of interest for having great impact on the safety of the driver. However, it remains some problems. First, it is difficult to track an object in an image sequence captured from a vehicle undergoing a generally non uniform motion. Second, the air pollution and the weather conditions may decrease the visibility of road signs. Instead of this, the outdoor lighting conditions may vary from day to night and may affect on the apparent colours of road signs. Finally, recognition system has to be fast and robust which increase the difficulty of the automatic detection of the

A Road Sign Detection and the Recognition for Driver Assistance Systems

Paper 7

A Smart Traffic Sign Recognition System

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Abstract: As technology is evolving we have seen an exponential increase for vision systems in various areas. This phenomenon is happening in automotive industries as well, where vision is playing an important role in achieving the main objective of driverless cars. This paper addresses some of the advantages and drawbacks that computer vision has in assisting Advanced Driver Assist Systems (ADAS) and proposes a new method for real time traffic sign recognition (TSR) system which combines intelligent algorithms with classical image recognition algorithms.

Keywords: Automotive, Vision, Traffic Recognition Systems, Intelligent Systems, ADAS

1- Introduction

With recent developments in automotive industry it has become a standard for every new automotive project to require vision as an integral part of it. One of the most common vision applications in automotive industry is traffic sign recognition system (TSR). While this technology is commercially available there is still room for improvement. As of now this technology is generally used for information purposes and many auto companies are still hesitant in including it as a resource in their cars. The performance and application of vision is crucial for Advanced Driver Assist Systems.

The purpose of this paper is to propose a new method for traffic sign recognition system by collaborating computer vision concepts along with intelligent algorithms. The paper is organized as follows: section 2 will provide the state of the art review of current TSR systems and their requirements, section 3 will present the requirements for our proposed method, section 4 will present the design phase of our proposed solution, section 5 will present the implementation phase, section 6 will present the testing phase of our solution, section 7 will present the performance of the new proposed method and section 8 will present the conclusion remarks.

2- State of the art

According to many papers [1], [2], [4] and [5] which implemented traffic signs recognition (TSR)

systems it is clear that most of the implementations are based on a "template" approach or similar technologies. What this means is that through different sensors and efficient techniques, present systems recognize the sign based on a template. They take the image from an external camera and through various image processing and computer vision techniques they transform it to a known state. The main objective is to transform the image to a pre-known image which is the template. After performing feature extraction and feature matching with SIFT (scale-invariant feature transform), for example, then it is easy to recognize a certain sign.

TSR systems have been available since the beginning of this century. TSR systems can be classified into three classes as follows:

- The first one is color-based detection systems,
- The second is shape-based detection systems and
- The third one is what is proposed in this paper, the machine-learning TSR systems.

2.1 Color based detection systems

They usually find the area of interest containing the right color and then they continue using thresholding and advanced image segmentation techniques to match the input image with the "template" one. The disadvantage with this method is that colors tends to be

Paper 8

Hindawi Publishing Corporation
 Mathematical Problems in Engineering
 Volume 2015, Article ID 250461, 11 pages
<http://dx.doi.org/10.1155/2015/250461>

*Research Article***An Automatic Traffic Sign Detection and Recognition System Based on Colour Segmentation, Shape Matching, and SVM**

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The main objective of this study is to develop an efficient TSDR system which contains an enriched dataset of Malaysian traffic signs. The developed technique is invariant in variable lighting, rotation, translation, and viewing angle and has a low computational time with low false positive rate. The development of the system has three working stages: image preprocessing, detection, and recognition. The system demonstration using a RGB colour segmentation and shape matching followed by support vector machine (SVM) classifier led to promising results with respect to the accuracy of 95.71%, false positive rate (0.9%), and processing time (0.43 s). The area under the receiver operating characteristic (ROC) curves was introduced to statistically evaluate the recognition performance. The accuracy of the developed system is relatively high and the computational time is relatively low which will be helpful for classifying traffic signs especially on high ways around Malaysia. The low false positive rate will increase the system stability and reliability on real-time application.

1. Introduction

In order to solve the concerns over road and transportation safety, automatic traffic sign detection and recognition (TSDR) system has been introduced. An automatic TSDR system can detect and recognise traffic signs from and within images captured by cameras or imaging sensors [1]. In adverse traffic conditions, the driver may not notice traffic signs, which may cause accidents. In such scenarios, the TSDR system comes into action. The main objective of the research on TSDR is to improve the robustness and efficiency of the TSDR system. To develop an automatic TSDR system is a tedious job given the continuous changes in the environment and lighting conditions. Among the other issues that also need to be addressed are partial obscuring, multiple traffic signs appearing at a single time, and blurring and fading of traffic signs, which can also create problem for the detection purpose. For applying the TSDR system in real-time environment, a fast algorithm is needed. As well as dealing with these issues, a recognition system should also avoid erroneous recognition of nonsigns.

The aim of this research is to develop an efficient TSDR system which can detect and classify traffic signs into different classes in real-time environment. For detecting the red traffic signs, a combination of colour and shape based algorithm is presented which will up the procedure of the detection stage and for recognition SVMs with bagged kernels are introduced.

This paper is organized as follows: Section 2 presents the related works in the field of development of the TSDR system. In Section 3, the overall methodology is discussed. The experimental results and discussions are summarized in Section 4. In Section 5, the conclusion and some suggestions are made for future improvement on the field of automatic traffic sign detection and recognition.

2. Related Work

According to [2], the first work on automated traffic sign detection was reported in Japan in 1984. This attempt was followed by several methods introduced by different researchers to develop an efficient TSDR system and minimize all the

An Automatic Traffic Sign Detection and Recognition System Based on Colour Segmentation, Shape Matching, and SVM

Appendix C

Presentation Certificate



**International Conference on ISMAC in
Computational Vision and Bio-Engineering
(ISMAC - CVB 2019)**

13-14, March 2019 | ismac-cvb.com/ismac-cvb2019

Letter of Acceptance

TO,
Albyn Babu,Mathews Ignatius,Roshin Jojo,Sreehari Rajeev,Sneha Sreedevi,
Muthoot Institute of Technology & Science,
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Herewith, the conference committee of the International Conference on IoT, Social, Mobile, Analytics and Cloud in Computational Vision and Bio-Engineering (ISMAC - CVB 2019) is pleased to inform you that the peer reviewed research paper "Paper ID: ISMAC-CVB_0114" entitled **Enhancing Vehicle Control System Using A Combined Sign Board Approach**" has been accepted for oral presentation as well as it will be recommended for inclusion into Lecture Notes in Computational vision and Biomechanics.

ISMAC-CVB will be held on March 13-14, 2019 at Vivekananda College of Technology for Women, Tamil Nadu, India. ISMAC-CVB encourages only the active participation of highly qualified delegates to bring u various innovative research ideas.

We congratulate you on being successfully selected for the presentation of your research work in our esteemed conference and we look forward in welcoming you at the conference site.

Yours' Sincerely



Dr. M. Durai Pandian, Professor,
Vivekanandha College of Technology for Women, Tamil Nadu, India.

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