

Traffic Sign Detection And Recognition Using Computer Vision

A Project Report
submitted in partial fulfillment of the requirements
for the degree of

Bachelor of Technology
in
Computer Science and Engineering
by

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UNDERTAKING

We hereby declare that the work presented in this dissertation entitled "**Traffic Sign Detection and Recognition in Computer Vision**" in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science and Engineering, submitted to Dr. A.P.J. Abdul Kalam Technical University, Lucknow, is our work carried out during the period from *25/07/2020* to *30/05/2021* under the guidance of **Mr. Pramod Sethy, Designation**, Krishna Engineering College, Ghaziabad.

The work reported in this dissertation has not been submitted by us for award of any other degree or diploma.

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CERTIFICATE

This is to certify that the Project report entitled “Traffic Sign Detection and Recognition in Computer Vision” done by (Kartik Jain - 1716110091, Mayank Vats - 1716110115, Eraa - 1716110070, Mayank Sinha - 1716110114), is carried out by them at Krishna Engineering College, Ghaziabad under my guidance. The matter embodied in this project work has not been submitted earlier for the award of any degree or diploma to the best of my knowledge and belief.

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ABSTRACT

Road sign identification has been one of the most important research subjects since the first paper was published in Japan in 1984. Many research organizations have been working on the topic since that time and have attempted to solve this challenge using various ways. Although the basic steps toward a solution appear to be well defined and straightforward at first glance, the intricacies of the procedures utilized reveal that there are various choices and many ideas for improving solutions, robustness, or classification rate. So yet, no single solution technique has dominated, and systems will undoubtedly take time to emerge on the market.

The detection and recognition of road signs are the two primary stages in the identification process. There are three types of research groups in "detection." The first set of researchers believes that traffic sign colors are significant information for detecting and classifying traffic signs. The second group argues that just traffic sign shape may be used to detect traffic signs, while the third group believes that color and shape together form the backbone of any road sign detection. As a result, there are three basic ways to identify traffic signs: color information detection, shape information detection, and color plus shape information detection. All of the reviewed papers used images from real traffic scenes which are similar to the images collected during this research.

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CHAPTER 1

INTRODUCTION

Automated tasks have simplified practically everything we perform in today's world. Drivers often miss signage on the side of the road in an effort to focus on the road, which can be dangerous for them and others. This issue may be avoided if there was a quick way to alert the driver without requiring them to divert their attention. By recognising a sign and alerting the motorist of any impending signs, Traffic Sign Detection plays a crucial function here. This not only assures road safety, but also puts the driver at ease when driving on unfamiliar or difficult routes. Another issue that arises frequently is the inability to comprehend the sign's meaning. Drivers will no longer struggle to grasp what the sign is saying thanks to an Advanced Driver Assistance Systems (ADAS) application.

The complex scene reveals a normal road in the center of many cities in the world. It may include people, vehicles, shops and their signs and various traffic signs for traffic control along that road. Basically, if the traffic sign in the image is requested from a person, they can do this easily.

However, from the point of view of computer vision, some difficulties which are addressed here:

- The presence of a multitude of similar things in the area (either in colour or shape).
- Obstacles in the scene that can partially or completely obstruct the sign.
- The scene has a large quantity of data, therefore analysing it and extracting the desired information will take some time.

Road and traffic sign recognition is a subject of study that can be used to help construct an inventory system (which does not require real-time recognition) or an in-car advising system (when real-time recognition is necessary). Both road sign inventory and road sign identification are concerned with traffic signs, have similar issues, and rely on automatic detection and recognition.

A road and traffic sign recognition system could theoretically be developed as part of an Intelligent Transportation System (ITS) that continuously monitors the driver, vehicle, and road to, for example, alert the driver to upcoming navigational decision points and potentially dangerous traffic situations in real time.

This project aims at creating a system using which, it is easily possible to automatically detect and recognize the traffic sign on the road ahead. This Advanced Driver Assistance System can also be a part of the self-driving car project which will provide the car the ability to make better decisions. The identification of the road signs is achieved by two main stages: detection, and recognition. In the detection phase, the image is pre-processed, enhanced, and segmented according to the sign properties such as colour or shape. The output is a segmented image containing potential regions which could be recognized as possible road signs. The detection phase simply discovers a sign from the environment. When a vehicle is moving at a certain speed, the camera captures the environment, and our algorithm checks to see if a sign is present in that frame or not. Detecting the traffic sign is based on color and shape. The efficiency and speed of the detection are important factors which play a strong role in the whole process, because it reduces the search space and indicates only potential regions. In the recognition stage, each of the candidates is tested against a certain set of features (a pattern) to decide whether it is in the group of road signs or not, and then according to these features they are classified into different groups. These features are chosen so as to emphasize the differences among the classes. The shape of the sign plays a central role in this stage and the signs are classified into different classes such as triangles, circles, octagons, etc. Pictogram analysis allows a further stage of classification. By analyzing pictogram shapes together with the text available in the interior of the sign, it is easy to decide the individual class of the sign under consideration.

The system can be implemented by either colour information, shape information, or both of them. Combining colour information and shape information may give better results. However, many studies showed that the detection and recognition can be achieved even if either of the colour or the shape is missing.

1.1. Problem Statement:

- Drivers frequently disregard signage on the side of the road, endangering themselves and those around them.
- The detection of traffic signs is crucial in this case. The driver will be alerted to approaching signals by detecting the signage.

1.2. Problem Definition:

- Given a real time video feed the system should be able to detect and recognize the traffic sign in the given frame and within a time frame until the sign moves out of the frame.

1.3. Expected Outcomes:

- The project is expected to estimate automatically whether the object in the frame is the traffic sign or not and also determine the type of the sign.
- The project is expected to give satisfactory results even when the conditions are not ideal (such as, if the sign is partially viewable).

CHAPTER 2

LITERATURE REVIEW

Road sign identification has been one of the most important research subjects since the first paper was published in Japan in 1984. Many research organizations have been working on the topic since that time and have attempted to solve this challenge using various ways. Although the basic steps toward a solution appear to be well defined and straightforward at first glance, the intricacies of the procedures utilized reveal that there are various choices and many ideas for improving solutions, robustness, or classification rate. So yet, no single solution technique has dominated, and systems will undoubtedly take time to emerge on the market.

The detection and recognition of road signs are the two primary stages in the identification process. There are three types of research groups in "detection." The first set of researchers believes that traffic sign colors are significant information for detecting and classifying traffic signs. The second group argues that just traffic sign shape may be used to detect traffic signs, while the third group believes that color and shape together form the backbone of any road sign detection. As a result, there are three basic ways to identify traffic signs: color information detection, shape information detection, and color plus shape information detection. All of the reviewed papers used images from real traffic scenes which are similar to the images collected during this research.

2.1 Color Based Detection

The methods used to recognize traffic signs differ from one author to the next. To address this problem, a variety of strategies are employed.

- Thresholding was used by Ghica et al. to divide pixels in a digital image into object and background pixels. The technique's foundation is calculating the distance in RGB space between the pixel colour and a reference colour. The

unknown pixel is deemed an object pixel if it is close enough to the reference colour.

- Estevez and Kehtarnavas suggested a method for recognising traffic warning signs such as stop, yield, and no-entry. Color segmentation, edge placement, RGB differentiating, edge detection, histogram removal, and classification are among the six modules included. The colour division is solely used to detect red rim areas; it is sparse, and the distance between pixels is calculated.
- Bénallal and Meunier created a computer vision system that can recognise road signs and is incorporated in an automobile. For numerous trials, several road signs were utilised to investigate colour stability in various lighting circumstances. Segmentation is achieved using the RGB colour space. The disparities between red, green, and blue are demonstrated to be significant and could be utilised as a segmentation criterion.

2.2 Shape Based Detection

Techniques using shapes could be a good alternative when colors are missing or when it is hard to detect colors. Shape-based techniques should be able to avoid difficulties related to invoking colors for sign detection and robust to handle in-plane transformations such as translation, scaling and rotation. Much effort has been exerted to develop these techniques and the results are very promising.

In the following reviewed papers the authors used shapes as the major source of information to detect traffic signs:

- Parodi and Piccioli used a priori information about the sign's supposed position in an image to recognise road signs. The search region had been subject to a Canny edge detector and the geometric analyses were performed on edge point clusters to extract the form desired. Each candidate's internal region was tested using a template matching sign database. For the detection of circles, the correlation of the border pixels

with appropriate ring masks was utilized. Triangles in vertical, horizontal, and oblique segments were detected by grouping edges.

- Aoyagi and Asakura proposed a method for detecting traffic signs that relied solely on brightness. After removing the noise with a smoothing filter, the object is extracted from the background using the Laplacian filter. A particular threshold is employed to obtain the binary image, and detection is carried out by genetic algorithms with the ability to look for the circular pattern that is given as gene information.
- Gavril described a method for classifying road signs using distance transforms and template matching. The approach was able to distinguish between circular and triangular signals. Edge orientations are employed as a feature on which the algorithm is based. For circles and triangles, different templates with radii ranging from 7 to 18 pixels are employed. Based on edge orientation, each template is divided into eight types. The method is used to detect road signs both on-line and off-line with a detection rate of about 90%.

2.3 Color-Shaped Based Detection

It is feasible to use both strategies to detect traffic and road signals by using a mix of colour and shape. Each method has its own set of advantages and disadvantages. Under some circumstances, an adaptive hybrid strategy may use one technique and not the other. While this adaptive strategy is not used, if colour and shape are combined with any sign-detection method, it is advantageous to use data from both sides of the problem.

Colour-shape-based systems were used in the following papers:

- To recognise traffic signs in night photos, Hibi exploited hue and saturation in an enhanced HSL colour space. For both hue and histograms, dynamic thresholds are used. A combination of the hue and saturation images with logical add-ons will create the final binary image. Depending on the target pixels and their neighbors, the pixels for a binary image are assigned to

seven limits. These limits are used to indicate the outline forms of the road sign.

- **Piccioli et al.** showed two different algorithms for the detection of road signs. In the first one, grey-levels are used to detect road signs according to simple geometrical criteria. In the second one, hue and saturation in a HSV colour space are used. The image is divided into 16×16 pixel regions, and each region is classified as 1 or 0 depending on whether the number of labelled pixels exceeds a certain threshold. A search is carried out only for regions labelled with '1'. Shape detection is based on the geometrical analysis of edge contours.
- Jiang and Choi employed fuzzy rules to convert the colour image to a grey-scale function, and then used a binary image to detect any landmark in the enhanced colour image, which was enhanced using hue invariance. To detect the red and blue colours, they used Rgb colour space, thresholds, and fuzzy rules. The three corners of triangles are extracted to identify warning indications, which are considered here. To detect these corners, a fuzzy technique is constructed by establishing two member functions that indicate the chance of pixels inside two masks forming a corner. In the same way, the other two corners are recognised. Damaged signs cause difficulty with the masks, therefore they are repaired.

Analysis Of Literature Review:

I. Color Based Approaches

In the identification of traffic signs, color is an important source of information. The first part is a color space conversion in which a color collected by an RGB-shaped camera can be turned into another color space to separate color information from the intensity information. Some researchers like to use RGB color space or the modified color space version while others prefer a color space conversion in order to achieve better results. The major colour-based techniques are summarised below:

1. **Colour Thresholding Segmentation:** This is one of the earliest colour picture segmentation techniques. To classify photos into the pixel or backdrop of traffic signs, the approach uses a threshold value. A reference colour is used to determine if a pixel is a traffic sign pixel or not.
2. **Dynamic Pixel Aggregation:** The insertion of a dynamic threshold in the HSV colour area pixel aggregation procedure segments this. The dynamic threshold's key advantage is that it reduces hue instability in real-world scenes caused by changes in external illumination.
3. **HSV Transformation:** These two color rooms separate the colour information from the total intensity value (hue and saturation) that makes them more immune to the changes of light. The transformation from the color area of the RGB to the color area of HSV is useful for color segmentation because the spatial color of the HSV is very close to the human color sensitivity.
4. **Region Growing:** This approach is based on a seed in a region and extends into pixel groups with a certain color-consistency. The HSV color space can be used for the approach. Since a seed is needed to begin and end when certain criteria are fulfilled, a problem can occur when finishing conditions are not met.

The literature study shows that traffic signs employ colour to express important driver information. Colors are an essential source of information in the detection and recognition of traffic signs. Since colors distinguish the traffic signs, this process can be simplified. Furthermore, the amount of false margins produced by low-level image processing operations is significantly reduced by color processing. An important part of color detection is 'color conversion' of color space, which converts RGB images into other forms to simplify the process of detection. The literature study shows that traffic signs employ colour to express important driver information. Colors are an essential source of information in the detection and recognition of traffic signs.

II. Shape Based Approaches

Grey scale images are employed in shape-based sign detection to circumvent the issues that come with dealing with colours. Many investigations in this field employ the outer margins of the signs. The following are some of the strategies used to extract road signs:

1. **Hierarchical Spatial Feature Matching:** The spatial features of traffic indicators are used to seek for geometric shapes. When such forms are discovered, a list is made and a classification module is assigned.
2. **Hough Transform:** The classic Hough transform was used to recognise regular features such as lines and circles. It's useful to be able to isolate attributes of a given form inside an image. The approach is computer complicated and memory intensive, making it an excellent fit for real-time applications. These limitations, on the other hand, have no bearing on the inventory of road signs.
3. **Similarity Detection:** This method involves determining a similarity factor between a segmented region and a set of binary pictures representing each road sign. The method presupposes that the sampled and segmented images have the same dimensions.
4. **Distance Transform Matching:** A hierarchy of templates for the capture of various object shapes is used in this approach. For the particular shape distribution using stochastic optimization techniques, efficient hierarchy can be generated offline. In online mode, the shape hierarchy and transformation are simultaneous gross to fine approaches. The approach can check objects of arbitrary shapes that are of benefit in non-rigid objects compared to other techniques.

It has been proven that using the shapes of road signs is sufficient for detecting them. The lack of a common colour system throughout countries, even within the European Union, is one of the arguments in favour of this theory. When shifting from one country to another, color-based systems must be adjusted. The fact that

colours change when lighting and reflectance qualities change is another factor in this argument.

III. Color-Shape Based Approach

It is clear that the combination of colour information and form information provides a good source of information for the detection of traffic signs. Shape information is as important as colour information. Such a combination reduces false alarms as all objects can possess these specifications, not just road signs or traffic signs. This color-shaped combination can be used to build adaptive traffic sign detectors, as mentioned above. The signs can be detected if the colours are available. Otherwise you can invoke a form-based algorithm. This type of traffic sign detection may require certain rules to check which method is used depending on whether the color information or shape information is available. Moreover, the combination of color and form in an algorithm can also reduce false alarms by avoiding certain problems due to the nature of either.

IV. Recognition and Classification

When a classifier is designed, a number of parameters should be considered:

1. The recognizer should have a high level of discrimination and a cheap computing cost.
2. It should be resistant to the sign's geometrical state, such as its vertical or horizontal orientation, size, and position in the image.
3. It should be noise-resistant.
4. If the recognition is to be used in real-time applications, it must be done rapidly.
5. The classifier must be able to learn a large number of classes, and it should be designed with as much prior knowledge of road signs as possible.

Neural networks are an appropriate alternative to recognizing and classifying road signs. The use of neural networks has two distinct

advantages. First, it is not necessary to transform the image input into another display space. Secondly, only the correlation of the network weights with the network is responsible for the result. Networks have their own difficulties, though. The training overhead remains available and because of its architecture, the multi-layer neural networks cannot be adapted for online use. As this is fixed, the number of classes without a heavy redesign penalty is not expected to increase and the new patterns cannot be recognized without retraining with the entire net. They offer no significant advantages over template matching in this respect.

Several regularly used approaches for recognising traffic signs have been given. To create a hybrid recognition system, some of these strategies can be merged with others.

The shape-based recognition faces more limitations compared with color-based recognition. However, color recognition deficiencies such as weather and fading colors on the road sign may be offset by the use of form-based recognition that gives greater performance. For color recognition, most approaches, except color indexing, can operate significantly quickly. While color indexing can divide an image by tilting the road sign slightly or by partial occlusion, in complex transport scenes, its time of calculation increases considerably.

CHAPTER 3

PROPOSED METHODOLOGY

In two ways the system of detection and recognition of road signs or traffic signs should be able to work; a training mode where a database can be established by collecting a series of road signs for training and validation, and a prediction mode where a traffic sign not previously seen can be recognized.

The system we proposed has been broken into two major steps:-

1. Detection will help to identify whether the image/sign is actually a traffic sign or not.
2. Recognition will help to identify what the traffic sign is.

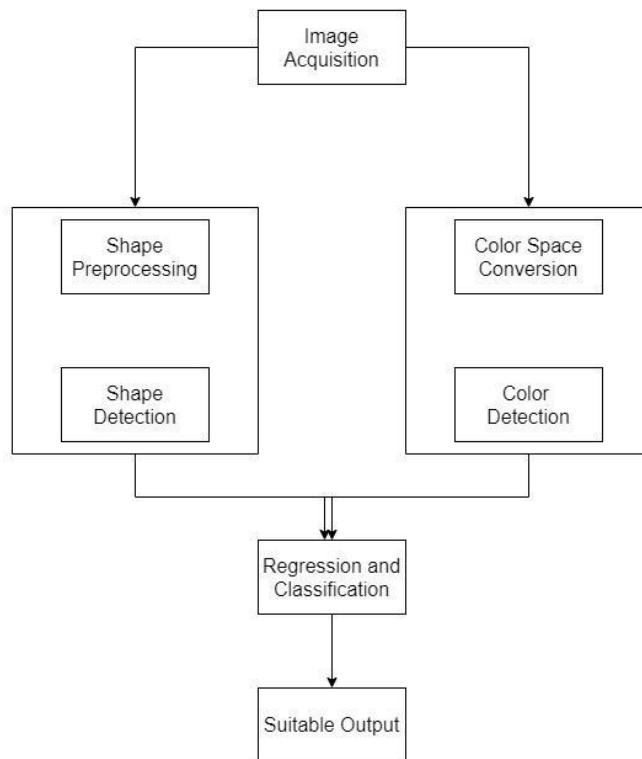


Fig 3.1: Proposed System

3.1 Detection

The goal of traffic sign detection is to locate the regions of interest (ROI) in which a traffic sign is more likely to be found and verify the hypotheses on the sign's presence. The initial detection phase of a traffic sign recognition system offers high costs due to the large scale of detection in a complete single image.

The detection of traffic signs using only a single frame image has some problems: 1) it is difficult to correctly detect traffic signs when temporary occlusion occurs; and 2) the correctness of traffic signs is hard to verify.

The detection step merely seeks out a sign in the surroundings. When a car travels at a given speed, the camera catches the surroundings, and our algorithm determines whether or not a sign is present in that picture. The colour and shape of the traffic sign are used to detect it.

The image is pre-processed, improved, and segmented in this step based on sign qualities such as colour, shape, or both. The result is a segmented image with probable locations that could be identified as traffic signs. The detection's efficiency and speed are significant since they minimise the search space and only show potential locations. Before the detecting procedure begins, the image collected from the vehicle's camera is preprocessed. Converting the resultant RGB image to an HSV image is a common preprocessing step. The HSV (Hue Saturation Value) colour space is preferable than the RGB (Red Green Blue) colour space for detection. When compared to an RGB image, HSV is closer to what the human eye actually sees. External light changes are likewise less noticeable in an HSV image. By altering the image's histogram, the HSV image is equalised to adjust the image's contrast. After obtaining the HSV image, the next stages would be to detect things based on their colour, determine their shape, and confirm that the object is a traffic sign.

So, the detection phase is of two types:

3.1.1 Color Based Detection

Dividing traffic signs into groups according to their colour combinations gives four alternatives:

- Red signs such as the Stop sign
- Red-Yellow signs such as Warning, Prohibitory, and Indicatory signs.
- Red-Blue signs such as No Parking and No-Stop signs.
- Blue signs such as Regulatory and Informative signs.



Fig 3.2: Traffic Signs

This color grouping helps the algorithm to perform better and to reduce the number of false alarms that this algorithm can generate. Thus it is necessary to check the presence, together with the presence of a specific shape, of different color combinations in the image. For example, a red color check with the octagon shape is searched for in the picture if a stop sign is to be detected. In contrast, a red-yellow combination with a triangular border would be the criteria to search for the image if a warning sign was detected.

Traffic signs are usually colored in strongly notice-able contrasting colors. Color-based methods refer to these colors to perform the detection.

Most of the traffic signs are supposed to be red in color. So our model will first detect whether the given image is red in color or not. If it is red in color then we will proceed for shape based detection. We are applying filters on each channel threshold to extract an image we suspect that it can be a traffic signal. Result of this phase is in the form of contours of image.

The main weakness of color-based methods is the fact that the color is not always reliable due to the weather condition changes, orientation of signs in relation to the sun, daytime, etc. These parameters vary frequently in outdoor scenes. Moreover, other objects with the same color as traffic signs appear frequently in the scenes. Therefore, colors are usually used to obtain the ROIs, not to perform the detection.

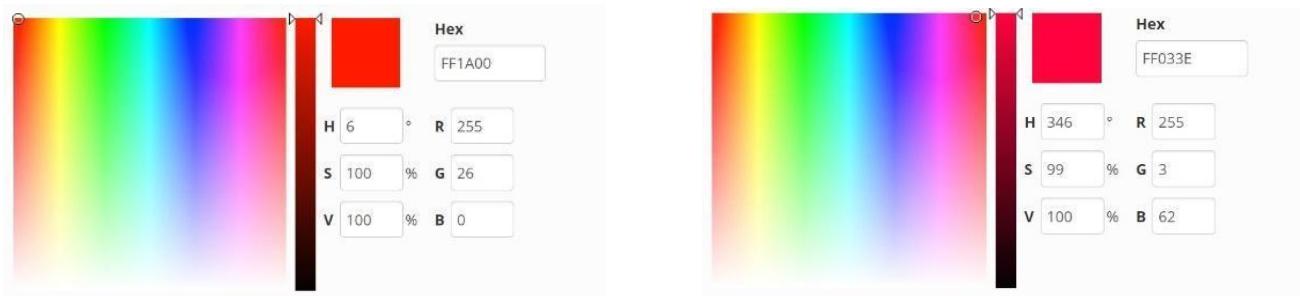


Fig 3.3 HSV color example

Algorithm:

Input: Capture video through webcam.

- Convert the image from BGR to HSV(hue-saturation-value) color space.
 - **Hue** represents the color
 - **Saturation** represents the amount of gray in the color
 - **Value** represents the brightness or intensity of the color.
- Define each color's range and make the corresponding mask.
- Dilation is a morphological transform used to reduce noise from photographs.
- To specifically detect that particular colour and discard others, bitwise and is performed between the image frame and mask.
- Create a contour for each distinct colour to help distinguish the detected coloured zone.

Output: Detection of the colors.



Fig 3.4: Color Based Detection Output

3.1.2 Shape Based Detection

An object's shape can also be used as a global characteristic to detect an object with a unique shape. A straight line, polygons, circles, or any other irregular shape can be used as this shape. To detect an object with a specific shape, object boundaries, edges, and contours might be used.

Shape-based methods are a good alternative when colors are missing or when it is hard to detect colors. Most of the existing methods refer to both color segmentation and geometric information to detect traffic signs. These methods should be able to avoid difficulties related to invoking colors for sign detection and robust to handle in-plane transformations such as translation, scaling and rotation.

The images which are passed in our color based detection phase will undergo a shape based detection phase. If the image is passed in this phase then we will be sure that the Region of Interest must have a traffic sign and we can move to our next part that is “recognition”.

3.1.3 Detection via Transfer Learning

Object detection can also be done with the help of transfer learning. In transfer learning, an already trained model is taken i.e. a Pre-trained model, and its top layers are retrained, so that the model can work as per the requirements.

In transfer learning, the machine uses the knowledge from the previous similar task, to get to the more generalized solution for a problem.

Pre-trained models are very popular these days because :-

- They can be trained within hours as per the configuration of the system, whereas training a new model may take days to get trained.
- Pre-trained models do not require a huge amount of data to get trained.
- Pre-trained models use the knowledge from the previous similar tasks.

YOLO-V3 Model

YOLO is a shortened form of You Only Look Once. And it uses Convolutional Neural Networks for object detection. It is one of the best models that is used for object detection.

YOLO can detect multiple objects on a single image. It means that apart from predicting classes of the objects, YOLO also detects locations of these objects on the image.

YOLO applies a single neural network to the whole image. This neural network divides images into regions and produces probabilities for every region. After that, YOLO predicts the number of bounding boxes that cover some regions on the image and chooses the best ones according to the probabilities.

YOLO uses convolutional layers. And YOLO version three, originally, consists of 53 convolutional layers that are also called Darknet-53. But for detection tasks, original architecture stacked with 53 more layers gives us 106 layers of architecture for YOLO version three.

```
C:\Windows\System32\cmd.exe - darknet no gpu.exe detector test cfg/traffic-sign-to-test.cfg weights/traffic-sign-to-test.weights
mini_batch = 1, batch = 1, time_steps = 1, train = 0
layer filters size/strd(dil) input output
0 conv 32 3 x 3 / 1 416 x 416 x 3 -> 416 x 416 x 32 0.299 BF
1 conv 64 3 x 3 / 2 416 x 416 x 32 -> 208 x 208 x 64 0.177 BF
2 conv 32 3 x 3 / 1 208 x 208 x 64 -> 208 x 208 x 32 0.177 BF
3 conv 64 3 x 3 / 1 104 x 104 x 32 -> 104 x 104 x 64 0.177 BF
4 Shortcut Layer: 1, wt = 0, wn = 0, outputs: 104 x 104 x 64 0.003 BF
5 conv 128 3 x 3 / 2 104 x 104 x 64 -> 104 x 104 x 128 1.595 BF
6 conv 64 1 x 1 / 1 104 x 104 x 128 -> 104 x 104 x 64 0.177 BF
7 conv 128 3 x 3 / 1 104 x 104 x 64 -> 104 x 104 x 128 1.595 BF
8 Shortcut Layer: 5, wt = 0, wn = 0, outputs: 104 x 104 x 128 0.001 BF
9 conv 64 1 x 1 / 1 104 x 104 x 128 -> 104 x 104 x 64 0.177 BF
10 conv 128 3 x 3 / 1 104 x 104 x 64 -> 104 x 104 x 128 1.595 BF
11 Shortcut Layer: 8, wt = 0, wn = 0, outputs: 104 x 104 x 128 0.001 BF
12 conv 256 3 x 3 / 2 104 x 104 x 128 -> 52 x 52 x 256 1.595 BF
13 conv 32 3 x 3 / 1 52 x 52 x 256 -> 52 x 52 x 32 0.177 BF
14 conv 256 3 x 3 / 1 52 x 52 x 32 -> 52 x 52 x 256 1.595 BF
15 Shortcut Layer: 12, wt = 0, wn = 0, outputs: 52 x 52 x 256 0.006 BF
16 conv 128 1 x 1 / 1 52 x 52 x 256 -> 52 x 52 x 128 0.177 BF
17 conv 256 3 x 3 / 1 52 x 52 x 128 -> 52 x 52 x 256 1.595 BF
18 Shortcut Layer: 15, wt = 0, wn = 0, outputs: 52 x 52 x 256 0.001 BF
19 conv 64 1 x 1 / 1 52 x 52 x 256 -> 52 x 52 x 128 0.177 BF
20 conv 128 3 x 3 / 1 52 x 52 x 128 -> 52 x 52 x 256 1.595 BF
21 Shortcut Layer: 18, wt = 0, wn = 0, outputs: 52 x 52 x 256 0.006 BF
22 conv 256 1 x 1 / 1 52 x 52 x 256 -> 52 x 52 x 128 0.177 BF
23 conv 256 3 x 3 / 1 52 x 52 x 128 -> 52 x 52 x 256 1.595 BF
24 Shortcut Layer: 21, wt = 0, wn = 0, outputs: 52 x 52 x 256 0.006 BF
25 conv 128 1 x 1 / 1 52 x 52 x 256 -> 52 x 52 x 128 0.177 BF
26 conv 256 3 x 3 / 1 52 x 52 x 128 -> 52 x 52 x 256 1.595 BF
27 Shortcut Layer: 24, wt = 0, wn = 0, outputs: 52 x 52 x 256 0.006 BF
28 conv 128 1 x 1 / 1 52 x 52 x 256 -> 52 x 52 x 128 0.177 BF
29 conv 256 3 x 3 / 1 52 x 52 x 128 -> 52 x 52 x 256 1.595 BF
30 Shortcut Layer: 27, wt = 0, wn = 0, outputs: 52 x 52 x 256 0.006 BF
31 conv 128 1 x 1 / 1 52 x 52 x 256 -> 52 x 52 x 128 0.177 BF
32 conv 256 3 x 3 / 1 52 x 52 x 128 -> 52 x 52 x 256 1.595 BF
33 Shortcut Layer: 30, wt = 0, wn = 0, outputs: 52 x 52 x 256 0.006 BF
34 conv 128 1 x 1 / 1 52 x 52 x 256 -> 52 x 52 x 128 0.177 BF
35 conv 256 3 x 3 / 1 52 x 52 x 128 -> 52 x 52 x 256 1.595 BF
36 Shortcut Layer: 33, wt = 0, wn = 0, outputs: 52 x 52 x 256 0.006 BF
37 conv 128 1 x 1 / 1 52 x 52 x 256 -> 26 x 26 x 512 1.595 BF
38 conv 256 3 x 3 / 2 26 x 26 x 512 -> 26 x 26 x 256 0.177 BF
39 conv 512 1 x 1 / 1 26 x 26 x 256 -> 26 x 26 x 512 1.595 BF
40 Shortcut Layer: 37, wt = 0, wn = 0, outputs: 26 x 26 x 512 0.006 BF
41 conv 256 1 x 1 / 1 26 x 26 x 512 -> 26 x 26 x 256 0.177 BF
42 conv 504 3 x 3 / 1 26 x 26 x 256 -> 26 x 26 x 512 1.595 BF
43 Shortcut Layer: 40, wt = 0, wn = 0, outputs: 26 x 26 x 512 0.006 BF
44 conv 256 1 x 1 / 1 26 x 26 x 512 -> 26 x 26 x 256 0.177 BF
45 conv 512 3 x 3 / 1 26 x 26 x 256 -> 26 x 26 x 512 1.595 BF
46 Shortcut Layer: 43, wt = 0, wn = 0, outputs: 26 x 26 x 512 0.006 BF
47 conv 256 1 x 1 / 1 26 x 26 x 512 -> 26 x 26 x 256 0.177 BF
48 conv 504 3 x 3 / 1 26 x 26 x 256 -> 26 x 26 x 512 1.595 BF
49 Shortcut Layer: 46, wt = 0, wn = 0, outputs: 26 x 26 x 512 0.006 BF
50 conv 256 1 x 1 / 1 26 x 26 x 512 -> 26 x 26 x 256 0.177 BF
51 conv 512 3 x 3 / 1 26 x 26 x 256 -> 26 x 26 x 512 1.595 BF
52 Shortcut Layer: 49, wt = 0, wn = 0, outputs: 26 x 26 x 512 0.006 BF
53 conv 256 1 x 1 / 1 26 x 26 x 512 -> 26 x 26 x 256 0.177 BF
54 conv 512 3 x 3 / 1 26 x 26 x 256 -> 26 x 26 x 512 1.595 BF
55 Shortcut Layer: 52, wt = 0, wn = 0, outputs: 26 x 26 x 512 0.006 BF
56 conv 256 1 x 1 / 1 26 x 26 x 512 -> 26 x 26 x 256 0.177 BF
57 conv 512 3 x 3 / 1 26 x 26 x 256 -> 26 x 26 x 512 1.595 BF
58 Shortcut Layer: 55, wt = 0, wn = 0, outputs: 26 x 26 x 512 0.006 BF
59 conv 256 1 x 1 / 1 26 x 26 x 512 -> 26 x 26 x 256 0.177 BF
60 conv 512 3 x 3 / 1 26 x 26 x 256 -> 26 x 26 x 512 1.595 BF
61 Shortcut Layer: 58, wt = 0, wn = 0, outputs: 26 x 26 x 512 0.006 BF
62 conv 1024 3 x 3 / 2 26 x 26 x 512 -> 13 x 13 x 1024 1.595 BF
63 conv 512 1 x 1 / 1 13 x 13 x 1024 -> 13 x 13 x 512 0.177 BF
64 conv 1024 3 x 3 / 1 13 x 13 x 512 -> 13 x 13 x 1024 1.595 BF
65 Shortcut Layer: 62, wt = 0, wn = 0, outputs: 13 x 13 x 1024 0.006 BF
66 conv 512 1 x 1 / 1 13 x 13 x 1024 -> 13 x 13 x 512 0.177 BF
67 conv 1024 3 x 3 / 1 13 x 13 x 512 -> 13 x 13 x 1024 1.595 BF
68 Shortcut Layer: 65, wt = 0, wn = 0, outputs: 13 x 13 x 1024 0.006 BF
69 conv 512 1 x 1 / 1 13 x 13 x 1024 -> 13 x 13 x 512 0.177 BF
70 conv 1024 3 x 3 / 1 13 x 13 x 512 -> 13 x 13 x 1024 1.595 BF
71 Shortcut Layer: 68, wt = 0, wn = 0, outputs: 13 x 13 x 1024 0.006 BF
72 conv 512 1 x 1 / 1 13 x 13 x 1024 -> 13 x 13 x 512 0.177 BF
73 conv 1024 3 x 3 / 1 13 x 13 x 512 -> 13 x 13 x 1024 1.595 BF
74 Shortcut Layer: 71, wt = 0, wn = 0, outputs: 13 x 13 x 1024 0.006 BF
75 conv 512 1 x 1 / 1 13 x 13 x 1024 -> 13 x 13 x 512 0.177 BF
76 conv 1024 3 x 3 / 1 13 x 13 x 512 -> 13 x 13 x 1024 1.595 BF
77 conv 512 1 x 1 / 1 13 x 13 x 1024 -> 13 x 13 x 512 0.177 BF
78 conv 1024 3 x 3 / 1 13 x 13 x 512 -> 13 x 13 x 1024 1.595 BF
79 conv 512 1 x 1 / 1 13 x 13 x 1024 -> 13 x 13 x 512 0.177 BF
80 conv 1024 3 x 3 / 1 13 x 13 x 512 -> 13 x 13 x 1024 1.595 BF
81 conv 27 1 x 1 / 1 13 x 13 x 1024 -> 13 x 13 x 27 0.009 BF
82 yolo
[yolo] params: iou loss: mse (2), iou_norm: 0.75, obj_norm: 1.00, cls_norm: 1.00, delta_norm: 1.00, scale_x_y: 1.00
83 route 79
84 conv 256 1 x 1 / 1 13 x 13 x 512 -> 13 x 13 x 256 0.044 BF
85 upsample 2x 13 x 13 x 256 -> 26 x 26 x 256
86 route 85 61
[yolo] params: iou loss: mse (2), iou_norm: 0.75, obj_norm: 1.00, cls_norm: 1.00, delta_norm: 1.00, scale_x_y: 1.00
87 conv 256 1 x 1 / 1 26 x 26 x 256 -> 26 x 26 x 768 0.266 BF
88 conv 512 3 x 3 / 1 26 x 26 x 768 -> 26 x 26 x 512 1.595 BF
89 conv 1024 3 x 3 / 1 26 x 26 x 512 -> 26 x 26 x 256 0.177 BF
90 conv 512 3 x 3 / 1 26 x 26 x 256 -> 26 x 26 x 512 1.595 BF
91 conv 256 1 x 1 / 1 26 x 26 x 512 -> 26 x 26 x 256 0.177 BF
92 conv 512 3 x 3 / 1 26 x 26 x 256 -> 26 x 26 x 512 1.595 BF
93 conv 27 1 x 1 / 1 26 x 26 x 512 -> 26 x 26 x 27 0.019 BF
94 yolo
[yolo] params: iou loss: mse (2), iou_norm: 0.75, obj_norm: 1.00, cls_norm: 1.00, delta_norm: 1.00, scale_x_y: 1.00
95 route 91
96 conv 128 1 x 1 / 1 26 x 26 x 256 -> 26 x 26 x 128 0.044 BF
97 upsample 2x 26 x 26 x 128 -> 52 x 52 x 128
98 route 97 36
99 conv 128 1 x 1 / 1 52 x 52 x 128 -> 52 x 52 x 384 0.266 BF
100 conv 256 3 x 3 / 1 52 x 52 x 128 -> 52 x 52 x 256 1.595 BF
101 conv 128 1 x 1 / 1 52 x 52 x 256 -> 52 x 52 x 128 0.177 BF
102 conv 256 3 x 3 / 1 52 x 52 x 128 -> 52 x 52 x 256 1.595 BF
103 conv 128 1 x 1 / 1 52 x 52 x 256 -> 52 x 52 x 128 0.177 BF
104 conv 256 3 x 3 / 1 52 x 52 x 128 -> 52 x 52 x 256 1.595 BF
105 conv 27 1 x 1 / 1 52 x 52 x 256 -> 52 x 52 x 27 0.037 BF
106 yolo
[yolo] params: iou loss: mse (2), iou_norm: 0.75, obj_norm: 1.00, cls_norm: 1.00, delta_norm: 1.00, scale_x_y: 1.00
Total BFLoss: 65.326
avg_Outputs = 517320
Loading weights from weights/traffic-sign-to-test.weights...
usage: 64, max: 88 K-images (1 Kilo-batches_64)
Done! Loaded 107 layers from weights-file
Detection layer: 82 - type = 28
Detection layer: 94 - type = 28
Detection layer: 106 - type = 28
data/traffic-sign-to-test.jpg: Predicted in 2860.473000 milli-seconds.
other: 605
```

Fig:- 3.5 - 106 layers of YOLO

3.2 Recognition

We are using a neural network algorithm, to classify the images into different categories. With the help of keras and TensorFlow we have built a CNN model which is used to classify the image.

In Neural Network Algorithm, a model is made and is trained on lots of training images. In particular, we have made a convolutional neural network (CNN) and used 60% of the data in training the model.

Date set chosen is not uniformly distributed because some of the images appear more often than others.

CHAPTER 4

EXPERIMENTAL RESULT

4.1. Detecting image based on color

4.1.1 Traffic sign having red color



Fig. 4.1.1



Fig. 4.1.2



Fig. 4.1.3



Fig. 4.1.4

Fig 4.1.1 showing the original image.

Fig 4.1.2 showing the detected color in our original image.

Fig 4.1.3 showing the masking of Fig. 4.1.1 and Fig. 4.1.2.

Fig 4.1.4 showing the image having the contour . This will undergo shape based detection

Here we are detecting whether the image has a red color or not. As most of the traffic signs are red in color.

4.1.2 Traffic sign which do not have red color



Fig. 4.1.5

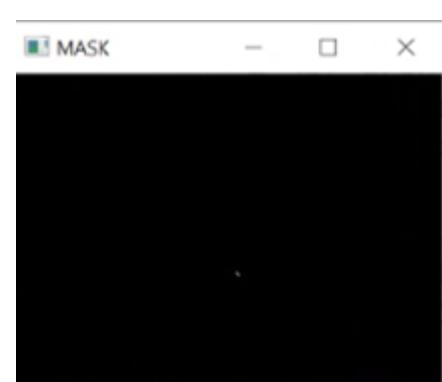


Fig.4.1.6

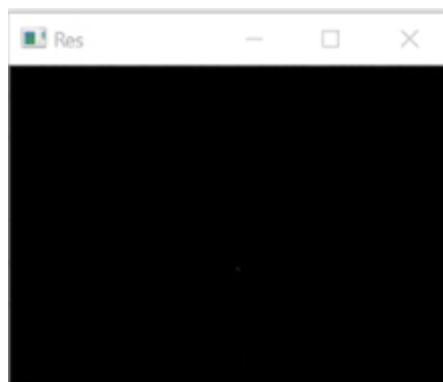


Fig. 4.1.7



Fig.4.1.8

As Fig.4.1.5 doesn't have any red color so no color is detected and no masking has been performed. Due to no masking in Fig.4.1.7, Fig. 4.1.8 doesn't have any contour. Hence it will not undergo the shape based detection.

Here, we are testing color detection on a sign which doesn't have red color.

4.2. Detecting Image with YOLO model

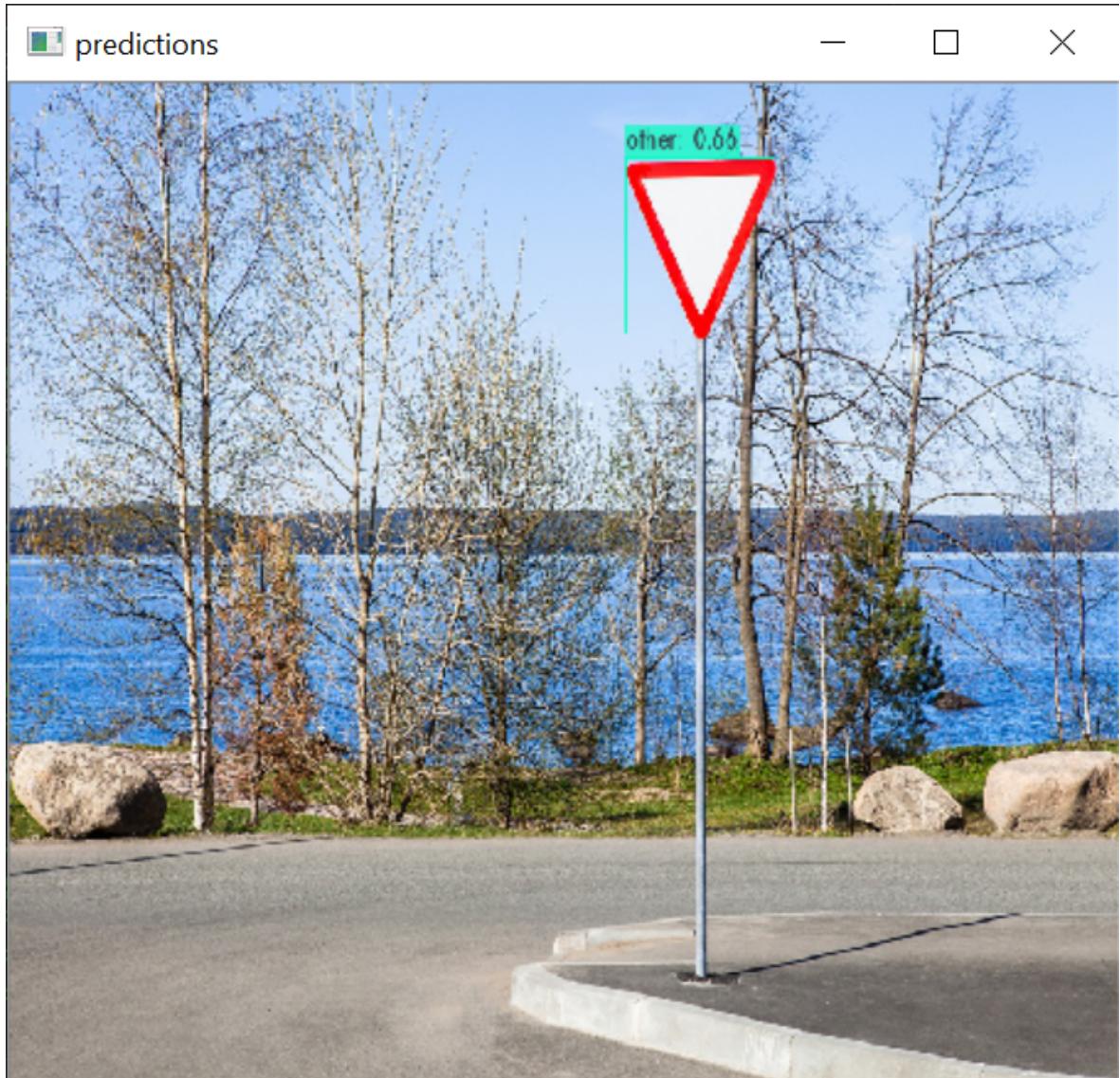


Fig 4.2.1 - Detecting the traffic sign from the image using Transfer Learning Model

4.3 Recognition

4.3.1 Testing against General caution



Fig 4.2.1: Testing against General Caution

Signs which have passed the Detection phase will undergo recognition phase. Our recognition has trained 43 globally accepted traffic signs. As we can see the sign of the Image is **General caution** and our model has successfully identified the name of the sign.

4.3.2 Testing against stop sign



Fig 4.2.2: Testing against Stop Sign

Signs which have passed the Detection phase will undergo recognition phase. Our recognition has trained 43 globally accepted traffic signs. As we can see the sign of the Image is **Stop Sign** and our model has successfully identified the name of the sign.

4.4 Detection and Recognition of Images with Transfer Learning

Example:- 1

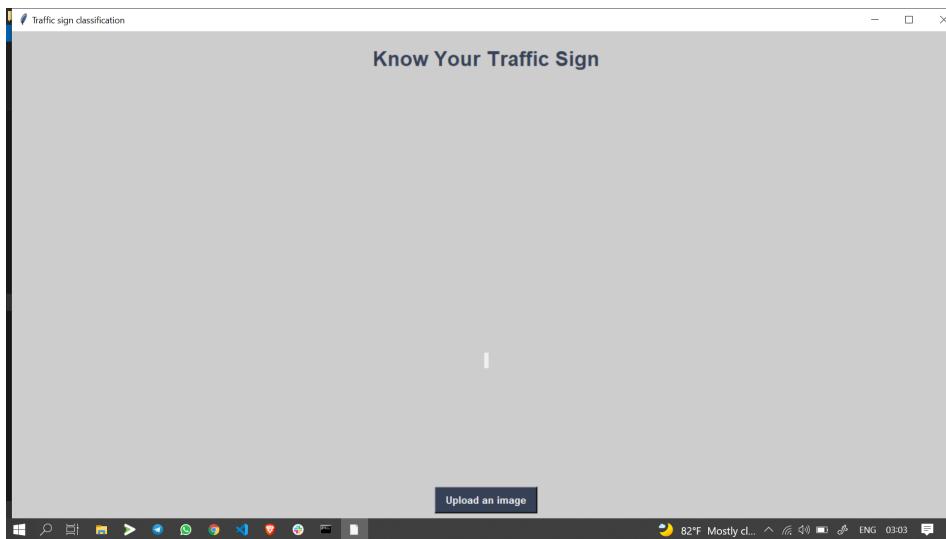


Fig 4.4.1:- First View

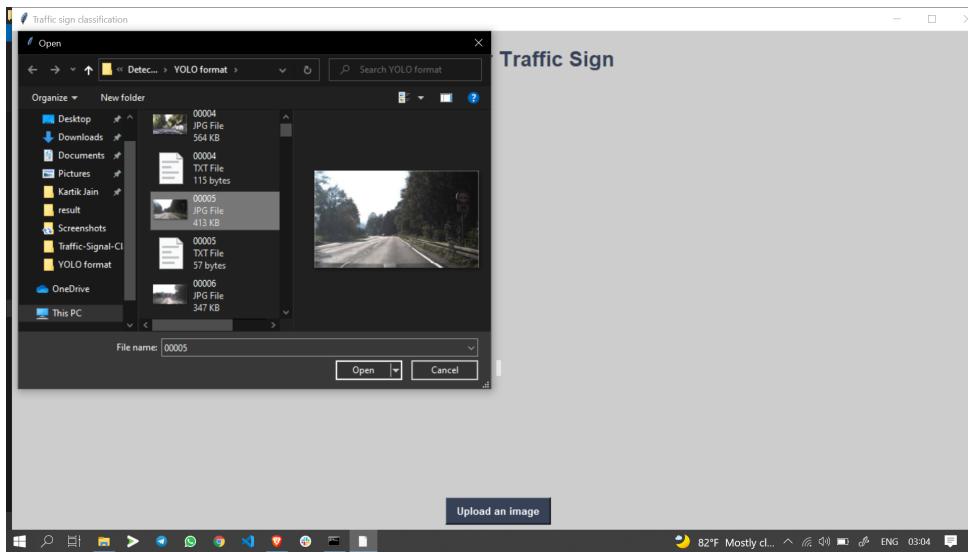


Fig 4.4.2 :- Loading the image

Traffic Sign Detection And Recognition Using Computer Vision

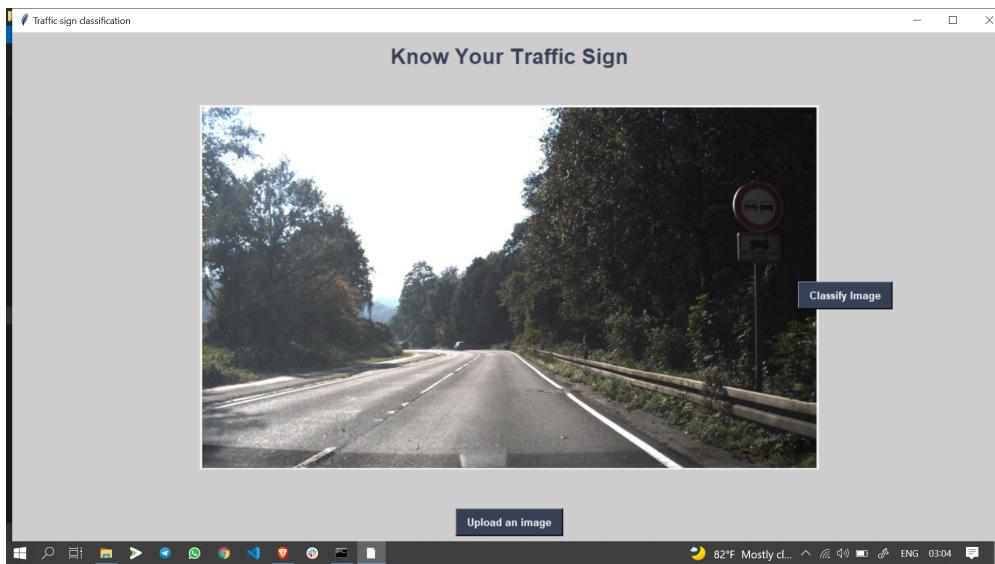


Fig 4.4.3 :- Image Loaded, click on ‘Classify Image’

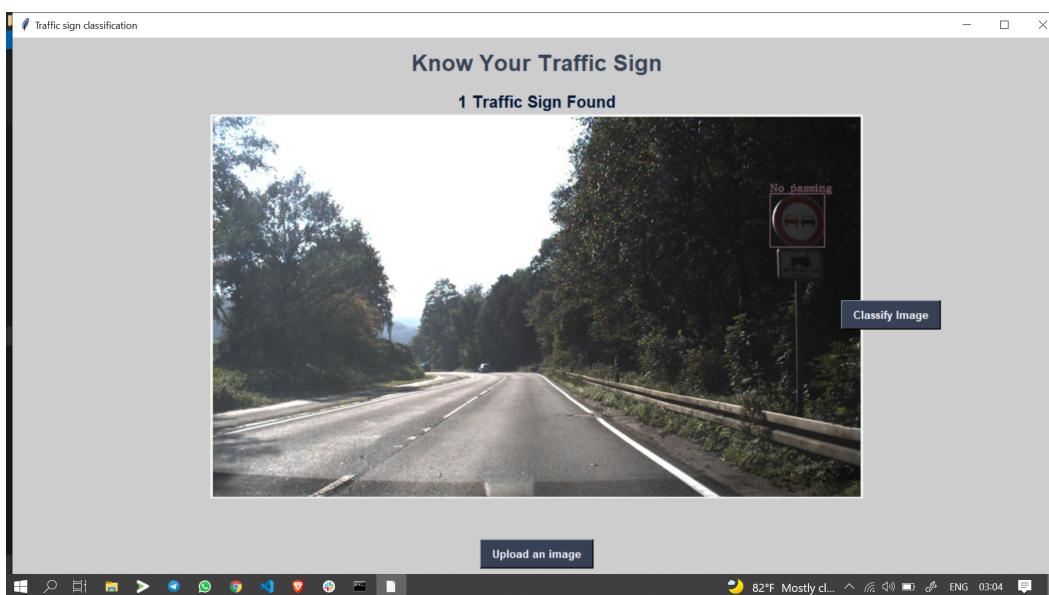


Fig 4.4.4 Final Result

Example:- 2

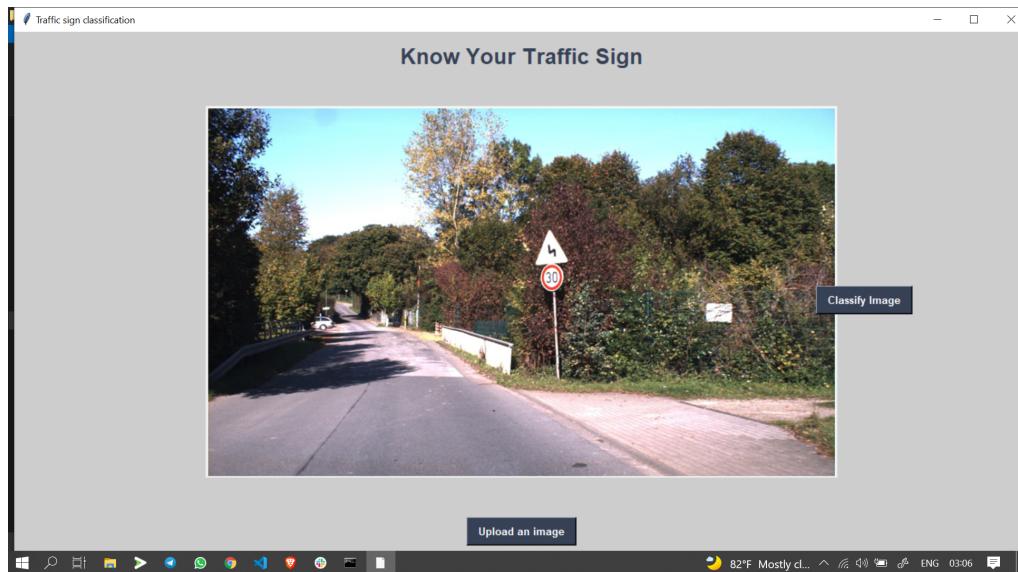


Fig 4.4.5 Loaded the image

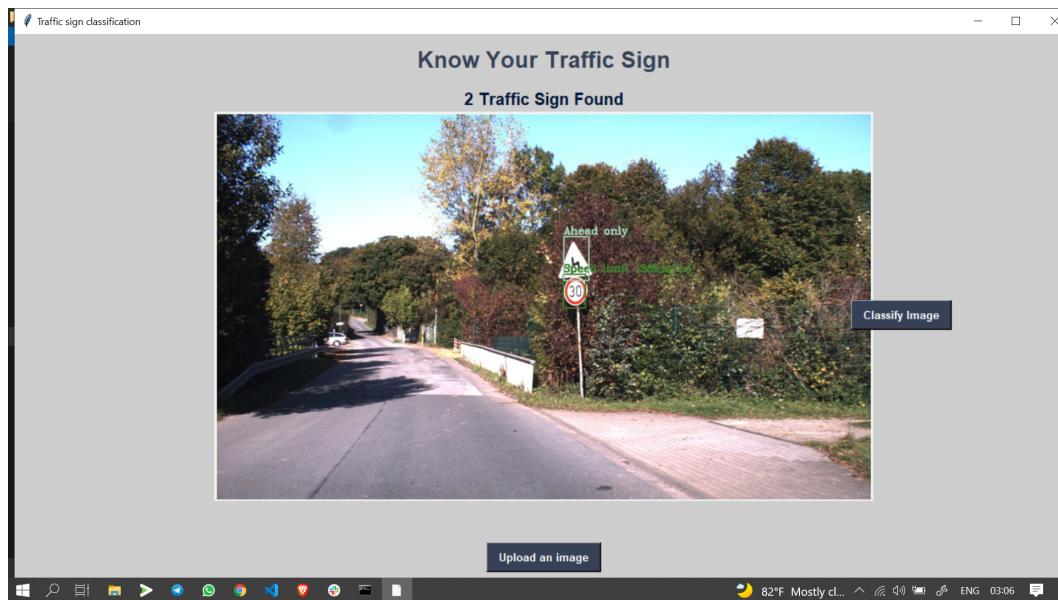


Fig 4.4.6 Final Result

CHAPTER 5

CONCLUSION

We built, installed, and assessed a real-time road and traffic sign recognition system that can assist in the creation of a road sign inventory. This system was able to extract traffic signs from still photos of complex situations with unpredictable illumination using a combination of computer vision and pattern recognition challenges. Algorithms were created in the computer vision section to segment the image using colours and recognise the sign using color-shape combinations as a priori knowledge.

ADVANTAGES:

- **Reduced errors**

TSDR reduces the risk of human error and ensures an easy, impartial, and orderly approach in addressing specific needs without any confusion. In fact, Time and Attendance software has been shown to have an accuracy rate of more than 99% versus manual systems by eliminating errors in data entry and calculations.

- **Increased efficiency**

Efficiency increases because the process is seamless and makes day-to-day operations more efficient and convenient.

- **Reduced manual work**

As the system is automated it doesn't require more resources, the system has less hardware requirements. It does not require additional components like microcontroller. It works with a camera and a computer.

- As the system uses fewer resources therefore the cost of the system is less.
- The system also reduces human effort.
- This system uses the symbol recognition technology and can be further used in various applications. This system is efficient and works perfectly in the ideal conditions.
- The system also works in real time.

SCOPE:

- To automatically recognize various traffic signals present on the road.
- It instantly assists drivers or automatic driving systems in detecting and recognizing traffic signs effectively.
- To detect Sign in different weather conditions such as rain, fog, winter.
- More efficient models can be made with high configuration systems.
- To analyse the focus of drivers in the class.
- To determine concentration of drivers while driving.
- In future, text to speech features can be added to make it more user friendly.

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Traffic Sign Detection and Recognition (TSDR)

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ABSTRACT

The world is evolving every day, as the people are continuously working to make things simpler and simpler by automating them and one of such task is the Advance Driver Assistance System(ADAS). The application of ADAS is ‘Traffic Sign Detection And Recognition’ (TSDR). TSDR is the system in which traffic signs are automatically detected and recognized. It plays a crucial role for the one who is driving the vehicle. As the driver needs to stay focused on the road while driving, the drivers might miss some of the road signs which can be dangerous for the driver of the vehicle as well as for other drivers. The TSDR will reduce this risk by automatically detecting the road sign using Computer Vision and machine learning algorithms such as Convolutional Neural Network (CNN) as well as recognizing them. This whole process will reduce the human efforts and the machine will accurately detect the sign without any human error.

Keywords: Computer Vision, Image Processing, CNN, Tensorflow, Traffic Sign Detection, Traffic Sign Recognition, Advance Driver Assistance System

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I. INTRODUCTION

Traffic Signs are the road facilities provided to warn, inform, guide or restrict the driver from getting into any kind of accident. But keeping an eye on the traffic signs is not the only task of the driver, they need to focus on the road to prevent accident from other vehicles, keeping balance of their own vehicle and while carrying out such task it may happen that the driver might miss the traffic sign, or may be if he sees the traffic sign but doesn't understand what this sign indicate, which might be dangerous for the everyone on the road.

So, for problems like this Advance Driver Assistance Systems comes into the play. Its application TSDR, can prevent many accidents by detecting the traffic sign by capturing the images from the cameras and informing the driver about the same. This will not only minimize the accident-rate over the road but also allows the drivers to drive with ease as they no more need to check for traffic Sign.

ADAS will become the future of automobiles, as the advancement in automobile technology in the industry is increasing what cars can do.

II. METHODOLOGY

The dataset we have used for the project to train our Traffic Sign Classifier is taken from the kaggle dataset([German Traffic Sign Recognition Benchmark \(GTSRB\)](#)). This dataset consists of 43 different traffic sign classes and 39,209 images.

Data Size & Shape

- Size of training set: 31,367(60%)
- Size of validation set: 7842 (15%)
- Size of test set: 12,631 (25%)
- Shape of a image: (30, 30, 3)
- Number of unique classes/labels: 43

The proposed System here, works in 3 phases:-

- Image Pre-processing
- Traffic Sign Detection
- Traffic Sign Recognition

Image Pre-processing :-

This phase plays a crucial role in our TSDR system. It is used to remove the background noise from the image and equalize the intensity of light. Moreover, it separates the RGB image into 3 different channels and converts it into an HSV (Hue Saturation Value) color space. Although instead of HSV other color space like YCrCb can also be used, we have used HSV color space here.

At first the input RGB image is separated into 3 different channels and filters are applied on each threshold to convert the RGB color space into HSV color space. This conversion is necessary because the RGB color space describes colors in terms of the amount of red, green, and blue color present whereas HSV color space describes colors similarly to how the human eye tends to perceive color.

After the color space conversion, the light intensity is taken care of. CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm is used here for over-amplification of the contrast. CLAHE operates on small regions in the image, called tiles, rather than the entire image. The neighbouring tiles are then combined using bilinear interpolation to remove the artificial boundaries.

Traffic Sign Detection :-

Once the pre-processing of the image is done, then comes the part for detecting the traffic signal from the captured image. This detection process is further divided in 2 different phases: **Color Based Detection** and **Shape Based Detection**. Since all objects that are red in color can't be a traffic sign, in order to attain more true positive results we use shape and area for verification of a traffic sign.

1) Color Based Detection

The most important feature of a traffic sign is its color. Whenever we see a red board on the road side we suspect that it could be a traffic sign. So, our detection system works around the same logic. In our proposed algorithm the captured image is processed for the red colour. We apply filters on each channel threshold to extract the part of the image we suspect that can be a traffic sign, following which the contours of the extracted image is found. The threshold of the channel R is in the range of 90-255 and that for channel G and channel B is in the range of 0-70.



Fig 1: (a) Original Image



(b) Color Detection



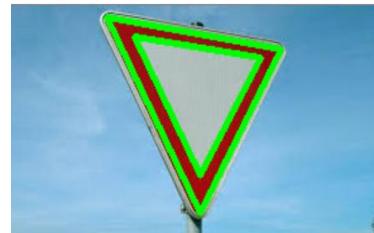
(c) With Contour



Fig 2: (a) Original Image



(b) Color Detection



(c) With Contour

2) Shape Based Detection

The contours that we found in the previous steps will help us further in the detection phase. The contours with a much smaller area are filled up for noise reduction and to better deal with the ROI(Region Of Interest}. The contours with much higher area are not considered for Traffic Sign. Once the area of the contour satisfies the minimum and maximum condition, we pass the image into the SVM.

We use SVM (Support Vector Machine) to classify different shapes of the extracted part of the image. Once the shapes are found, to circular, triangular or octagonal, we can be sure that the ROI contains the traffic sign and we can continue further for the recognition part.

Recognition

Once the sign is detected, we proceed to the recognition part, where we classify the image into different categories. For this part we have used the neural network algorithm. With the help of machine learning frameworks such as keras and TensorFlow, a CNN(convolutional neural network) model is built for the classifications.

The dataset used here does not have uniform distribution. This is the real case scenario because there are certain signs that appear more from others, but it is generally good to have normal distribution so that the model gets equal opportunity to learn every sign.

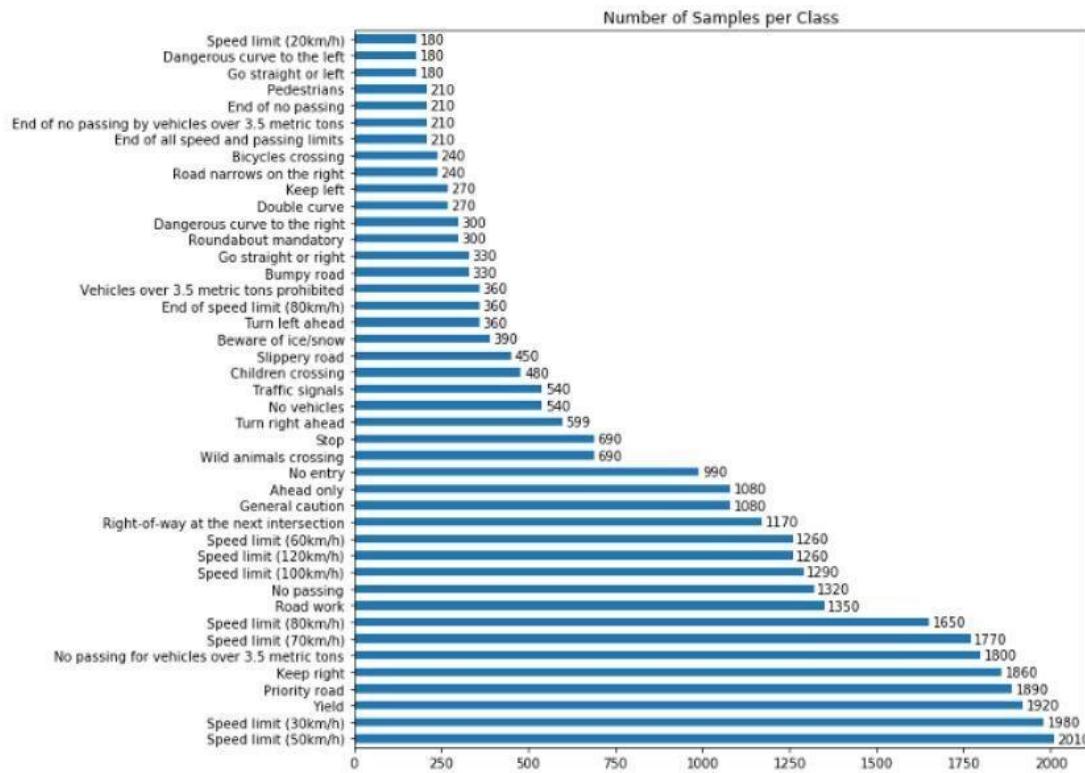


Fig 3: Image Distribution

In Neural Network Algorithm, a model is made and is trained on lots of training images. In particular, we have made a convolutional neural network (CNN) and used 60% of the data in training the model.

The Convolutional Neural Network (CNN) is a multi-layered feed-forward neural network, which is made by assembling hidden layers on top of each other in a definite order. A CNN can have multiple layers, adding more and more layers to the CNN, makes the model complex. The 1st layer is called the Input layer and the last layer is known as the output layer. All the layers between them are called the hidden layers. In CNN, some of them followed by grouping layers and hidden layers are typically convolutional layers followed by activation layers. We have also used dropout layers to prevent over-fitting.

Algorithms used :-

1. **Loss:** categorical cross-entropy
2. **Optimization:** Adam
3. **Activation Function:**
 1. **ReLU:** Rectified Linear Unit => $f(x) = \max(0, x)$
 2. **SoftMax:** The outputs of the Softmax transform are always in the range [0,1] and add up to 1. Hence, they form a **probability distribution**.

Epochs: 15

Batch size: 32

Learning rate: 0.004

Model Details

Model: "sequential_1"		
Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 26, 26, 32)	2432
conv2d_2 (Conv2D)	(None, 22, 22, 32)	25632
max_pooling2d_1 (MaxPooling2D)	(None, 11, 11, 32)	0
dropout_1 (Dropout)	(None, 11, 11, 32)	0
conv2d_3 (Conv2D)	(None, 9, 9, 64)	18496
conv2d_4 (Conv2D)	(None, 7, 7, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(None, 3, 3, 64)	0
dropout_2 (Dropout)	(None, 3, 3, 64)	0
flatten_1 (Flatten)	(None, 576)	0
dense_1 (Dense)	(None, 256)	147712
dropout_3 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 43)	11051
=====		
Total params: 242,251		
Trainable params: 242,251		
Non-trainable params: 0		

Fig 4: Model Summary

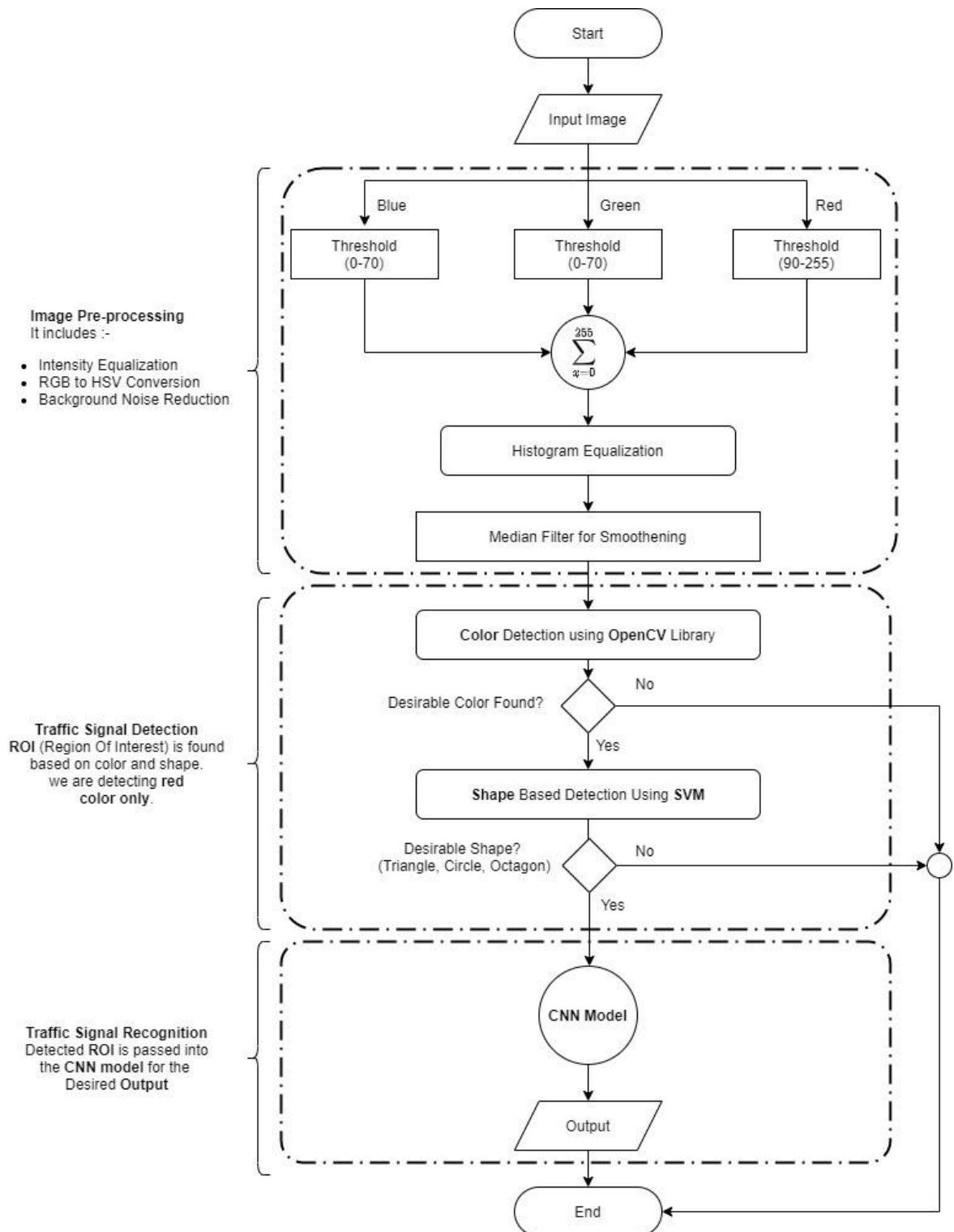


Fig 5: The overall block diagram of the proposed system.

III. RESULTS AND DISCUSSION

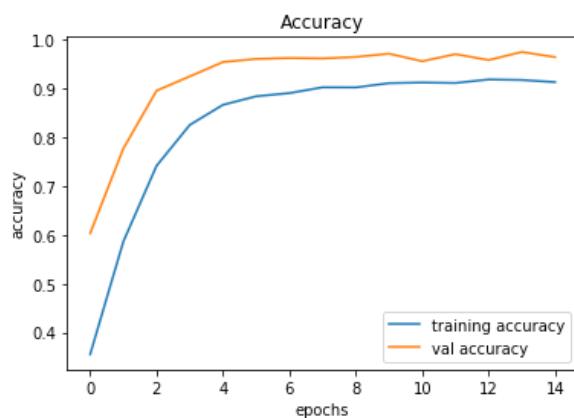


Fig 6: Training Accuracy

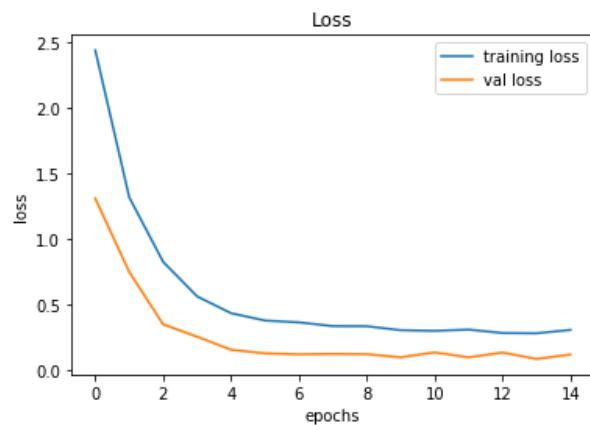


Fig 7: Training Loss

Upon training our CNN model, we achieved an accuracy of 91.24% and 92.61% when tested.

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