International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 05 | May - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

# Traffic Sign Detection and Recognition using Computer Vision

**Chandra Shekhar Azad[1], Hemant Bisht[2], Mohit Aggarwal[3], Naman Gupta[4], Varun Sharma[5]**

Department of Computer Science and Engineering (Data science)

Inderprastha Engineering College, Ghaziabad, India.

Chandrashekhar.azad@ipec.org.in , bishthemant169@gmail.com

mohitaggarwal775@gmail.com[3], namanguptapersonal@gmail.com[4],

Varun4229sharma@gmail.com[5]

**ABSTRACT**

The rapid evolution of technology is simplifying tasks through automation, with one significant example being Advanced Driver Assistance Systems (ADAS). ADAS encompasses a range of safety features and technologies aimed at assisting drivers and enhancing vehicle safety. These systems, including adaptive cruise control, lane departure warning, automatic emergency braking, and blind-spot monitoring, among others, exemplify the integration of technology into everyday life. 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 implementation of the Traffic Sign Detection and Recognition (TSDR) system aims to mitigate risks by employing Computer Vision and machine learning algorithms like Convolutional Neural Networks (CNN). This technology automates the detection and recognition of road signs, minimizing human intervention and the potential for errors. Through this process, the system can accurately identify signs without relying on human interpretation.

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

## I. INTRODUCTION

Traffic Signs are the facilities for road 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. The application of TSDR has the potential to prevent numerous accidents by utilizing cameras to capture images of traffic signs and promptly notifying the driver. This proactive approach enhances driver awareness by providing real-time information about road signage, thereby reducing the likelihood of accidents. 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 an 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 utilized for the removal of background noise from images and for equalizing the intensity of light. Moreover, it separates the RGB image into 3 different channels and converts it into an HSV (Hue Saturation Value) colour space. Although instead of HSV other colour space like YCrCb can also be used, we have used HSV colour 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 colour space into HSV colour space. This conversion is necessary because the RGB colour space describes colours in terms of the amount of red, green, and blue colour present whereas HSV colour space describes colours similarly to how the human eye tends to perceive colour. After the colour 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. A method known as bilinear interpolation is employed to merge neighbouring tiles, effectively eliminating any artificial boundaries.

**Traffic Sign Detection: -**

Following the completion of image preprocessing, the next step involves detecting the traffic signal within the captured image. This detection process is further divided in 2 different phases: Colour Based Detection and

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 05 | May - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Shape Based Detection. Since all objects that are red in colour cannot be a traffic sign, to attain truer positive results, we use shape and area for verification of a traffic sign.

**1) Colour Based Detection**

The most important feature of a traffic sign is its colour. 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. Filters are applied to each channel threshold to isolate segments of the image that potentially represent traffic signs. Subsequently, the contours of these extracted segments are identified. 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. Contours with smaller areas are filled to reduce noise and improve the handling of the Region of Interest (ROI).The contours with much higher area are not considered for Traffic Sign. Once the contour areas satisfy the minimum and maximum condition, we pass the image into the SVM. We use SVM (Support Vector Machine) to classify different shapes of the obtained 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. 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 architectures, there is a common sequence of layers: convolutional layers, activation layers, and often, grouping layers. These are followed by hidden layers. To combat overfitting, dropout layers are employed.

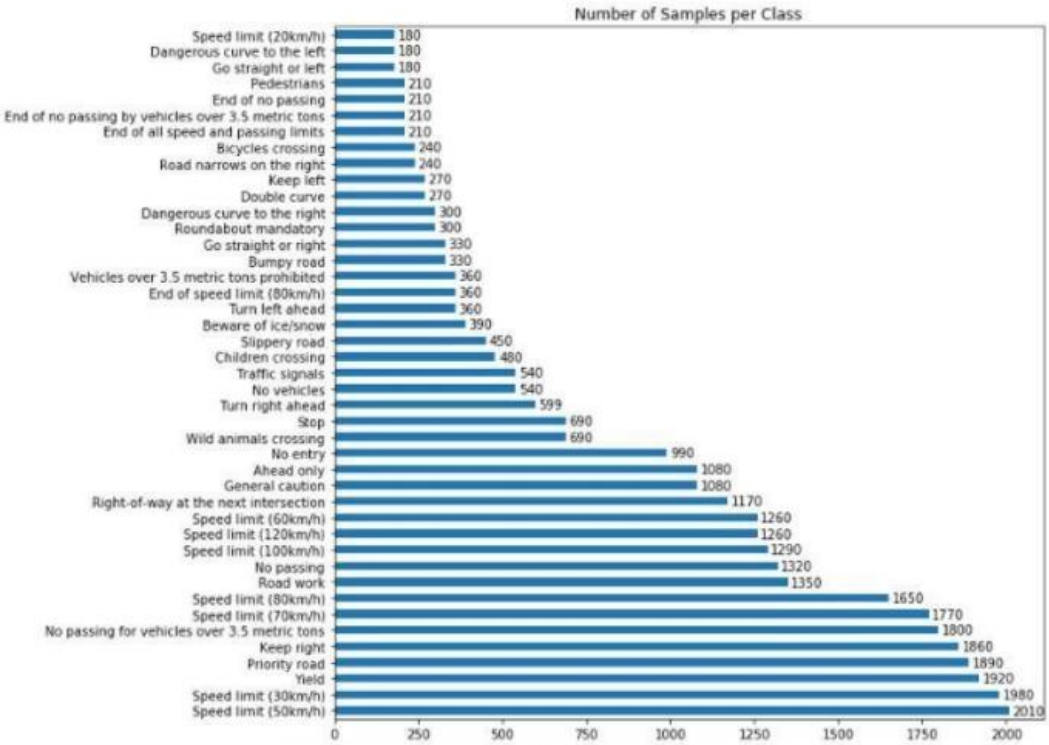


**Fig 3: Image Distribution**

**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

**Model Details**

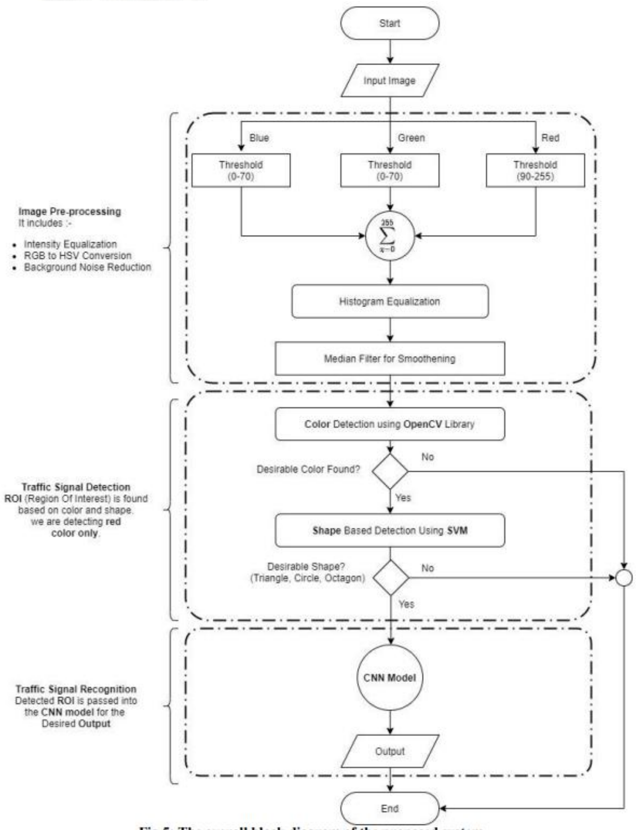


**Fig 5: The overall block diagram of the proposed system.**

Learning rate: 0.004

## III. RESULTS AND DISCUSSION

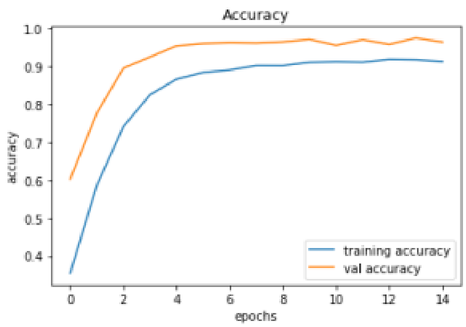


**Fig 6: Training Accuracy**

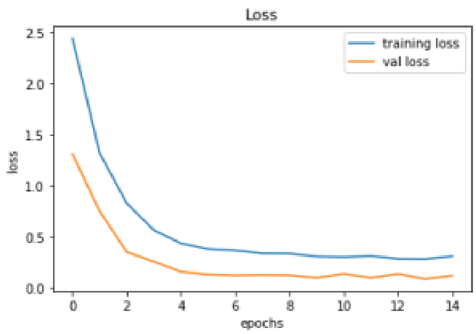


**Fig 7: Training Loss**

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

**REFERENCES**

[1]. Traffic Sign Detection and Recognition using a CNN Ensemble Aashrith Vennela Kanti, Smriti Shreya, Resmi Rajendran, Debasis Sarkar, Deepak Mudde Gowda, Phanish Hana gal Affiliation: Qualcomm India Private Limited, Bangalore.

[2]. An Automatic Traffic Sign Detection and Recognition System Based on Colour Segmentation, Shape Matching, and SVM Safat B. Wali, Mahammad A. Hannan, Aini Hussain, and Salina A. Samad Department of Electrical, Electronic & Systems Engineering, University Kebangsaan Malaysia, Jalan Reko, 43600 Bangi, Selangor, Malaysia.