# Traffic Sign Recognition Using Neural Networks

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***Abstract*—Road signs give out a number of messages regarding the road and what you as a driver should expect on the road. They keep the traffic flowing freely by helping drivers reach their destinations and letting them know entry, exit and turn points in advance. Pre-informed drivers will naturally avoid committing mistakes or take abrupt turns causing bottlenecks. Road signs, indicating turns, directions and landmarks, also help to save time and fuel by providing information on the route to be taken to reach a particular destination. Road signs are placed in specific areas to ensure the safety of drivers. These markers let drivers know how fast to drive. They also tell drivers when and where to turn or not to turn. In order to be a terrific driver, you need to have an understanding of what the sign mean. Our project implements a procedure to extract the road sign from a natural complex image, processes it and alerts the driver using voice command. It is implemented in such a way that it acts as a boon to drivers to make easy decisions.**

***Index Terms*—Neural Networks,Accuracy,Cross Entropy,Recognition**

## I. Introduction

Traffic signs provide valuable information to drivers and other road users. They represent rules that are in place to keep you safe, and help to communicate messages to drivers and pedestrians that can maintain order and reduce accidents. 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.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 non signs.


Fig. 1. Traffic sign detection model

## II. INDIAN ROAD TRAFFIC SIGNS

Indian Road Traffic Signs are standardized and pertinent nationwide, these are broadly classified into the following categories.
1) Regulatory signs-These signs inform the road users about the laws and regulations they have to follow. Violation of these signs is legal offence. They are circular in shape with red circumference.

2) Compulsory signs-These signs are an extension to regulatory signs and similar to the violation of regulatory signs, violation of these is a legal offence, which makes them most important signs. They are circular in shape and are filled with blue color and white circumference.
3) Warning signs-These signs warn road users of certain hazardous conditions. They are triangular in shape and possess a red circumference.
4) Informatory signs - These signs provide information and guidance to road users. They are rectangular and may vary in color, in some cases they might be green with white circumference whereas in others it might be white filled rectangle with blue circumference. Further classification of each of these categories is based on the information contained by these signs which may be a picture, alphanumeric string or a particular direction indicating arrow.

## III. SYSTEM OVERVIEW

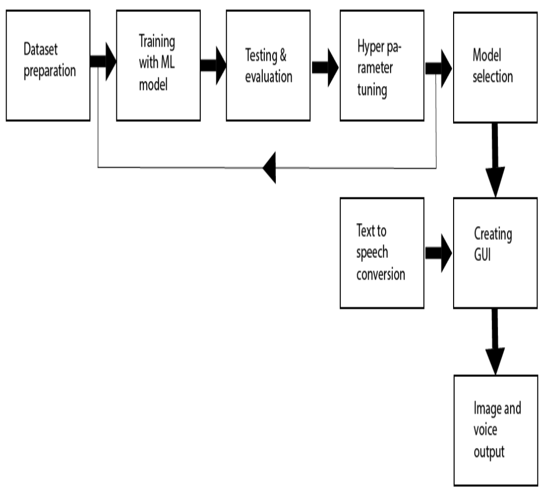


Fig. 2. Block Diagram

### A. Dataset Preparation

Collecting the images of these traffic signs is the most time consuming process. In our project we have used a German traffic sign dataset from the site kaggle.com. The signs which are common among German and Indian signs are filtered. There were around 35 signs which are common. After thorough research we have selected 12 signs, that if the driver didn't notice any of these sign boards the chances of getting to accident is very high. The signs are selected based on the collision accident rates in India.

### B. Training

The model for traffic sign detection is implemented with the help of Convolutional Neural Network (CNN).The observations in the training set form the experience that the algorithm uses to learn.

### C. Testing

In order to calculate the efficiency of the model, we need to test it under various conditions. Real time images from the roads were taken. The images were taken under the following conditions. • Morning • Evening • Tilted • Real time using web camera


Fig. 3. Test image - morning

### D. Voice Assisted Messages

If a particular sign is detected a voice message is given according to the sign. Suppose "School Ahead" traffic sign is detected, then a voice message "School is Ahead, so please control your speed" is given by the system. This is implemented with the help of Google Text to Speech library.

## IV. SYSTEM ANALYSIS

Machine learning model accuracy is the measurement used to determine which model is best at identifying relationships and patterns between variables in a dataset based on the input, or training, data. The better a model can generalize to 'unseen' data, the better predictions and insights it can produce, which in turn deliver more business value.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative Cross-entropy loss is used when adjusting model weights during training. The aim is to minimize the loss, i.e, the smaller the loss the better the model. A perfect model has a cross-entropy loss of 0.

$$loss = -\sum_{i=0}^{n} t_i \log(p_i) \tag{2}$$

n= total no. of classes
t = Truth label for i th class
p = Softmax probability for i th class
Categorical cross-entropy is used when true labels are one-hot encoded.

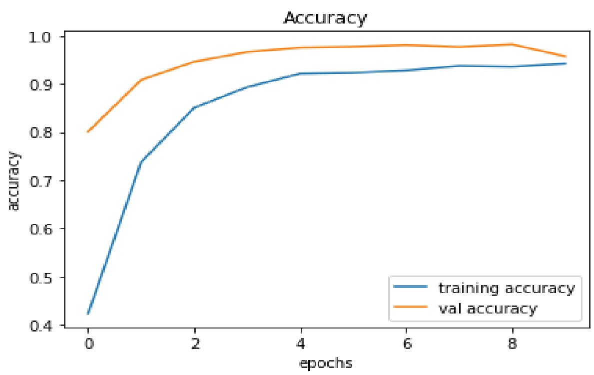


Fig. 4. Accuracy plot

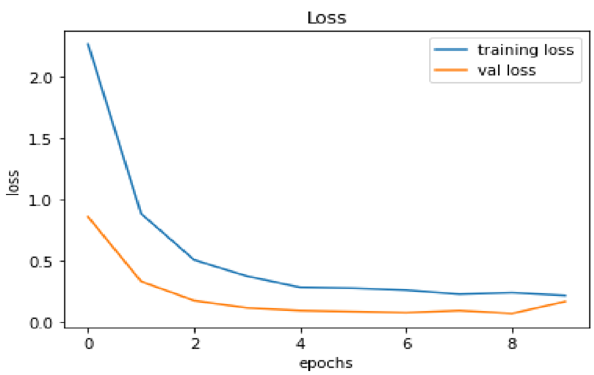


Fig. 5. Loss plot

## V. RESULTS

The German Traffic sign dataset containing over 43 traffic signs were preprocessed and trained using CNN algorithm.A User Interface is build for traffic sign detection. The text to speech conversion is done for Voice assisted message system. The model is tested with real time images and works perfectly. The CNN algorithm shows an accuracy of 0.9573. Categorical cross-entropy is calculated as a part of evaluating the performance of model.CNN shows a loss of 0.1633.

## CONCLUSION

This paper focuses on a new way of traffic sign detection using CNN which is very effective among the Indian traffic signs on the road without the use of extensive and expensive evaluations.The model developed remains to be a foundation that can be adjusted to different types of vehicles, such as bus or trucks, by considering the properties and constraints that defines each one. This also serves as a meaningful development in field of neural networks and its learning systems, as well as provide valuable insights for future progress

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