

TRAFFIC SIGN CLASSIFICATION

A COURSE PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this mini project report " **TRAFFIC SIGN CLASSIFICATION** " is the bonafide work of “ **MODUGURU VISHAL (RA2011003010986), INTURI ABHIRAM (RA2011003011031), T PURNA CHARITH (RA2011003011041)**” who carried out the project work under my supervision.

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1. ABSTRACT

Road traffic accidents are primarily caused by driver error. Safer roads infrastructure and facilities like traffic signs and signals are built to aid drivers on the road. But several factors affect the awareness of drivers to traffic signs including visual complexity, environmental condition, and poor driver education. This study implements a traffic sign detection and recognition system with voice alert using Python. It aims to establish the proper trade-off between accuracy and speed in the design of the system. Four pre-processing and object detection methods in different color spaces are evaluated for efficient, accurate, and fast segmentation of the region of interest. In the recognition phase, ten classification algorithms are implemented and evaluated to determine which will provide the best performance in both accuracy and processing speed for traffic sign recognition.

This study has determined that Shadow and Highlight Invariant Method for the pre-processing and color segmentation stage provided the best trade-off between detection success rate (77.05%) and processing speed (31.2ms). The Convolutional Neural Network for the recognition stage not only provided the best trade-off between classification accuracy (92.97%) and processing speed (7.81ms) but also has the best performance even with a lesser number of training data.

2. INTRODUCTION

Machine learning algorithms have gained importance nowadays. Spam filtering, speech understanding, face recognition, road sign detection are only a few examples where machine learning is deployed. In traffic zones, Traffic Sign Recognition and classification can be used to automatically identify traffic signs. This is done automatically by the system as the traffic sign is detected and the sign name is displayed. So, even if any sign is missed by the driver or has any lapse in concentration, it will be detected. This helps to accordingly warn the drivers and forbid certain actions like over speeding. It also disburdens the driver and hence, increases his/her comfort. Thus, ensuring and keeping a check on the traffic signs and accordingly following them. Traffic signs, indeed, provide us a multitude of information and guide us accordingly so that we can move safely. Traffic Sign Classification is very useful in Automatic Driver Assistance Systems.

A convolutional neural network is a class of deep learning networks, used to examine and check visual imagery. It is used to train the image classification and recognition model because of its high accuracy and precision.

The World Health Organization (WHO) in 2013 reported that road traffic accidents that result to loss of lives and damages to properties will continue to become a global challenge due to rapid motorization and insufficient action of national governments.

This paper “Traffic Sign Detection and Recognition System for Assistive Driving” is an extension of work originally presented by the authors in International Symposium on Multimedia and Communication Technology (ISMAT) 2019 entitled “Traffic Sign Detection and Recognition for Assistive Driving”. The goal of this study is to help solve the problem of drivers neglect and lack of road education. Traffic signs defined by the Department of Public Works and Highways to be recognized must be strategically positioned, clear and fully visible and captured in good weather condition during daytime. The system will be able to provide voice alert.

3. REQUIREMENT ANALYSIS

SYSTEM REQUIREMENT SPECIFICATIONS

The System Requirement Specification (SRS) is a document, which describes completely the external behavior of the software as well as the behavior of the hardware. The first and foremost work of the developer is to study the system to be developed and specify the user requirements before going for the designing phase. It includes the set of use cases that describes all the interaction the users will have with software. Use cases are also known as functional requirements. In addition to use cases, the SRS also contains non-functional requirements. Non-functional requirements are requirements, which impose constraints on the design or implementation.

SOFTWARE REQUIREMENTS

- Programming language: Python • Operating System: Windows 7 or Above
- Platform Used: Anaconda, Spyder

HARDWARE REQUIREMENTS

- RAM: 4 GB • CPU: Intel Core i3 or Above • Disk: 1 TB • Camera & Speaker

LITERATURE REVIEW

The identification of road signs can be carried out by two main stages: detection, and recognition. In 'detection' research groups are categorised into three groups. The first group of researchers believes that traffic sign colours are important information by which traffic signs can be detected and classified. The second group believes that detection of traffic signs can be achieved by traffic sign shape only, and the third believes that colour together with shape make the backbone for any road sign detection.

Thus, there are three major approaches to detecting traffic signs: detection using colour information, detection using shape information, and detection using both colour and shape information. All of the reviewed papers used images from real traffic scenes which are similar to the images collected during this research.

1. DETECTION USING CNN ENSEMBLE:

The method described by Shustanov, P. Yakimov used for Road Sign Detection and Recognition is image processing technique which consists of a group of (CNN) for the recognition called as ensemble.

The recognition rate for the CNN is very high, which makes it more desirable for various computer-based vision tasks. The method used for the execution of CNN is TensorFlow. The members of this paper achieved more than 99 percent of accuracy for circular signs on using German data sets.

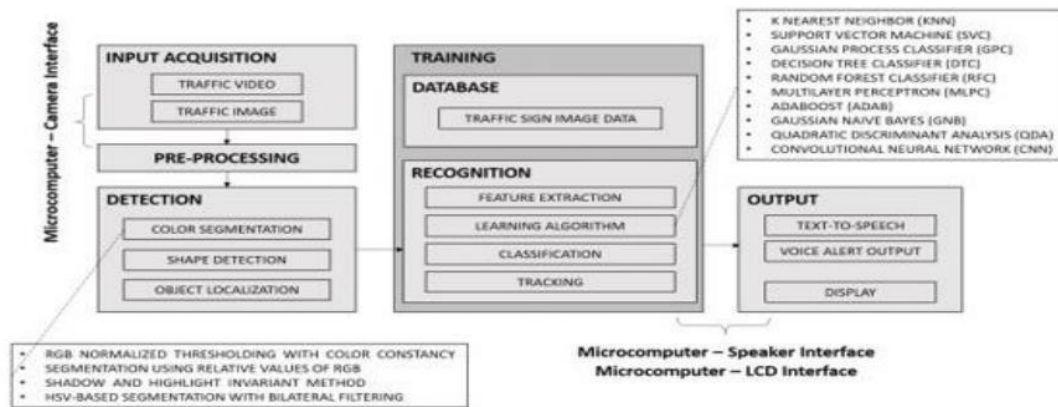
2. RECOGNITION USING COLOR SEGMENTATION:

Wali et al describes how they have used to implement a novel method for sign recognition. They used advanced ARK-2121 technology which is small computer which they installed this tech on the car. The major techniques in the recognition step of the sign were SVM and HOG. They achieved an accuracy of 91% in detection and about 98% average on the classification process.

3. THE GERMAN TRAFFIC SIGN RECOGNITION:

R. Qian et al describes the analysis and design process of “German Traffic Sign Recognition Benchmark” dataset. The outputs of this project showed that algorithms of machine learning showed very well in recognition of traffic signs. The participants got a very good percentage of 98.98 recognition rate which is as high as human perfection on these datasets.

4. ARCHITECTURE & DESIGN



Overview of Methodology The methodology for the proposed real-time traffic sign detection and recognition system starting with image acquisition for training the detection and recognition models followed by testing.

- (a) **Data Acquisition:** Input traffic data will be acquired by the system using a camera interfaced to the microcomputer. Videos taken will be processed per frame by the system. Some testing process will make use of traffic images to be stored in the microcomputer.
- (b) **Pre-processing and Detection:** The detection phase is composed of pre-processing, color-based segmentation, shape-based detection and object localization. Methods to be evaluated that use different filtering techniques in different color spaces are RGB Normalized Thresholding with Color Constancy Algorithm
- (c) **HSV-based Segmentation with Bilateral Filtering (BFM):** Traffic images undergo pre-processing in the RGB color space before the detection stage. Bilateral filtering smoothens the image while preserving the edges by means of a nonlinear combination of nearby pixel values

5. IMPLEMENTATION

A. Traffic Sign Dataset

Dataset A total of 2,194 images are used to test the detection phase of the models. Of these, 2,170 are traffic images from online sources with traffic sign having different viewing angle and position on image

Before moving on to detection or classification, the most important part is the availability of a generalized dataset. A prediction model is trained using this dataset and predictions are done for test dataset. Table I below shows sample datasets:

TABLE I Dataset Information

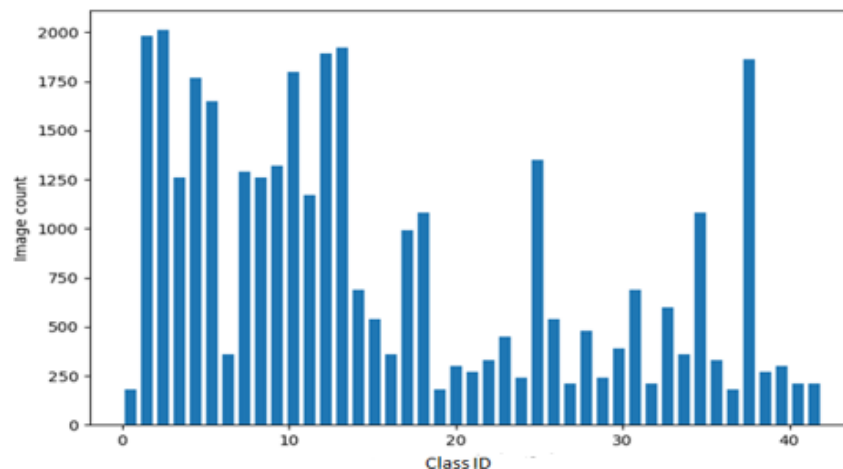
Dataset	Information
GTSRB	Total traffic sign images more than 50,000 and classes = 43
GTSDb	Total traffic sign images = 900
BTSCB	Total traffic sign images = 10,000 and classes = 62
BTSDb	Total traffic sign images = 7000

Among these, the most common dataset is the GTSRB (German Traffic Sign Recognition Benchmark) dataset. The reason for its popularity is:

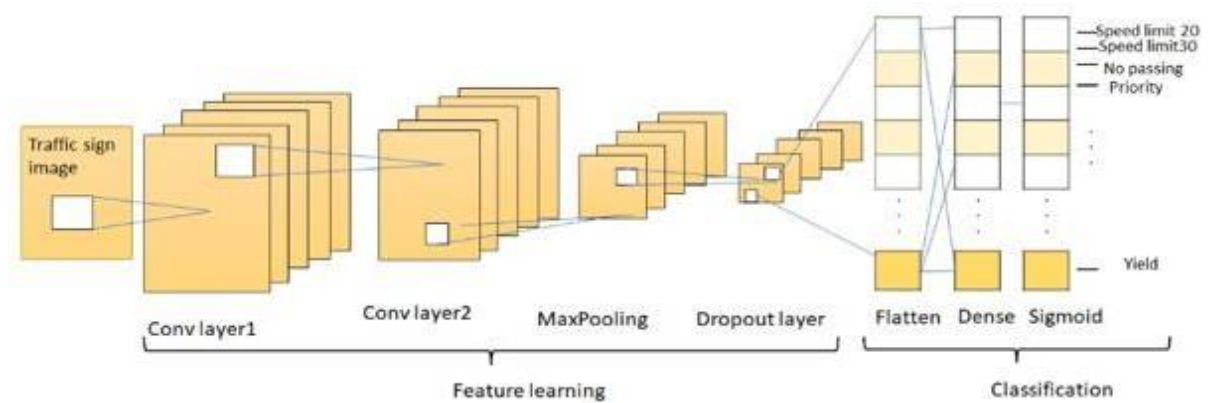
1. It consists of large number of images
2. The traffic signs are of different variety, background, and colour variation which in turn will help the model to perform accurately.

As the GTSRB dataset can be used for both detection as well as classification, the proposed system makes use of the same. The dataset is further split into training, testing and validation dataset. The training dataset is the one which is used to train the model. The validation dataset, in general, is used to evaluate the model and update the hyper parameters. Hyper parameters are used to control the learning process and improve the accuracy, for example, number of epochs, the choice of activation function. The test dataset is only used once the model is trained. It is used to check whether the model can make correct predictions or not.

Further, histogram graphs are plotted to show the number of images in each class, for the training, testing and validation data sets respectively, where the X label denotes the “Class ID”, and the Y label denotes the number of images. Plotting the graph helps to visualize the dataset.



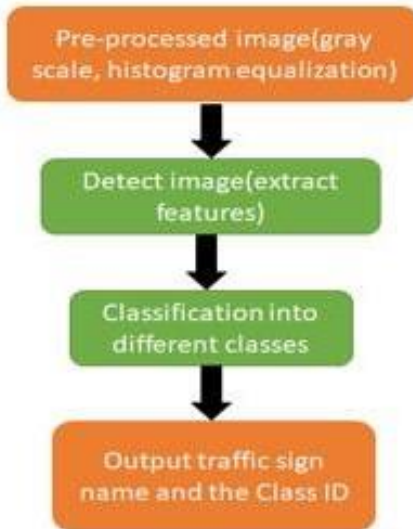
B. FLOWCHART



Initially, the CNN model architecture is built. The following steps are followed :

1. Sequentially add the layers in the order: two convolutional layers, one pooling layer, dropout layer, flattening layer, dense layer, again a dropout layer and finally the dense layer.
2. In the convolutional layer, number of filters is specified. It performs the convolution operation on the original image and generates a feature map.
3. The ReLU performs the maximum function to convert the negative values to zero without changing the positive ones and generate a rectified feature map. The Pooling layer takes the rectified feature map and performs a down-sampling operation (like Max Pooling or average pooling) and thus reduces the dimensionality of the image.
4. The flattening layer is used to convert the input feature map to a 1-dimensional array.
5. The dropout layer is used to avoid over fitting by setting some of the input neurons to 0 during the training process. The dense layer, on the other hand, feeds all the outputs from the preceding layer to all its neurons and perform the matrix- vector multiplication (the row vector of the output from the preceding layer should be equal to the column vector of the dense layer), to generate a m-dimensional vector.

6. After addition of the layers, the model is to be compiled (final step in the creation of model to define the loss function and apply optimization techniques) and assign the loss function as “sparse_categorical_crossentropy” and use the “Adam optimizer”. The reason for specifying this loss function is that the proposed system is a multiclass classification problem, where multiple classes are considered but one image belongs to exactly one class.
7. Next, the model is trained using the training dataset, by passing the pre-processed images from the training dataset.
8. Finally, the predictions on the test data are done using the trained model and the traffic sign name along with the class Id is shown as an output.



C. Design/Method

Traffic Sign Classification is one of those rare topics of discussion. Most of the existing systems focus on detection only. Detection is mainly the extraction of features and find out the important coordinates in the image. Classification is the categorization of image into different classes.

The most common dataset used for the purpose is GTSRB which consists of 43 classes. In the proposed system, a prediction model is trained using this dataset. It performs best for image classification. Lately, Convolutional Neural Network has been adopted in object recognition for its high accuracy and less computational cost.

In the proposed system, the primary focus is towards the traffic sign classification which also prints the traffic sign name once the detection of the image is done. There is a csv file which consists of the pairs of traffic sign name and the class ID. This file helps to load the labeled data.

D. Gray Scale

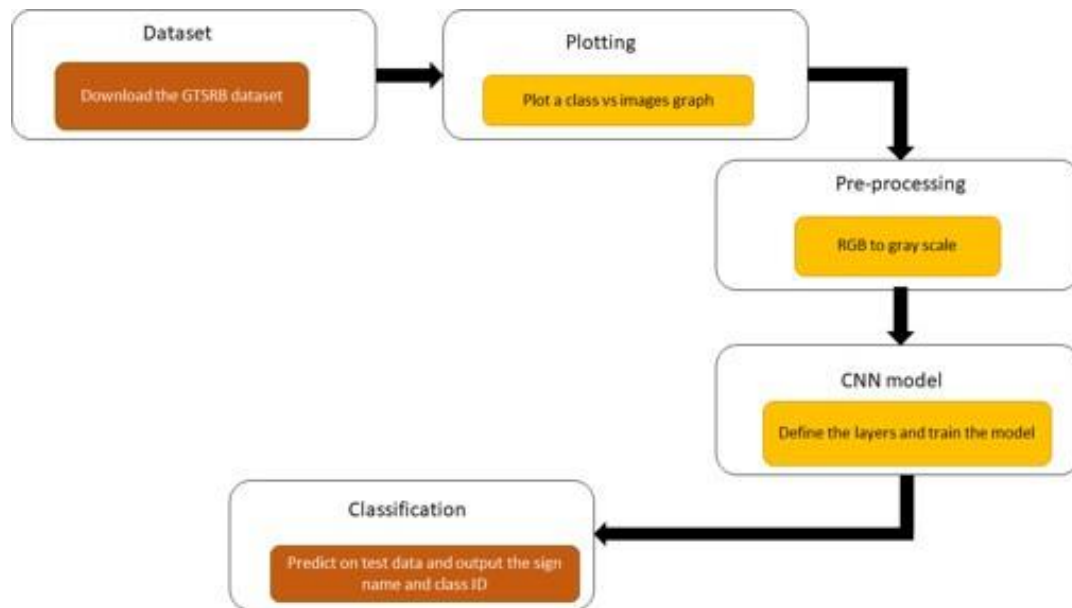
Converting the RGB data set into gray scale is one of the important steps before classification using CNN. This has several advantages like:

1. Images after converting to gray scale, help the neural network to process them easily as the unwanted biases are removed.
2. Gray scaling the images helps to reduce the number of computations, as the number of channels will get reduced after conversion.
3. This in turn helps to improve the model accuracy.

Before gray scaling, image data shape (of training data set) is: (34799, 32, 32, 3).

This means that the images were of 32x32 size and colored in rgb format (3 channels).

After gray scaling, image data shape (of training data set) becomes: (34799, 32, 32, 1). After gray scaling the size of the image remains the same (32x32) but the number of channels is reduced to 1.



The proposed system consists of different functions corresponding to each operation.

1. **Building of the model:** This primarily focuses on converting the images to gray scale, normalizing the images (normalization is done to accelerate the training process and improve the model performance), histogram equalization (to improve image contrast), addition of the layers to the model, train the model, get predictions on the test data set, and finally show some sample images with their traffic sign name and class Id as the output. The train, test and validation split percentage is 65%, 25% and 10% respectively for the proposed system.
2. One of the main functionalities which are implemented in this work, is prediction of unknown images. Here, a small dataset was generated gathering images from different sources. This was the most crucial part as this dataset includes some different images with different colour and structure. Although there are several existing datasets available, a small dataset (consisting of 13 images) is built. The dataset includes some speed limit symbols, yield sign, caution signs (like stop and no entry), informatory signs (like pedestrians, ahead only, no passing, roundabout mandatory, and right-of-way at the next intersection). Extracting features from these images is not easy for the model. The reasons being, these images are enlarged, having different background colours and reduced clarity. Despite all the issues, the model successfully predicted around 9 images out of 13. Only the images which are curvilinear or

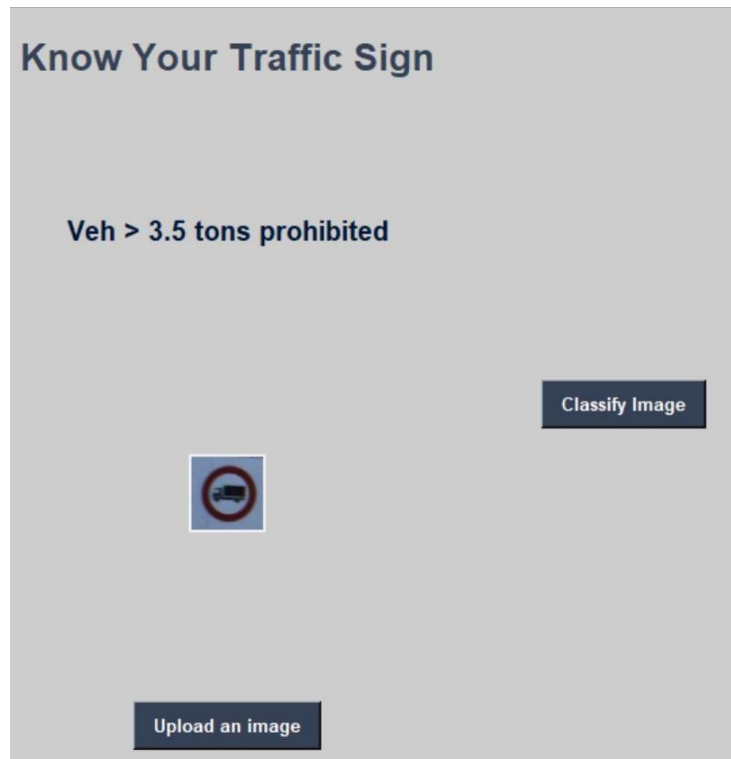
in circular format, are not predicted accurately. The model predicts the closest traffic sign name found for such images.

The activation function used is “ReLU”. ReLU is one of those non-linear activation functions that is used in multi-layer neural networks. The reason being, ReLU applies a function $f(x) = \max(0, x)$ to all the values given as input. The ReLU layer just changes the negative values to 0 and keeps the positive values as it is. ReLU has become the default activation function to be used in the hidden layers of the neural network. The ReLU function is simple and less computationally expensive since there are no complex mathematical calculations involved and thus makes the model learn and train faster.

The model successfully predicts majority of the images with 93%. The only images which are not accurately predicted are the ones including circular shapes in it. This can be resolved by augmenting the images and using one hot encoding technique.

6. EXPERIMENT RESULTS & ANALYSIS

6.1. RESULTS



Know Your Traffic Sign

Pedestrians

Classify Image



Upload an image

Know Your Traffic Sign

Right-of-way at intersection

Classify Image



Upload an image

6.2. RESULT ANALYSIS

Traffic sign classification is the process of automatically recognizing traffic signs (like speed limit, yield, and caution signs, etc.) and accordingly classifies them as to which class they belong to. The project has two main functionalities: Prediction on the newly generated dataset and live web cam traffic sign detection.

Accuracy is the ratio of number of correct predictions to the number of total predictions (eqn. 1).


A. Equation 1: Formula for accuracy

Accuracy = (The Number of Correct Predictions) / (Total predictions).


The accuracy achieved on the test dataset is 93%. The accuracy on the GTSRB dataset and the built dataset are shown in Table II.


Table II Accuracy Statistics


Sr No.	Dataset used	Accuracy
1.	GTSRB	93%
2.	Generated dataset	69%

Predict 16, Actual 16 Sign Vehicle > 3.5 tons prohibited


Predict 33, Actual 33 Sign Turn right ahead


Predict 18, Actual 18 Sign General caution



Predict 35, Actual 35 Sign Ahead only



Predict 23, Actual 23 Sign Slippery road



Predict 1, Actual 1 Sign Speed limit (30km/h)



Predict 11, Actual 11 Sign Right-of-way at intersection


Predict 12, Actual 12 Sign Priority road


Predict 12, Actual 12 Sign Priority road


Predict 8, Actual 7 Sign Speed limit (120km/h)


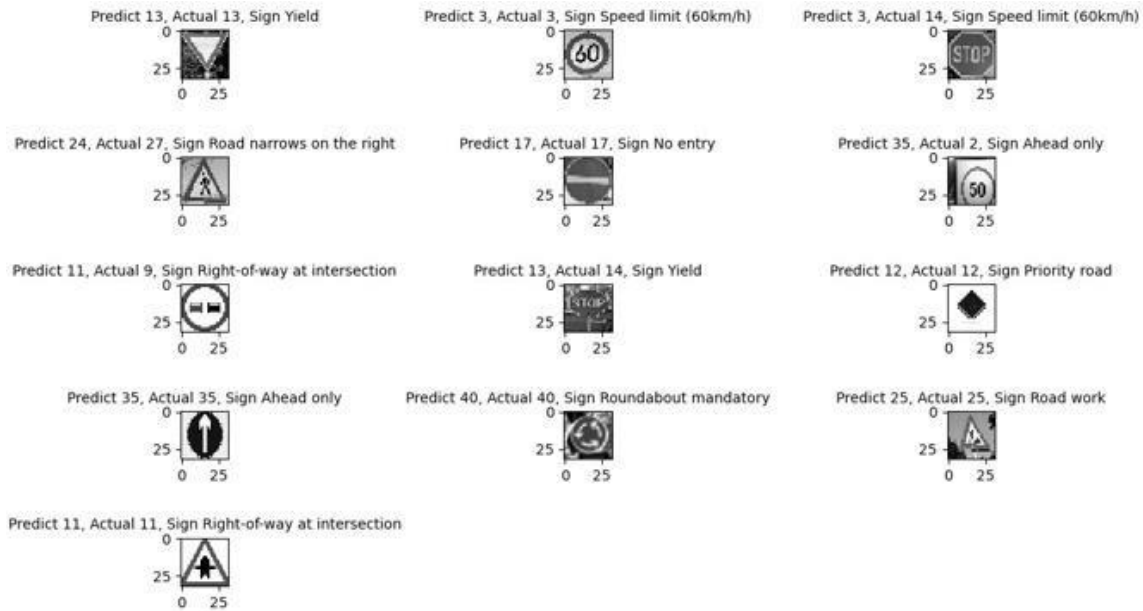
Predict 38, Actual 38 Sign Keep right


Predict 38, Actual 38 Sign Keep right


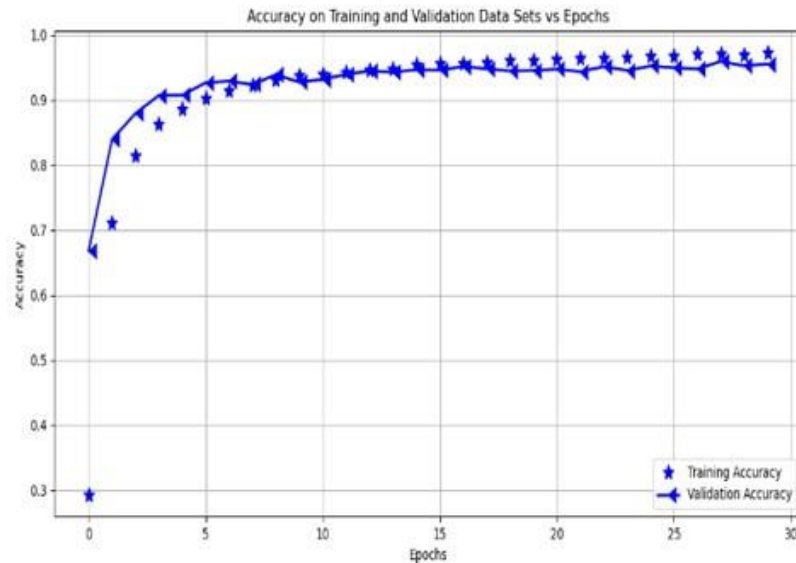
Predict 25, Actual 25 Sign Road work


Predict 7, Actual 7 Sign Speed limit (100km/h)


Predict 4, Actual 4 Sign Speed limit (70km/h)

The Training accuracy and Validation accuracy graph is as follows:



The training accuracy is the accuracy generated from the predictions on the training dataset. Similarly, validation accuracy depicts the one using the validation dataset. The number of epochs is a hyper parameter that defines the number times that the learning algorithm will work through the entire training dataset. It is the number of iterations the training dataset will go through each time during training of

the model. As seen, at around 30 epochs, the training and validation accuracy match and is a straight line. Here, the training and validation accuracy are maximum. If these lines start separating consistently, then we should stop the training process at an earlier epoch by visualizing the graph. This shows that 30 epochs are enough for the model to extract features.

The loss on training and validation dataset vs epochs graph is shown:

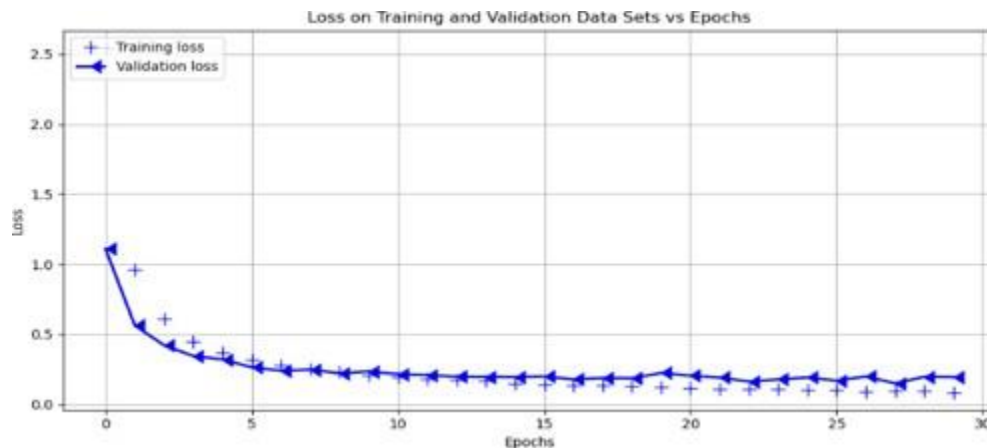


Table III

Loss Statistics After 30 Epochs

Sr No.	Dataset	Loss
1.	Training Loss	0.0929
2.	Validation Loss	0.1648

The loss statistics are shown in the Table III. The loss is minimum (nearly 0.2) at around 30 epochs. The mean square loss is calculated as the average of the squared differences between the predicted and actual values. In the Cross- Entropy loss, each

predicted value is compared to the actual class output value and a score is calculated that penalizes the probability based on the distance from the expected value. Cross Entropy calculates the difference between the actual and the predicted probabilities. The formula is mentioned in the eqn. 2:

B. Equation 2: Mathematical formula

$$\text{Cross Entropy Loss} = - (y_i \log(y'_i) + (1 - y_i) \log(1 - y'_i))$$

where,

i is the i th training example in the data set,

y_i - ground truth label for i th training example, y'_i - prediction for i th training example.

The traffic sign when shown from the web cam, automatically classifies the symbol and shows the corresponding class ID and the sign name.

6.3. CONCLUSION & FUTURE WORK

The proposed system is simple and does the classification quite accurately on the GTSRB dataset as well as the newly generated one (consisting of truly existing images of all type), and finally the model can successfully capture images and predict them accurately even if the background of the image is not much clear. The proposed system uses Convolutional Neural Network (CNN) to train the model. The images are pre-processed, and histogram equalization is done to enhance the image contrast. The final accuracy on the test dataset is 93% and on the built dataset is 69%. The web cam predictions done by the model are also accurate and take very less time. The benefits of “Traffic Sign classification and detection system” are generally focused on driver convenience. Despite the advantages of traffic sign classification, there are drawbacks. There can be times when the traffic signs are covered or not visible clearly. This can be dangerous as the driver won't be able to keep a check on his vehicle speed and can lead to accidents, endangering other motorists or pedestrians, demanding further research.

The hardware used in this project is very less when compared to other models, which reduces cost and also free from hardware Impairments

The following sections summarise the main findings and the contribution made by this research,

6.3.1. Colour Segmentation Algorithms

In this research, four colour segmentation algorithms are developed. They are as follows:

- Shadow and Highlight invariant colour segmentation algorithm,
- The dynamic threshold algorithm,
- A modification of de la Escalera's algorithm,
- The Fuzzy colour segmentation algorithm.

The experiments and tests carried out show that the Shadow and Highlight invariant algorithm is the best performer, compared with the other algorithms. The reasons behind this can be attributed to:

1. The high segmentation performance achieved by this algorithm which is 97.6%
2. The ability of the algorithm to achieve colour segmentation under a wide range of weather, sign, and image conditions
3. The highest segmentation speed among the other algorithms
4. Its ability to enhance the recognition speed by suppressing noise and producing fewer objects in the segmented image

The performance of the developed algorithms, however, may be affected by several parameters, including weather conditions under which the image is taken, poor environmental lighting and the age of the sign under consideration.

6.3.2. Colour Segmentation in Poor Light Conditions

Colour segmentation in poor light conditions is a process which is specially developed by this research to eliminate the effect of fog and snowfall which often occur in many parts of Europe and more frequently in Scandinavia.

These light conditions affect the general brightness of the image and hence affect the stability of the colours. In order to eliminate these effects, the colour segmentation algorithm is enhanced by invoking a special treatment of colour.

The histogram equalisation technique is separately applied to the RGB channels of the captured image and the resultant RGB image is further treated by the colour constancy algorithm. The superiority of this algorithm in enhancing the image for colour segmentation. In this research, the user selects this algorithm manually when snowfall is noticed.

In the future, however, an automated method can be adopted to switch to this algorithm when snow fall is detected. This could be part of the future work in which metrological sensors can be attached to the computer to detect the snow fall.

6.3.3. The Fuzzy Shape Recogniser

A Fuzzy shape recogniser which relies on the four shape measures is developed during this research. A set of fuzzy rules are invoked to decide the shape of the sign. To recognise the right sign, simple IF-THEN rules are developed. These rules check the presence of a certain combination of information which includes the shape of the object under consideration, its rim colour, and its interior colour. Once a sign with these specifications is found it is sent to the classification stage, otherwise the object is deleted from the object list.

This method prevents any unknown object with a specification different from traffic signs being sent to the classifier, and hence reduces the number of false alarms and the amount of calculations. The recogniser is tested in different test environments and it shows high robustness. The overall performance of the recogniser is 88.4%. It performs even better in some difficult environmental conditions such as snowfall, rainfall, dusk and dawn.

6.3. Future Works

There are several avenues for further research which could follow from work begun here. They are given as follows:

6.3.4 Real Time Applications

Another direction for further research is to develop a real time traffic sign recognition system which captures a video by a camera mounted on the vehicle, detects and recognises the traffic signs in real time and gives the result to the driver within a sufficient time frame in order to take the right action. The crucial issue in real time applications is the time spent to recognise the traffic sign.

This should be reduced to the minimum by choosing the proper techniques for real time applications and by optimising the code. The methods presented in this thesis can be modified to fit the real time requirements. After detecting the border of the traffic sign and its interior, it can be tracked by a Kalman filter or by a suitable blob tracking algorithm which can be developed for this purpose. The main objective of this blob tracking algorithm is to minimize the search region from the whole image to an area which fits the traffic sign. Taking into consideration that the size of the traffic sign increases as the vehicle approaches the sign, the blob tracking algorithm should be able to match the traffic sign in the current frame with that in the next frame.

The algorithm should be immune to the in-plane transformations. Tracking the traffic sign has an advantage that if the traffic sign is occluded in some frames or disappeared, it is still possible to follow that sign in the frames that follow. If such a system is integrated with a GPS, it can be used to provide the driver with useful information about the actual speed limit on a certain road. By comparing the signed limit with the GPS speed reading, the driver can be warned when the speed limit is exceeded or when the driver does not stop before a STOP sign.

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