

**INDIAN TRAFFIC SIGN DETECTION USING MACHINE LEARNING AND
DEEP LEARNING**

Main Project work submitted to Avinashilingam Institute for Home Science and
Higher Education for Women

POST GRADUATE IN INFORMATION TECHNOLOGY

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DECLARATION

DECLARATION

I hereby declare that the project entitled “ **INDIAN TRAFFIC SIGN DETECTION USING MACHINE LEARNING AND DEEP LEARNING** ” is a record of the original work done by Dharani T (19PIT001) under the guidance of Dr. D. Shanmuga Priya M.Sc., M.Phil., Ph.D., Head and Assistant Professor, Department of Information Technology, school of physical sciences and computational sciences, Avinashilingam Institute for Home Science and Higher Education for Women, in the partial fulfilment for the degree of Master of Science in Information Technology and this project has not formed the basis for any Degree/Diploma/Associates.

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CERTIFICATE

CERTIFICATE

This is to certify that this project work entitled **“INDIAN TRAFFIC SIGN DETECTION USING MACHINE LEARNING AND DEEP LEARNING”** done by Dharani T (19PIT001) has been submitted to Avinashilingam Institute for Home science and Higher education for women, Coimbatore-43 in partial fulfillment of the requirement for the award of the **POST GRADUATE IN INFORMATION TECHNOLOGY**. This Project has not found the basis for the award of any Degree/Associate/fellowship or similar title to any Candidate of any University. Certified as a bonafied record of the work submitted for the Viva voce held on _____.

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This is to certify the student **Ms DHARANI. T(19PIT001)** pursuing her final year **MSC INFORMATION TECHNOLOGY** in **AVINASHILINGAM INSTITUTE FOR HOME SCIENCE & HIGHER EDUCATION FOR WOMEN, COIMBATORE** has completed her project entitled **“INDIAN TRAFFIC SIGN DETECTION USING MACHINE LEARNING AND DEEP LEARNING”** in our concern starts on February 2021 to April 2021.

Wish her for the best!

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ABSTRACT

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Indian traffic sign detection using machine learning and driver alert system which has a number of important application areas that include advance **driver assistance systems, road surveying and autonomous vehicles**. It uses a novel approach for traffic signs detection using machine learning and deep learning that is it uses Convolutional Neural Network and Support Vector Machine (CNN-SVM). This dataset was collected in different scenarios of real traffic scenes. Dataset consists of 40 traffic sign classes, with 4575 images. The image data contains 90% and 10% of train and test set images within 62 labels. The training and testing dataset is loaded and displayed. And the data is also pre-processed. Adam is used for the whole processing of CNN such as batch normalization, activation and maxpooling. The feature extraction work of traffic signs is led with the algorithms. Contrasted with the algorithms on the basis of HOG will be used to train the SVM for higher accuracy. In this on-going work, an acceptance model is carried out, which constructs the training machine by using a new pattern popularity technology, Support Vector Machines. Actually, the blend of both methods makes the system to understand which algorithm plays more stable and reliable accuracy in traffic sign detection. System uses variety of image processing techniques to enhance the image quality and to remove non-informational pixel and detecting edges. Feature extractor are used to find the features of image. If features of sign image that matches with the trained traffic signs then it will generate **alert to the driver**. The efficiency and speed of the detection play an important role in the system. To recognize traffic signs, various methods for automatic traffic sign detection have been developed and shown promising results.

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INTRODUCTION

1. INTRODUCTION

1.1. An Introduction to Indian Traffic Sign

The computerized detection of traffic signs is a challenging problem, with several important request areas, including advanced drivers assistance systems, autonomous vehicles and street surveying. Traffic signs afford crucial direction to traffic supervision, differing between admonitions, street condition data and goal information. Traffic signs detection using machine learning and deep learning has a significant job in the unmanned autonomous driving. Distinct methods were contemplated in the previous years to handle this problem; still the performance of these approaches needs to be enhanced to fulfil the necessities in real time applications. Continuous traffic-sign identification algorithms must be utilized if self-driving vehicles are turned out to be exemplary in the streets of the future. Deep learning and Machine learning methods aids to get accuracy in the process of traffic sign detection. The dataset can include all types of images. The images are divided for training and testing.

Intelligent vehicles are becoming a part of our day to day life. Due to carelessness of drivers while driving and Violation of traffic rules, a large number of accidents occur today. Intelligent Transport Systems (ITS) play a great role in safe driving and in saving lives of pedestrians as well as in saving time and money. These systems are interconnected to the emerging technologies such as internet, General packet radio service (GPRS), Artificial Intelligence, smart sensors, Geographical Information Systems (GIS) and many more. ITS gives great importance to the field of road sign detection and recognition as it is a part of driving assistance system and autonomous navigation system. These systems must be fast and robust to detect sign in real time. The efficient methods such as Convolution Neural Network and Support Vector Machine are used for the mechanism.

1.2. Characteristics of Road Signs

Traffic signs have been designed so that they are easily recognisable from natural and driving environment. The colour for traffic sign are chosen such that, it serves different purposes and is also distinguishable for the driver while driving. The signs are represented by fixed shapes like triangle, circle, octagon, and rectangle. The combined feature of colour and shape are used by driver to distinguish a traffic sign. Hence an automated system also uses the same principle of 'the colour and shape property of traffic signs'. With respect to the road the traffic signs are located at well-defined locations so that the drivers can more or less expect the position of the sign. The road sign may contain text as a string of characters or pictogram or both to represent the meaning of the sign. They are characterised by using fixed text fonts and character heights. There are a number of traffic signs in India categorized as Mandatory (36), Cautionary (38) and Informatory (14). This makes a total of 88 traffic signs all together. These signs are mainly characterized by colour and shape. Figure 1 shows the different types of Indian traffic sign and their description are discussed below.

Informatory signs- These signs provide information and guidance to road users. They are rectangular and may vary in colour; in some cases they might be green with white circumference whereas in others it might be white filled rectangle with blue circumference.

Color	Shape	Sign
Red	Triangle	Warning
Red	Circle	Compulsary
Red	Inverted Triangle	Give Way
Red	Octagon	Stop
Blue	Rectangle	Informatory
Blue	Circle	Regulatory
Green	Rectangle	Informatory

Table 1: Traffic sign based on colour and shape

The traffic sign based on colour and shape are discussed in the above Table 1. However identification of traffic sign is still a challenging task due to different geographic and weather conditions like cloudy day, raining or foggy day. The lighting conditions are uncontrollable since it is time dependent and seasonal, for example day light and night fall. More over the signs are of different types. Distance between the sign and video capturing device is a factor. The blurring of the image is dependent on the speed of the moving vehicle. Other problems are sign may be disoriented, damaged, faded or occluded. There may be similar objects as in colour or shape. Hence most sign detection system use both colour and shape as distinguishing feature and pre-processing techniques for image enhancement for coping with the varying lighting conditions.

1.4. Problem statement

- To detect Indian traffic signs.
- Achieve high accuracy

1.5. Objectives of the project

Traffic-sign detection is an intriguing part in computer-vision and it is particularly important with regards to self-governing vehicle innovation. Traffic sign detection is an innovation by which a vehicle can perceive to detect the traffic sign put on the street for example, "speed limit" or "turn ahead". Traffic signs can be analysed utilizing front oriented cameras in numerous modern vehicles and trucks. They insist the driver by providing commands, admonitions and some of the times by taking control of the vehicle itself. The Indian traffic sign dataset is used for experiment and evaluation the proposed approach. This dataset was collected in different scenarios of real traffic scenes. Dataset consists of 40 traffic sign classes, with 4575 images. The image data contains 90% and 10% of train and test set images within 62 labels. The training and testing dataset is loaded and displayed.

One specific alternative of deep neural networks is convolutional neural networks (CNNs), have delineated their qualities for errands consisting image detection. Traffic signs might be partitioned into various classes based on to the function, and in every classification they might be further divided into subclasses with comparative nonexclusive shape and appearance however changed subtleties. This proposes traffic-sign recognition ought to be completed as a two-stage task: detection pursued by classification. The detection step uses shared data to recommend bounding boxes that may contain traffic-signs in a specific classification, while the step utilizes contrasts to figure out which specific sort of sign is present. And the data is also pre-processed. Adam is used for the whole processing of CNN such as batch normalization, activation and maxpooling. Adam is a versatile learning rate enhancement algorithm that has been structured explicitly for training deep neural networks. Adam is a flexible learning rate approach, which implies, it registers singular learning rates for various parameters.

In this algorithm, the feature extraction work of traffic signs is led with the algorithms. Contrasted with the algorithms on the basis of HOG will be used to train the SVM for higher accuracy. System uses variety of image processing techniques to enhance the image quality and to remove non-informational pixel and detecting edges. Feature extractor is used to find the features of image. The proposed method is broadly divided in five part **data collection, data processing, data classification, training and testing**. In this on-going work, an acceptance model is carried out, which constructs the training machine by using a new pattern popularity technology, Support Vector Machines.

Actually, the blend of both methods makes the system to understand which algorithm plays more stable and reliable accuracy in traffic sign detection. This work is to apply traffic sign detection accuracy on artificial neural network (ANN) and image handling technologies, which is applicable a deep learning method, Support Vector Machines for machine learning. Finally the accuracy for data is obtained, which is used for comparison. Finding the accuracy for both algorithms, comparing the accuracy and decide which algorithm forecast the best. The CNN and SVM are the finest techniques of Deep Learning and Machine Learning which ensures accuracy in the achieved output. This method incorporates all the aspects of CNN. The work includes processing images gives more accuracy i.e. 81%.

Indian traffic sign data set is classified in to three classes hence system detects that the traffic sign is mandatory, cautionary or informative. Most of these systems typically involve two tasks finding the locations and sizes of sign board in natural scene images (sign board detection) and recognizing the detected signs board to interpret its meaning (sign board detection). Being designed with regular shapes and conspicuous colours, sign board attract human driver attention so as to be easily captured by human drivers. The algorithm is robust and can detect signs even when the traffic sign board is rotated. The present method emphasis on Convolution Neural Network and Support Vector Machine.

LITERATURE SURVEY

2. LITERATURE SURVEY

In this section we includes both the paperwork review and the complex review of the techniques found in this research which include colours, machine learning, feature abstraction and detection predicated on the artificial neural network. The completeness of results obtained for the diagnosis and detection steps implies that method is encouraging for the program recognition and inventory of traffic indicators in street mapping applications. In article towards real-time traffic sign detection and recognition they focused on popularity taken on an important role in drivers associated systems and wise autonomous vehicles. It is real-time performance is appealing in addition to its recognition performance highly. The harvest from a convolutional neural network to help expand classifies the recognized signs to their subclasses within each superclass. Experimental results on both German and Chinese language highways show that both diagnosis and detection methods achieve similar performance with the state-of-the-art methods, with increased computational efficiency significantly. They suggest accurate and reliable vehicle localization is an important requirement for many vehicular applications. In challenging environments like urban areas, the GNSS accuracy often degrades due to blocked or reflected satellite signals. To improve the standalone positioning accuracy, they propose a landmark based localization method using traffic signs. There are many algorithms and methodologies have been proposed for road traffic sign detection. Reza Azad proposed the system with Iranian Traffic signs with detection and recognition and the letters are segmented with SVM classifier. Another method has also been proposed by Gauri Tagunde based on colour and shape Features by Detection and Recognition approaches have been proposed to deal with sign board detection and recognition..

Background Study

SI. NO	TITLE	METHOD	USES	ACCURACY
1	Indian traffic sign detection & recognition	Machine Learning- Neural Network	Driver assistance system, Autonomous driving vehicles	Day- 98%, Night- 94%, Foggy- 92%
2	Real time detection & recognition of Indian traffic sign using mat lab	Machine Learning- Neural Network	Autonomous navigation system	Correctness- 90.45%, False- 9.55%
3	Recognition and Classification of Traffic Signs using Machine Learning Techniques	Machine Learning- Artificial neural network, K-mean clustering and Support Vector Machines	Automated signboard recognition, Driver Alert System, road surveying and autonomous vehicles	99.0%
4	Traffic Sign Classification and Detection using Deep Learning	Deep learning- Convolution Neural Network	Advanced drivers assistance systems, Autonomous vehicles and street surveying	98.3%
5	Traffic sign detection and recognition based on convolutional neural networks	Machine learning- CNN classifiers, support vector machine (SVM).	Autonomous driving system	Ukraine and Bangladesh- 0.90
6	Traffic sign detection and classification methods	Deep Learning- Image pre-processing, Object detection	Sign inventory	high accurate rate >99%, 5% false positive
7	A vision based Indian traffic sign classification	Machine Learning- SVM (Support Vector Machine) classifier	Driver support system, intelligent transportation system	Cautionary sign 99%, Informatory sign 90%

8	IMPROVED TRAFFIC SIGN DETECTION AND RECOGNITION ALGORITHM for intelligent vehicles	Deep Learning- Convolutional Neural Network- threshold segmentation, HSV colour space	Intelligent vehicle driving system, Driving assistance, Intelligent vehicles	99.75%
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Table 2: Table for back ground study

A vision based Indian traffic sign classification. In this paper, Machine learning method in that SVM (Support Vector Machine) classifier algorithm is used. An algorithm is proposed to classify the Indian traffic sign as mandatory cautionary and informatory class. It is used for the application such as Driver support system, intelligent transportation system. Accuracy is calculated for the Cautionary sign 99% and the Informatory sign 90%.

Indian traffic sign detection & recognition. Machine learning method in that Neural Network is used. Some of the applications are Driver assistance system, Autonomous driving vehicles. Accuracy is calculated in different conditions Day- 98%, Night- 94%, Foggy- 92%.

Improved Traffic Sign Detection and Recognition Algorithm for intelligent vehicles. In Deep Learning, *Convolutional Neural Network algorithm is used*. It has threshold segmentation, HSV colour space. Uses of the intelligent vehicle driving system, Driving assistance, intelligent vehicles. Accuracy: 99.75%

Indian traffic sign detection & classification using neural networks Method: Machine Learning- Neural Networks. Algorithm proposed for Traffic Sign Detection and classification consists of three main stages.

- 1) Image colour segmentation using RGB, YCbCr and NTSC colour space
- 2) Blob Detection to attain the Region of Interest

3) Classification using Multiple Neural Networks

Indian traffic sign board recognition & detection using ml. In this machine learning, SVM classifier is used. They uses for automated signboard recognition, Driver Alert System, road surveying and autonomous vehicles. The working of the system is broadly divided in three phase:

1. Colour Segmentation
2. Shape Classification
3. Recognition

Real time detection & recognition of Indian traffic sign using matlab Method: Machine Learning- Neural Network. In this the Accuracy value is calculated as Correctness- 90.45%

False- 9.55%

Recognition and Classification of Traffic Signs using Machine Learning Techniques Method: Machine Learning- Artificial neural network, K-mean clustering and Support Vector Machines. The uses are advanced drivers assistance systems, Autonomous vehicles and street surveying. Both the Accuracy: 99.0% and the Average Accuracy and reliability are 0.99 is calculated.

Traffic Sign Classification and Detection using Deep Learning Method: Deep learning- Convolution Neural Network and Support Vector Machine. Accuracy: 98.3%

METHODOLOGY

3. METHODOLOGY

The proposed system for Traffic sign detection of the traffic sign boards. The Identification and Detection of traffic sign image model are being used for the Acknowledgement process for the getting the effective results among well-known techniques of image handling area for the improved research work. It's the basic model for the simulation process where we acquired the acceptable results. Here we use the unique image data establish for the initializing over the procedure of traffic highway sign acknowledgement and detection.

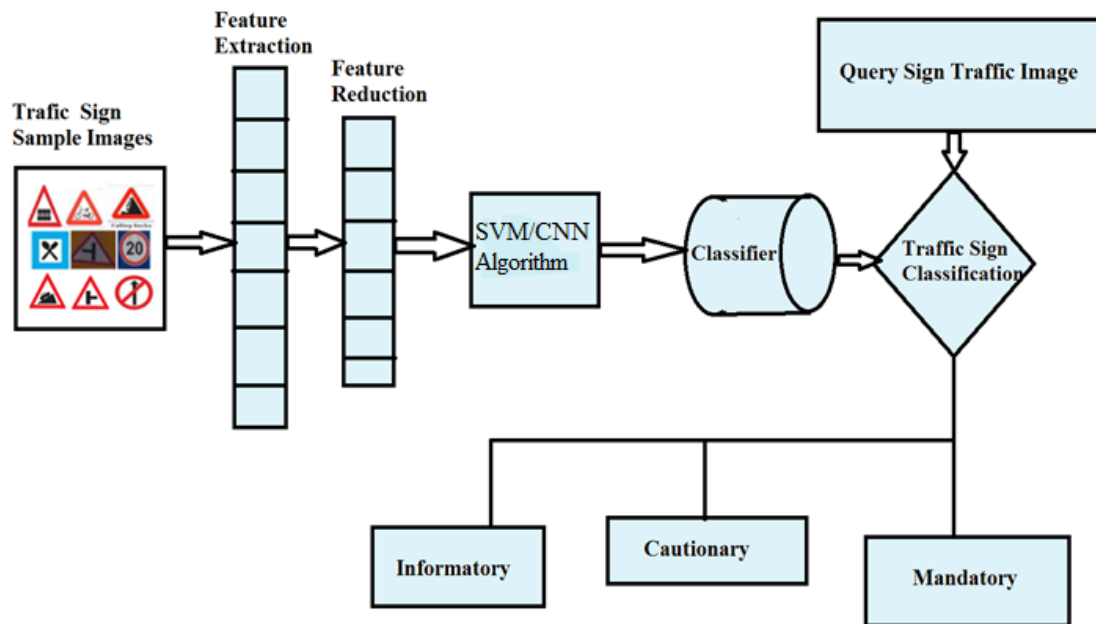


Figure 2: Methodology of the proposed model

Data pre-processing is a data mining technique which is used to transform the raw data in a useful and efficient format such as Data augmentation, Feature extraction. The data can have many irrelevant and missing parts. Data pre-processing is done by image resizing,

noise reduction, image extract to grayscale and HOG algorithm are used to handle this part. That is why we use pre-processing before sending through model. Finding the accuracy for both algorithms, comparing the accuracy and decide which algorithm forecast the best. Indian traffic sign data set is classified in to three classes hence system detects that the traffic sign is mandatory, cautionary or informative.

3.1. Dataset description

While several datasets for autonomous navigation have become available in recent years, they have tended to focus on structured driving environments. This usually corresponds to well-delineated infrastructure such as lanes, a small number of well-defined categories for traffic participants, low variation in object or background appearance and strong adherence to traffic rules. We propose a novel dataset for road scene understanding in unstructured environments where the above assumptions are largely not satisfied The Indian Traffic Sign and it has More than 40 classes in total. It includes traffic sign 4575 images and 62 labels collected from Indian roads. The label set is expanded in comparison to popular benchmarks such as Cityscapes, to account for new classes. Traffic sign data can divide into train and test dataset.

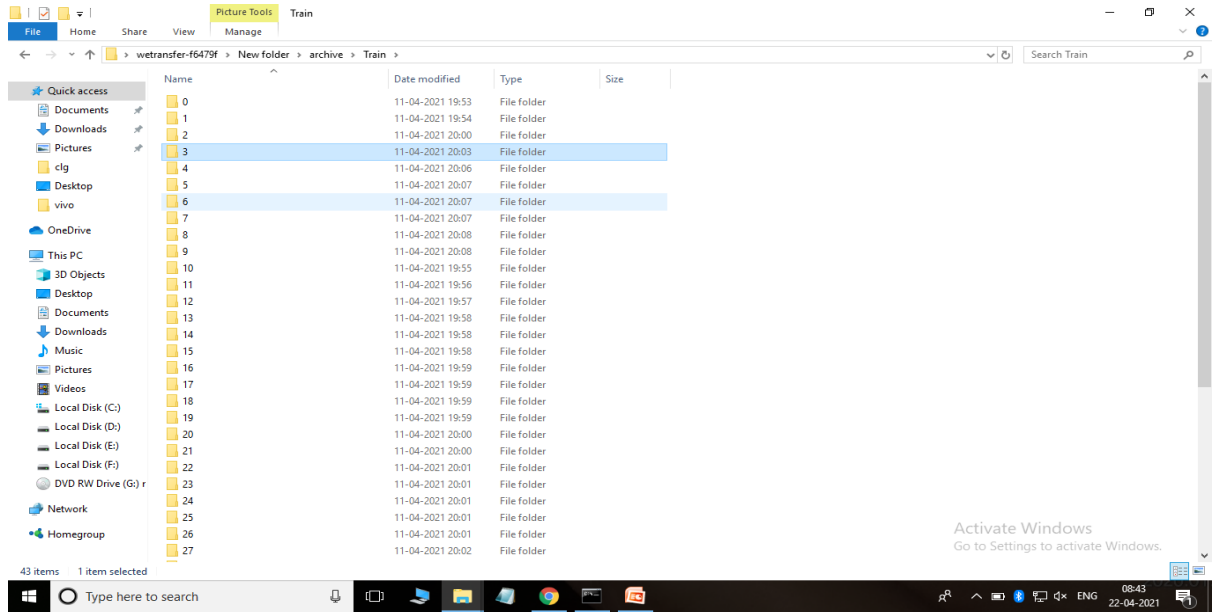


Figure 3: Trained dataset

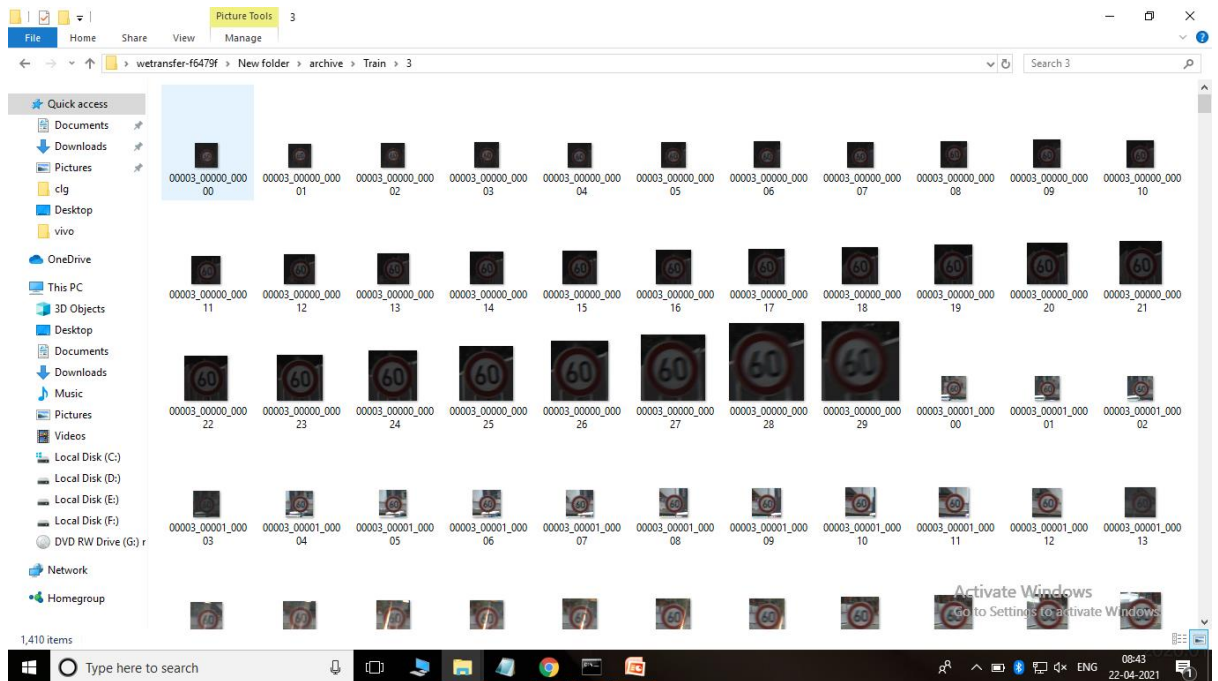
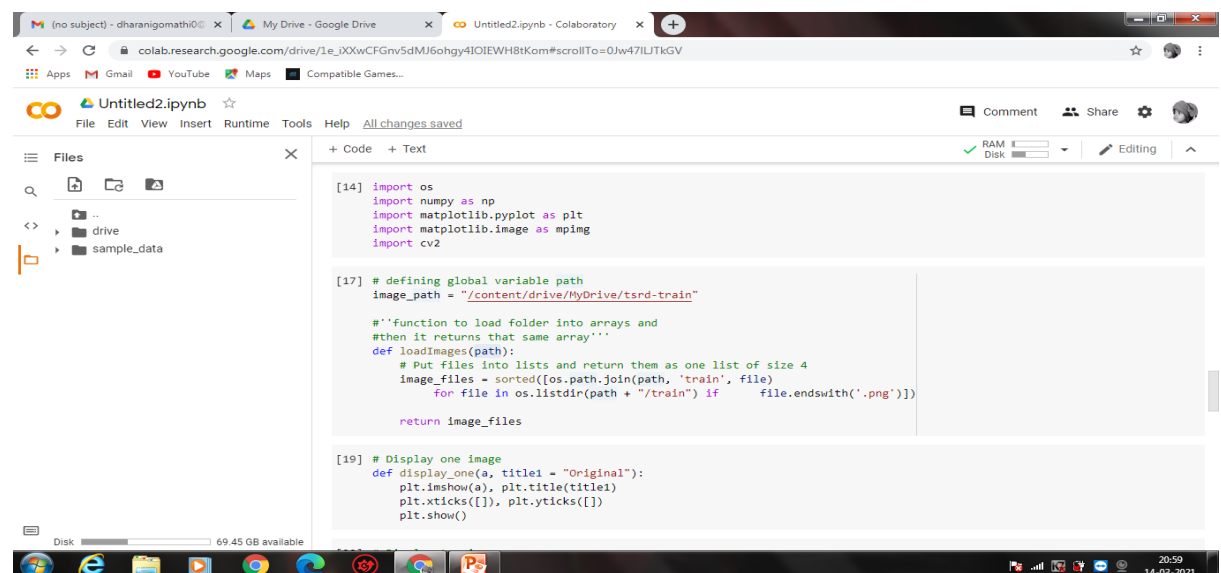


Figure 4: Train dataset images

3.2. Data pre-processing

In traffic sign detection, the system extracts the traffic sign location in an acquired image. Localizing the region of interest in an image involves many processing steps such as image resizing, image extract to grey scale and HOG algorithm, etc. A detailed description of traffic sign detection implementation is given. Mostly traffic sign detection system detects the false candidates due to illumination changes and environmental changes. The purpose of pre-processing is to increase the detection rate for a traffic sign. In this work, combined information of colour and shape is utilized for localizing the traffic sign. Colour information is highly sensitive for illumination variation hence in pre-processing step the system tried to make this colour information more robust. RGB colour information is used by the proposed system to normalize the colour in the pre-processing step. The acquired image and the colour normalized image of the acquired image are done. Data pre-processing is done by are used to handle this part. That is why we use pre-processing before sending through model.



```
[14] import os
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import cv2

[17] # defining global variable path
image_path = "/content/drive/MyDrive/tsrd-train"

#function to load folder into arrays and
#then it returns that same array'''
def loadImages(path):
    # Put files into lists and return them as one list of size 4
    image_files = sorted([os.path.join(path, 'train', file)
                          for file in os.listdir(path + "/train") if file.endswith('.png')])
    return image_files

[19] # Display one image
def display_one(a, title1 = "Original"):
    plt.imshow(a, plt.title(title1))
    plt.xticks([], plt.yticks([]))
    plt.show()
```

Figure 5: Import libraries and dataset

Pre-process the image and bring down the width to height ratio to 1:2. The image size should preferably be 64 x 128. This is because we will be dividing the image into 8*8 and 16*16 patches to extract the features. Having the specified size (64 x 128) will make all our calculations pretty simple. The size 64 x 128 to be the standard image size for now. Here is the resized image:



Figure 6: Resize image

3.3. Data transformation

The HOG descriptor focuses on the structure or the shape of an object. In the case of edge features, we only identify if the pixel is an edge or not. HOG is able to provide the edge direction as well. This is done by extracting the gradient and orientation of the edges. Additionally, these orientations are calculated in ‘localized’ portions. This means that the complete image is broken down into smaller regions and for each region, the gradients and orientations are calculated. We will discuss this in much more detail in the upcoming

sections. Finally the HOG would generate a Histogram for each of these regions separately. The histograms are created using the gradients and orientations of the pixel values, hence the name 'Histogram of Oriented Gradients'

The histograms created in the HOG feature descriptor are not generated for the whole image. Instead, the image is divided into 8×8 cells, and the histogram of oriented gradients is computed for each cell. By doing so, we get the features (or histogram) for the smaller patches which in turn represent the whole image. If we divide the image into 8×8 cells and generate the histograms, we will get a 9×1 matrix for each cell. This matrix is generated using method. That each 8×8 cell has a 9×1 matrix for a histogram. So, we would have four 9×1 matrices or a single 36×1 matrix. To normalize this matrix, we will divide each of these values by the square root of the sum of squares of the values. Mathematically, for a given vector V:

$$V = [a_1, a_2, a_3 \dots a_{36}]$$

We calculate the root of the sum of squares:

$$k = \sqrt{(a_1)^2 + (a_2)^2 + (a_3)^2 + \dots + (a_{36})^2}$$

And divide all the values in the vector V with this value k:

$$\text{Normalised Vector} = \left(\frac{a_1}{k}, \frac{a_2}{k}, \frac{a_3}{k}, \dots, \frac{a_{36}}{k} \right)$$

The resultant would be a normalized vector of size 36×1 . 105 (7×15) blocks of 16×16 . Each of these 105 blocks has a vector of 36×1 as features. Hence, the total features for the image

would be $105 \times 36 \times 1 = 3780$ features. The HOG feature descriptor and the features are calculated.

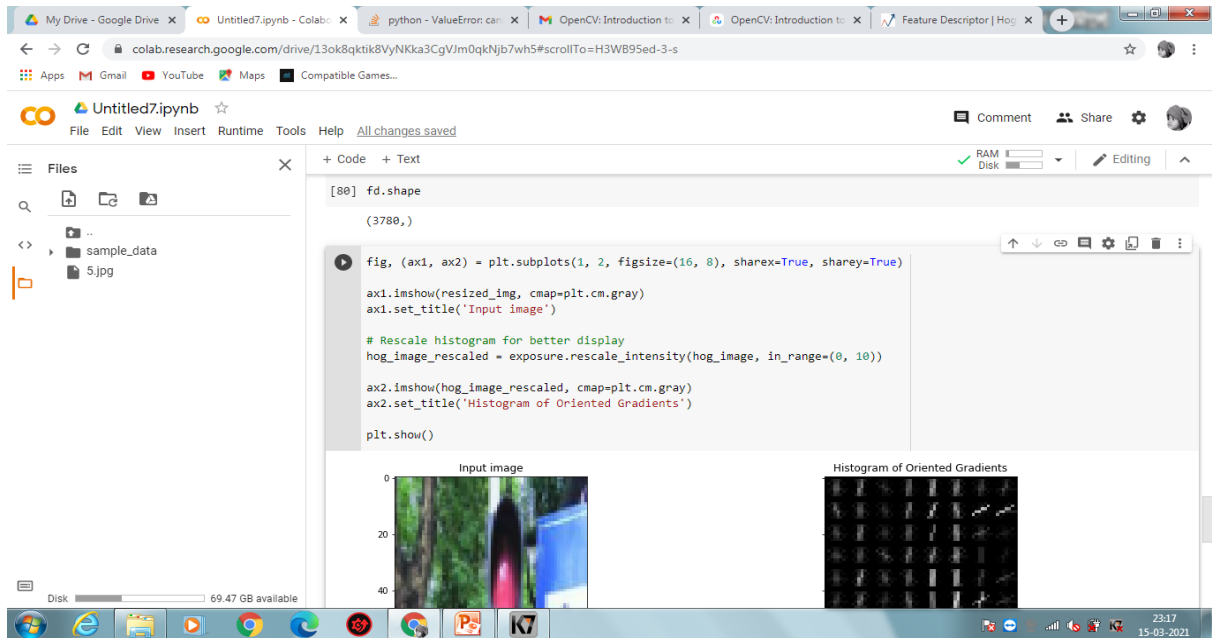


Figure 7: Rescale histogram for better display

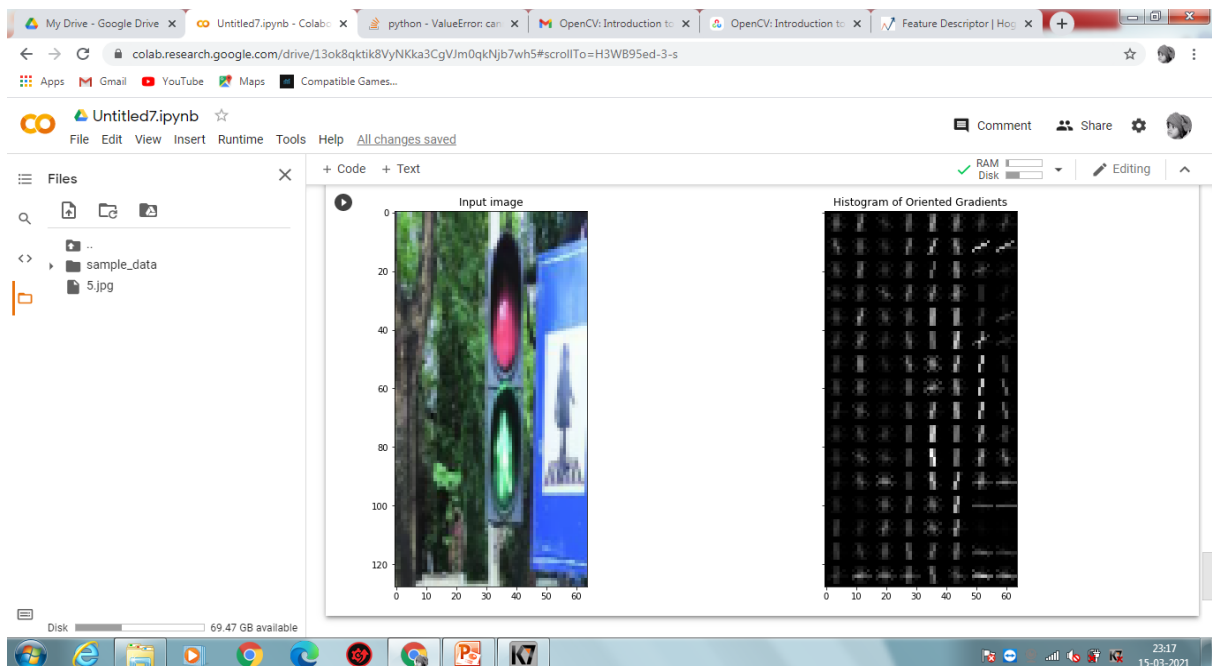


Figure 8: Histogram of oriented gradients

3.4. Algorithm specification

3.4.1. Support Vector Machine (SVM)

This support vectors would be the facts factors that will be better to the taking away hyper plane; these varieties of factors usually are within the boundary from the slab. The next determine demonstrates these varieties of definitions, along with + showing facts factors regarding form 1, in addition to - showing facts factors regarding form -1. Figure 9: SVM hyper plane for two classes.

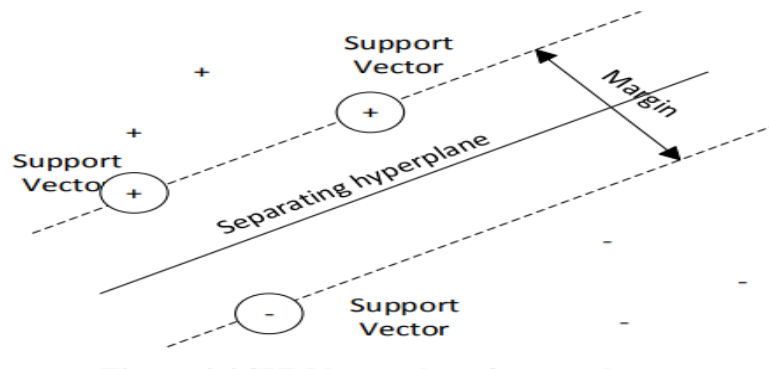


Figure 9: SVM hyper plane for two classes

For the comparative study we have taken only images and used to improve the image quality for better visualization Contrast Limited Adaptive Histogram Equalization is been applied on the RGB images. The enhanced images are been used as input and by using tensor flow with LeNet architecture and Adam optimizer the data is been trained and tested.

Many times we see that many road accidents take place. This can be due to driver's ignorance of traffic sign board and road signs. As the road traffic is increasing day by day there is a necessity of following the traffic rules with proper discipline. Traffic signboard detection is an important part of driver assistant systems. The basic idea of proposed system is to provide

real time voice signal to the driver about the presence of traffic sign board at a particular distance apart. The project is divided in to two parts:

1. Training

2. Implementation

The system provides the driver with real time information from road sign board, which consist the most important and challenging tasks. It generates a voice signal to the driver in advance of any danger. This warning allows the driver to take some appropriate actions in order to avoid the accident.

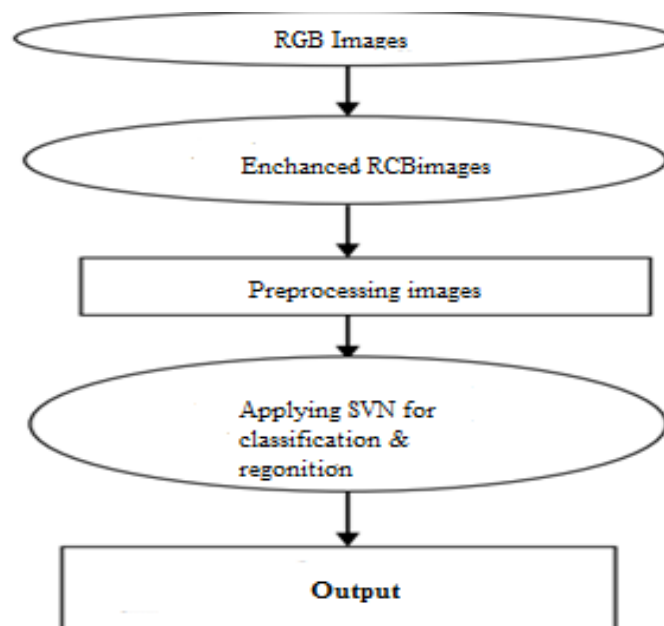


Figure 10: Flow diagram of the proposed system

The alertness to the driver is given as a voice signal through speaker as an output. There are two method to detect the images in machine learning, convolution neural network (CNN) and

Support Vector Machine (SVM). The proposed system uses support vector machine (SVM) for detection.

1 Working of the System Support Vector Machine is a supervised machine learning algorithm which is also known as the linear classifier mostly used for the detection purpose. The main advantage of SVM algorithm is its strong ability to classify any data. When the dataset have a clear detection boundary in that situation SVM is best option than other available method. SVM is considered as one of the best classifier and it is simple to use and understand than other classifier. The proposed system uses 90% of sample data for training and 10% for testing.

The Label Encoder () class from the ski-kit learn library. Training set denotes the subset of a dataset that is used for training the machine learning model. Here, you are already aware of the output. A test set, on the other hand, is the subset of the dataset that is used for testing the machine learning model. The ML model uses the test set to predict outcomes. Usually, the dataset is split into 70:30 ratios or 80:20 ratios. This means that you either take 70% or 80% of the data for training the model while leaving out the rest 30% or 20%. The splitting process varies according to the shape and size of the dataset in question. The train_test_split () function includes four parameters, the first two of which are for arrays of data. The test size function specifies the size of the test set. The test size maybe .5, .3, or .2 – this specifies the dividing ratio between the training and test sets. The last parameter, “random state” sets seed for a random generator so that the output is always the same. For the test dataset, you can directly apply transform () function (you need not use the fit transform () function because it is already done in training set). All the variables in the output are scaled between the values - 1 and 1. Training and Testing Using Linear SVM: Once the feature Vector for the ROI is created then the detection is initiated. For Detection of the shape eight linear SVM is used. SVM is machine learning algorithm which can classify the data in different group. It is based

on concept of decision plane where the training data is mapped to higher dimensional space and separated by plane defining two or more classes of data. The extensive introduction can be found.

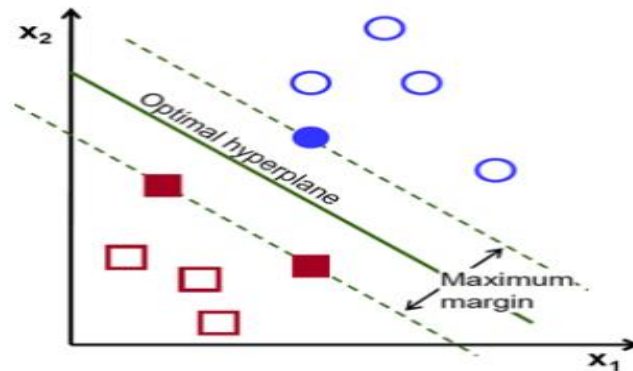
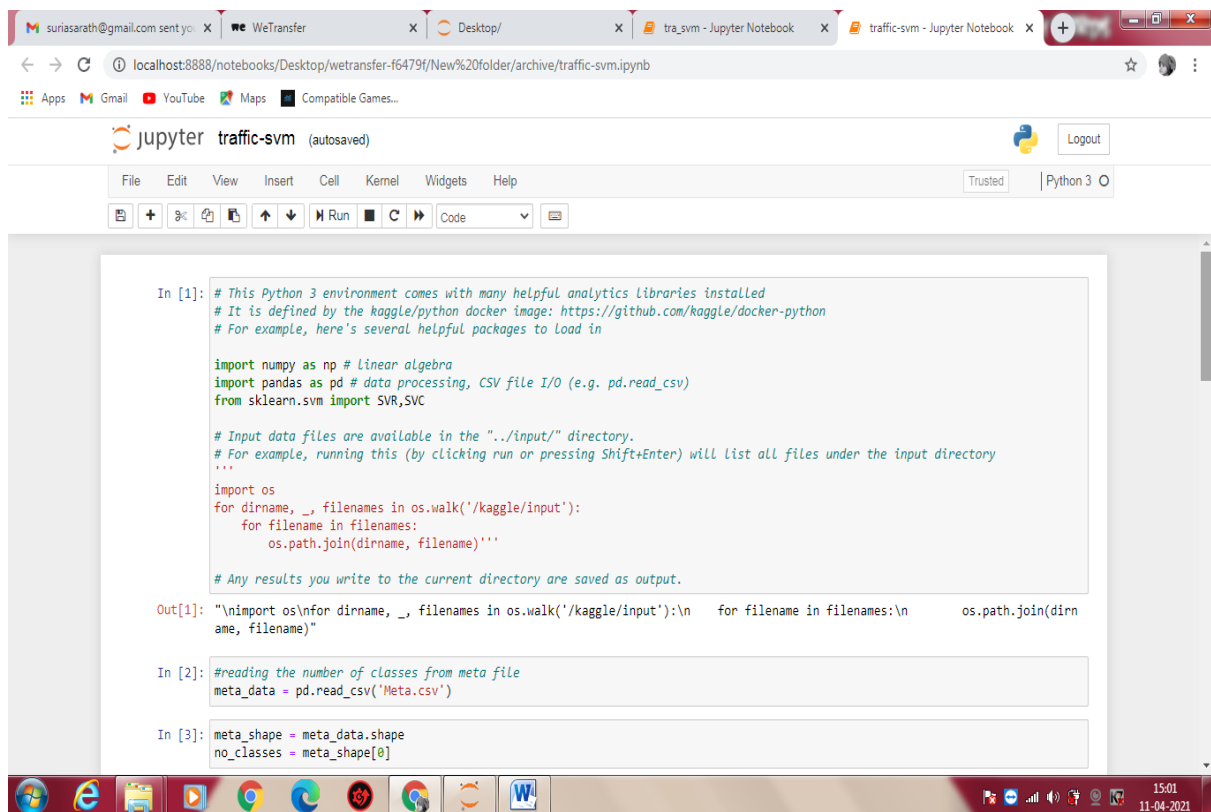


Figure 11: shows possible hyper planes

The proposed system is trained for ten traffic signs and the image of signs. The possible hyper planes we can see in fig.11. In this 90% of the sample data is used to train the system and 10% of the sample data is used for testing the system. In this phase nonlinear SVM is used to recognize. In this classified blob is first converted into grey scale image then applying feature extractor to extract the features of the blob. Non-linear SVM is used to recognition purpose in which extracted features are compared with all blobs that are having the same shape and colour.

In the stage, eight different traffic sign trained images are randomly selected from the dataset and numbered automatically. The auto-numbered traffic sign train images. The traffic sign test images are inputted into the detection screen and recognition. For each train image, the traffic sign indicated by the first five probabilities are outputted, and the maximum

probability is selected as the detection result. The auto-numbered traffic sign train images. For each train image, the traffic sign indicated by the first five probabilities are outputted, and the maximum probability is selected as the detection result and compared with the actual reference meaning. Figure 12 shows the detection results of traffic sign test images in the network testing stage.



```
In [1]: # This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load in

import numpy as np # Linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
from sklearn.svm import SVR,SVC

# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory
...
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        os.path.join(dirname, filename)

# Any results you write to the current directory are saved as output.

Out[1]: "\nimport os\nfor dirname, _, filenames in os.walk('/kaggle/input'):\n    for filename in filenames:\n        os.path.join(dirname, filename)"

In [2]: #reading the number of classes from meta file
meta_data = pd.read_csv('Meta.csv')

In [3]: meta_shape = meta_data.shape
no_classes = meta_shape[0]
```

Figure 12: Importing the packages

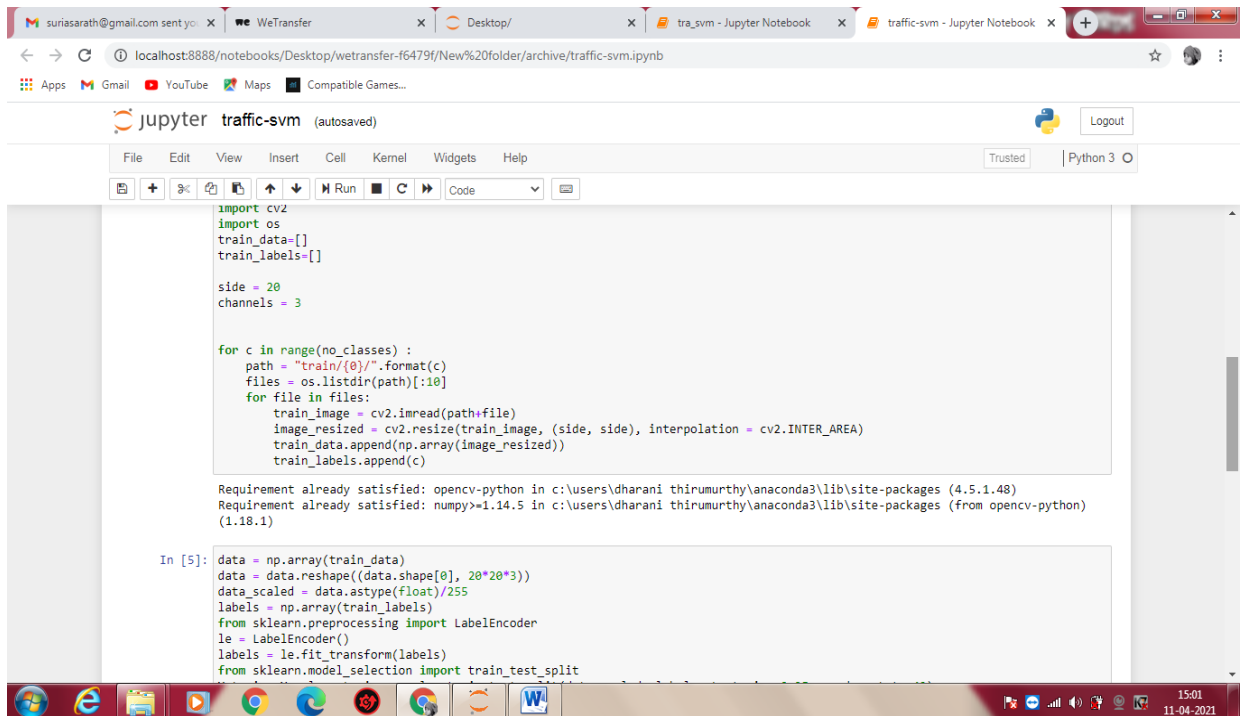


Figure 13: Training and testing split

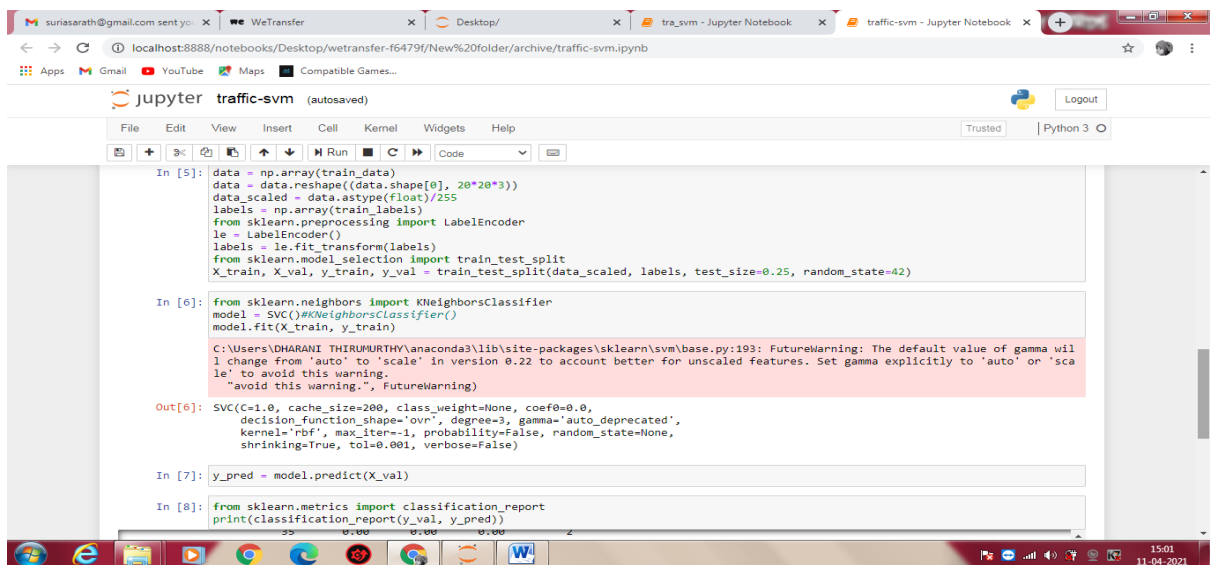


Figure 14: Accuracy prediction

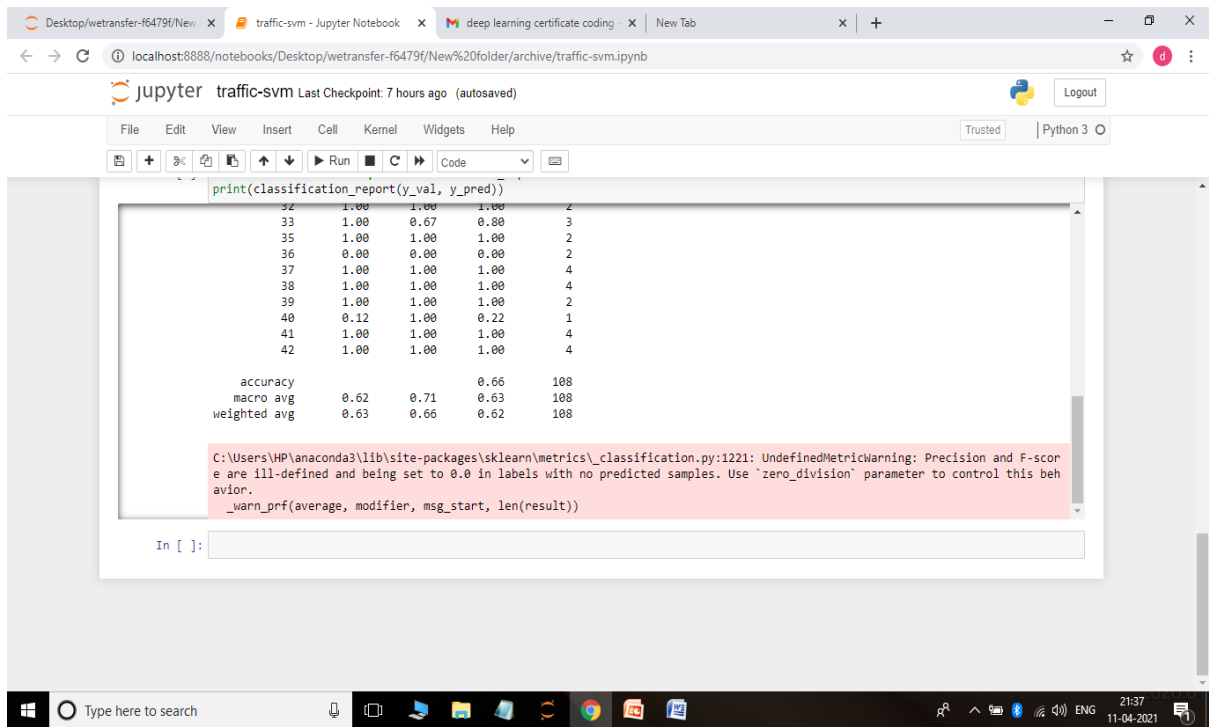


Figure 15: Accuracy

3.4.2. Artificial Neural Networks (ANN)

In this specific operate most of us use feed forward Artificial Neural Network using again propagation criteria. This is actually the preferred ANN, as well as style is made up of one insight part, at least one concealed covering, and another output layer. Every part consists of non-linear control models termed neurons, and the network relationships among neurons inside successive levels take affiliated dumbbells. Associates are aimed and certified inside the forward course simply, e. g. from information so that we can concealed, or possibly from hidden level to our pursuing hidden or production coating maybe. Back-propagation is absolutely a gradient-descent criterion where decreases our malfunction between productivity in the instruction input/output twos and the real network productivity for will see the original results the better result; original results for the more relevant towards our goal.

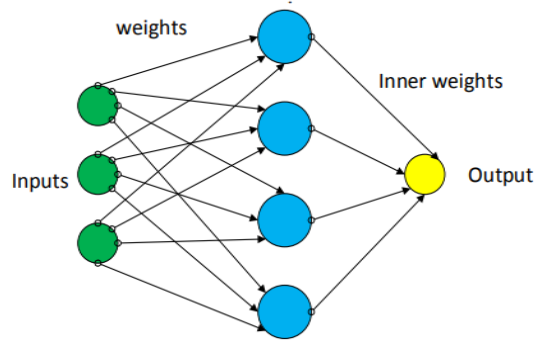


Figure 16: Artificial Neural Network

These RGB images are been pre-processed using multiple techniques namely Shuffling, Gary scaling, Local Histogram Equalization and Normalization. To generate additional training data transform image function is been used which includes Rotation, Sharing, and image Translations. Using tensor flow with LeNet architecture the data is been trained and tested. The parameters values that are been used are: Learning Rate = 0.0009, Epoch = 70, batch Size = 100, Dropout at FC 0 layer = 0.6, Dropout at FC 2 layer = 0.6, Dropout at Conv 1 layer = 0.7. Figure 16 represents the data flow of the experiment done.

Improved LeNet-5 Conventional Neural Network Model Traffic sign detection is based on existing dataset resources and uses effective classification algorithm to recognize detected traffic signs and feedback to smart cars accurately in real time. The Conventional neural network extracts features directly from the input detection image and outputs the detection results via the trained classifier based on image features. This condition indicates that conventional neural network has good graphic recognition performance. Furthermore, Conventional neural network does not need to extract features manually. The sensory cognitive process of human brains can be well simulated via forward learning and feedback mechanism, thereby gradually improving the ability of traffic sign classification and recognition. In this section, the shortcomings of the classical LeNet-5 network model are

analysed, and the model is considerably improved to further expand the outstanding advantages of conventional neural network in graphics recognition.

Deficiency Analysis of Classical LeNet-5 Network Model

The LeNet-5 network model, which was mainly used for digital recognition. The LeNet-5 network model consists of seven layers, including two convolutional layers, two pooling layers, two fully-connected layers and one output layer. The input image size is 32×32 , and the output is a 10-dimensional classification vector, which can identify numbers from 0 to 9. The classic LeNet-5 network model has good classification and recognition effects for a single target. However, in the traffic signs recognition training, it is difficult to ensure a high enough accurate recognition rate, the training network cannot converge, and the recognition efficiency of the network decreases dramatically. Analysis and summary of the root causes of these problems show the following:

- (1) The interference background in the traffic sign training image is much more complicated than that in a single digital image. The original convolutional kernel does not perform well in feature extraction. Consequently, the extracted features cannot be properly used for the accurate classification of the subsequent classifier.
- (2) Different kinds of traffic sign training images exist, and the number of datasets is large. Gradient dispersion easily occurs during network training, and the generalization ability is significantly markedly reduced.
- (3) The size of the ROI in the input traffic sign training image varies, and the effective features obtained by the current network model are insufficient to meet the target requirements of accurate traffic sign detection. The learning rate and the iterations number of

the training network are not adjusted accordingly, and the relevant parts are rationally optimized, thereby resulting to the emergence of the over-fitting phenomenon during training.

Improved LeNet-5 Network Model.

The ROI in the traffic sign training image is not 100% in the centre of the image, and some edge background information is included around the traffic sign. With the change of illumination conditions, these useless interference areas will increase the influence on traffic sign detection, thereby undoubtedly raising the computational complexity of the training network and the misrecognition rate of traffic signs. Therefore, image pre-processing is necessary.

Image pre-processing mainly includes the following three stages:

(1) Edge clipping. Edge cropping is a particularly important step in the image pre-processing. Some background parts in the edge are not related to traffic signs, and these parts can account for approximately 10% of the entire image. The bounding box coordinates are used for proportional cropping to obtain the ROI. The removal of the interference region helps to reduce redundant information and speed up the network training.

(2) Image enhancement. The recognition effects of the same type of traffic signs in the training network under different illumination conditions are significantly different. Therefore, reducing or removing the noise interference caused by the light change via image enhancement is necessary. Direct grey-scale conversion method is used to adjust the grey value of the original image using the transformation function, which presents clear details of the ROI and demonstrates a blurred interference area. Thus, this method effectively improves the image quality and reduces the computational load of the training network.

(3) Size normalization. The same type of traffic signs may have different sizes. The different sizes of training images may have different feature dimensions during the CNN training process, which leads to difficulties in the subsequent classification and recognition. In this paper, the image is uniformly normalized in size, and the normalized image size is 32×32 .

Improved LeNet-5 Network Model

The LeNet-5 network model has been considerably improved due to the shortcomings of the classic model in traffic sign recognition. Figure 17 Shows the improved LeNet-5 network model structure.

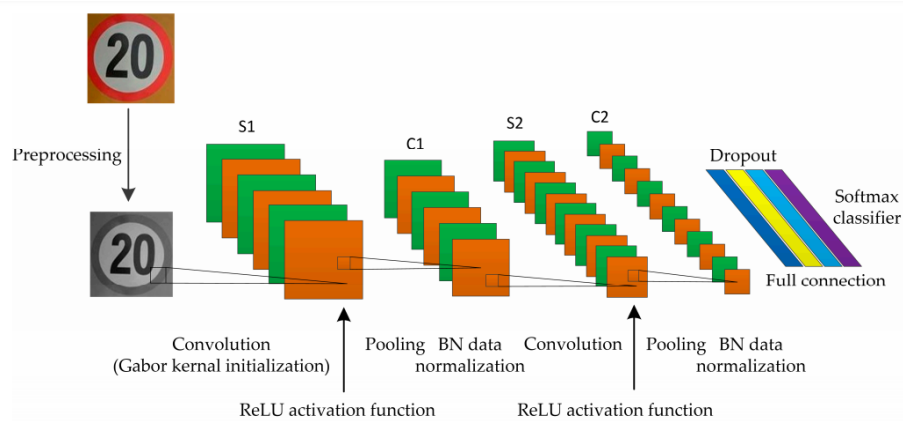


Figure 17: The improved LeNet-5 network model structure

The improvement of LeNet-5 network model includes the following five aspects.

The Gabor kernel is used as the initial convolutional kernel between the input layer and the first convolutional layer. In the actual road scenes, the change of light, the damage of traffic signs, and the obstruction of obstacles will affect the quality of the training image. Nonetheless, Gabor wavelet can solve such problems commendably. The Gabor wavelet is

insensitive to changes in light; therefore, it has good adaptability to light. Furthermore, it has superior scale and direction selection characteristics that are sensitive to the edges of the training image.

The two-dimensional Gabor filter is a band-pass filter whose impulse response function is as follows:

$$g(x, y, f, \theta) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left(-\frac{k_1^2}{2\sigma_x^2} - \frac{k_2^2}{2\sigma_y^2}\right) \exp(i(f_x x + f_y y))$$

$$k_1 = x \cos \theta + y \sin \theta, k_2 = -x \sin \theta + y \cos \theta$$

Where f is the centre frequency of the bandwidth; θ is the spatial direction whose value ranges $[0, \pi]$; σ_x and σ_y are the standard deviations in the x and y directions, respectively; $f_x = f \cdot \cos \theta$ and $f_y = f \cdot \sin \theta$ are both frequencies in space.

When $\sigma_x = \sigma_y$, the Equation (1) can be converted to:

$$g(x, y, f, \theta) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \exp(i(f_x x + f_y y))$$

Given that Gabor filters vary in different scales and directions, the mean value of Gabor kernels in different directions at the same scale is taken as the initial convolutional kernel in this project.

(2) After each pooling layer, the BN is added for data normalization. In the deep learning network model, as the number of training increases, the hidden layer gradient near the output layer expands and the parameter updating accelerates. Meanwhile, the hidden layer gradient near the input layer shows the opposite; that is, presenting a state of random distribution called gradient dispersion, while BN data normalization can effectively solve this problem

The BN data normalization is as follows:

Input: Mini-batch input x : $B = \{x_1, \dots, x_m\}$.

Output: Normalized network response $y_i = \text{BN}(\gamma, \beta)(x_i)$.

1. The mean of training batch data:

$$\mu_B = \frac{1}{m} \sum_{i=1}^m x_i$$

2. The variance of training batch data:

$$\sigma_B^2 = \frac{1}{m} \sum_{i=1}^m (x_i - \mu)^2$$

3. Normalization:

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

where ϵ is the minimum positive number used to avoid division by 0.

4. Scale transformation and offset:

$$y_i = \gamma \hat{x}_i + \beta$$

5. The learning parameters γ and β are returned.

The BN data normalization results in the output mean of 0 and the variance of

(1) These results are beneficial to the non-linear expression of the model and provide consistent output distribution with the real data distribution. The application of deep network models is not only appropriate but also has good effects in shallow network models.

(3) The ReLU function is selected as the activation function. Compared with the traditional Sigmoid and Tanh functions, the ReLU function is simple in calculation but effectively solves the gradient disappearance and explosion problem of the two functions. By making a part of the neuron output to 0, the network can be sparse, which helps reduce computational complexity and accelerate network convergence. Therefore, this function performs well in deep network training.

(4) The Adam method is chosen as the optimizer algorithm. This method is an extended first-order optimization algorithm based on the stochastic gradient descent method, which can dynamically adjust the learning rate of related parameters by using the moment estimation of

the gradient. After the offset correction, the Adam method can control each iterative learning rate within a certain range, thereby ensuring a smooth updating of the network parameters.

The first moment of the gradient is as follows:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

The second moment of the gradient is as follows:

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

Where β_1 and β_2 are the attenuation factors, and g_t is the gradient value of the loss function at time t . The first moment deviation estimate of the gradient is as follows:

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

The second moment deviation estimate of the gradient is as follows:

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

The gradient update formula of the Adam method is as follows:

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t$$

Where η is the initial learning rate.

The Adam method is computationally efficient and requires less memory space. Thus, this method is suitable for solving optimization problems with large-scale data and parameters. The Adam method can effectively solve the problems of learning rate disappearance, slow convergence and large fluctuation of loss function in the optimization process, thereby possessing a good convergence mechanism.

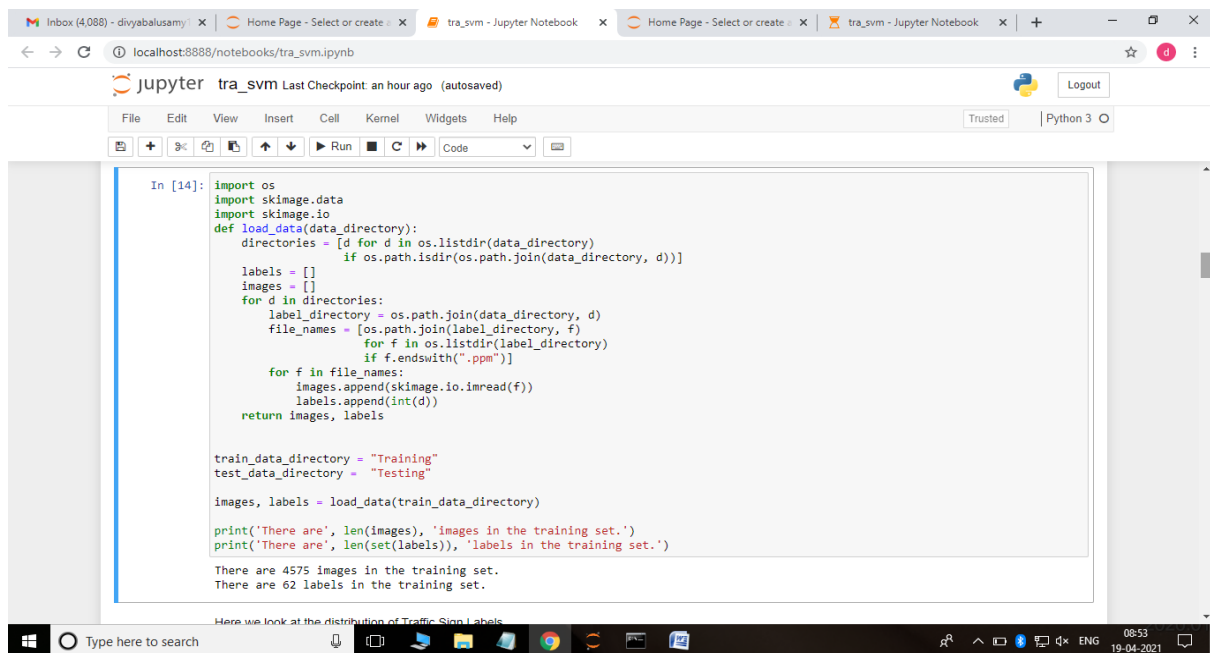
(5) The dropout is added to the fully-connected layers. It temporarily discards half of the data flowing through the network by discarding some neurons. Before the new round of data iteration, the original fully connected model is restored, and then some neurons are randomly removed. The dropout can considerably reduce the amount of network computation, help weaken the joint adaptability between neuron nodes, enhance the generalization ability of the training model and play a regularization role to a certain extent to prevent over-fitting problems.

Layer Number	Type	Feature Map Number	Convolutional Kernel Size	Feature Map Size	Neuron Number
1	Convolutional Layer	6	5×5	28×28	4704
2	Pooling Layer	6	2×2	14×14	1176
3	Convolutional Layer	12	5×5	10×10	1200
4	Pooling Layer	12	2×2	5×5	300
5	Fully-connected Layer	120	1×1	1×1	120
6	Fully-connected Layer	84	1×1	1×1	84
7	Output Layer	43	-	-	43

Table 3: The parameter settings of the improved LeNet-5 network model

In this project, the classical LeNet-5 network model is improved in many aspects and multiple levels. Considering the different interference conditions that may occur in the actual road scenes, the improved LeNet-5 network model integrates multiple advantages into one, thereby fostering strengths and avoiding weaknesses and complementing each other. The

robustness and stability of the training network are considerably enhanced, and the overall convergence speed is improved, thereby further enhancing the performance levels of traffic sign detection and recognition.



```
In [14]: import os
import skimage.data
import skimage.io
def load_data(data_directory):
    directories = [d for d in os.listdir(data_directory)
                  if os.path.isdir(os.path.join(data_directory, d))]
    labels = []
    images = []
    for d in directories:
        label_directory = os.path.join(data_directory, d)
        file_names = [os.path.join(label_directory, f)
                      for f in os.listdir(label_directory)
                      if f.endswith(".ppm")]
        for f in file_names:
            images.append(skimage.io.imread(f))
            labels.append(int(d))
    return images, labels

train_data_directory = "Training"
test_data_directory = "Testing"

images, labels = load_data(train_data_directory)

print('There are', len(images), 'images in the training set.')
print('There are', len(set(labels)), 'labels in the training set.')

There are 4575 images in the training set.
There are 62 labels in the training set.
```

Figure 18: Import Libraries and Dataset

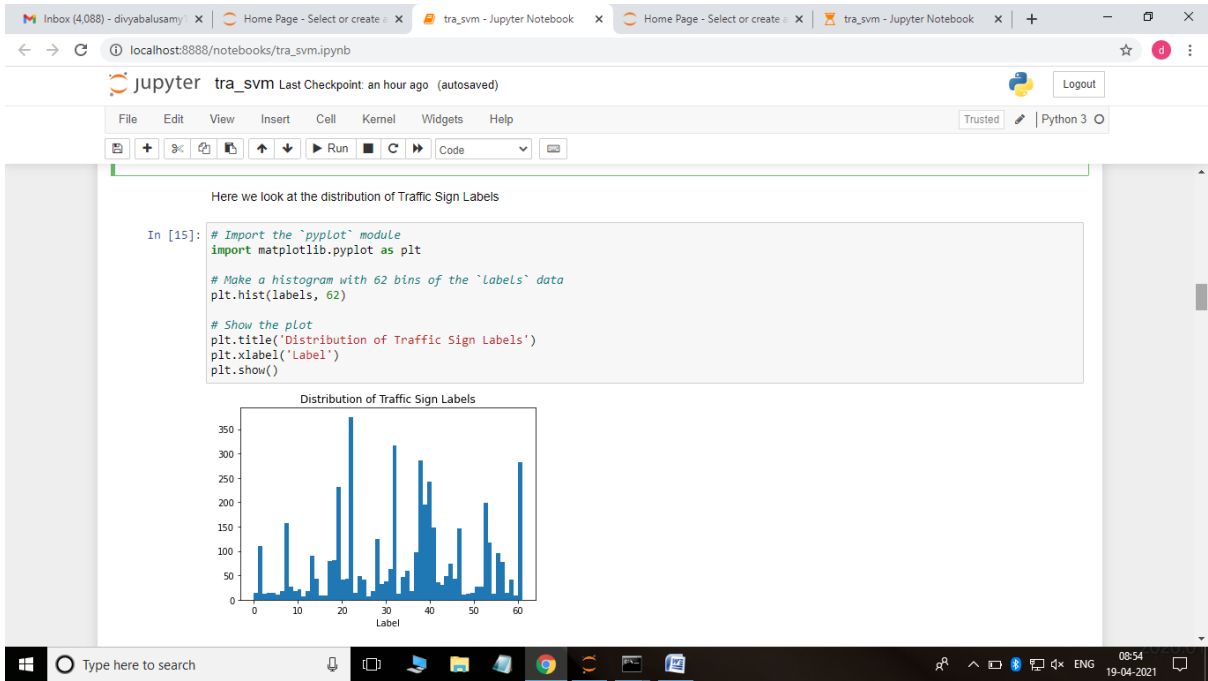


Figure 19: Distribution of Traffic Sign Labels

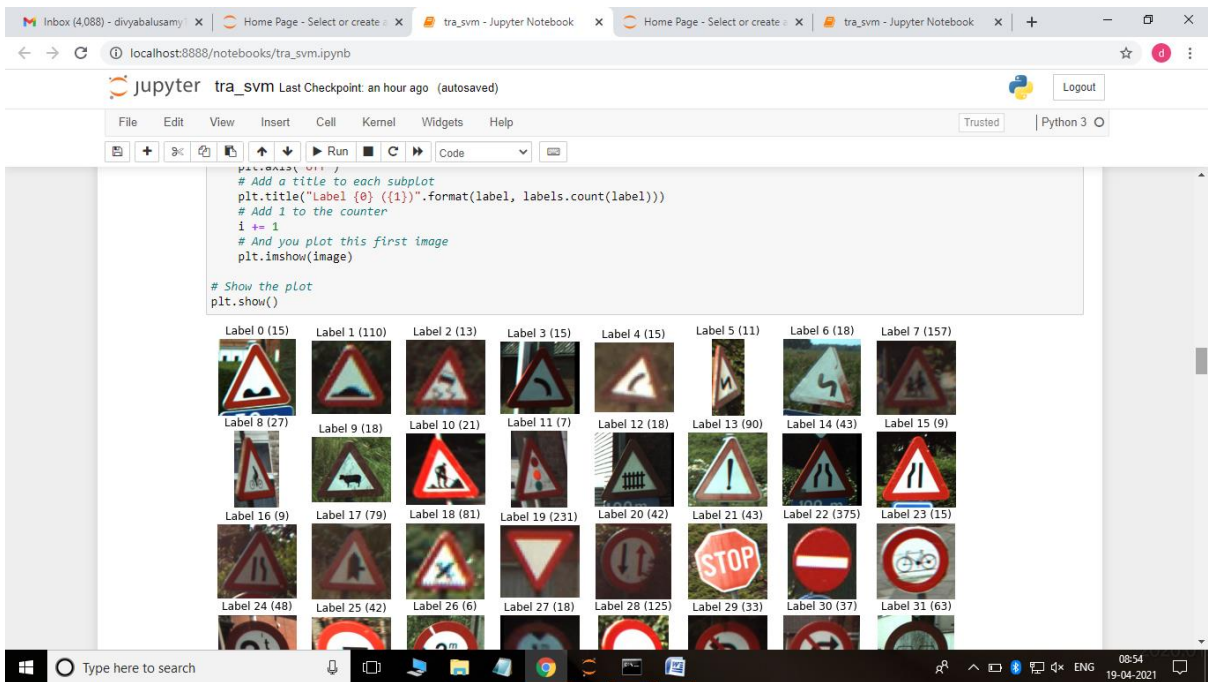


Figure 20: Visualizing Traffic Sign

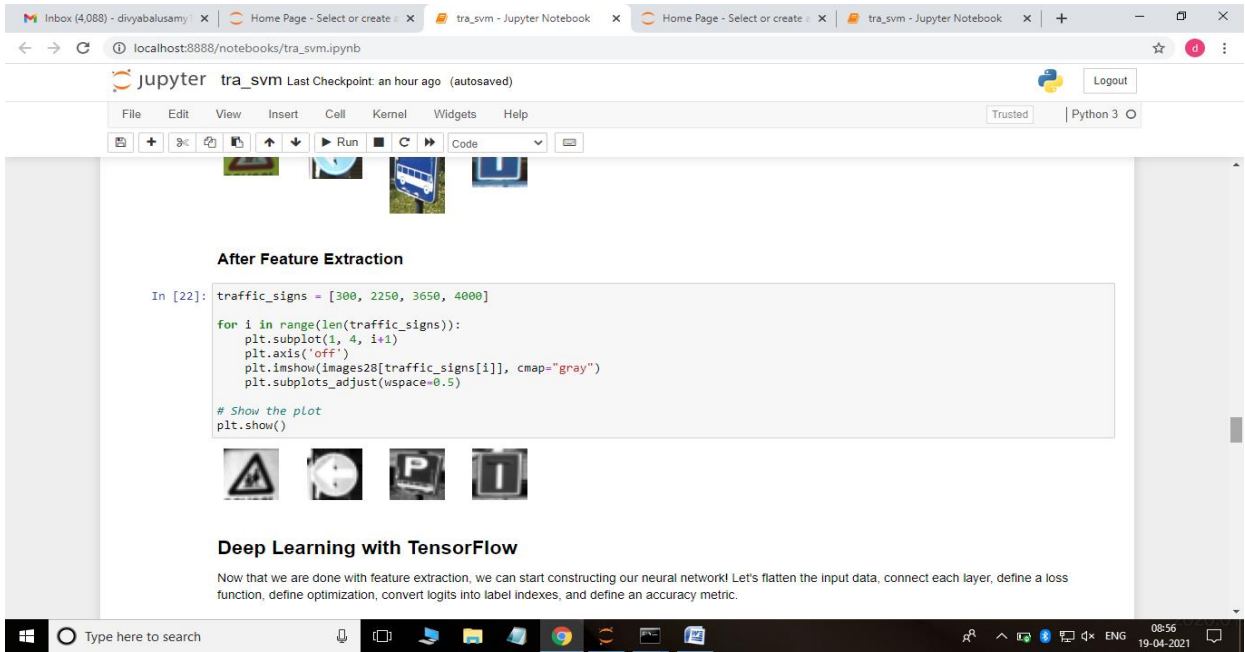


Figure 21: Feature Extraction

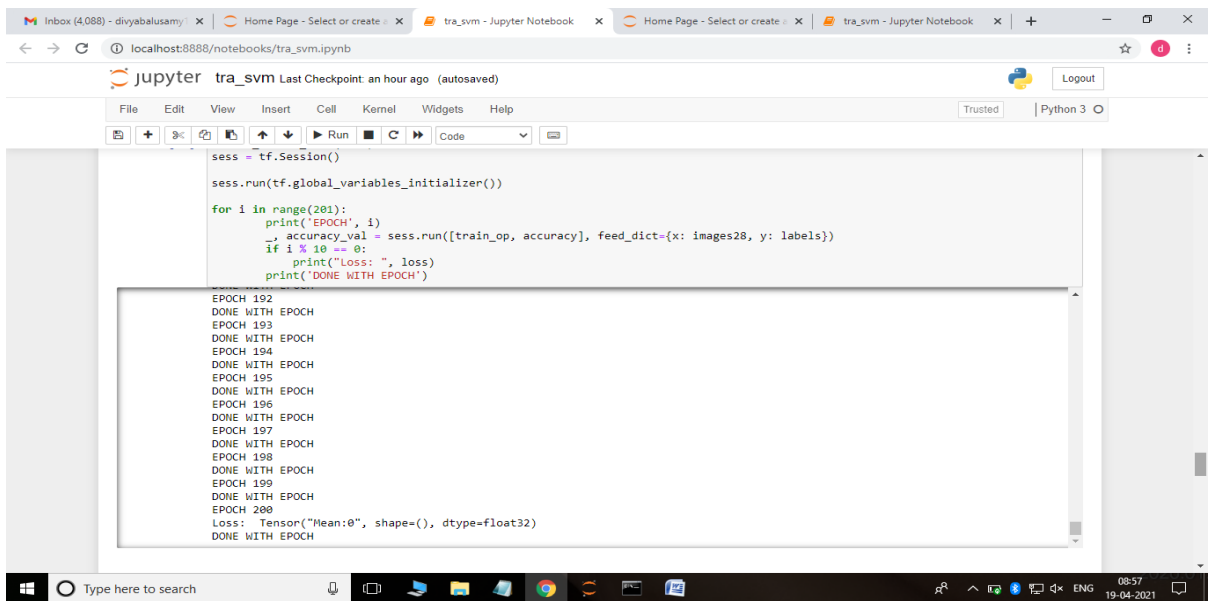


Figure 22: Running Deep Learning CNN

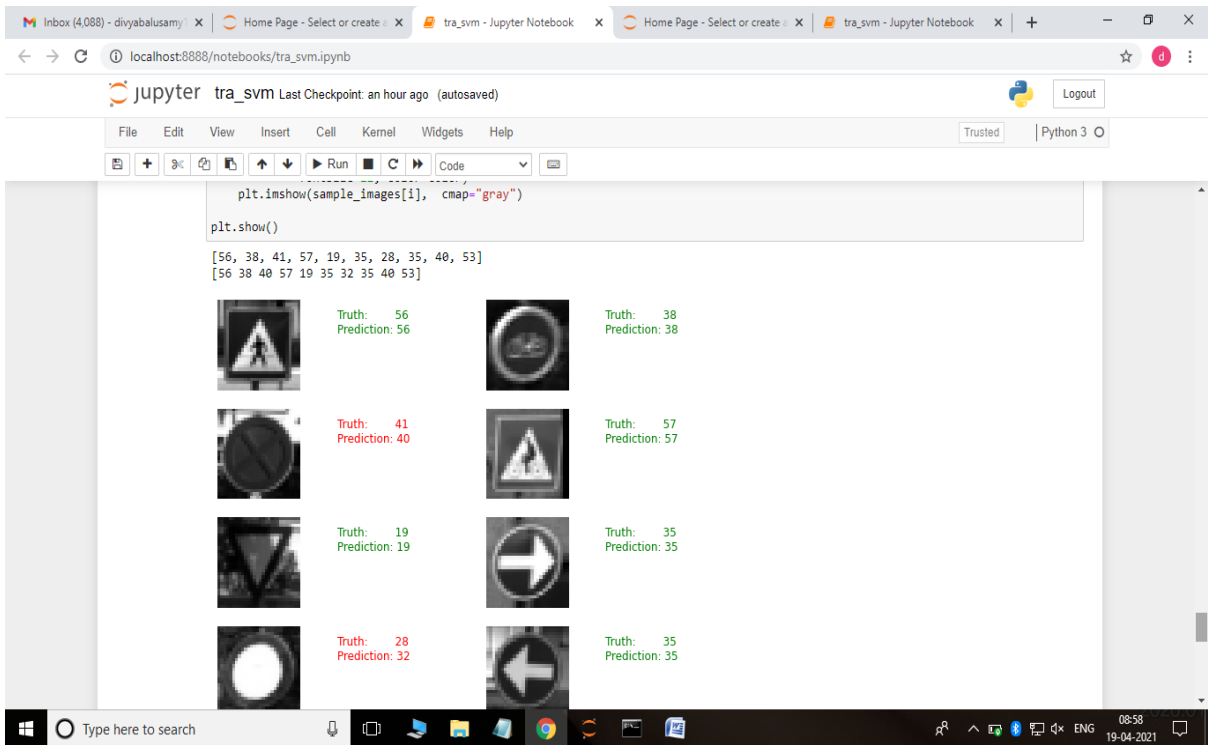


Figure 23: Evaluating Neural Network

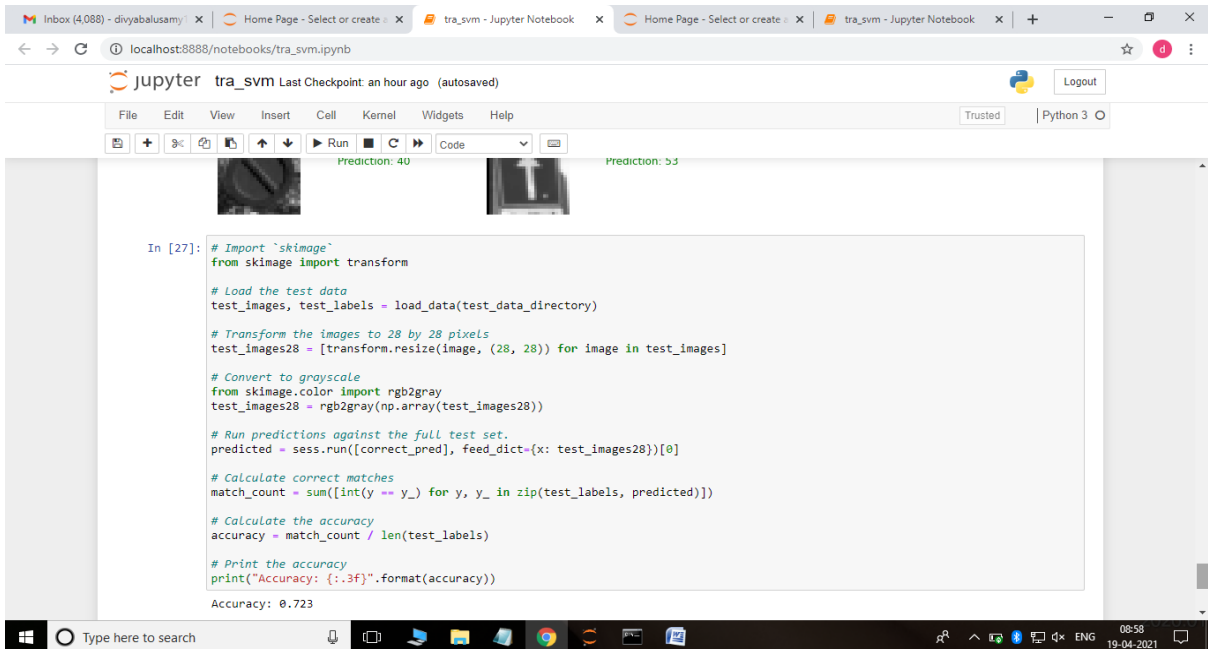


Figure 24: Accuracy

3.5. System specification

Hardware Specification

Intel(R) Pentium(R) CPU A1018 @ 2.10GHz (2 CPUs), ~2.1GHz (Processor)

RAM: 2048 MB

512 KB Cache Memory

Hard disk: 100 GB

Microsoft Compatible 101 or more Key Board

Software Specification

Operating system : Windows 7 Ultimate

IDE : Anaconda, Google colab

Framework : Tensor flow, Keras, Open CV

Front End : PYTHON/ML

Back End : CSV Excel Dataset

RESULT & DISCUSSION

4. RESULTS AND DISCUSSIONS

A total of the Indian Traffic Sign and it has More than 40 classes in total. It includes traffic sign 4575 images and 62 labels. The traffic sign images are completely consistent with their true meaning, and all of them have achieved effective recognition with an absolute probability. The recognition results in the screen testing stage show that the trained improved. The proposed system recognized the traffic sign correctly when the traffic sign are stable while accuracy of the system is decreases while in motion. The environment and light also have the adverse effect on the system. Sometimes the images which are captured from the real time have high contrast or low contrast in such cases system was not able to detect the traffic sign. So performance of the propose system in different environment not well but if the system have sample images with that environment then it works well. So we can say that accuracy of the system depend on number of sample images for a particular sign in that environment. Multiple features were used for detection, and sparse representations were adopted for detection, thereby achieving good recognition performance. The accuracy of the Support vector machine is 66% and the accuracy of Conventional neural network is 81%.

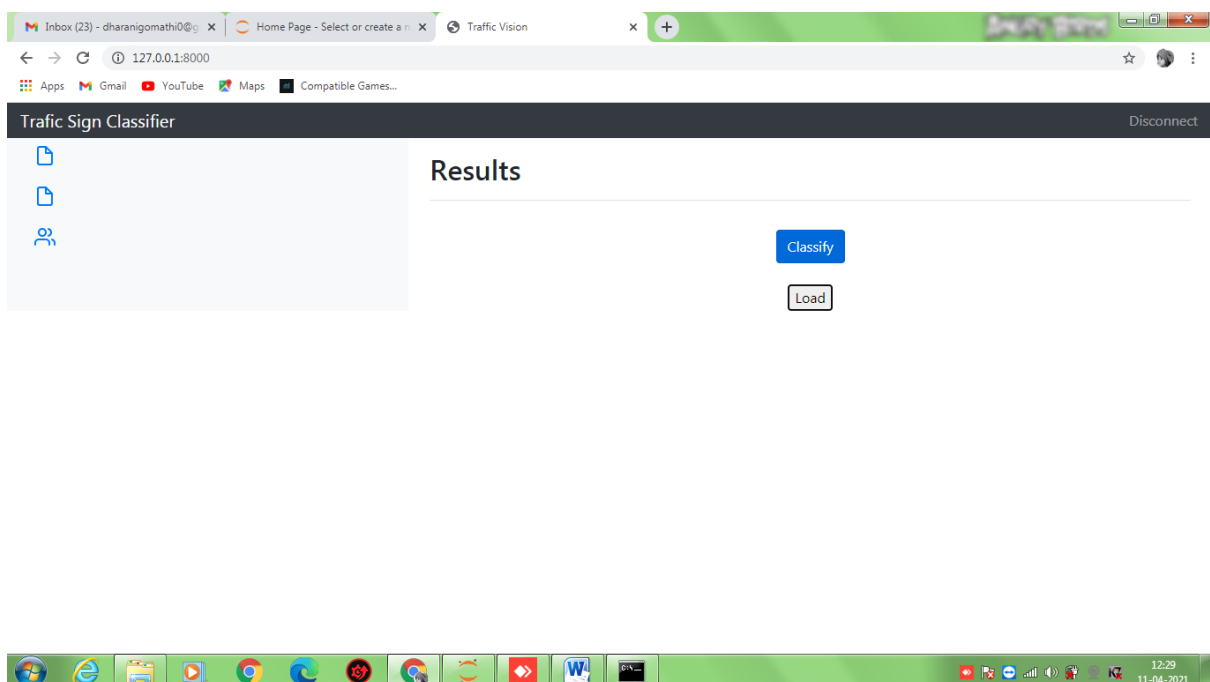


Figure 25: Indian Traffic Sign Detection Screen

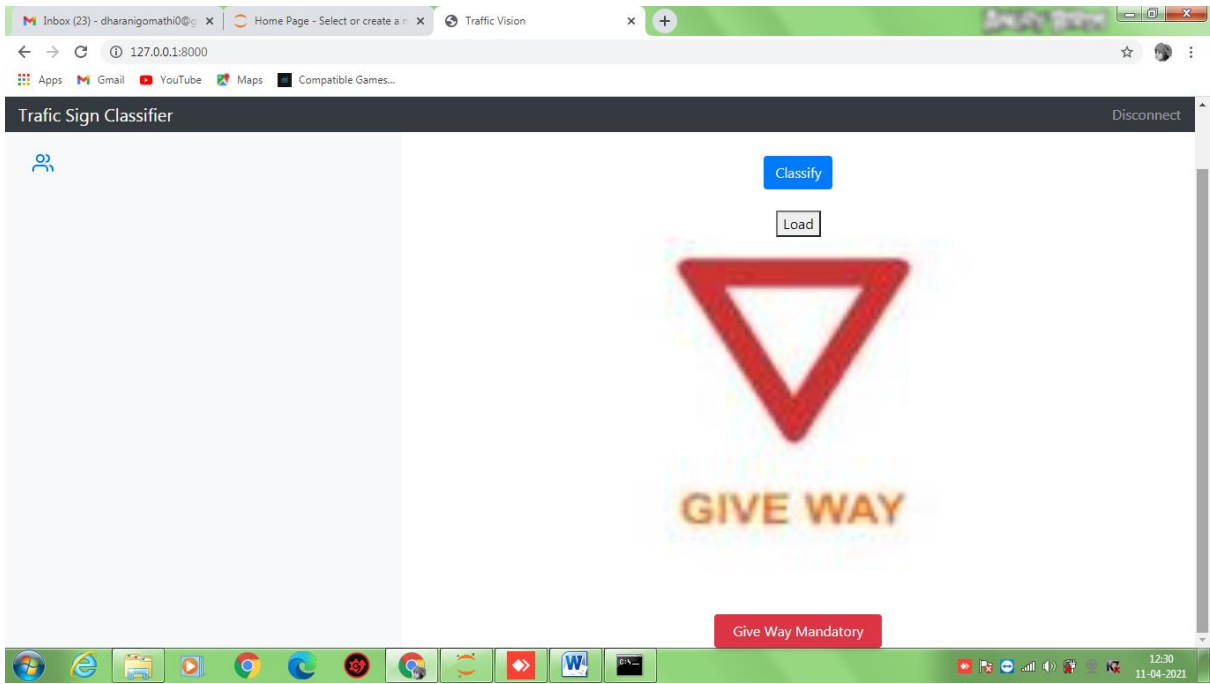


Figure 26: Detect the give way symbol in mandatory classification

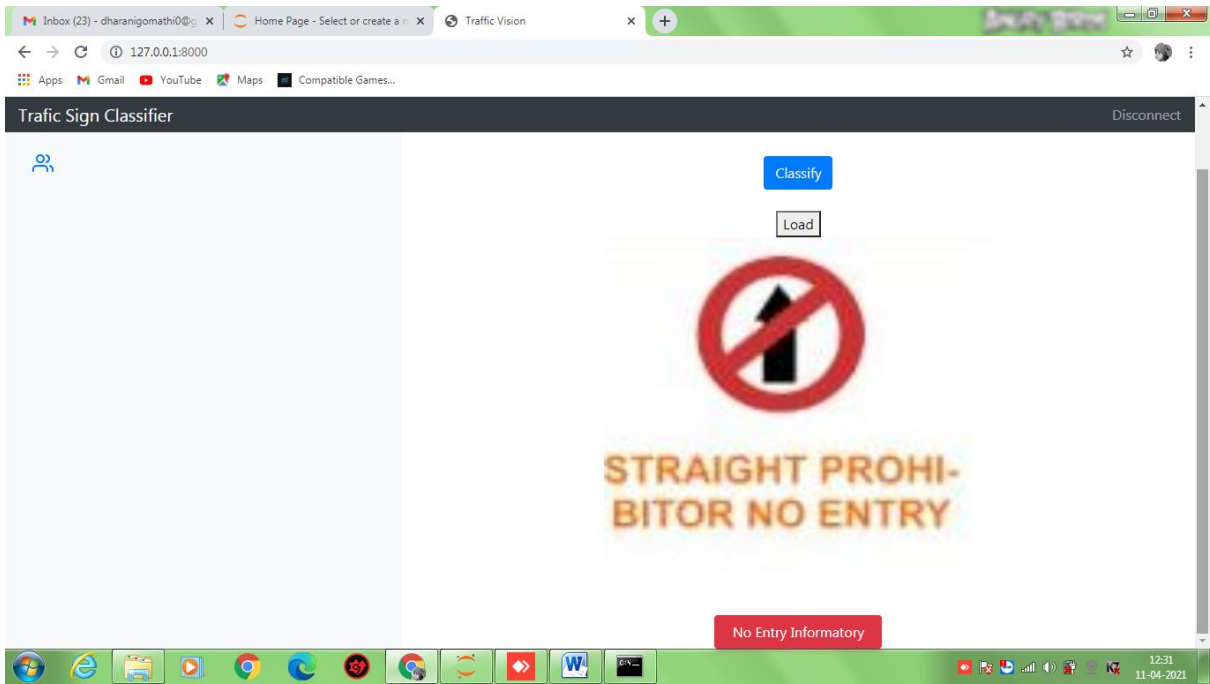


Figure 27: Detect the no entry symbol in informatory classification

The generalization ability and recognition efficiency of the screen model are also remarkably improved. In terms of performance improvement, evident advantages are observed. Indian traffic sign data set is classified in to three classes hence system detects that the traffic sign is mandatory, cautionary or informative. The fully improved traffic sign recognition is conducive to considerably enhancing the driving safety of intelligent vehicles in the actual driving environments.

4.1. Predictive accuracy

Predictive accuracy is expressed as the correlation between the prediction and actual score. Accuracy is often the starting point for analysing the quality of predictive model.

Classifier	Accuracy
SVM	66
CNN	81

Table 4: Table for accuracy of algorithms

The above table describes the accuracy value of two classifiers on Indian traffic sign dataset. The accuracy of CNN is efficient than the SVM classifier. The accuracy levels are calculated by using the formula:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / \text{nrow}(\text{set}) * 100$$

CONCLUSION & FUTURE SCOPE

5. CONCLUSION

The proposed system includes efficient feature extraction methods which results in appropriate outcomes. The CNN and SVM are the finest techniques of Deep Learning and Machine Learning which ensures accuracy in the achieved output. This method incorporates all the aspects of CNN. The work includes processing images gives more accuracy i.e. 81%. This algorithm has a best speculation, and it can be trusted that it is used to identify more conventional traffic signs.

6. FUTURE SCOPE

The system can be enhanced by using cost-effective techniques, which would assist the driver in notifying the distance between the road sign and the current position of the car. The most important future work would be to work on a collection of large number of road sign images, expanding the database, retrain the neuron network. This would also involve studying more robust techniques for detection of images which will recognize traffic signs during poor lighting conditions also. The system can be enhanced by using cost-effective techniques, which would assist the driver in notifying the distance between the road sign and the current position of the car. Even the system could be expanded to detect and differentiate between inanimate and living objects for example people crossing the roads.

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