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Colour Based Traffic Sign Detection and Recognition using Support Vector Machine (SVM), Convolutional Neural Networks (CNN)

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Abstract: Today's world uses artificial intelligence to automate nearly every field, simplifying everything. This decreases risk while simultaneously increasing accuracy, dependability, and minimizing physical contact. While operating a car, it is crucial to adhere to traffic laws and regulations, but occasionally drivers fail to see the signs that are posted along the sides of the road. This can be fatal for both drivers and pedestrians. Hence the system has to be integrated with ADAS system, which will automatically send the driver a text or voice message to warn them of an approaching traffic sign. In this paper we proposed the model which will detect the traffic sign in diverse background using color information and SVM. Detected Traffic sign is recognized and classified using convolutional neural network. We used Lenet-5 CNN architecture and was found more efficient about traditional CNN model. Thus, making it desirable to apply in real-time computer vision tasks. Proposed design has high detection rate and it is having less complexity

I. Introduction

According to world Health Organization global statistics on road traffic accidents death stands at 1.35 million in 2018 which accounts for 2.37% of total death around world. The failure of the driver to properly understand all of the visual information available to them while operating a vehicle is the main contributor to these collisions. Advanced driver assistance systems (ADAS) automate the car's systems for safety and improved driving to prevent these accidents. The primary uses of ADAS are lane departure warning, emergency braking aid, traffic sign recognition, and blind spot identification. The traffic sign recognition system, which is an ADAS application, is crucial in supporting drivers on highways.

The use of traffic sign recognition in driver assistance systems and intelligent autonomous vehicles has a significant commercial potential. Two tasks are often required of a traffic sign recognition system: spotting and evaluating traffic signs in imagery of natural environments, and classifying the signs that are found. Standardized shapes and vivid colours are used to create traffic signs so that human drivers may easily see them and rapidly read them. However, there are numerous challenges for computer algorithms to recognise traffic signs due to variations in lighting, colour degradation, motion blur, a crowded background, partial occlusion, etc.

Fig 1: Several instances of traffic signage

Traffic authorities have installed traffic signs along the highways to warn motorists of potentially dangerous road conditions and to provide them with the information they need. Traffic signs can be divided into three categories: mandatory, cautionary, and informative. Mandatory signage advises drivers about the laws and regulations they must abide by. The driver is forewarned by caution signs about the potentially dangerous driving conditions. By offering information about the route directions, informative signs help drivers along the roads. Sometimes, things like high traffic, bad weather, or drivers who aren't paying attention put them at danger of missing a sign and causing accidents. These traffic signs must be automatically found and recognised, and the motorist must be informed of the situation.

Numerous scholars have proposed a variety of techniques based on colour and shape information for the detection and recognition of traffic signals. The ROI was obtained using colour information and validated using the HOG feature in [1]. Based on the colour and shape information of the traffic sign, they were able to reach an accuracy of 98.11% and 99.18% for triangles and circles, respectively, using the ensemble CNN model in [2]. Weiner and Gaussian noise filter were utilised in [3] to discard irrelevant information extracted from color segmentation and CNN model is used for classification after template matching of shape-based detection. Douglass-Peucker algorithm was employed in [5] for shape-based traffic sign detection, implemented in real time environment and was found high detection rate across three distinct time zones during the day.

The development of an algorithm that can recognise traffic signals in real-time natural input image is the main objective of this paper. In this study, only images of red and blue traffic signs were taken into consideration for implementation. The structure of this paper is as follows: The proposed approach for detecting and recognising traffic signs is described in Section II. The experimental findings are presented in Section III, and the conclusion and discussion of this study are presented in Section IV.

II. Proposed Methodology

A. Overview of the designed System.

Figure 2 depicts the proposed system's block diagram. The two stages of the developed system are detection and recognition. Developed system has two stages – Detection and Recognition. In the detection stage the ROI is extracted using color and dimensional information. Feature extracted from the potential traffic sign is validated using SVM technique. Finally, the recognized traffic sign is classified by trained Lenet CNN model.

B. Color Space Conversion

Since the RGB colour model is easily influenced by light and the HSV colour model functions well in a variety of lighting circumstances, the RGB colour space is first transformed to the HSV colour space. The hue H, saturation S, and value V make up the HSV colour space [1]. Because the hue shows the proportion of pure colour to grey colour, which is directly proportional to the primary wavelength of the light wave, different hues correlate to different colours. Hue can be used to extract various colours for traffic sign detection. The saturation, which may be used to extract several saturation zones, represents the depth of the colour. The ratio of three pure colours is known as saturation. Value is related to the energy of light and reflects the brightness of reflected light.

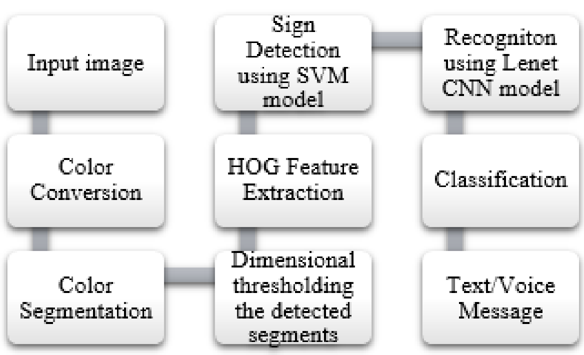

Fig 2: Block diagram of designed System.

According to the literature [5], the formula for converting each component's RGB to HSV is as follows:

$$R' = R/255, G' = G/255, B' = B/255$$

$$H = \begin{cases} 0^\circ, & If\ V - \min(R',G',B') = 0 \\ 60^\circ \times \left(\frac{G'-B'}{V-\min(R',G',B')} mod 6\right), & If\ V = R' \\ 60^\circ \times \left(\frac{B'-R'}{V-\min(R',G',B')} + 2\right), & If\ V = G' \\ 60^\circ \times \left(\frac{R'-G'}{V-\min(R',G',B')} + 4\right), & If\ V = B' \end{cases}$$

$$S = \left\{\frac{max(R',G',B') - min(R',G',B')}{max(R',G',B')}\right., \quad If\ V \neq 0$$

$$V = max\ (R',G',B') \qquad (1)$$

C. Color Segmentation

A critical component of traffic sign detection is segmentation. It lowers the search area in the image frames by removing the undesirable backdrop portion. Traffic signs with a red and blue colors are taken into consideration for implementation in this work. Segmentation is carried out by establishing the threshold values of hue and saturation since they give the chromatic information in the HSV colour space [5]. OPENCV's value, saturation, and hue parameters have a range of 0 to 255, 0 to 255, and 0 to 180, respectively.

D. Dimensional thresholding the detected sign

The Region of interest (ROI) is extracted using dimensional thresholding of the obtained segments. Traffic signs have forms and shapes. By using the information of area, width, height of the obtained segment we can eliminate the unwanted portions in the image.

E. Detection of traffic sign based on HOG and SVM

A multi-class SVM model is trained to detect the traffic sign using HOG feature extraction. Based on the probability function used in SVM model training, extracted ROI is validated whether it is a traffic sign or not.

1) HOG Feature Extraction

The image's pixel (x, y) gradient is determined as follows:

$$G_x = I\ (x+1, y) - I\ (x-1, y)$$

$$G_y = I\ (x, y+1) - I\ (x, y-1)$$

$G_x\ (x, y)$ and $G_y\ (x, y)$ in the calculations above stand in for the input image's horizontal and vertical gradients, respectively. $I\ (x, y)$ denote the image's pixel values. The following formula is used to determine the pixel's gradient direction and magnitude:

$$G\ (x,y) = \sqrt{G_x^2 + G_y^2} \quad \text{.... (2)}$$

$$\theta = arctan \frac{G_y}{G_x} \quad \text{..... (3)}$$

Gradient computation is applied using equations in (2) and (3) and corresponding values are extracted [1]. The gradient information is computed using a histogram with nine bins, which divides each cell's 360-degree gradient direction into nine directions. If the gradient direction of the pixel is between 0 and 20 degrees, the first bin of the histogram needs to be raised by one. We weigh the gradient direction in the histogram for each pixel in the cell, and then we can get the cell's HOG, which is its corresponding 9-dimensional feature vector.

The image in ROI is extracted and resized to 48x48 pixels. 4x4 pixels constitutes each cell and 9 bin orientation is employed here. To create a 9-dimensional feature vector, the gradient direction of each cell's pixels is multiplied by the number of bins in each direction. A block is made up of 3x3 cells, and each block has a 3x3x9=81-dimensional feature vector. The ROI is then scanned using these blocks, and each ROI's retrieved feature vector has a length of 10 x 10 x 81, or 8100.

2) Validation of traffic sign using SVM

Support vector machines (SVMs) are classification and regression prediction tools that minimise projected error while automatically avoiding overfitting to the data. Support vector machines are described as systems that employ a statistical learning theory-derived learning bias and the hypothesis space of linear functions in a high-dimensional feature space.

In the high-dimensional space where the support vector machine maps the vector, a maximum interval hyperplane is created. The separated data's hyperplane has two parallel planes placed parallel to one another, and by separating the hyperplane, the space between the two parallel hyperplane is widened. To identify the optimum hyperplane, one must maximise the geometric distance $\frac{||w||^2}{2}$, which is equivalent to reducing $|w|$. The ideal hyperplane can be discovered if the training data can be separated.

During training the SVM model, we used attributes like probability which is used further for detection of traffic sign. If the probability of detected sign is greater than the defined then that sign is used for classification.

F. Recognition using Lenet-5 CNN model

From the previous steps, the traffic sign is detected in the input frame of image. Now algorithm has to recognition and classify using Lenet-5 CNN model which tells us the meaning of the detected sign.

Given that convolutional neural networks are composed of neurons with weights and biases, they can be compared to the brain very favourably. Every neuron gets a signal, processes it, and then delivers the result to the cell following it as input. The input layer and output layer of a convolutional neural network are always the first and last layers, respectively. A hidden layer is anything else that lies in between those two.

LeNet-5 CNN architecture has seven fundamental layers. 3 - convolutional layers, 2 - pooling layers, and 2 - fully connected layers make up the layer composition. Table 1 displays the detailed layers.

Table 1: Lenet-5 CNN Layers

Lenet– 5 Layers
Conv (Filter=60, Kernel size=5x5, ReLU)
Conv (Filter=60, Kernel size=5x5, ReLU)
Max Pooling (Pool size=2x2)
Conv (Filter=30, Kernel size=3x3, ReLU)
Max Pooling (Pool size=2x2)
Fully Connected (500 nodes, ReLU) + Dropout (0.2)
Fully Connected (43 nodes, *Softmax*)

III. Experimental Results

For implementation of the developed algorithm, we used GTSDB (German Traffic Sign Detection Benchmark) and GTSRB (German Traffic Sign Recognition Benchmark) for training and testing.

There are 39209 images total in the 43 classes of traffic signs that make up the GTSRB. Data were split 75:25, meaning that 75% of the data were used to train the model and 25% were used to test it.

Metrics passed in SVM was Accuracy score and was found 97.85%. In CNN model, categorical cross-entropy, Adam optimizer, Accuracy was passed for loss, optimizer and metrics respectively. Test loss was 6%, test accuracy was 98% and Accuracy score was found to be 98.71% in Lenet-5 CNN Model. The output of CNN model in shown in fig 3 & 4.

GTSDB consists of more than 900 natural images which may or may not contain traffic signs. The Final results is shown in fig 5. The algorithm is implemented in computer with Intel core i5 generation with 2.40GHz and takes less than 8 seconds to execute each Input image.

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Accuracy 0.9785779863307151
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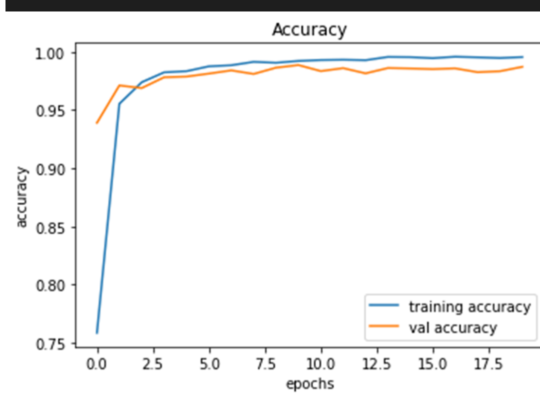

Fig 3: Accuracy plot for training and validation

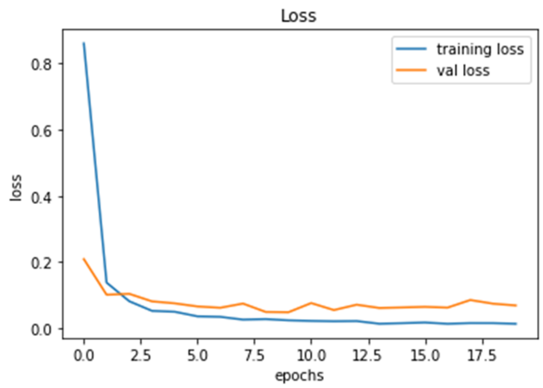

Fig 4: Training and Validating loss plot

IV. Conclusions and Discussions

In this paper, we created an algorithm that uses colour features to identify traffic signs and HOG features to verify prospective traffic signs. Support vector machines and convolutional neural networks, two artificial intelligence systems, were used in the algorithm's latter steps to aid with recognition. In training and testing using data from a German traffic sign database, the generated model demonstrated great accuracy. Finally, the traffic sign recognition and labelling capabilities of this model were successful shown in figure5.

There is still more that can be done to improve the model, even though it puts us one step closer to realising the perfect Advanced Driver Assistance System or perhaps a fully autonomous system. It's important to carefully consider night-time detection while making a sign identification. The sign cannot be seen if the scene is too dark for the camera to capture at night. The use of new information and data from other nations can help to improve and adapt the overall performance.

Fig 5: Final output results of the proposed system.

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