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Traffic Sign Board Detection and Voice Alert System

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Abstract: *Automated tasks have simplified practically everything we perform in today's world. Drivers often miss signage on the side of the road in an effort to focus on the road, which can be dangerous for them and others. This issue may be avoided if there was a quick way to alert the driver without requiring them to divert their attention. TSDR (Traffic Sign Detection and Recognition) is useful in this situation because it detects and recognizes signs, alerting the motorist to any forthcoming signs. This not only assures road safety, but also puts the driver at ease when driving on unfamiliar or difficult roads. Another issue that arises frequently is the inability to comprehend the sign's meaning. Drivers will no longer struggle to grasp what the sign is saying thanks to this Advanced Driver Assistance Systems (ADAS) application. In this paper, we propose a method for detecting and recognizing traffic signs that uses image processing for detection and an ensemble of Convolutional Neural Networks (**LeNet**) for recognition. Because LeNet CNN have a high recognition rate, they are ideal for a variety of computer vision tasks. For the CNN implementation, Tensor Flow is employed. And here for object detection we implement yolo frame work On the German data sets, we achieved recognition accuracies of more than 99 percent for circular signs.*

Keywords: Self-Driving Car, traffic sign, recognition and detection, YOLO, Lenet

I. INTRODUCTION

Because of the benefits that such a system may give, traffic sign detection and recognition has become more important with developments in image processing. The interest in self- driving automobiles has grown as a result of recent breakthroughs and interest. Smart automobiles and smart driving will be possible thanks to an automatic traffic sign detection and recognition technology. Even while a driver is atthe wheel, the system may provide crucial information, decreasing human errors that cause accidents. It is certain that with such a system integrated into automobiles, the frequency of car accidents will be considerably decreased, saving both human lives and the monetary value involved with car accidents. Traffic will be controlled by automated systems on both open roadways and intersections. The use of deep learning for an unsupervised learning strategy is deliberate in this paper because, while basic traffic signs are limited, when supplemented with road signs, street name signs, and other signs, the dataset grows exponentially with limitless possibilities. The ultimate goal is recognize any traffic sign, assisting the driver or assisting withself-driving. Unlabeled data can be used with deep learning algorithms, and the system can extract features without the need for human intervention.

The benefits of such a system in saving lives and reducing costs are evident motivations for implementing such a system. As a result, the goal of this project is to create a deep learning- based automatic traffic sign detection and recognition system. The suggested system is capable of identifying indications in images collected by cameras and processed by a Deep CNN network. The majority of car accidents are caused by human mistake, such as drivers failing to notice a traffic sign or driving in the opposite way of a traffic sign (i.e., traffic sign setting speed at 100 KM and driver driving at a greater speed).As a result, the primary goal of this paper is to develop and improve the efficiency and robustness of a traffic sign detection system, as well as to address related issues. A recognition system should also classify traffic signs into different classes in real-time and avoid recognition errors.

II. LITERATURE SURVEY

[1]The "German Traffic Sign Recognition Benchmark" dataset and competition are proposed in this study, as well as their design and analysis. The competition's results reveal that state- of-the-art machine learning algorithms excel at the

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difficult task of traffic sign recognition. On this dataset, the participants attained a high performance of up to 98.98 percent correct identification rate, which is comparable to human performance.

[2] This study provides a real-world traffic sign detection benchmark data set, as well as carefully defined evaluation metrics, baseline findings, and a web-interface for comparing techniques. They separated sign detection from categorization in their study, and they also tested performance on important categories of indicators to enable for benchmarking of specialized systems. The baseline methods considered are the Viola-Jones detector based on Haar features and a linear classifier based on HOG descriptors, which are two of the most popular detection approaches. A recently suggested problem- specific method that uses shape and color in a model-based Hough like voting mechanism is also assessed.

[3] This study focuses on real-time traffic sign recognition, which entails quickly determining which sort of traffic sign occurs in which part of an input image. A two-module system (detection and classification modules) is developed to achieve this goal. The input color image is transformed to probability maps using the color probability model in the detection module. The road sign proposals are then extracted by locating the maps' most stable extremal zones. Finally, an SVM classifieris utilized to further filter out false positives and classify the current proposals into their super classes using color HOG characteristics. They employed CNN in the classification module to classify the detected traffic signs into sub-classeswithin each super class.

[4] The HIS color model is utilized in this study to detect the traffic sign, followed by circle detection. Color-detected zones can't be pinpointed to the millimeter. region of the precise sign The edge of those who are interested is used in this manner. After morphologic analysis, regions are traced to obtain their contours. operations. The Hough circle is then used to locate the target location. The transform function is used. The object has been discovered. After the preceding two processes, the result was extracted. Next, we'll look at the in the destination area, there is a symbol. The image has been pre-processed in order to get rid of the noise to get a clean silhouette boundary of the silhouette a traffic signal symbol Segmentation and identification of edges are utilized to create a specific image. The context of shape is based onthe shape of the thing

[5] The purpose of this work is to discuss a novel technique for automatically detecting and recognizing traffic signs. Candidates are identified as maximum stable extremal regions (MSERs), which are resistant to changes in illumination conditions. A cascade of support vector machine (SVM) classifiers was trained utilizing histogram of oriented gradient (HOG) features to achieve recognition. This system is precise at high vehicle speeds, works in a variety of weather situations, and runs at a pace of 20 frames per second on average.

III. PROBLEM DEFINITION

When it comes to identifying and recognizing sign images shot against an undesirable background, road sign recognition is a difficult challenge. The assignment is challenging and difficult due of the complex background, weather conditions, lighting, and shadows. The following are some of the issues that an intelligent transportation system must address:

1. Signs that are disoriented or damaged make it difficult for the system to identify and recognize them.
2. Because of the car's shaking and speed, the images obtained are frequently blurry.
3. Because of the lighting and the weather, visibility ispoor.
4. The presence of a traffic sign is also necessary for the system to detect it. Parts of signs placed near trees are frequently obscured by tree branches.
5. Because of the continual exposure to sunshine, the colour fades.
6. The presence of objects in backdrops that are likely to be of a certain shape and colour

IV. IMPLEMENTATION STUDY

Recognizing and classifying traffic signs is critical nowadays, especially for unmanned automated driving. The recognition and classification of traffic and road signs has been the subject of extensive research. The authors proposed a system for traffic sign detection and categorization using Convolutional Neural Networks and Support Vector Machines (CNN-SVM). The YCbCr color space is employed in this method, and it is fed into a convolutional neural network to separate the color channels and extract some unique properties. SVM is then utilized to classify the data. For

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traffic sign recognition and classification, introduced a color-based segmentation algorithm that used Histogram Oriented Gradients (HOG) for feature extraction and SVM for classification On low-cost embedded systems, traffic sign detection is possible. Color thresholding, form identification, and sign validation are all part of their system. They used a color thresholding technique based on the red-blue angle color transformation (RBAT) and normalized red color. The circular indications are also detected using the ellipse fitting technique. Validation is done via HOG.

4.1 Proposed Approach

This study will make two contributions: the first will be to create a new database for traffic and road signs, and the second will be to create and construct a deep CNN architecture for traffic sign detection. The high-level view of the system is depicted. For training, validation, and testing, the acquired dataset is fed into the suggested CNN architecture. In the following part, we'll go through the CNN architecture in detail. Once the CNN has been trained, it can be used to categories fresh images that were not included in the dataset. The AATS system is based on a set of traffic signs. Although a number of authors have worked in this topic in recent years, this is the first time, to the author's knowledge, that a comprehensive database for traffic has been built. For traffic sign identification, a Deep CNN architecture is also proposed. Between the input and output layers, CNNs typically have numerous hidden layers. And we implement the yolo frame work for annotation points for the sign dataset and then train them using Lenet model. We should supply the dataset as the input for any model and pre-process it before selecting the model and determining its correctness. Our model will be best served by an algorithm that gives high accuracy.

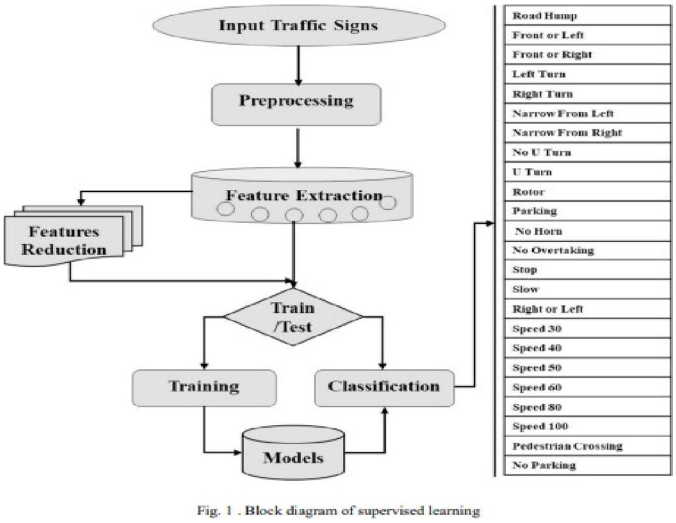

Fig 1: - proposed model

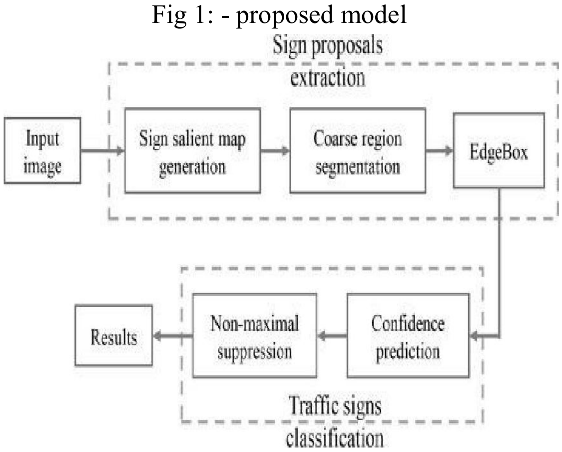

Fig 2: - overall model of the proposed system

4.2 Algorithms Used

A. Lenet

To show how to create a convolutional neural network-based image classifier, we'll create a 6-layer neural network that can distinguish one image from another. This network that we will construct is a verymodest network that can also be run on a CPU. Traditional neuralnetworks, which are excellent at picture classification, contain many more parameters and take a long time to train on a standard CPU.However, our goal is to demonstrate how to use TENSORFLOW to create a real-world convolutional neural network. We should supply the dataset as the input for any model and pre-process it before selecting the model and determining its correctness. Our model will be best served by an algorithm that gives high accuracy.

Neural Networks are mathematical models that are used to tackleoptimization problems. They're made up of neurons, which are the fundamental computational units in neural networks. A neuron takes an input (say x), does some computations on it (for example, multiplying it with a variable w and adding another variable b), and outputs a value (say, z= wx + b). To produce the final output (activation) of a neuron, this value is transferred to a non-linear function called activation function (f). Activation functions come in a variety of shapes and sizes. Sigmoid is a well- known activation function. A sigmoid neuron is a neuron that uses the sigmoid function as an activation function. Neurons are named based on their activation functions, and there are many different types, such as RELU and TanH. A layer is the nextbuilding component of neural networks, and it is formed by stacking neurons in a single line. Layers can be seen in the image below.

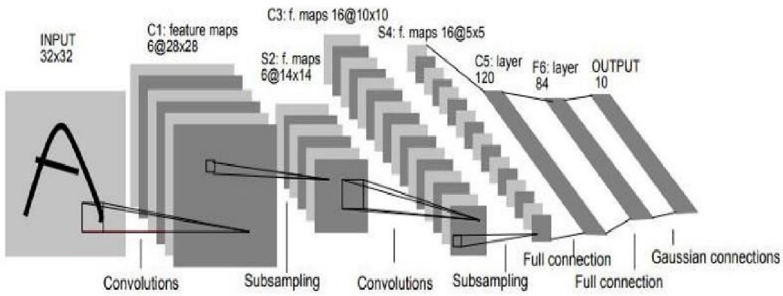

Fig 3:- lenet architure diagram

Two sets of convolutional and average pooling layers are followed by a flattening convolutional layer, two fully-connected layers, and lastly a softmax classifier in the LeNet-5 architecture.

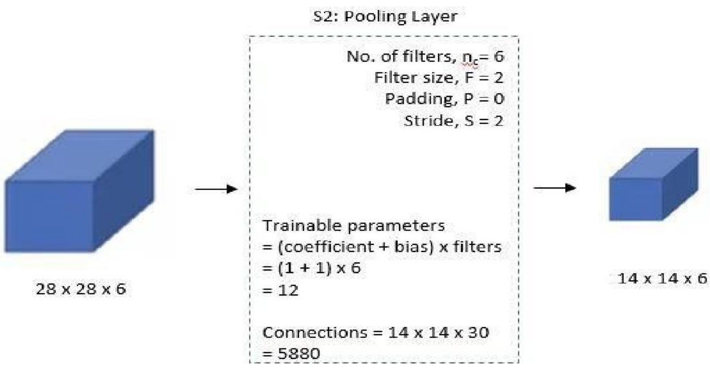

Fig 4:- Lenet process of encoding and decoding

A second convolutional layer with 16 feature maps of size 55 and a stride of 1 follows. Only 10 of the 16 feature maps in this layer are connected to the 6 feature maps in the preceding layer, as shown below.

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0	X				X	X	X			X	X	X	X		X	X
1	X	X				X	X	X			X	X	X	X		X
2	X	X	X				X	X	X			X		X	X	X
3		X	X	X			X	X	X	X			X		X	X
4			X	X	X			X	X	X	X		X	X		X
5				X	X	X			X	X	X	X		X	X	X

TABLE I

EACH COLUMN INDICATES WHICH FEATURE MAP IN S2 ARE COMBINED BY THE UNITS IN A PARTICULAR FEATURE MAP OF C3.

Fig 5:- feature mapping which is performed using leTnet Architecture

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	32x32	-	-	-
1	Convolution	6	28x28	5x5	1	tanh
2	Average Pooling	6	14x14	2x2	2	tanh
3	Convolution	16	10x10	5x5	1	tanh
4	Average Pooling	16	5x5	2x2	2	tanh
5	Convolution	120	1x1	5x5	1	tanh
6	FC	-	84	-	-	tanh
Output	FC	-	10	-	-	softmax

Fig 6: Summary of LeNet-5 Architecture

B. Yolo Frame Work

The YOLO framework (You Only Look Once) takes a novel approach to object recognition. It predicts the bounding box coordinates and class probabilities for these boxes using the full image as a single instance. The primary benefit of utilizing YOLO is that it's simple and straightforward. It's also extremely fast, processing 45 frames per second. YOLO is also aware of the concept of generic object representation. This is one of the best object detection algorithms, with a performance that is comparable to the R-CNN algorithms. As a result, bx, by, bh, and bw will only be calculated in relation to this grid. For this grid, the y label will be

$$y = \begin{bmatrix} 1 \\ bx \\ by \\ bh \\ bw \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

Fig 7:- pc = one c2 = 1 because there is an object in this grid and it is an automobile. The coordinates assigned to all grids (bx, by, bh, and bw) in YOLO

C. Yolo Algorithm Steps

The algorithm just selects the boxes with the highest probability and ignores the boxes with lower probabilities. The Non-Max suppression algorithm is summarized as follows:

1. Remove any boxes with probabilities that are less than or equal to a pre-determined threshold (say, 0.5).
2. Fill in the blanks in the remaining boxes:

As the output forecast, choose the box with the highest likelihood.

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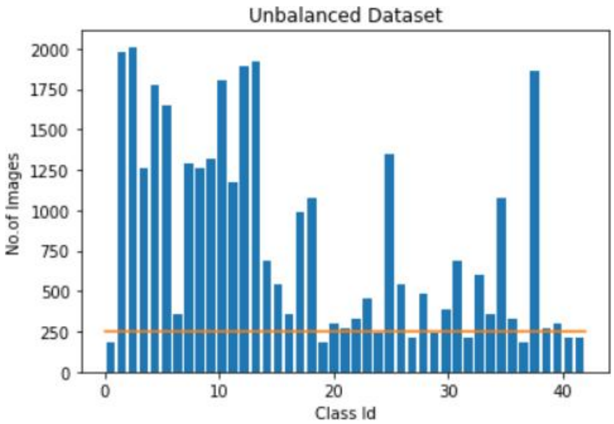
Any other box with an IoU larger than the threshold should be discarded together with the output box from theprevious phase. Step 2 should be repeated until all of the boxes have been either selected as the output prediction or rejected. The Anchor Boxes method can also be used to boost a YOLOalgorithm's performance.

V. RESULTS AND EVOLUTION METRICS



1

Fig 8:- above graph showing unbalanced dataset

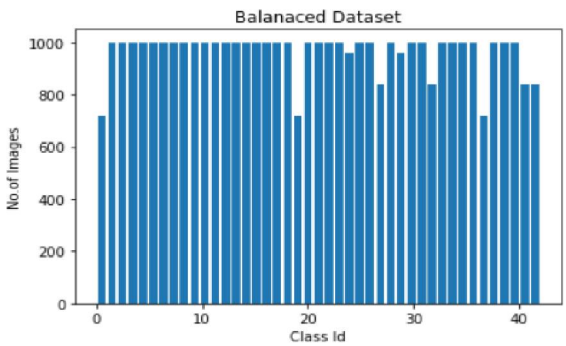


Fig 9:- The above graph showing the dataset after balanced

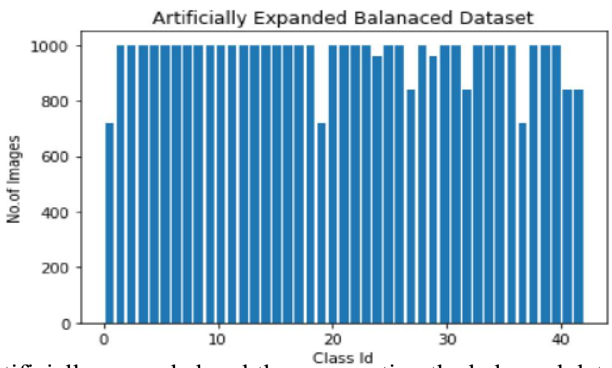


Fig 10: the dataset is artificially expanded and then generating the balanced dataset in the above graph

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 28, 28, 24)        1824
conv2d_1 (Conv2D)            (None, 24, 24, 36)        21636
conv2d_2 (Conv2D)            (None, 20, 20, 48)        43248
conv2d_3 (Conv2D)            (None, 18, 18, 64)        27712
conv2d_4 (Conv2D)            (None, 16, 16, 64)        36928
flatten (Flatten)            (None, 16384)             0
dense (Dense)                (None, 250)               4096250
dense_1 (Dense)              (None, 125)               31375
dense_2 (Dense)              (None, 75)                9450
dense_3 (Dense)              (None, 43)                3268
=================================================================
Total params: 4,271,691
...
Trainable params: 4,271,691
Non trainable params: 0

None
```

Fig 11:-In above screen we can see different layers on generate for each image with different sizes to make prediction better. In first layerimage features extracted using 28X28 height and width and in next layer 24X24 height and width

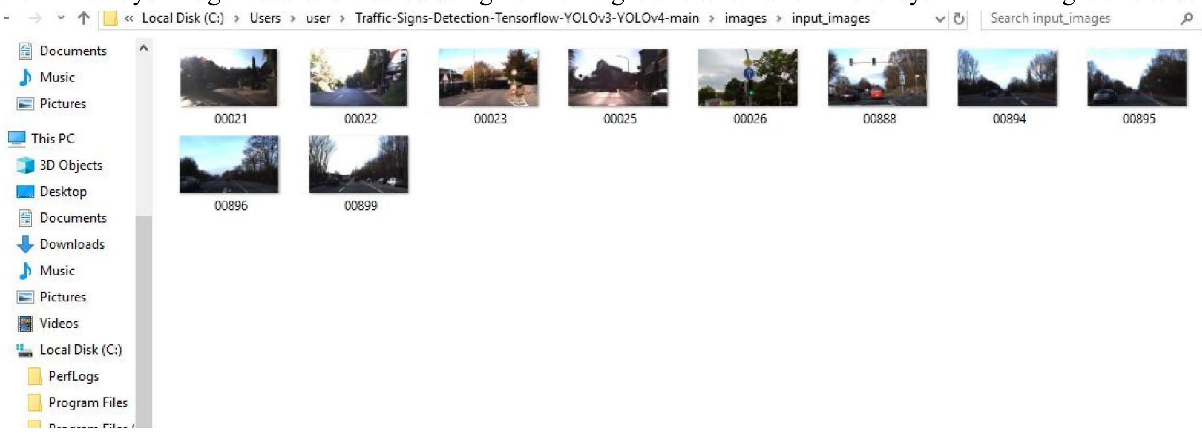


Fig 12: - In above screen uploading images into the input folder. These images will be captured by front camera in car. After uploading image run the application so that the traffic signs in the image will be detected and voice alert will come.

Fig 13: - In above screen we can see Traffic Sign A detected and we can see traffic sign detection in blue Color message as annotation and then the sing name is sent to voice to speech for getting type of sign symbol

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Fig 14: In above screen we can see speed limit 30km/h and narrow road sign board detected. Like this vehicle move and display detection information and the text are sent to input voice and a voice speaker speaks the identified symbol.

VI. CONCLUSION

Convolutional Neural Networks were used to create an automatic Traffic Sign (AATS) identification system (CNN). More than 2,728 sign samples were collected for different traffic signs in the training and testing dataset. Before being fed into the network, the dataset went through a preprocessing stage. It was divided into three datasets: training, testing, and validating. The initial design was based on similar past work, which served as a foundation for the better design that followed. Two convolutional layers, two maxpooling layers, one dropout layer, and three thick layers make up the final Deep CNN architecture described in this paper. For all batch sizes, 99% accuracy was achieved for epoch 150. We showed that the planned CNN rationally low- cost recognition systems are beneficial.

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