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TRAFFIC SIGN BOARD RECOGNITION AND VOICE ALERTSYSTEM USING CONVOLUTIONAL NEURAL NETWORK

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Abstract: Road signs are crucial for ensuring a safe and orderly flow of traffic. Ignorance in failing to read traffic signs correctly is a key contributor to auto accidents. The suggested system assists in identifying traffic signs and alerting the driver through speaker so that he or she may make the appropriate selections. The Convolutional Neural Network (CNN) used in the proposed system's training assists in the detection and categorization of images of traffic signs. To increase the accuracy of a given dataset, a set of classes are created and trained. We used the German Traffic Sign Benchmarks Dataset, which includes 51,900 images of traffic signs in about 43 categories. Around 98.52 percent of the execution was accurate. Following the detection of the sign by the system, a voice alert is sent through the speaker notifies the driver. The proposed system also has a section where drivers of moving vehicles are informed of nearby traffic signs so they are aware of the rules they should follow. The system's goal is to protect the driver, passengers, and pedestrians from harm.

Keywords: Convolutional Neural Network,Road signs, Traffic Sign Benchmarks, voice alert

INTRODUCTION:

Traffic sign identification has grown to be a very difficult area in both academia and business. The primary purpose of these systems will be in the emerging field of artificial intelligence (AI), where it will be utilized to comprehend the surroundings and play a crucial role in advanced driver assistance systems (ADAS). The majority of the time, recognition offers a distinct visual description of the fact that every traffic. A sign may have a variety of forms, colors, and visuals that depict the surroundings and the limitations of the road so that the motorist may notice and be ready for whatever may come their way. Road signs may not be very visible to vehicles, there may be some sign misunderstanding, or some signs may not be recognized by many drivers. This might cause misunderstanding and increase the likelihood of accidents. It might be problematic if there is difficulty in identifying warning indicators. Yet, there are a few instances due to various environmental circumstances when the road signs would become utterly distorted, making their appearance difficult for both people and machines. The use of various artificially generated data could solve the problems with the Road sign collection

without putting too much strain on the classifier. Two key methods of sign recognition are covered in our paper: classification and extraction. A signal can be recognized in a variety of ways. In paper [1], the Hough Transform is adjusted to find the coordinates of the road sign, but in paper [2], the circular prohibitory sign is located using the circular Hough Transform. The detection stage of the techniques described in papers [3] and [4] uses information about the geometry of the road sign based on histogram characteristics and support vector machines. classifiers. The look of the sign is constant in each example using these publications as a guide. Moreover, each sign just modifies the view reference. The pattern of a sign never changes; the only thing that does is the view that a recognition camera or a driver sees, as well as the environment, which makes it difficult to recognise. This contributes to the various variations in recognition, and it can be done by updating various traffic sign conditions in the training set. Because we employed a training data set that is made up of images that are highly close to real-world data, our technique does not require real-time data. With the use of this data collection, we want to improve our detecting precision, which should be more than 90% near to real observation. Hence, even though the scanned version of a sign may not exactly match the real-world version, our system utilises CNN to identify any similarities and identifies it as the same sign.

LITERATURE REVIEW:

ASSASSINMENT USING THE CNN ENSEMBLE. [1] The system described by Shustanov and P. Yakimov [1] for road sign detection and recognition is an image processing technique that includes a group of (CNN) for recognition termed an ensemble. The CNN has a very high recognition rate, which raises its appeal for a variety of computer-based vision applications. TensorFlow is the technique employed for CNN execution. Using German data sets, the authors of this article were able to attain more than 99 percent accuracy for circular signs.

COLOR SEGMENTATION FOR RECOGNITION [2] According to Wali etal [2], they implemented a revolutionary approach for sign recognition. They fitted this cutting-edge ARK-2121 technology, a tiny computer, on the vehicle. SVM and HOG were the two main algorithms used in the sign's recognition phase. Their detection accuracy was 91%, and their average classification accuracy was at 98%.

THE RECIPIENT OF THE GERMAN TRAFFIC SIGN. [5] The investigation and creation of the "German Traffic Sign Recognition Benchmark" dataset are described by R. Qian et al. in [5]. The results of this experiment demonstrated that machine learning algorithms performed admirably in the recognition of traffic signals. On these datasets, the participants achieved a highly respectable identification rate of 98.98 percent, which is higher than human perfection.

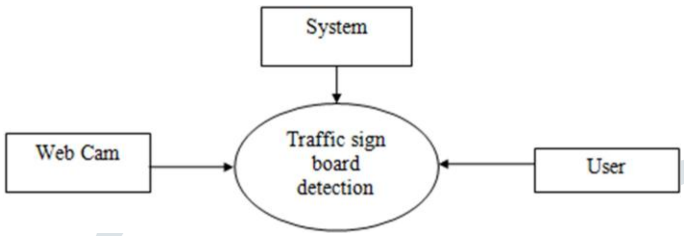
EXISTING SYSTEM: To ensure the safety of themselves and their passengers on the road, drivers must accurately recognise signboards at the appropriate time and location. Unfortunately, there are situations when indicators are impossible to perceive until it is too late owing to changing weather conditions or viewing angles. Nowadays, applications for computer vision have been made possible by advancements in processing power. Road accidents are more common in areas with unique road features, such one-way streets, tight turns, and crossroads. Installing "STOP," "NO LEFT TURN," and other signs to warn drivers of traffic conditions is one potential defense. The suggested method has four separate components that work together to recognize and verify road signs. Candidate locations and to prevent the color's light sensitivity. The region of interest is further defined in the next section utilizing labeling, filtering, and other geometrical attributes including area, aspect ratio, and perimeter for categorization.

DISADVANTAGES OF EXISTINGSYSTEM:

I. Irregular Detection
II. Duplication (inter pixelredundancy)
III. Decreased effectiveness(compared to our model)
IV. Problems with costs

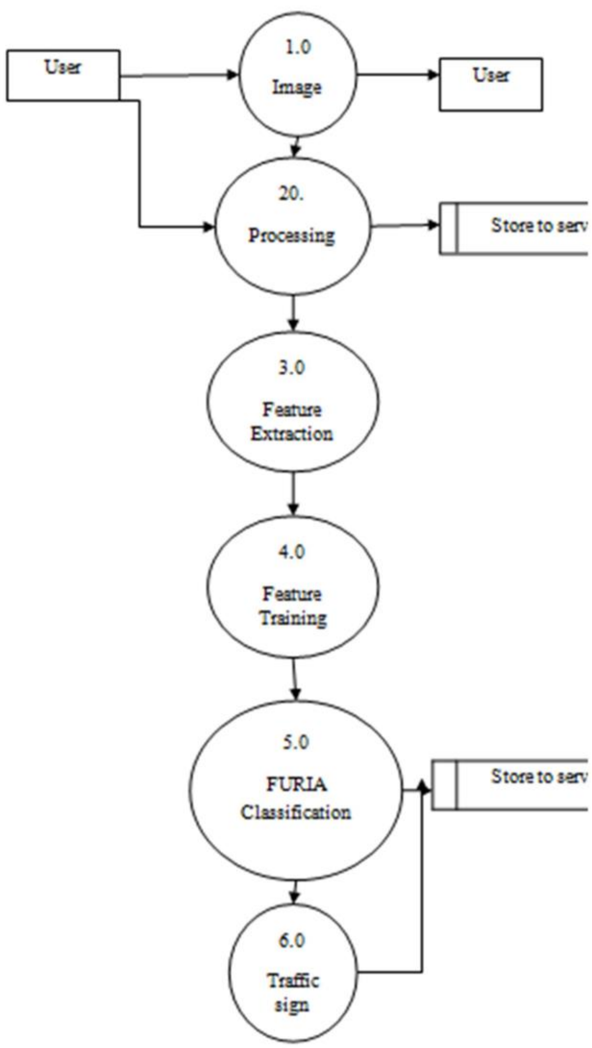
PROPOSED SYSTEM: The three steps of the framework we suggested are detection, feature extraction, and recognition. Finding a traffic sign is all that the detection step is utilised for. When a car is moving at a certain speed, the camera captures a road sign in its natural setting, and our formula confirms whether or not a sign is there in that perimeter. The traffic sign's shape and colour must be distinguished. The suggested algorithm describes the distinctive road sign during the feature extraction step. The "Convolutional Neural Network" algorithm, which divides the picture into subclasses,helps achieve this.

DATAFLOW DIAGRAM:



Level-0

Level-1



MODULE DESCRIPTION:

Enter an image: A camera installed inside the car takes a sequence of pictures, which are then combined to create a video. There are typically 24 frames per second. These images pass via computers that look for signs. The camera's quality should be very good so that the traffic sign may be seen clearly at the very minimum distance needed. Typically, this method calls for a camera with greater than 8MP.

Pre-Processing: Convolution neural networks are used for pre-processing scanned images and movies. For easier processing by "Convolution Neural Networks," the image with the greater esolution is scaled down to a smaller resolution and transformed from RGB to grayscale. The neural networks perceive the image and provide the processor with the appropriate information, just like the neurons in our brains do. The image below, which depicts a left or straight sign, has been sent to CNN in grayscale. After being sampled and cut up into smaller parts, the output is compared to the data set that was provided, and the appropriate voice output is then provided. Similar to the neurons in our brain, neural networks perceive the image and provide the processor with the required information. Convolution neural networks require fewer steps for pre-processing than do other types of neural networks.

RGB based detection: The color is the most important aspect of a sign. After the red color is noticed, it is obvious that the object is a roadside traffic sign. Our detection procedure makes advantage of the same concept. Our algorithm is built to check for a sign dependent on the red color based on the frames that were taken. The picture is transmitted for additional processing to determine whether or not it is a sign if a portion of it resembles the red color threshold values. The primary indicator in the red area is to be identified once the red threshold has been checked.

Detection Based On Sign Shape: We determine the number of edges using the Douglas-Peucker algorithm based on the prior detection technique. Due to the fact that circles and triangles are used on traffic signs the most, we primarily focus on these two forms. The number of edges and the region of interest are discovered using the Douglas-Peucker method. Today it is regarded a triangle if the number of edges detected is equal to or higher than six and the major section fulfils the minimal requirement. The majority of the picture is identified as a circle if the edges are equal, more than six, and meet the minimum requirement. The crucial next step after identifying the forms is to identify the bounding box. The Region of Interest (ROI) is isolated from the surroundings by the enclosing box, making it crucial. The box often touches the main region's circle or triangle. There are two triangles—an outer and an inner triangle—in a triangular symbol. The inner triangle is the only one that does not touch the box of bounding,while the outer triangle barely touches it.

Recipient Phase: The categorization of signs must be done at the time of sign detection. Convolutional Neural Networks are created using Google's machine learning tool TensorFlow. Preprocessing the image that we obtained from earlier rounds is the initial step in this phase. The CNN's training and testing are thought to be the most important aspects of the recognition phase. We used "German Traffic Sign Benchmark and the Belgian Traffic Signs" for the testing and training of the data set. CNN is regarded as the brain since it has the same functions and qualities as a typical brain. Each neuron gets information, which is then sent to the cell after it. CNN has a lot of levels. The first layer is the input layer and the last layer is the output layer. Between the first and the last lies a hidden layer. This technique uses six CNN layers. There is a properly linked concealed layer present to prevent overfitting in the midsection. We employed Keras' "sequential stack," which runs on top of TensorFlow, in this model. Each layer has a "Rectified Linear Unit activation." ReLu is the most crucial activation function in neural networks. The output of the sixth convolutional layer serves as the input to the fully connected layer, which uses a level capacity to straighten the yield by that point. Softmax activation makes up the last layer, which receives the output that has been flattened. A max pooling layer is added right after the second layer to speed up processing. If CNN is like this, we utilise three in a collection or group to provide more accurate results. If we employ many CNNs as opposed to just one, the results will be more accurate. You must provide things like the optimizer, the loss, and the metric. Instead of using percentages, the loss works with numbers between 0 and 1. "Stochastic Gradient Descent with Nesterov momentum" is used by the optimizer. Epochs are utilised to enhance training, which enhances the accuracy of prediction. Last but not least, a text to speech module is added to the system, allowing the traffic sign to be detected and the voice output to be created, making it easier for the driver to see the signs and prevent accidents.

RESULTS:

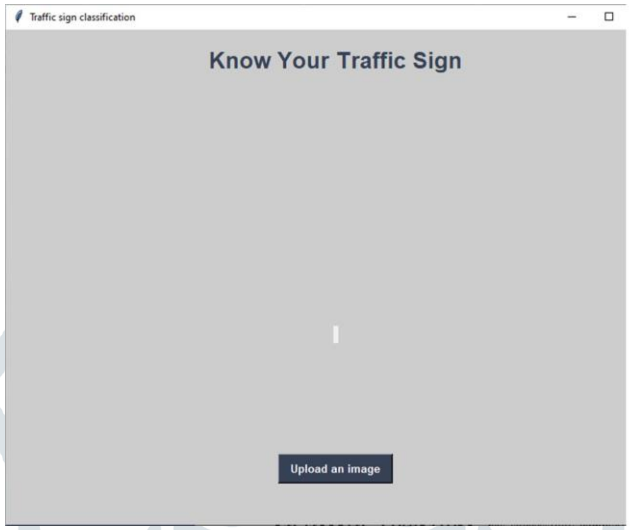


Fig : 1

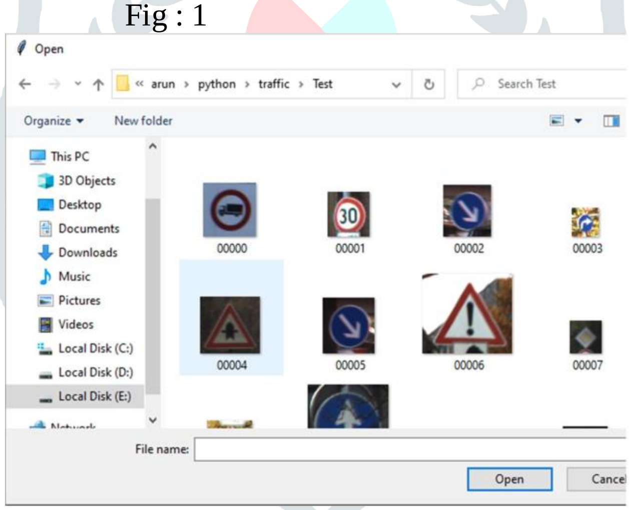


Fig 2

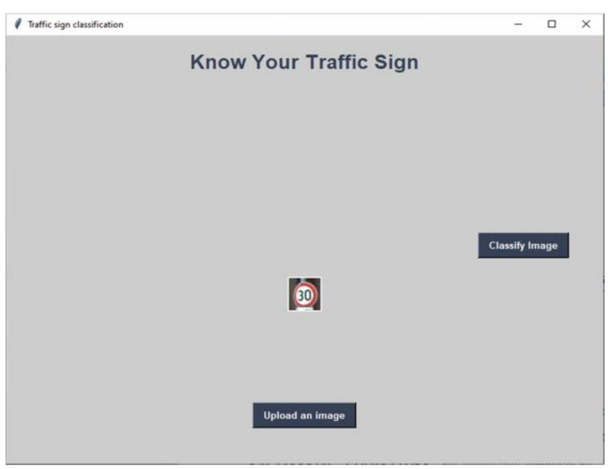


Fig 3

Fig 4

CONCLUSION: The model which we proposed will bring us a step closer to achieving the ideal Advanced Driver Assistance System (Autonomous Car) or even a completely driverless system, there is a lot that can be improved. For detection of a sign, this paper depends on color and shape of the sign. CNN algorithm is preferred more compared to other algorithms since it provides high efficiency and There is a problem if there is a reflection on the sign which impacts its color. Similarly, if the sign is not proper or cut off, the shape of the sign is impaired, thus resulting in improper detection of the sign which leads to fault detection. Another important issue to consider is detection in the night. If the camera used is infrared then there is no problem in detecting signs but in case of non-infrared webcam which may not detect signs accurately which causes high chance of accidents. Adding text to speech module in our model makes the driver effortless and makes him to concentrate completely on driving rather than checking for traffic signs. This reduces the occurrence of accidents during night and as well as day time. Since we used low GPU (GRAPHICAL PROCESSING UNIT) system, we could not get 100 percent efficiency if the traffic sign is too far away from the system. But we provided a text to speech module which can be equipped in advanced Driver Assistance system. The hardware used in this project is very less when compared to other models, which reduces cost and also free from hardware Impairments.

FUTURE SCOPE: Due to the continuous nature of our algorithm's sign detection, it can recognise signs even when there are none nearby, resulting in a constant output stream. This leads to erroneous or pointless detection. By raising the threshold value for detecting sign, this might be made better. With the aid of new datasets from other nations, the total performance may also be enhanced and tailored.

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