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Traffic Sign Recognition for Automated Vehicles using ML Algorithm

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***Abstract* -- The categorization and understanding of traffic signs is crucial for the development of autonomous vehicles. While driving, paying attention to the traffic signs posted on the highways is crucial. Traffic sign classification is used to recognize and categorize traffic signs in order to alert and warn a vehicle in advance to prevent breaking the law. Traffic signals can be misinterpreted by drivers, which can lead to accidents and car damage. To deal with these sorts of challenges, this research study presents the idea of Traffic Sign Detection and Classification. These days, convolutional neural networks (CNN) are used to perform an increasing number of object identification tasks. The indicators in the images are first detected and recognized after it gets processed. These two processes take place simultaneously. Then the system generates output that promptly and automatically warn the driver. Additionally, it results in the design and development of a smart car.**

Keywords -- Traffic Sign Recognition, Traffic sign Detection, Convolutional Neural Network, Traffic signs, Classification.

I. INTRODUCTION

Traffic signs are fixtures that are installed alongside, above, or in other locations along a highway, trail, or other route to direct, warn against, and control the flow of traffic, which includes automobiles, pedestrians, equestrians, and other visitors. As consumer safety becomes increasingly important, one of the existing research topics focusing on enhancing driving safety is traffic sign recognition. These systems are currently being developed to simply alert drivers to significant traffic signs, but eventually may take around driving duties in certain circumstances.

Traffic signs can be outlined automatically using classification and recognition. Whenever a traffic sign is encountered, the software automatically displays its name. As a result, even if the motorcyclist is preoccupied for a brief amount of time or overlook a sign, it will still be picked. This aids in the prevention of certain behavior patterns, such as exceeding the speed limit, and properly alerts drivers. It also reduces the driver's stress, increasing comfort. It is critical to pay a lot of attention to and obey traffic signs in order to avoid accidents. In reality, traffic signs provide us with information on a variety of topics and direct us in the right direction allowing us to travel safely. Traffic sign classification is an excellent way to assist automated vehicle assistance systems.

The use of new technologies to develop automation and human conveniences is expanding quickly, especially in the automobile industry. Smart traffic systems have made fully automated recognition and detection of traffic signs useful in assisting drivers throughout ensuring a secure journey. The primary intention of traffic sign recognition technology is to lessen the possibility of disregarding crucial road indicators. Additionally, the resulting system is not impacted by any human-related problems, such as fatigue, insomnia, or similar issues. The safety of driving is enhanced as a result.

II. LITERATURE REVIEW

1. The survey [1] is based on support vector machines published in the year 2009. The detection module and classification module of the [1] proposed two-module framework are employed. Utilizing a colour probability model, the detection module converts the input colour image into probability maps. Afterwards, the most stable extremal zones on these maps are found before extracting the road signs. The present ideas are then classified to their super classes using an SVM classifier that has been prepared with colour HOG features, which further filters out the false positives. They classified the observed traffic signs using CNN and assigned them to the subclasses under each superclass.

2. The survey [2] is based on supervised learning of color and shape which was published in the year 2013. It suggested Shape-based approaches for detecting signs compare them to a set of predetermined models, rendering them vulnerable to target rotation and complete or partial occlusion. The pixel intensity in RGB or HSI colour spaces is used in color-based techniques to identify signs in a scene. The most used colour space is HSI since each component contains a variety of pieces of information. The fact that the HSI colour space is unaffected by brightness and shadow detail is another benefit. The HSI colour space is also perfect for extracting colour features in challenging situations like bad weather and damaged road signs. This work offers a general method for identifying and categorizing traffic signs from image sequences using colour information and CNN.

3. In the survey [3], real time detection is based using CNN. The classification algorithm for the job of recognising traffic signs is implemented in this study together with preprocessing and localisation techniques from earlier studies. Utilizing CNN and the TensorFlow framework, the suggested classification approach is put into effect. A device with an Nvidia Tegra K1 CPU was used to apply the developed method. The performance of the approaches mentioned was accelerated using CUDA.

4. The survey [4] is based on classification using capsule networks published in the year 2018. The most popular deep learning methods for traffic signal categorization in [4] are CNN, but they are unable to capture the stance, view, and orientation of the photos due to the inherent limitations of the max pooling layer. In this study, they provide a brand-new approach for detecting traffic signs that makes use of a deep learning architecture called capsule networks and produces exceptional results on the German traffic sign.

III. METHODOLOGY

A. Dataset

The availability of generalized datasets is critical before proceeding to detection or classification. The dataset used in this study is a German traffic sign recognition benchmark that contains over 50,000 images of diverse traffic signs (speed limits, intersections, traffic lights, etc.). Images have various brightness and background conditions. Its appeal can be attributed to the following:

1. There are numerous images in it.
2. The traffic signs come in a variety of patterns, backgrounds, and colours, which in turn will aid in the model's performance accuracy.

The dataset contains about 43 different image classification classes. The size of the record classes varies, with some classes having few images and others having many. The data set file size is approximately 314.36 MB. It has two independent folders, train and test folders, where in train folder it contains classes and each subclass contains a different image. The set of samples used to fit the model and used to train the model is known as the training data set. Validation datasets are used to evaluate models and show how accurately they predict new data. Updates to hyperparameters are another use for them.

The variables known as hyperparameters are used to regulate the learning process, which has an impact on the model's accuracy. For example, epoch number and activation function. To provide impartial evaluation we test the model against test dataset. It is used to assess the model's predictive capability.

B. Convolutional Neural Network

Although there are a number of alternative methods, including k-means, video streaming, LIDAR, and vision-based techniques, they have a number of limitations, such as false detection and lower efficiency. K-means results in an accuracy of 87 percent.

In order to discern patterns in images, convolutional neural networks (CNNs), which are a type of artificial neural networks employ network configurations. They are used for image perception, categorization and data processing. While there are other kinds of neural networks in deep learning, CNNs are the preferred network architecture for labelling and recognising objects. Although CNNs are extremely effective tools, their training procedure calls for millions of labelled data points. For processing visual images, a multilayer feedforward network was used. Beyond picture analysis and recognition, there are several applications, including image categorization, natural language processing, and health risk assessment. CNNs are helpful for estimating depth in autonomous vehicles. The various layers that make up CNN are listed below.

<u>Convolution Layer:</u>

In order to extract significant information from the image, a number of filters in this initial layer perform convolution. We compute the scalar product after applying a filter matrix with a specific size M*M to the picture to obtain the convolution matrix.

<u>Pooling Layer:</u>

Through downsampling, the pooling layer is used to scale down the image's magnitude. Furthermore, it helps to decrease processing power while accelerating system throughput.

<u>Fully Connected Layers:</u>

The input image is smoothed or compressed using FC, or fully connected layers, into a column vector. For each training iteration, the outputs of pooling layers are combined and backpropagation is used.

<u>Dropout:</u>

Dropout enhances performance by reducing overfitting through network simplification in machine learning models. During training, neurons are removed from the network.

<u>Activation Function:</u>

The term "transfer function" also refers to the activation function. This is due to the fact that by calculating the weighted total and adding its bias, we may decide which model information should and shouldn't be sent to the network's end.

IV. IMPLEMENTATION

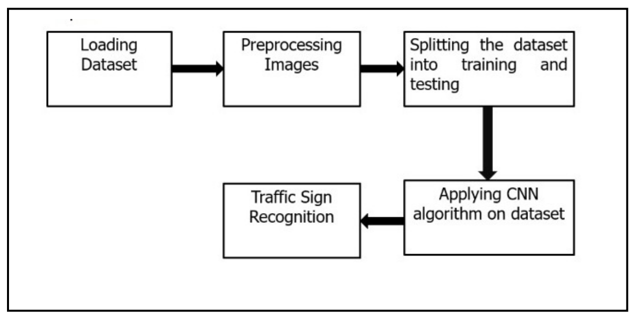

Fig 1: Proposed Model Flow

A. Process

The first step is to collect a meaningful and legitimate dataset which is then entirely explored and analyzed. The German Traffic Sign Recognition Benchmark dataset (GTSRB) is being loaded into the model. There are various traffic sign images present in the dataset. These images are passed as input to the model. The input image is then passed through various layers before it is classified. The images present in the dataset should be preprocessed before being passed to the model. Then, we will find the total number of classes present in the input dataset. The training folder contains name of labels or classes which are of total 43 ranging from 0 to 42 Here we create dictionary for different classes. For example, 0 for speed limit (20kmph), 1 for speed limit (30kmph) and so on for various traffic signs.

The dataset will be visualized in the following phase. The second phase will involve visualizing the dataset. It provides a graphic representation of the number of photos in each class. The outcomes are presented as a graph. For instance, the dangerous curve left graph in Figure 2 has approximately 200 photographs, which is a relatively low quantity, while the speed limit (50kmph) has a high number of images. The class of every subsequent image is shown in a manner similar to this. We will then begin gathering the training data. The first list is used to hold all of the images, while the second is used to store the labels for the images. Following that, the list is transformed into numPy arrays so the model can be fed. The dataset is divided into training and testing portions in the following stage, with training portions comprising 80% of the dataset and the rest for testing.

The CNN algorithm is then applied on the dataset and a model is built. It is fitted against training dataset. There are several layers in the CNN model that is built. The input images are first passed to the convolutional layer. In convolutional layer several filters are applied on an input image to extricate the features from the image. Further, the image is passed on to the Max pooling layer. By presenting an abstracted representation of the convolved features, the Max pooling layer helps reduce their spatial size and over-fitting. Overfitting occurs when a model is unable to generalise and instead fits too intricately to the training dataset. As a result, the model starts catching noise and inaccurate values, which reduce the efficiency and precision of the model. This is diminished using the max pooling layer. ReLU(Rectified Linear Unit) is an activation function that is being used in the model. It is a piecewise linear function that returns zero if it is negative, otherwise, it will return the input directly. Dense layer is for the feed-forward neural network and flatten layer is used to convert the parallel layers to compress the layers. Fully connected layers support in understanding non-linear variations of the convolutional layers high-level output characteristics. Here we select the output size based on our application. We use an activation function as softmax for multiclass classification at the last layer.

The model is finally validated against testing data for the ability to recognize traffic signs. As a result traffic sign recognition is achieved. The ultimate determined accuracy for the model is 98%. Therefore, we can conclude that the model is not overfit. To determine the model's accuracy, activities including reading the data, transforming it into an array, resizing and appending, rescaling, and testing are carried out on test data. We will check the model accuracy against actual labels.

B. Procedure for Implementation

- Libraries such as numPy, pandas, tensorflow, keras are imported into the proposed model.
- The Dataset is then read from the drive.
- Data is analyzed and a dictionary is created for different classes.
- Visualizing the dataset in the form of a graph.
- Collecting the training data.
- Splitting the data into training and testing sets.
- Building the CNN Model.
- Augmenting the data.
- Evaluating the model.
- Loading the test data and making predictions.
- The traffic signs are then classified and recognized.

V. RESULTS

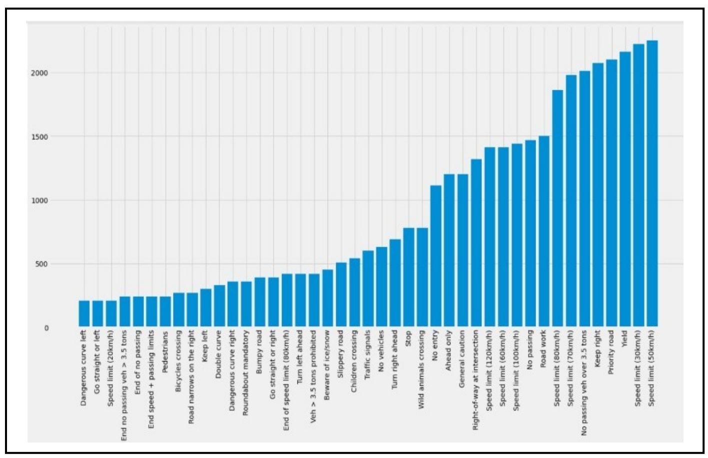

Fig 2: Dataset Visualization

The outcome of data visualization is displayed in Fig.2 as a graph. The total number of photos in each class may be observed in this graph.

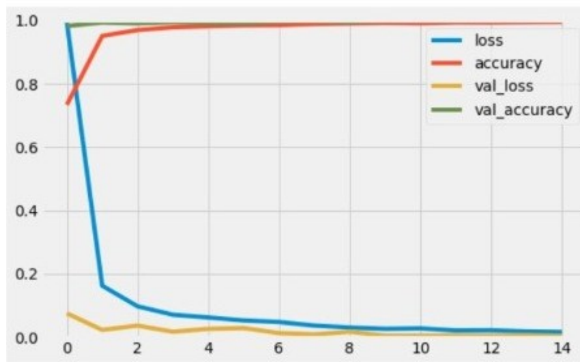

Fig 3: Evaluation of the model

The evaluation of the model is represented in form of a graph. In the fig 3, we can notice that the loss, validation loss is nearly to 0 and accuracy, validation accuracy is nearly 1 indicating accuracy for the model is 98%.

Fig 4: Result of the model

The output of the model is shown in fig. 4 . The result is positive if the actual and predicted values in any case are equal. Using a specific image as an example, the predicted value is also 16, whereas the actual value is also 16. Similarly other images are also determined.

VI. CONCLUSION AND FUTURE DEVELOPMENT

CNN is used as a paradigm for the suggested system. A sizable dataset known as the German Traffic Sign Recognition Benchmark is employed, which often includes more than fifty-thousand (50,000) images of various traffic signs. These images are preprocessed and classified using the model. In the end, the images are recognized, yielding a total accuracy of 98%. The proposed system is straightforward and performs classification precisely on the GTSRB dataset. Finally, the concept could also effectively capture the image and estimate them accurately. The advantages of the Traffic Sign classification and detection system are often geared toward driver comfort. There may be instances when the traffic signs are obscured or difficult to see. This can be risky because the driver won't be able to control how fast his vehicle is moving. This could result in accidents that put other drivers and pedestrians in danger, necessitating more study. All drivers who are operating a motor vehicle on the road can benefit from traffic signs. Traffic signs direct motorists to obey all traffic laws and not obstruct pedestrians in any way. Environmental restrictions such as luminance, projection, proximity (sign is much farther away), smog, and weather conditions, as well as blurriness and vehicle acoustic noise, which are likely in any real-time system, may impair detection and, subsequently, categorization. As a result, more studies and scientific advancements are needed to address these issues.

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