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TRAFFIC SIGN RECOGNITION USING CNN FORDRIVERLESS CARS

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ABSTRACT

Road signs are essential for ensuring a safe and smooth flow of traffic. Negligence in viewing traffic signs and incorrectly interpreting them is a major cause of road accidents. The proposed system is trained using a Convolutional Neural Network (CNN), which aids in the recognition and classification of traffic signs. To improve accuracy, a set of classes is defined and trained on a specific dataset. The German Traffic Sign Benchmarks Dataset, which contains approximately 43 categories and 50,000 traffic sign images, was used. The accuracy of the execution is about 98.52 percent. Following the detection of the sign by the system. The proposed system also contains a section where the vehicle driver is alerted about the traffic signs in the near proximity which helps them to be aware of what rules to follow on the route. The aim of this system is to ensure the safety of the vehicle's driver, passengers, and pedestrians.

Keywords: Convolutional Neural Network, GTSRB Dataset, Object Detection.

I. INTRODUCTION

There have been many technological advancements, and cars with auto-pilot modes have become available. Autonomous vehicles have become a reality. The self-driving car industry has experienced a surge. However, these features are only available in high-end vehicles that are not affordable to the general public. We wanted to create a system that would help to ease the burden of driving.

We discovered that the magnitude of road accidents in India is alarming after conducting a survey. According to reports, approximately 53 accidents occur on the roads every hour. Furthermore, more than 16 people are killed every hour as a result of these mishaps [18]. When someone fails to obey traffic signs while driving, they endanger their own life as well as the lives of other drivers, passengers, and those on the road. As a result, we developed this system in which traffic signs are automatically detected using the live video stream and read aloud to the driver, who can then make the necessary decision. Another area of emphasis in our system is determining the location of the user using GPS. In addition, all traffic signs and their locations will be saved in a database so that drivers can be notified in advance. in relation to the next approaching Traffic Sign.

The following is a breakdown of the structure of the paper: Section II summarizes the literature review, Section III describes the technique and how the models work, and Section IV presents the Results and Analysis. Section V contains the paper's conclusion, while Section VI contains theFuture Scope.

II. LITERATURE SURVEY

In this era of a fast-paced life, people generally tend to miss out on recognizing the traffic sign and hence break the rules. A lot of research has been done in this domain in order to reduce the number of accidents. Researchers have used a variety of classification algorithms and a number of CNN architectures to classify the traffic signs and alert the driver. Our system aims to optimize the process of recognition and atthe same time provide other benefits such as early alert to the driver.

Numerous studies have used a variety of techniques to detect traffic signs. [1] The Support Vector Machine technique is used in one of the processes. The dataset was divided into 90/10 for training and testing, and linear classification was used. A series of phases called Color Segmentation, Shape Classification, and Recognition were used to achieve the desired result..

The Raspberry Pi is used to detect and recognise traffic signs with very little coding [2]. However, it requires the Raspberry Pi board for implementation, which is quite expensive.

Image recognition is required for traffic sign recognition [3]. A video is acquired and divided into frames. Image preprocessing is performed, which includes foreground and background separation, thinning, and contrast enhancement. Following these operations, the signs are classified as hexagonal, triangular, or circular in shape and transmitted for template matching. The pretrained algorithm matches the objects with a specific shape.

Caffe, an open source system, that helps to detect and recognise road traffic signs with high accuracy and efficiency[4]. A CNN approach is proposed for training trafficsign training sets and obtaining a model that can categorise

Signs of traffic Another method for using the CNN scheme is proposed in [11], in which the actual border of the goal sign is estimated by projecting the boundary of a corresponding template sign image into the input picture plane. When we transform the boundary estimation problem into a pose and shape prediction job based on CNN, the method advances to become end-to-end trainable. It is less susceptible to occlusion and has narrower objectives than other boundary estimating techniques that focus on contour estimation or image segmentation.

Proposes a multi-resolution feature fusion network architecture for sign detection that aids in the separation of alarge number of small objects from sign boards. A vertical spatial sequence attention (VSSA) module can also be used to collect additional context information for better detection. Augmented Reality technology is integrated into mobile apps using GPS-based tracking [5]. It employs the coordinates of a user's smartphone as a pointer to assist people in dynamically and simply locating possible resources in the immediate vicinity based on the user's camera view.

The AlexNet structure of CNN is used in [7], and the architecture has eight layers. The first five layers are convolutional, while the last three are all connected. This architecture's accuracy is calculated to be 92.63 percent. In addition, the GoogleNet architecture is implemented in [7], which aids in working with large amounts of data and a large number of parameters. However, the large amount of data causes network overfitting, lowering the accuracy to 80.5 percent. VGG CNN is proposed in [8] and has significantly better performance than other available architectures. In order to optimise and speed up the calculation, the number of parameters in this approach is significantly reduced. The BN is also part of the network (batch normalisation) and GAP (global average pooling)layers, which help to improve accuracy without adding more parameters. However, we discovered in [10] that by deleting the pool4 layer of VGG16 and using dilation for ResNet, we can combine the improved Faster-RCNN architecture with Online Hard Examples Mining (OHEM), making the system more resilient and assisting in the detection of minor traffic signs.

Chuanwei Zhang et al. [9] proposed an improved Lenet-5 network-based traffic sign recognition method. The Lenet-5 CNN model is used in this method, which allows for overall network improvements. In terms of accuracy and real-time performance, the improved Lenet-5 classifier outperforms the convolutional neural network and the classic Gabor and SVM classifiers.

[12] propose a CNN-based traffic sign identification system To predict category codes, they used CNN as a feature extractor and MPPs as an effective classifier. Using MPPs greatly improved recognition precision.

We find a gist of all of the above papers in as it presents a mini-batch proposal selection mechanism in conjunction with a deep hierarchical architecture that allows the neural network to detect both traffic signs and traffic lights by training them on separate datasets. The method addresses the issue of instances from one dataset not being labelled in the other. The system adds a new dimension to our project by suggesting traffic sign localization for driver assistance [15]. The location of the traffic sign can be determined with a one-metre precision. A single colour camera and a high precision GNSS (global navigation satellite systems) receiver were used. Another application of GPS, as suggested in [16], is determining driving style, in which GPS data is collected from a person's mobile phone while also detecting Traffic Signs in the vicinity. It aids in categorising driving styles as safe or aggressive.

III. METHODOLOGY

A. Dataset

The German Traffic Sign Benchmarks (GTSRB) Dataset is used in the proposed system. Figure 1 depicts the 43 different traffic signs used to train the model. It has 50,000 single images spread across 43 classes, including the training and test datasets. Figure 2 depicts the number of photos taken in each class. There is no ambiguity

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because the images are solely focused on the traffic signs, each of which is distinct. Each of the present classes has its own folder in the training dataset. A CSV file is also included, which contains the path to each image, its class, and other information such as width and height.

Fig. 1. Traffic Signs Taken into consideration

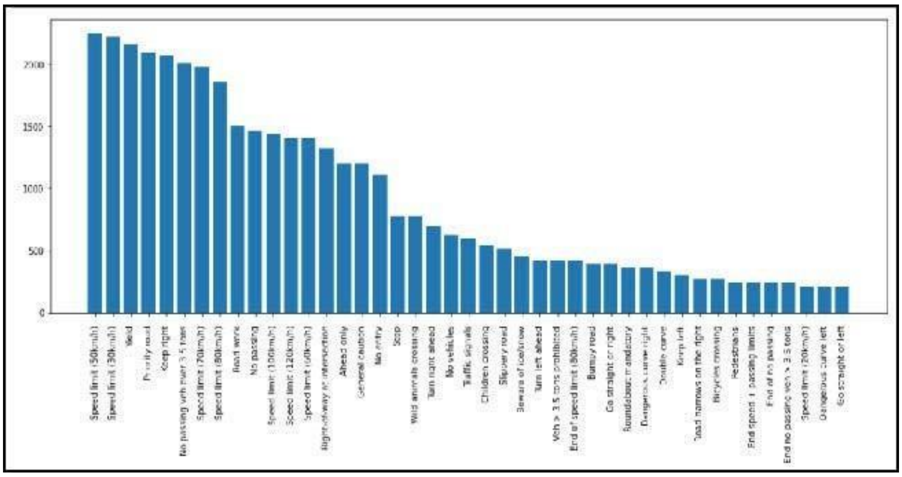

Fig. 2. Number of images per class in the dataset

B. Data Preprocessing

Images must be converted into numpy arrays before they can be processed (i.e. numeric values). The images are resized to 30*30 pixels after they are loaded. Following this, the image's labels are mapped to the image, and the dataset is ready to betrained..

C. Model

The Convolutional Neural Network (CNN) algorithm is a Deep Learning algorithm. CNN can take a picture as input and prioritise different items in the image. picture, and tell them apart from one another It requires far less preprocessing than other classification algorithms. Convolutional Networks are capable of learning. filters or characteristics in the images as opposed to the primitive methods filters where they are done manually.

A Convolutional Network's architecture can be compared to the connectivity pattern of neurons in the human brain. The design was inspired by the organisation of neurons found in the human brain's Visual Cortex. The neurons only respond to stimuli in a specific region of the field of view known as the Receptive Field. The visual area is a collection of such receptive fields that assist us in viewing objects. Once trained over a number of epochs, or iterations, the model gains the ability to distinguish between dominant features and specific low-level features in images. The model uses the Softmax Classification technique to classify them based on this training.

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The number of layers in the model is depicted in Fig. 3. There are four convolution layers, two max pooling layers, dropout, flatten, and dense layers. The neural network employs the Adam optimizer. The image's input size is 30*30*1. The ReLU activation function is used in the model. Following the Flatten layer, we have a fully connected layer. Finally, the output is calculated using the softmax activation function.

D. Proposed Solution

Fig. 4 demonstrates the accuracy of the trained network. This model turned out to give the best accuracy as comparedto the other models that we analysed.

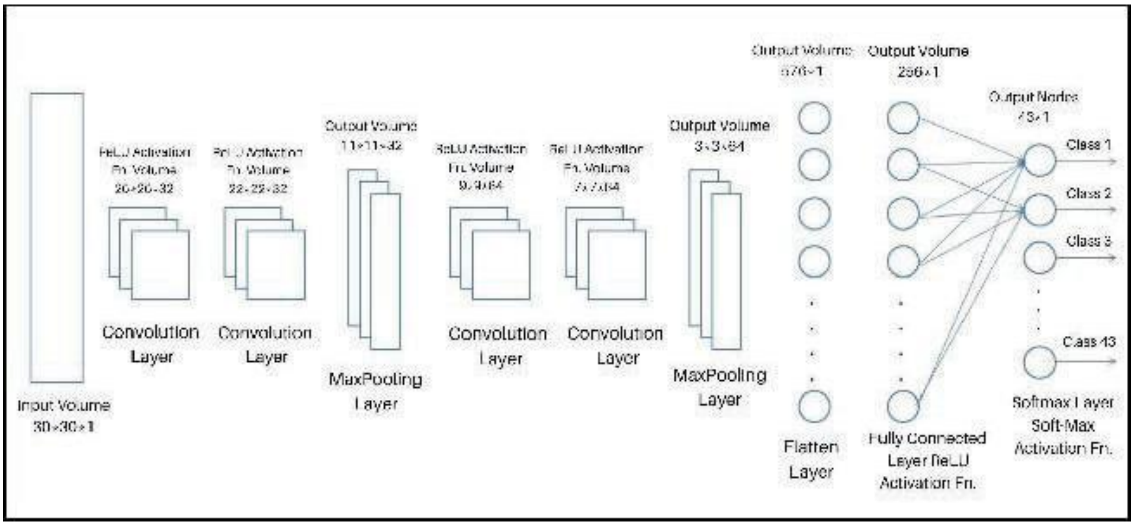

Fig. 3. Neural Network Representation

```
Epoch 18/20
981/981 [==============================] - 135s 137ms/step - loss: 0.1820 - accuracy: 0.9542
 - val_loss: 0.0652 - val_accuracy: 0.9838
Epoch 19/20
981/981 [==============================] - 105s 107ms/step - loss: 0.1819 - accuracy: 0.9558
 - val_loss: 0.1869 - val_accuracy: 0.9484
Epoch 20/20
981/981 [==============================] - 104s 106ms/step - loss: 0.1947 - accuracy: 0.9530
 - val_loss: 0.0573 - val_accuracy: 0.9852
```

Fig. 4. Accuracy of the model on running for 20 epochs

E. Implementation

The model is saved after training, and the saved model is used for prediction. This model was used to predict a full stack web application built with NodeJs and Express Handlebars. It incorporates various logics to create a product that can be used with certain improvements. The Flow is depicted in Fig. 5. This diagram depicts the proposed system.

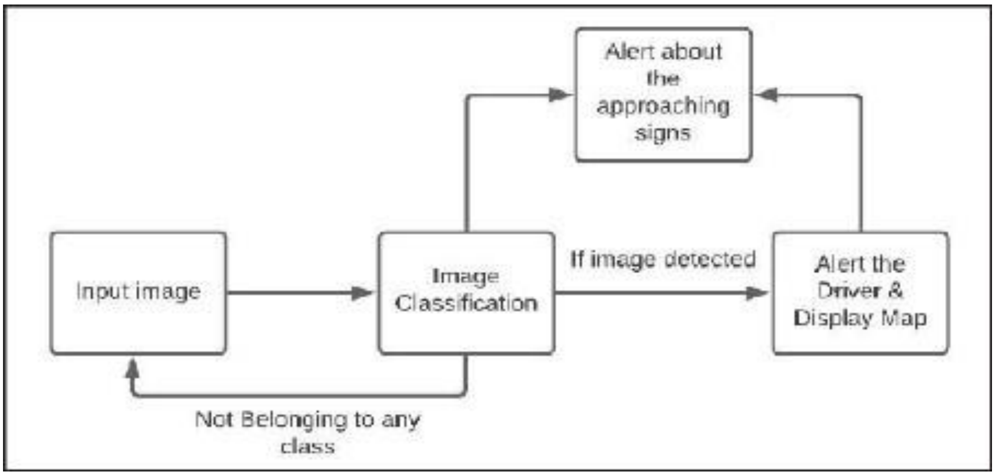

Fig. 5. Flow Diagram

In the first part, where the input is an image, the CNN model is used. As a result of the processing, one of the 43 classes is obtained as the output. If a particular image does not contain a traffic sign, the user is prompted with "No Sign Detected." This is accomplished by analysing the Python's "model.predict" function returns an array. The "model.predict" function returns an array of values indicating how closely the image matches each of the 43 classes, and then predicts the class based on the highest Value.

After several iterations, it was discovered that even if an image does not fall into any of the given classes, the model, despite not having been trained for an additional class, classifies it into one of the 43 classes, but the value predicted by the "model.predict" function is quite low. As a result, 0.68 is chosen as the threshold value for distinguishing images that do not contain a traffic sign but are predicted to contain one.

The classes in "model.predict" have values ranging from 0 to 1, so if the model classifies it in a specific class with a value less than 0.68, it will be identified as none of theabove, otherwise it will be assigned a class.

Once the image has been classified, the meta data from the image is extracted using "exif-parser," and the sign text and GPS coordinates are saved in the database.

All this data is then available to the user in a map. The map has markers containing the latitude and longitude along with the name of the traffic sign. Another important feature that needs to be highlighted here is that the aim of the proposed system is to alert the drivers. Therefore, rather than just alerting about the sign which the car is approaching i.e. the sign which has been detected, an algorithm in which the traffic signs that are in proximity i.e. the ones that will be approached within the next 5 minutes (or 1 km) are also to be alerted to the driver, is implemented. The computation of this is done by taking into account the locations of the signs which was stored by extracting themetadata.

Fig. 6 is a sample test case given to the model and Fig.7 represents the predicted output which will be voiced out to the driver. It also contains a map depicting the location of the various traffic signs in the database

Fig. 6. No Entry Sign (Input)

IV. RESULTS AND ANALYSIS

The trained neural network, which includes four convolution layers and two max pooling layers, as well as dropout, flatten, and dense layers, outperformed the other CNN Architectures used in AlexNet, GoogleNet, VSSANet, VGGNet. As mentioned in Table 1, the accuracy ofthe trainednetwork is 98.52%.

Table 1. Accuracy Of Various Models Available

Method	Accuracy
AlexNet	92.63%
GoogleNet	80.5%
VSSANet	94.42%
VGGNet	98.03%
Trained Neural Network	98.52%

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V. CONCLUSION

Convolutional Neural Network is used to implement theTraffic Sign Board Detection. Several CNN models were investigated, and the one with the highest accuracy on the GTSRB dataset was implemented. The addition of different classes for each traffic sign has aided in the model's accuracy. After recognising the sign, a voice message is sent to alert the driver. A map is displayed on which the signs in the driver's vicinity are displayed, assisting him or her in making appropriate decisions. This paper representsa significant advancement in the field of driving because it would make the driver's job easier without sacrificing safety. . Also this system can easily be implemented withoutthe need of much hardware thusincreasing its reach.

VI. FUTURE SCOPE

The prototype can be expanded to include an inbuilt alert system with a camera in the centre of the vehicle. Additionally, the feature of obtaining an estimated time for reaching that specific traffic sign can be added. This system can also be expanded to identify traffic signals and thus notify the user of the time required to reach that particular signal as well as its status. The user can thus plan their trip start time accordingly and cross all signals without having to wait. Driver verification will also be performed with the assistance of an API that provides information about the licence holder and the licence number.

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