Road Sign Detector And Driver Alert System

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Abstract- Road traffic has been the major issue that most cities are facing these days. People neglect the importance of traffic signs which could prove deadly. Currently, the maps services assist us about some details of navigation, but it fails to provide essential information such as “U-turns, prohibited roads, speed-limits, speed breakers and diversions etc.”, which are generally present on the signboards. These are of utmost importance for road safety but the drivers often miss out on them. There is urgent need for a mechanism which would be able to detect these signs and alert the drivers. So, an expert system based on Convolutional Neural Network, will detect & recognize the signboards in real time. Traffic Sign Classification is used to detect and classify traffic signs.

Keywords: Convolutional Neural Network (CNN), Traffic Sign Classification.

I.INTRODUCTION

Since Karl Benz's development of the automobile in 1885, traffic signs have been used for hundreds of years. King Peter II passed what is believed to be the first traffic regulating law in all of Europe. The statute controls where priority signs—which show which vehicles should yield—are placed in Lisbon. By 1900, the International League of Touring Organizations Congress in Paris was debating plans to standardise road signs.

In 1903, the British government introduced four "national" signs based on shape. In 1909, nine European governments agreed to use four visual symbols to denote "bump," "curve," and "intersection." At the first Paris convention, the shapes of traffic signs were established, with warning signs having a triangular design, regulatory signs having a circular design, and guide or instructional signs having a rectangular design. Between 1926 and 1949, there was extensive work on international road signs, which eventually led to the creation of the European road sign system. The United States and Great Britain both had their own systems for directing traffic. In 1964, the UK adopted a variant of the European road signs, and in recent years, North American signage has begun to incorporate some symbols and visuals in addition to English. Most signs have been made of sheet aluminium since 1945, with retroreflective plastic coatings for visibility at night and in poor light conditions. Before the invention of reflective plastics, the letters and symbols' reflectivity was provided by glass reflectors embedded in the signs. Additionally, previous research had looked into the relationship between traffic accidents and roadside signage.

Obstructions such as trees, parked cars and other objects placed in front of or next to traffic signs can block their visibility. Also, inclement weather like dense fog, rain, or snow can reduce visibility of the sign which can make them less effective or even invisible to drivers. Drivers often encounter this issue, and city officials rely on drivers to report any obstruction of traffic signs to them so that they can resolve the issue.

II. LITERATURE SURVEY

Author & Year	Adopted Scheme	Features	Challenges
Md Tarequl Islam (2020)	Two Convolutional Neural Network using Classifier.	HSV Color space is used, RGB to HSV conversation, Moderate to high accuracy.	Ability to label the signs, manually clicked pictures & online downloaded. Classifier Challenges.
V.KOKILA, Mr. N.VASUDEVAN(2020)	(ADS) auto driving frameworks. Sign based strategies, Shape-based techniques.	Advanced machine learning Classification. Image pre-processing methods.	Image quality, Non-informational Pixel, Unwanted picture edges.
Chai K. Toh (2018)	Wireless digital traffic signs	Wireless Transmission of traffic signs Reduce complex image recognition	Positioning of Traffic Signs Cost of Installation is high
Ying Sun (2019)	Convolutional Neural Network	Better Image recognition Minimal Error	Need Consideration on climatic factors.
Arturo de la Escalera(1997)	Image processing, Neural networks, traffic signs recognition Using Neural Network Model, Keras.	Accuracy of image recognition.	The highly probable sign regions are extracted. The most preferred are "pure" colors for better visibility.

Fig. 1: Literature Review

III. PROPOSED SOLUTION

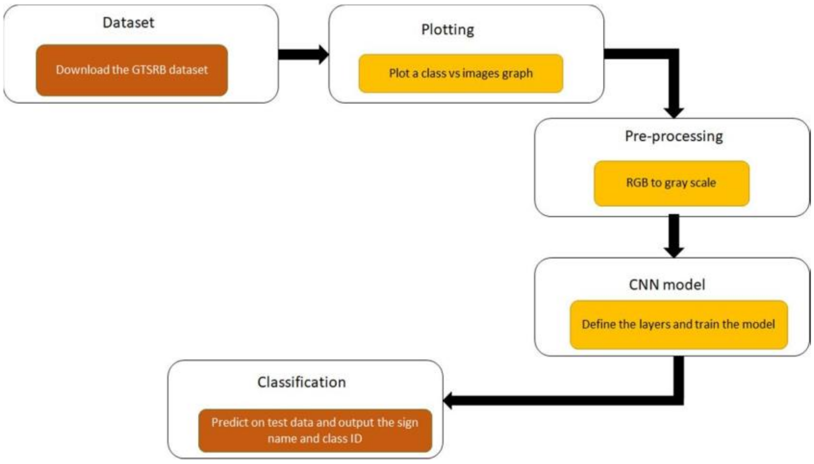

Fig.2: Flowchart of the proposed system

IV. METHADOLOGY

A. Dataset

The presence of a generalised dataset is crucial before moving on to the detection or classification.

The GTSRB (German Traffic Sign Recognition Benchmark) dataset is the most popular of them.

• There are numerous images in it.

• The variety, backdrop, and colour variation of the traffic signs will aid in the model's performance accuracy.

For this project, we are using the public dataset available at Kaggle:

Traffic sign Dataset

The dataset contains more than 50,000 images of different traffic signs. It is further classified into 43 different classes the dataset is quiet varying, some of the classes have many images while some classes have few images. The size of the dataset is around 300MB. The dataset has a train folder which contains images inside each class and a test folder which we will use for testing our model.

B. Road sign detector

During the detection phase, the main goal is to identify and locate the relevant parts of the image for further analysis. The colour and shape of traffic signs are important factors for identification, as each sign has a unique colour and shape. This project will focus on detecting traffic signs by using both colour and shape information.

C. Road sign classifier

A Convolutional Neural Network (CNN) is a type of deep learning neural network that is commonly used in image and video processing tasks, such as object recognition, image classification, and object detection. CNNs are designed to process data with a grid-like topology, such as an image. They consist of multiple layers of artificial neurons that are designed to extract features from the input data and pass them on to the next layer. The layers of a CNN include convolutional layers, pooling layers, and fully connected layers. The convolutional layers are responsible for learning spatial hierarchies of features from the input image through a process called convolution. The pooling layers are used to reduce the dimensionality of the feature maps, while the fully connected layers are used to classify the objects in the image.

Convolutional Neural Networks (CNNs) are widely used in traffic sign recognition due to their ability to effectively extract features from images. In a traffic sign recognition system, a CNN is used to process images of traffic signs and classify them into different categories, such as stop signs, speed limit signs, and yield signs.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 26, 26, 32)	2432
conv2d_3 (Conv2D)	(None, 22, 22, 32)	25632
max_pooling2d_2 (MaxPooling2D)	(None, 11, 11, 32)	0
dropout (Dropout)	(None, 11, 11, 32)	0
conv2d_4 (Conv2D)	(None, 9, 9, 64)	18496
conv2d_5 (Conv2D)	(None, 7, 7, 64)	36928
max_pooling2d_3 (MaxPooling2D)	(None, 3, 3, 64)	0
dropout_1 (Dropout)	(None, 3, 3, 64)	0
flatten_1 (Flatten)	(None, 576)	0
dense_2 (Dense)	(None, 256)	147712
dropout_2 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 43)	11051

Total params: 242,251
Trainable params: 242,251
Non-trainable params: 0

Fig. 3: CNN model layers Representation

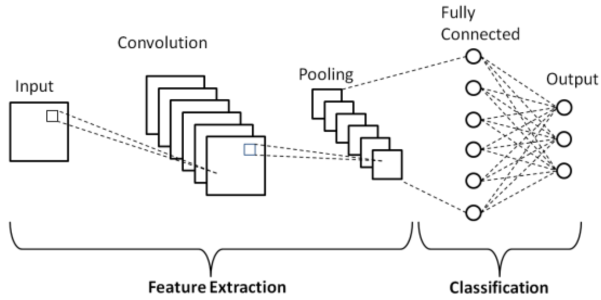

Fig. 4: Schematic diagram of a basic convolutional neural network (CNN) architecture.

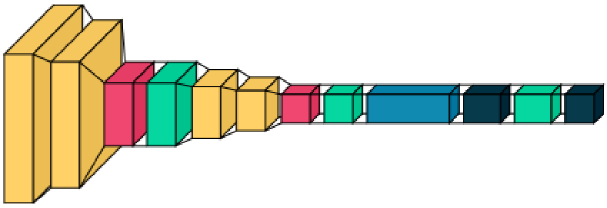

Fig. 5: Visualization CNN model with its layers

The CNN model used in traffic sign recognition typically consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers are responsible for learning spatial hierarchies of features from the input image, such as edges, corners, and shapes. The pooling layers are used to reduce the dimensionality of the feature maps and extract the most important features from the image. The fully connected layers are used to classify the objects in the image.

Additionally, CNNs can also be trained to detect traffic signs within an image, using object detection techniques such as YOLO, Faster R-CNN, or RetinaNet. These object detection models are able to detect and classify traffic signs within an image, by using a combination of CNN and a region proposal network (RPN) which can detect the location of the traffic signs.

Overall, CNNs are able to effectively extract features from images and classify traffic signs with high accuracy, making them a popular choice for traffic sign recognition systems.

Below is the accuracy and loss graph:

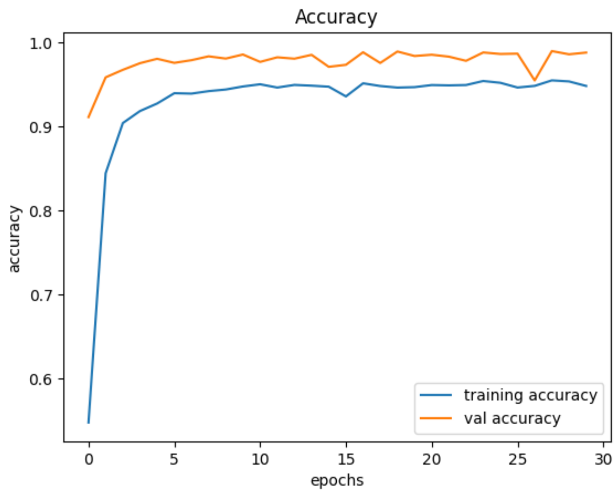

Fig. 6: Accuracy

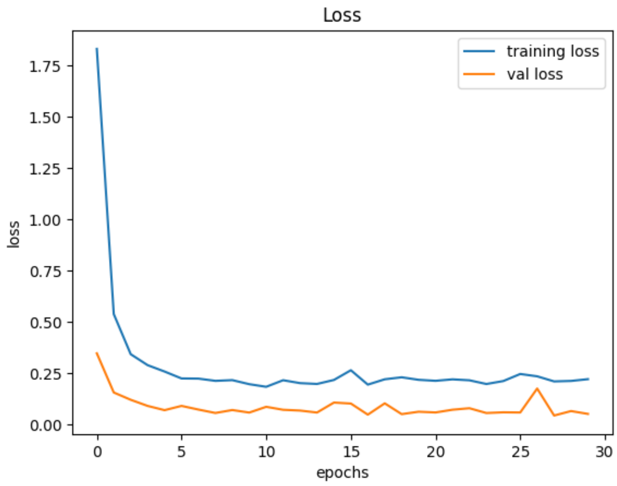

Fig. 7: Loss

```
# Score
score = model.evaluate(X_test, y_test, verbose=0)
print('Test Loss', score[0]*100)
print('Test accuracy', score[1]*100)
```

✓ 8.1s

```
Test Loss 4.988387227058411
Test accuracy 98.81407618522644
```

Fig. 8: Test loss And Accuracy Score

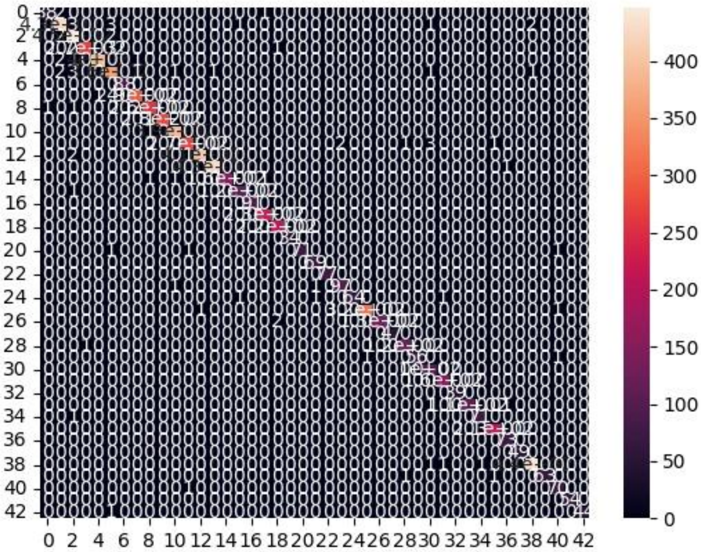

Fig. 9: Confusion Matrix for testing data

D. Data Visualization:

According to testing data visualization of our testing data shown below:

Fig. 10: Testing data visualization(images)

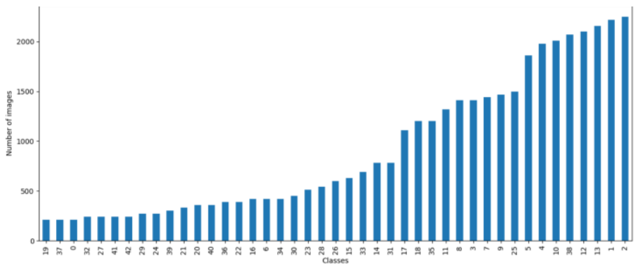

Fig. 11: Data Visualization

E. ADAM Algorithm

Each algorithm must either develop from another algorithm or fill in some gaps left by another; they do not all appear out of thin air. Adam is also affected by this. In general, the optimization techniques progress through:

Adaptive gradient follows from vanilla gradient descent, sgd, and momentum.

Adam sort of combines the benefits of several algorithms into one, where SGD adds randomness to gradient descent, momentum quickens convergence, and adaptive gradient, as its name suggests, adapts to varied learning rates for different parameters.

$$v_t = \beta_1 v_{t-1} + (1 - \beta_1) g_t$$

$$s_t = \beta_2 s_{t-1} + (1 - \beta_2) g_t^2$$

The creators of the Adam optimizer point out that because the variables v and s are initially set as vectors of zeroes, they can be skewed in that direction, particularly during early time steps and when the decay rates are low. To correct for these biases, first and second moment estimates are calculated that take into account these issues.

$$v_t' = \frac{v_t}{1 - \beta_1^t}$$
$$s_t' = \frac{s_t}{1 - \beta_2^t}$$

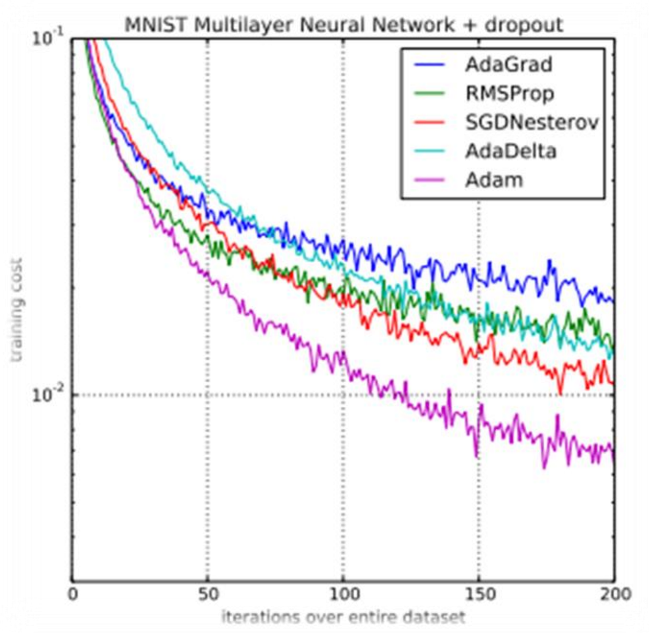

Fig. 12: Comparison of Adam algorithm to Other Optimization Algorithms

The final formula would be:

$$g'_t = \frac{lr * v'_t}{\sqrt{s'_t} + \epsilon}$$

$$\theta_t = \theta_{t-1} - g'_t$$

The final update process in Adam, with the exception of the gradient in the numerator being replaced by v, is actually similar to the formula used in adaptive gradient descent. It is clear that Adam incorporates ideas from its predecessors and improves upon them to become a more advanced optimization technique.

V. RESULTS

The trained CNN's test results reveal that the model is 98.81% accurate at identifying and detecting traffic signs. The experimental finding demonstrates the Cnn model's strong recognition accuracy for detecting and identifying road signs.

Fig. 13: Uploading the Images of Traffic Signs

Fig. 14: Prediction and Sign Recognition

VI. CONCLUSION

This project presents a method for recognizing traffic signs using deep learning. This approach is efficient in identifying and recognizing traffic signs by utilizing image pre-processing, road sign detection, and classifying. Results of the testing show that the accuracy of this method is 98.81%.

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