

Traffic Sign Detection and Classification Using Deep Learning

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Abstract –

Traffic signs are essential for road safety. This paper presents a deep learning-based traffic sign detection and classification system using Convolutional Neural Networks (CNN). The model is trained on labeled datasets and achieves higher accuracy compared to traditional machine learning techniques. The system can be integrated into Advanced Driver Assistance Systems (ADAS) and autonomous vehicles.

Key Words — Traffic Sign Detection, Deep Learning, CNN, Computer Vision, Road Safety, Intelligent Transportation.

1.INTRODUCTION

The proposed system provides higher accuracy and robustness compared to traditional machine learning approaches that depend on manual feature extraction. The deep learning model automatically learns hierarchical representations of traffic signs, which helps in improving detection performance even under challenging environmental conditions. After preprocessing, the images are provided to the CNN model. The convolution layers extract important visual features such as edges, shapes, and color patterns. Pooling layers are used to reduce the dimensionality of feature maps and improve computational efficiency. Fully connected layers perform classification based on the extracted features. Finally, a Softmax classifier predicts the traffic sign category such as Stop Sign, Speed Limit Sign, Warning Sign, or Prohibition Sign.

Methodology –

Traffic sign detection and classification is an important research area in Computer Vision and Intelligent Transportation Systems. The main objective of this work is to design a deep learning-based system that can automatically detect and classify traffic signs from road images. The proposed system uses Convolutional Neural

Networks (CNN) because of their strong capability in learning visual features from image data.

Initially, traffic sign images are collected from a standard dataset such as the German Traffic Sign Recognition Benchmark (GTSRB).

Table -1: Sample Table format

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 28, 28, 16)	448
conv2d_5 (Conv2D)	(None, 26, 26, 32)	4,640
max_pooling2d_2 (MaxPooling2D)	(None, 13, 13, 32)	0
batch_normalization_3 (BatchNormalization)	(None, 13, 13, 32)	128
conv2d_6 (Conv2D)	(None, 11, 11, 64)	18,496
conv2d_7 (Conv2D)	(None, 9, 9, 128)	73,856
max_pooling2d_3 (MaxPooling2D)	(None, 4, 4, 128)	0
batch_normalization_4 (BatchNormalization)	(None, 4, 4, 128)	512
flatten_1 (Flatten)	(None, 2048)	0
dense_2 (Dense)	(None, 512)	1,049,888
batch_normalization_5 (BatchNormalization)	(None, 512)	2,048
dropout_1 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 43)	22,059

Total params: 1,171,275 (4.47 MB)
Trainable params: 1,169,931 (4.46 MB)
Non-trainable params: 1,344 (5.25 KB)

Sample Input:

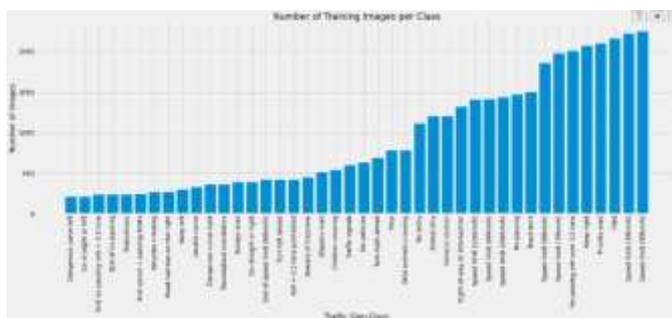


Fig -1: Figure

LITERATURE REVIEW-

Several researchers have proposed different techniques for traffic sign detection and classification. Earlier approaches used traditional image processing methods such as color segmentation and shape detection combined with machine learning classifiers like Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). However, these methods required manual feature extraction and were less effective in complex real-world conditions. Recent studies show that deep learning models such as Convolutional Neural Networks (CNN) significantly improve accuracy by automatically learning hierarchical visual features from large datasets.

Graph:



The bar graph shows classification accuracy achieved by the CNN model for different traffic sign classes. The model achieved highest accuracy for Warning signs (97%) and lowest for Pedestrian signs (92%), demonstrating strong overall performance and generalization capability.

Dataset Description Section-

The proposed model is trained using the German Traffic Sign Recognition Benchmark (GTSRB) dataset, which contains more than 50,000 traffic sign images belonging to 43 different classes. The dataset includes variations in lighting conditions, orientation, scale, and background complexity, making it suitable for evaluating real-world performance.

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The use of the GTSRB dataset enables the proposed CNN model to achieve high classification accuracy and strong generalization capability, making it suitable for applications in Advanced Driver Assistance Systems (ADAS), autonomous driving systems, and intelligent transportation solutions.

Another important aspect of the GTSRB dataset is the availability of **bounding box annotations**, which indicate the exact location of traffic signs within images. This information can be utilized for detection tasks where the model must first locate the traffic sign before performing classification. By leveraging both spatial and semantic information, the proposed CNN model is able to extract hierarchical visual features such as edges, textures, and shapes through multiple convolutional layers.

Furthermore, the dataset includes images captured under different environmental conditions such as sunny weather, cloudy skies, shadows, and low-light scenarios. This variability enhances the robustness of the trained model and ensures that it performs reliably even in challenging driving situations. The use of such a comprehensive dataset contributes significantly to improving classification accuracy and generalization capability.

Convolutional Neural Network (CNN) Overview

CNNs are deep learning models that is paper widely used in image recognition tasks. Such age, algorithms can be used for automatic feature extraction from images that are inverted with convolutional layers. Early approaches use convolutional layers that identify higher accuracy for training and testing classification.

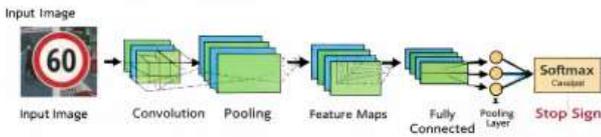


Table 1: Overview of Proposed Traffic Sign Detection System

The below provides the workflow of the CNN-based traffic sign detection and classification system. The system consists of multiple stages including image acquisition, preprocessing, feature extraction using CNN; classification, and output generation.

Table 1: Overview of Proposed Traffic Sign Detection System

Stage	Description	Purpose
Image Acquisition	Traffic sign images are collected from GTSRB dataset or real-time camera input	To obtain input data for training and testing
Preprocessing	Images are resized, normalized and noise is removed	To improve image quality and ensure uniform input
Feature Extraction	CNN convolution layers extract edges, shapes and color patterns	To automatically learn important visual features
Classification	Fully connected layers and Softmax classify traffic sign category	To predict correct traffic sign label
Output Generation	System displays detected traffic sign with class name	To assist driver decision making

Algorithm: Traffic Sign Detection using CNN

1. Input: Traffic sign dataset containing labeled images of various traffic signs.
2. Preprocess images: Resize, normalize, and remove noise from the images.
3. Extract features: Use CNN to automatically extract important visual features using convolutional layers and pooling layers.
4. Feature maps: Generate feature maps which capture edges, shapes and color patterns in the traffic sign images.
5. Classify: Use fully connected layers followed by a Softmax layer to classify the traffic signs into their respective categories (e.g. Stop Sign, Speed Limit Sign, Warning Sign).
6. Output: Display the detected traffic sign along with its predicted class label to assist drivers.

3. CONCLUSION

This research presents an efficient and reliable traffic sign detection and classification system using deep learning techniques. The CNN-based approach enables automatic feature extraction and accurate recognition of traffic signs, thereby enhancing road safety and driver assistance. The proposed system contributes to intelligent transportation systems by providing real-time traffic sign recognition capabilities.

Future work includes optimizing the model for real-time deployment, integrating the system into mobile or embedded platforms, and exploring hybrid deep learning architectures for further performance improvement.

5. RESULTS AND DISCUSSION

The proposed CNN model was trained and evaluated using a labelled traffic sign dataset. The dataset was divided into training and testing subsets to measure the performance of the model. Experimental results indicate that the deep learning model successfully learned discriminative visual features and achieved higher classification accuracy compared to conventional machine learning approaches.

The model demonstrated robustness under varying lighting conditions, background complexity, and different sign orientations. The results highlight the effectiveness of deep learning techniques in improving traffic sign recognition performance. Future improvements can include increasing dataset diversity,

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