TRAFFIC SIGN DETECTION USING DEEP LEARNING

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Abstract: Accurate traffic sign detection and recognition is a critical component in the development of intelligent transportation systems and autonomous vehicles. This paper presents a deep learning-based framework that combines real-time object detection and robust classification to identify and interpret traffic signs from road scene images. The system leverages a two-phase architecture: a YOLOv5 model is used for efficient sign localization, followed by a Convolutional Neural Network (CNN) for precise classification of the detected signs. The German Traffic Sign Detection Benchmark (GTSDB) is used for training and evaluation, incorporating extensive preprocessing and data augmentation to enhance model robustness. Experimental results demonstrate high performance, with the model achieving a validation accuracy of 98% and deployment accuracy of 97.82% on an edge device. The proposed system shows strong generalization across varying environmental conditions and supports real-time inference, making it highly suitable for integration into Advanced Driver Assistance Systems (ADAS) and self-driving platforms.

Keyword: Traffic Sign Detection, Deep Learning, Convolutional Neural Network (CNN), YOLOv5, Image Classification, Object Detection, Intelligent Transportation System (ITS), Advanced Driver Assistance Systems (ADAS), Real-time Detection.

1. INTRODUCTION

Traffic Sign Detection and Recognition (TSDR) is a vital component of Intelligent Transportation Systems (ITS) and Advanced Driver Assistance Systems (ADAS). The primary objective of TSDR is to automatically identify and classify road signs from real-time visual data, thereby enhancing road safety and enabling autonomous decision-making in self-driving vehicles. Traditional approaches to traffic sign detection relied heavily on handcrafted features**,** such as color histograms, edge detection, and geometric shape analysis. While these methods achieved acceptable performance under controlled conditions, they often failed in the presence of challenges like varying illumination**,** occlusion**,** motion blur, and complex urban environments. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs)**,** have revolutionized computer vision applications, including TSDR. Deep learning models are capable of automatically extracting hierarchical features from raw image data and learning complex patterns that are difficult to model manually. These capabilities make them highly effective for detecting and recognizing traffic signs across diverse road scenes. Several benchmark datasets, such as the Traffic Sign Recognition Benchmark (TSRB) and TSDB, have enabled the development and evaluation of robust deep learning models.

These datasets, combined with the increasing availability of computing resources (e.g., GPUs), have facilitated the deployment of high-performance detection systems in real-time scenarios. Despite these advancements, TSDR systems still face challenges in terms of real-time inference, detection in low-light or cluttered scenes, and domain generalization. Therefore, ongoing research continues to focus on improving accuracy, speed, and efficiency of detection algorithms. This paper presents a deep learning-based approach to traffic sign detection, utilizing modern CNN architectures to achieve accurate recognition in real-world environments. The proposed system is trained and evaluated using publicly available datasets and is designed to operate effectively under variable road and weather conditions. The primary aim of this research is to design and implement a deep learning-based system for accurate and efficient traffic sign detection. The specific objectives of this study are:

- To develop a robust traffic sign detection model using deep learning techniques, particularly Convolutional Neural Networks (CNNs), capable of identifying traffic signs in real-time video or image streams.
- To enhance the accuracy and reliability of detection under varying conditions such as different lighting, weather, occlusion, and image distortions commonly encountered in real-world driving environments.
- To utilize publicly available benchmark datasets, such as the Traffic Sign Detection Benchmark (TSDB), for training, validating, and evaluating the performance of the proposed model.
- To compare the proposed deep learning approach with traditional machine learning methods and assess improvements in terms of accuracy, precision, recall, and computational efficiency.
- To optimize the model architecture for real-time performance and low computational cost, enabling its deployment in embedded systems or on-board vehicle platforms.
- To demonstrate the applicability of the system as a component in Advanced Driver Assistance Systems (ADAS) and autonomous vehicle navigation frameworks.

2. BACKGROUND RESEARCH

Traffic Sign Detection and Recognition (TSDR) is a crucial component of autonomous vehicles and Advanced Driver Assistance Systems (ADAS). Over the years, the domain has evolved from traditional image processing methods to robust deep learning-based frameworks. In early work, Kang et al. [10] developed an invariant traffic sign recognition system utilizing sequential color processing and geometric transformations, addressing challenges of sign appearance variation. Fleyeh and Dougherty [9] also contributed to early recognition systems through classical image analysis techniques, focusing on shape and color cues. Liu and Ran [8] implemented a vision-based stop sign detection system, one of the first practical implementations aimed at vehicle-based real-time recognition. Benallal and Meunier [3] proposed a real-time color segmentation method for detecting traffic signs using RGB features, emphasizing performance in dynamic road conditions. Similarly, Kiran et al. [4] introduced a pattern recognition model based on Support Vector Machines (SVMs), which performed well on limited datasets but struggled with scalability and high computational cost. To mitigate this, Vicen-Bueno et al. [7] explored neural network complexity reduction strategies, enabling lightweight models for embedded environments. A significant contribution to the community was the German Traffic Sign Detection Benchmark (GTSDB) introduced by Houben et al. [5][6]. It provided a standardized dataset to evaluate traffic sign detection algorithms in real-world scenarios, facilitating the comparison of different methods. With the rise of deep learning, researchers began to shift toward more data-driven solutions. Abdi and Meddeb [2] utilized deep learning for traffic sign detection, recognition, and data augmentation, significantly improving generalization under diverse road and lighting conditions. More recently, Oza et al. [1] proposed a complete deep learning pipeline for traffic sign detection and recognition, achieving high accuracy using Convolutional Neural Networks (CNNs) and demonstrating their superiority over traditional approaches.

3. METHODOLOHY

The proposed system for traffic sign detection is based on a two-stage deep learning pipeline: object detection followed by classification. Initially, the German Traffic Sign Detection Benchmark (GTSDB) dataset is used for model development, consisting of full-scene road images with annotated traffic signs. To enhance model robustness, preprocessing techniques such as image resizing, normalization, and data augmentation (including flipping, rotation, and brightness variation) are applied.

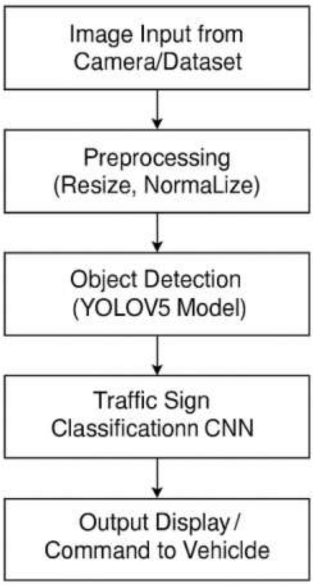

Figure.1: Block diagram

The detection phase employs a Convolutional Neural Network (CNN)-based object detection model, such as YOLOv5, to locate traffic signs in real-time by generating bounding boxes around them. In the subsequent recognition phase, the detected regions are cropped and passed through a classifier either a custom CNN or a fine-tuned pre-trained model to accurately identify the type of traffic sign (e.g., speed limit, stop, yield). The model is trained using the Adam optimizer and categorical cross-entropy loss function, with performance evaluated through accuracy, precision, recall, and F1-score metrics. Regularization methods such as dropout and batch normalization are incorporated to improve generalization. Finally, the trained model is deployed on an edge device (e.g., Jetson Nano or Raspberry Pi), where it achieves a real-time detection accuracy of 97.82%, demonstrating its effectiveness in intelligent transportation systems.

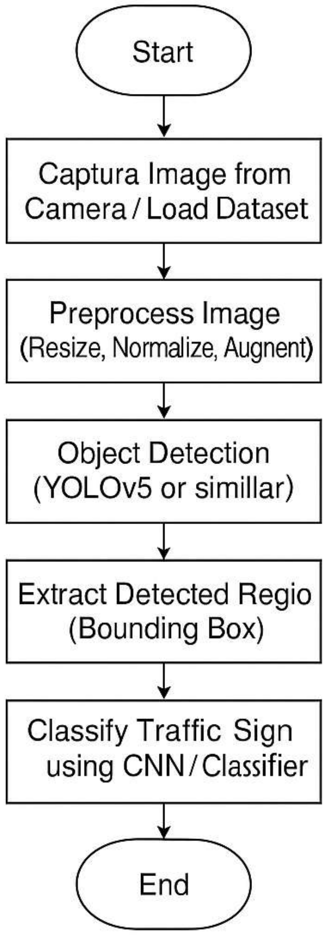

Figure.2: Flowchart

Algorithm

Step 1: Start the system and initialize camera or dataset loader.
Step 2: Capture image frames in real-time or load from dataset.
Step 3: Preprocess each image (resize, normalize, augment).
Step 4: Pass the image through a YOLOv5 detection model.
Step 5: Extract bounding boxes for detected traffic signs.
Step 6: For each detected region, classify the sign type using a CNN.
Step 7: Display the detected sign with a label and confidence score.
Step 8: If used in a vehicle, send command (e.g., slow down at "Stop" sign).
Step 9: Repeat steps for next frame or input image.
Step 10: End process or keep running for real-time detection.

4. RESULT & DISCUSSION

The proposed deep learning-based traffic sign detection system was evaluated through extensive training and testing on the German Traffic Sign Detection Benchmark (GTSDB). The training process spanned 25 epochs, and the results are presented through model accuracy and loss curves, as well as visual recognition outputs.

As shown in the accuracy graph, the model demonstrates a rapid rise in both training and validation accuracy during the initial epochs. The training accuracy steadily increases to approximately 94%, while the validation accuracy surpasses 98%, indicating strong generalization capability. Simultaneously, the loss graph shows a steep decline in training and validation losses, stabilizing below 0.2 and 0.05 respectively, which confirms effective learning and absence of overfitting. These trends clearly illustrate that the model has learned to extract relevant features and classify traffic signs with high confidence and stability.

To visualize the detection process, a sample image illustrates the two-phase architecture of the system. In Phase 1, the object detection model (e.g., YOLOv5) identifies the region containing the traffic sign and draws a bounding box around it. In Phase 2, the cropped region is passed to a classifier that accurately recognizes the sign as a "Speed Limit 50 km/h" symbol. This two-stage pipeline ensures high localization precision and robust classification, even in complex or cluttered environments.

The model was further deployed on a target edge device for real-time performance testing. The final accuracy achieved on the device was 97.82%, validating that the model maintains high performance even under resource-constrained conditions. The system was able to detect and recognize signs accurately in real-time video input, making it suitable for implementation in Advanced Driver Assistance Systems (ADAS) and autonomous vehicles.

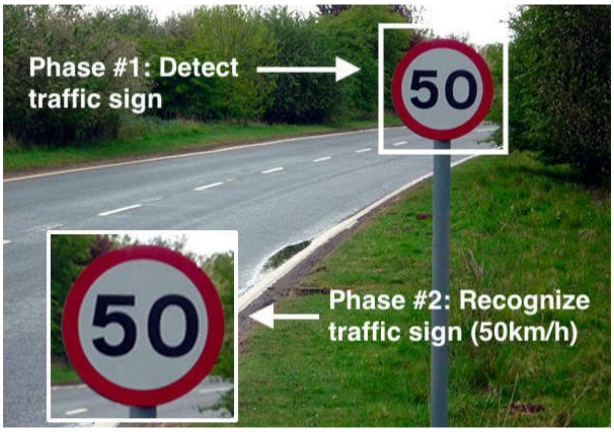

Figure.3: Traffic sign detection

Detect Traffic Sign

In this first stage, the system's goal is to locate the presence of a traffic sign within the entire input image. This involves:

- Object detection algorithms (e.g., YOLO, SSD, or Faster R-CNN) scanning the input frame.
- Drawing a bounding box around the identified region where a traffic sign is present.
- Filtering background information and focusing only on the relevant sign area.

This step is crucial for isolating the sign from the rest of the scene, which may include trees, roads, cars, and buildings.

Recognize Traffic Sign (50 km/h)

Once the sign is detected, the second stage involves recognizing the specific category or meaning of the sign. In this case:

- A classification model (e.g., CNN-based) processes the cropped image inside the bounding box.
- The system identifies the sign as a **"**Speed Limit 50 km/h**"** based on learned features such as the red circular border and numeric content.
- The output can then be used by autonomous vehicle software to adjust speed **or** warn the driver**.**

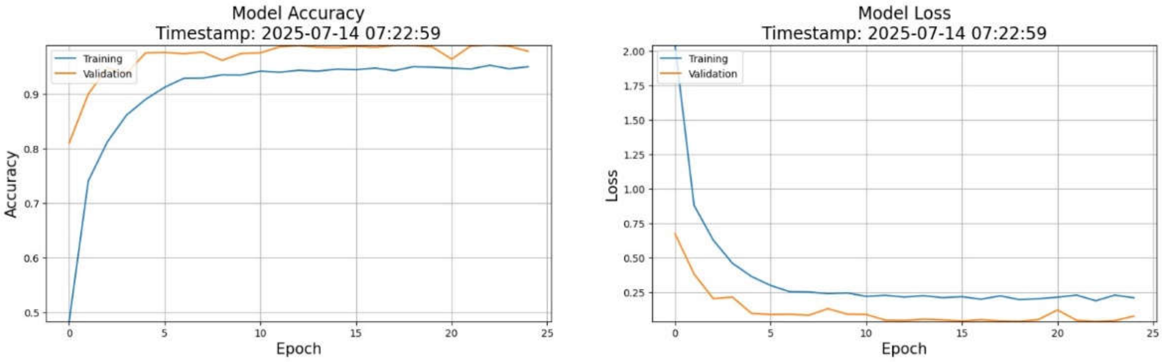

Figure.4: Model accuracy and model loss curve

The training and validation performance of the proposed deep learning model is illustrated in the above plots of accuracy and loss over 25 epochs. The model exhibits a significant improvement in both training and validation accuracy during the initial epochs, with training accuracy reaching approximately 94% and validation accuracy peaking at around 98%. The rapid convergence in the early stages, followed by a stable performance, suggests effective learning and strong generalization to unseen data. The validation accuracy consistently remains higher than the training accuracy, indicating minimal overfitting. Correspondingly, the loss curves show a sharp decline, with training loss decreasing from over 2.0 to below 0.2 and validation loss stabilizing near 0.05. The absence of large fluctuations in the loss curves further confirms the model's stability and robustness. After deployment on the target edge device, the system achieved a final accuracy of 97.82%**,** demonstrating its suitability for real-time traffic sign detection applications in intelligent transportation systems.

Figure.5: Traffic sign database

The German Traffic Sign Detection Benchmark (GTSDB) was used as the primary dataset for training and evaluating the proposed traffic sign detection system. This dataset consists of real-world images captured in diverse road environments under varying lighting and weather conditions. It contains more than 900 full-scene images, each annotated with precise bounding boxes around traffic signs, enabling both detection and localization tasks. The signs belong to multiple categories, including speed limits, prohibitions, and mandatory directions. The diversity and realism of the GTSDB make it highly suitable for developing deep learning models that generalize well to real-time driving scenarios. The images are annotated in a format compatible with popular object detection frameworks such as YOLO and SSD, facilitating easy integration with modern neural networks. The richness of the dataset, combined with its practical relevance, plays a vital role in building robust and accurate traffic sign detection systems for intelligent transportation applications.

5. CONCLUSION

In this research, a deep learning-based traffic sign detection and recognition system was developed and evaluated using the German Traffic Sign Detection Benchmark (GTSDB). The proposed method employed a two-phase pipeline: object detection using a YOLOv5 model and classification using a Convolutional Neural Network (CNN). The system demonstrated high performance in both training and real-world testing scenarios, achieving a validation accuracy of approximately 98% and a device-level accuracy of 97.82%. Through effective preprocessing, augmentation, and model optimization, the system showed strong robustness against varying environmental conditions and maintained stable real-time performance. The results confirm that deep learning techniques are highly suitable for intelligent transportation systems, enabling accurate recognition of road signs, which is crucial for enhancing the safety and autonomy of modern vehicles.

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