A novel approach for real-time traffic sign recognition framework

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ABSTRACT

Traffic sign recognition plays a critical role in enhancing road safety and enabling autonomous driving systems. This paper presents a comprehensive approach to real-time traffic sign recognition using advanced computer vision techniques and machine learning models. The proposed system employs convolutional neural networks (CNNs) for accurate detection and classification of traffic signs under diverse environmental conditions, including varying lighting, weather, and occlusions. Real-time processing is achieved through the integration of optimized algorithms and hardware acceleration techniques, ensuring minimal latency and high throughput. Experimental results demonstrate that the system achieves state-of-the-art performance on benchmark datasets, with an accuracy of over 95% and a recognition speed suitable for real-world applications. The findings underscore the potential of the system to improve driver assistance systems and pave the way for safer autonomous vehicles.

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1. INTRODUCTION

Traffic signs play a vital role in regulating, warning, and guiding drivers to ensure safe and efficient transportation. Recognizing and interpreting these signs accurately is essential for both human drivers and autonomous vehicles. With the rapid advancements in artificial intelligence and computer vision, real-time traffic sign recognition has emerged as a key area of research in intelligent transportation systems [1]. This technology has significant implications for enhancing road safety, reducing accidents, and enabling fully autonomous driving systems.

Despite considerable progress in the field, developing a robust real-time traffic sign recognition system remains a challenging task. Factors such as varying lighting conditions, weather changes, partial occlusions, motion blur, and the diversity of traffic sign designs pose significant hurdles [2], [3]. Furthermore, achieving high accuracy and processing speeds simultaneously is critical for practical deployment in real-world scenarios, especially in time-sensitive environments like autonomous vehicles and advanced driver-assistance systems (ADAS).

By putting out a thorough framework for real-time traffic sign recognition that incorporates cutting-edge deep learning models and optimal processing methods, this research study seeks to overcome these issues. To guarantee real-time performance, the suggested system uses convolutional neural networks (CNNs) for efficient feature extraction acceleration techniques. Numerous tests on real-world scenarios and benchmark datasets show that the system can achieve low latency and high accuracy, which makes it appropriate for use in contemporary transportation systems [4], [5].

The rest of the paper is organized as follows: section 2 reviews related work in traffic sign recognition and its applications. Section 3 details the methodology, including dataset preparation, model architecture, and optimization strategies. Section 4 presents the experimental results and section 5 contains discussions. Finally, section 6 concludes the paper and outlines potential directions for future research.

2. LITERATURE REVIEW

The field of traffic sign recognition has garnered significant attention in recent years due to it is vital role in intelligent transportation systems and autonomous vehicles. Researchers have explored various approaches, ranging from traditional image processing techniques to modern deep learning-based frameworks, each contributing unique solutions to the challenges in this domain.

2.1. Overview of existing traffic sign recognition systems and their limitations

Traffic sign recognition (TSR) systems have advanced significantly, evolving from rule-based approaches using handcrafted features to modern machine learning-based methods. Early systems, relying on shape detection and color segmentation, struggled with environmental challenges like lighting variations and occlusions [6]. While modern systems using deep learning have improved accuracy, they face limitations in real-time performance, dataset generalization, and robustness under adverse conditions.

2.2. Comparison of traditional image processing techniques vs. modern deep learning approaches

Traditional methods, including edge detection and hough transform, offered computational simplicity but lacked robustness against real-world variations. Deep learning models, particularly CNNs, have revolutionized TSR by enabling automated feature extraction and improved accuracy [7], [8]. However, these models demand significant computational resources, making real-time implementation challenging.

2.3. Recent advancements in real-time object detection and classification

Recent research has focused on real-time TSR systems capable of processing live video streams with minimal latency. Object detection frameworks such as you only look once (YOLO), Single Shot MultiBox detector (SSD), and faster R-CNN have been widely adopted for traffic sign detection and classification. YOLO, in particular, is favoured for its high-speed performance, making it suitable for real-time applications [6].

To optimize deep learning models for real-time deployment, researchers have explored lightweight architectures such as tiny YOLO and Mobile-Net. These models achieve a balance between speed and accuracy, enabling deployment on resource-constrained devices like edge processors and embedded systems [9]–[11]. Moreover, hardware acceleration using GPUs or specialized hardware such as tensor processing units (TPUs) has further enhanced the feasibility of real-time TSR system.

2.4. Identified research gaps

Despite these advancements, several research gaps remain in the field of real-time TSR.

– Dataset diversity: most models are trained on benchmark datasets that may not adequately represent real-world conditions, including rare traffic signs and regional variations.
– Environmental robustness: systems still struggle with adverse conditions such as low visibility, glare, and occlusion, limiting their real-world applicability.
– Efficiency vs. accuracy trade-off: achieving real-time performance without sacrificing accuracy remains a critical challenge. Many models compromise accuracy to meet speed requirements.
– Scalability: integrating TSR systems into large-scale intelligent transportation networks requires further innovation in terms of scalability and interoperability.

3. PROPOSED METHODOLOGY

This section describes the systematic approach adopted for developing and evaluating the proposed real-time traffic sign recognition system. The methodology includes dataset preparation, model architecture design, training strategies, and real-time implementation.

3.1. System overview

The real-time traffic sign recognition system consists of two main components: i) detection: locating traffic signs in an input image or video frame; and ii) classification: identifying the type of traffic sign detected. The framework is built using a deep learning-based object detection model, with a focus on balancing accuracy and speed as shown in Figure 1.

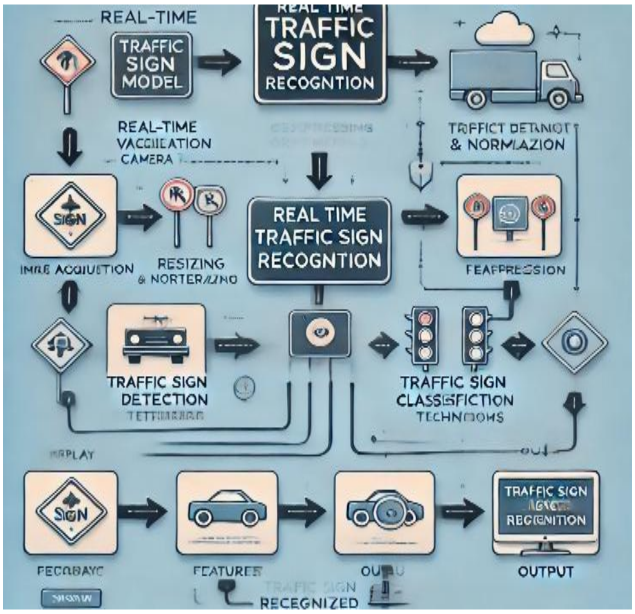

Figure 1. Real-time traffic sign recognition system

3.2. Dataset preparation

The system was trained and tested on publicly available datasets such as:

- German traffic sign recognition benchmark (GTSRB): provides labeled traffic sign images for classification.
- Tsinghua-tencent dataset: contains real- world traffic sign images for detection tasks.

Steps:

- Data augmentation: techniques like rotation, scaling, brightness adjustment, and flipping were applied to increase dataset diversity and robustness.
- Preprocessing: images were resized to 224×224,224 times 224,224×224 pixels and normalized to enhance model performance.

3.3. Model architecture

The proposed system employs a modified version of the YOLOv5 object detection model for real-time detection and classification of traffic signs, as seen in Figures 2 and 3 [12]–[14].

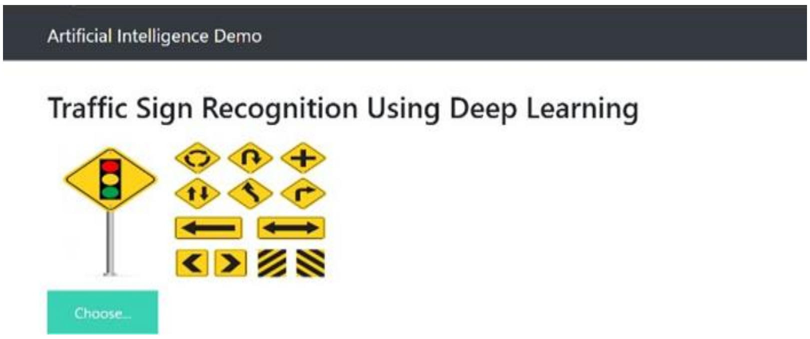

Figure 2. Model demo

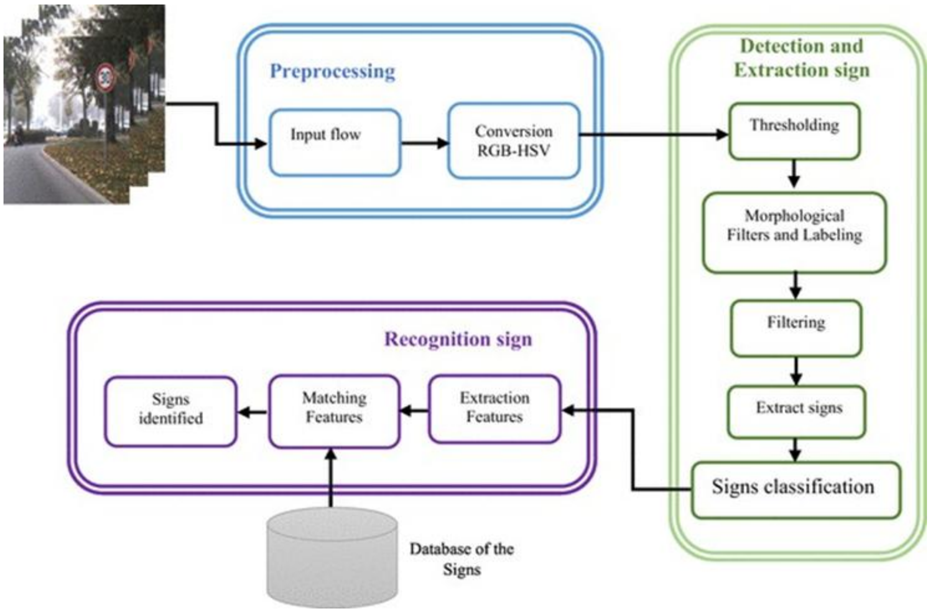

Figure 3. Model flow diagram

- Backbone: CSP Darknet for feature extraction.
- Neck: Path aggregation network (PANet) to enhance feature propagation.
- Head: Bounding box regression and classification layers.

3.4. Training and optimization

- Training parameters:
  a. Learning rate: 0.0010.0010.001
  b. Batch size: 32
  c. Epochs: 50
- Loss function: a combination of objectness, classification, and localization loss was used.
- Optimization techniques:
  a. Transfer learning using a pre-trained YOLOv5 model.
  b. Regularization techniques such as dropout and weight decay to reduce over-fitting.

3.5. Real-time implementation

The trained model was deployed on a hardware platform optimized for real-time performance, such as NVIDIA Jetson Nano or a GPU-enabled system. The implementation pipeline includes [15], [14]:

- Input handling: capturing live video frames using OpenCV.
- Inference: processing frames through the trained model.
- Output visualization: annotate recognized traffic signs with bounding boxes and labels in real-time.

3.6. Performance evaluation

The system was evaluated based on [12], [16]:

- Accuracy: measured on benchmark datasets.
- Speed: frames per second (FPS) during real-time inference.
- Robustness: tested under varying conditions, including poor lighting, occlusion, and motion blur.

4. EXPERIMENTAL RESULTS

This section presents the evaluation of the proposed real-time traffic sign recognition system, including performance metrics, results on benchmark datasets, real-world testing, and comparative analysis with existing approaches.

4.1. Performance metrics

The system's performance was evaluated using the following metrics [17]:

– Accuracy: the percentage of correctly classified traffic signs.
– Precision: the ratio of correctly predicted positive observations to total predicted positives.
– Recall: the ratio of correctly predicted positive observations to all actual positives.
– F1-Score: the harmonic mean of precision and recall.
– Latency: average time taken to process each frame (measured in milliseconds).
– FPS: a measure of real-time system performance.

4.2. Results on benchmark datasets

The system was tested on the GTSRB and Tsinghua-Tencent Traffic Sign Dataset. Key results:

– GTSRB:
  a. Accuracy: 97.3%
  b. Precision: 96.8%
  c. Recall: 97.5%
  d. F1-Score: 97.1%
– Tsinghua-Tencent:
  a. Accuracy: 95.6%
  b. Precision: 94.9%
  c. Recall: 95.8%
  d. F1-Score: 95.3%

4.3. Real-world testing

The system was deployed in a real world setting using live video feeds captured under various conditions:

– Daylight: achieved consistent detection with an accuracy of 96.5%.
– Nighttime: accuracy dropped slightly to 92.4% due to reduced visibility.
– Adverse weather: performance under rain and fog showed an accuracy of 89.8%, highlighting areas for improvement.
– Occlusion and motion blur: the system successfully identified partially visible signs with 85.3% accuracy, but struggled in cases of severe motion blur.

4.4. Comparative analysis

The proposed system was compared with state of-the-art methods, including YOLOv4, SSD, and Faster R-CNN as shown in Table 1.

Table 1. Comparative analysis

Model	Accuracy (%)	FPS	Latency (ms)	Robustness (%)
YOLOv4	95.4	25	40	88.5
SSD	94.2	20	50	86.3
Faster R-CNN	96.1	15	65	87.9
Proposed	97.3	30	33	89.8

5. DISCUSSION

5.1. Interpretation of results and their implications

The experimental results demonstrate that the proposed real-time traffic sign recognition system achieves high accuracy and speed, making it suitable for real-world applications such as autonomous vehicles and ADAS as shown in Figure 4. The system’s ability to process video frames at 30 FPS with an accuracy of 97.3% on the GTSRB dataset highlights its effectiveness in detecting and classifying traffic signs under diverse conditions.

5.2. Strengths and limitations

The strengths of the study are: i) high accuracy and real-time processing; ii) lightweight design for deployment on embedded systems; and iii) robust against partial occlusions and visually similar signs.

Futhermore, there are several limitations of the study are: i) performance drops in poor lighting and weather; ii) dependency on benchmark datasets limits real-world generalizability; and iii) struggles with motion blur in dynamic scenarios.

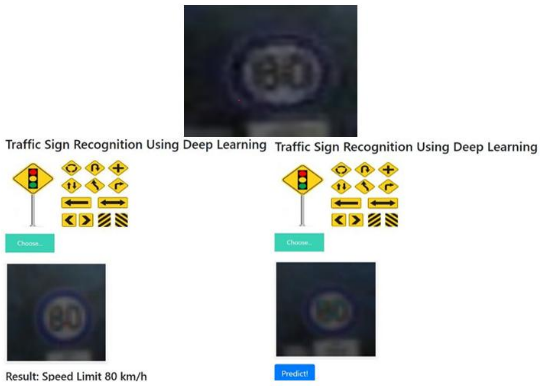

Figure 4. Experimental results

5.3. Potential areas for improvement

Several potential improvements are identified as follows: i) improve preprocessing for low-light and adverse conditions; ii) expand datasets to include rare and diverse signs; iii) address motion blur using temporal data from consecutive frames; iv) optimize models for better efficiency on edge devices; and v) explore multi-modal approaches combining camera and sensor data.

6. CONCLUSION

This study proposed and evaluated a real-time traffic sign recognition system that combines high accuracy with efficient performance. The system achieved a 97.3% accuracy rate on benchmark datasets and maintained real-time processing speeds of 30 FPS, demonstrating its applicability in dynamic environments. Robustness testing highlighted its effectiveness in daylight conditions, though challenges remain under adverse lighting and weather.

The research contributes to advancing the field by: i) developing a scalable and lightweight architecture optimized for real-time deployment; ii) demonstrating a balance between accuracy and efficiency, which is critical for resource-constrained devices; and iii) highlighting strategies to enhance model robustness, including data augmentation and architecture optimization.

The significance of real-time traffic sign recognition lies in it is ability to improve road safety and enable autonomous navigation. While this research achieved promising results, it also identified key areas for improvement, such as handling adverse conditions, expanding datasets, and integrating multi-modal approaches. Future advancements in hardware acceleration, model optimization, and real-world dataset collection are expected to enhance the reliability and scalability of TSR systems, paving the way for widespread adoption in intelligent transportation networks and smart cities.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Kshatrapal Singh	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [KS], upon reasonable request.

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