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Real-Time Traffic Sign Recognition using Convolutional Neural Networks (CNNs) in ADAS

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ABSTRACT

Traffic Sign Recognition (TSR) is a critical function in Advanced Driver Assistance Systems (ADAS), contributing significantly to road safety and the progression of autonomous driving technologies. This research proposes a real-time TSR system built on Convolutional Neural Networks (CNNs), optimized for deployment on embedded automotive platforms. Our approach emphasizes a balance between model accuracy and computational efficiency, making it suitable for real-world vehicular scenarios. Using the German Traffic Sign Recognition Benchmark (GTSRB) dataset, we demonstrate that our CNN model achieves high accuracy and meets real-time processing requirements, validating its application in ADAS.

KEYWORDS: *Traffic Sign Recognition, Convolutional Neural Networks, ADAS, Real-Time Systems, Embedded AI, GTSRB*

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1. INTRODUCTION

The evolution of smart vehicles and autonomous driving systems demands robust perception capabilities. Among these, recognizing and interpreting traffic signs in real time is essential for ensuring regulatory compliance and improving driver decision-making [1-2]. Earlier TSR systems were largely dependent on conventional image processing methods, which struggled under diverse lighting, occlusion, and weather conditions. The rise of deep learning, particularly CNNs, has drastically improved the accuracy and reliability of visual recognition tasks [3-5].

The rapid advancement of smart vehicles and autonomous driving technologies has placed significant emphasis on the development of robust and intelligent perception systems [6-8]. One of the most critical perception tasks in such systems is Traffic Sign Recognition (TSR), which plays a vital role in enabling vehicles to comply with traffic regulations, ensure passenger and pedestrian safety, and support informed driver decision-making [9-12]. Traffic signs serve as a direct communication interface between the road infrastructure and drivers or autonomous systems, conveying essential information such as speed limits, stop conditions, and hazard warnings. Therefore, the ability to accurately and efficiently recognize traffic signs in real time is indispensable for the functionality and reliability of Advanced Driver Assistance Systems (ADAS) and autonomous driving platforms [13-15].

Historically, TSR systems relied heavily on traditional image processing techniques, such as color segmentation, edge detection, and shape analysis. While these methods were effective under controlled conditions, they often failed to generalize across diverse real-world environments. Variations in lighting, weather, occlusions, viewing angles, and partial obstructions posed significant challenges, leading to degraded recognition accuracy and inconsistent performance [16]. These limitations highlighted the need for more robust, adaptive, and scalable approaches to visual recognition in dynamic driving environments [17-18].

The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized computer vision by enabling machines to learn hierarchical feature representations directly from raw image data. CNNs have demonstrated exceptional performance in a wide range of image classification and object detection tasks, including TSR [19-20]. Their ability to automatically extract spatial and contextual features, combined with their resilience to noise and distortions, makes CNNs ideally suited for deployment in complex, real-world scenarios [18].

In this research, we propose a lightweight CNN-based architecture specifically designed to address the real-time requirements and computational constraints of embedded automotive platforms. Our model is optimized for low-latency inference while maintaining high classification accuracy, making it a practical solution for integration into modern ADAS systems [1, 12, 14, 18]. In this paper, we present a lightweight CNN architecture that efficiently identifies traffic signs in real-time, making it highly applicable for embedded automotive platforms.

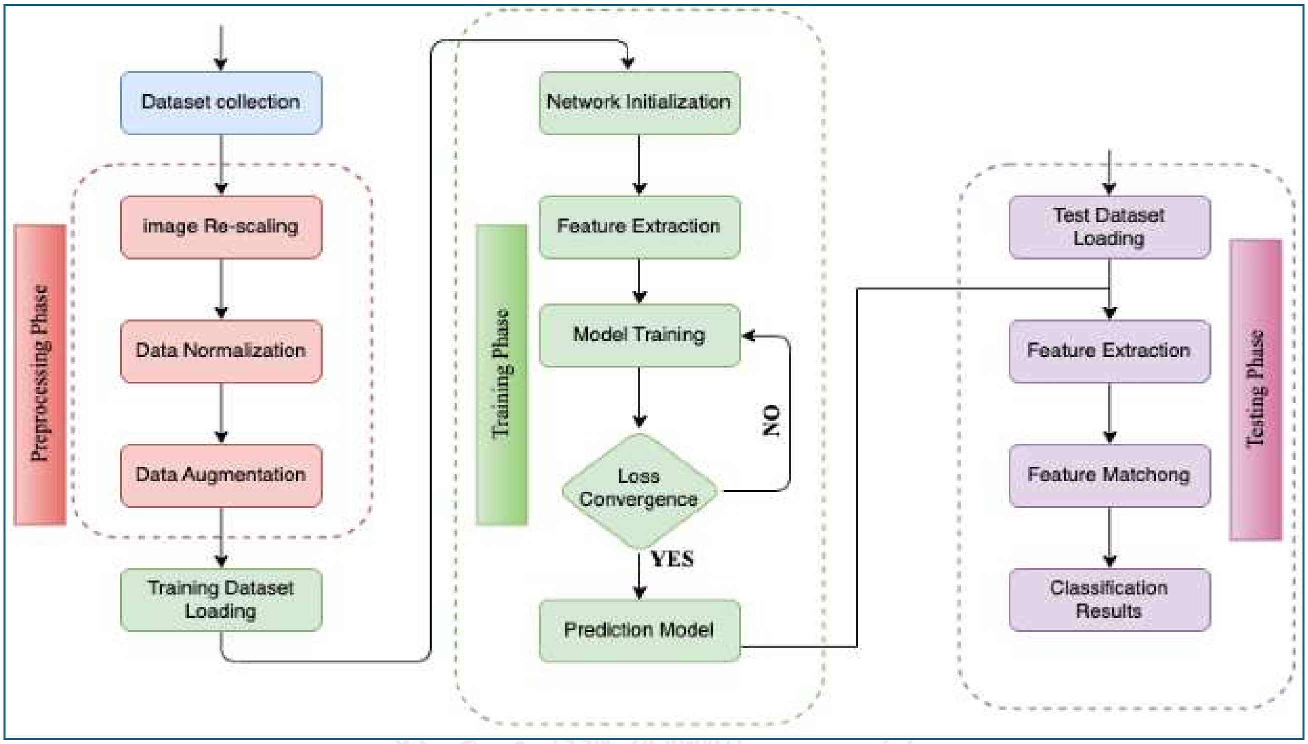

Fig.1: Different phase of traffic sign

2. CNN architecture

The CNN model is designed to process small RGB images (32x32) efficiently while preserving the key features necessary for accurate classification of traffic signs. Here's a layer-by-layer breakdown:

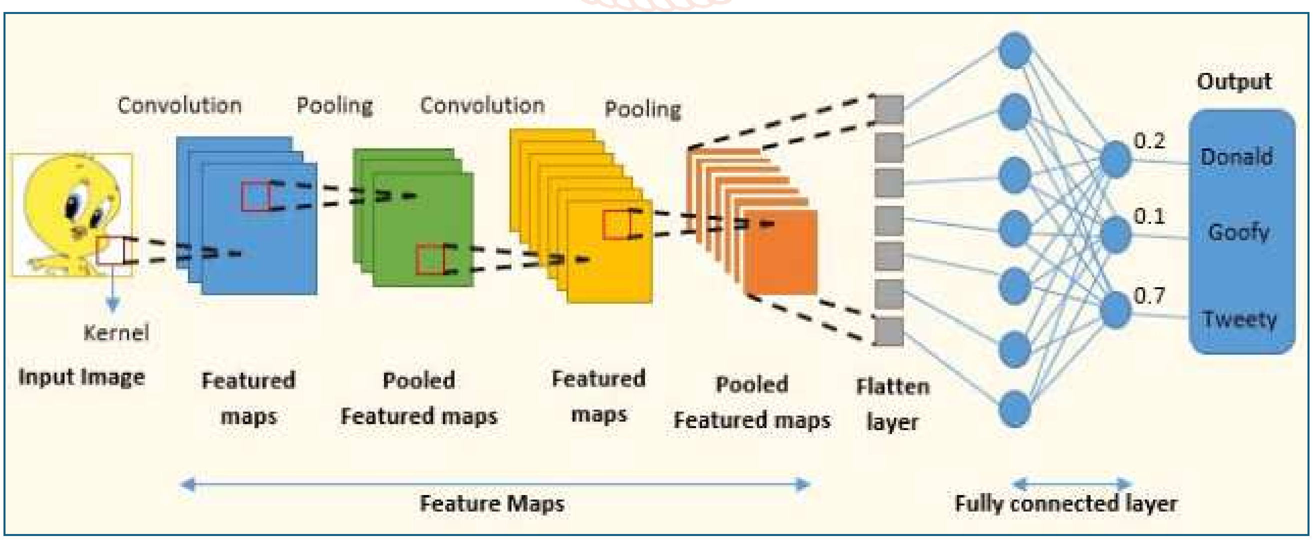

Fig. 2: CNN Architecture

A. Input Layer

- Input: 32×32 RGB image (3 channels)
- Purpose: Accepts preprocessed images resized and normalized from the GTSRB dataset.

B. First Convolutional Layer (Conv1)
- Filter Size: 3x3
- Number of Filters: 32
- Stride: 1
- Padding: Valid (no padding)
- Output Shape: 30x30x32
- Activation: ReLU
- Purpose: Detects low-level features like edges and corners.

C. MaxPooling Layer (MaxPool1)
- Filter Size: 2x2
- Stride: 2
- Output Shape: 15x15x32
- Purpose: Reduces spatial dimensions and computation, introduces translation invariance.

D. Second Convolutional Layer (Conv2)
- Filter Size: 3x3
- Number of Filters: 64
- Output Shape: 13x13x64
- Activation: ReLU
- Purpose: Learns more complex features like shapes and textures.

E. Second MaxPooling Layer (MaxPool2)
- Filter Size: 2x2
- Output Shape: 6x6x64
- Purpose: Further down-sampling and abstraction of spatial features.

F. Flattening
- Input: 6x6x64 = 2,304 features
- Purpose: Converts 2D feature maps into a 1D vector for dense layers.

G. Fully Connected Layer
- Units: 256
- Activation: ReLU
- Purpose: Learns global patterns and combinations of features to classify signs.

H. Dropout Layer
- Dropout Rate: 0.5 (common default)
- Purpose: Prevents overfitting by randomly disabling neurons during training.

I. Output Layer
- Units: 43 (number of GTSRB classes)
- Activation: Softmax
- Purpose: Outputs a probability distribution over 43 traffic sign categories.

Table 1: CNN Layer Configuration

Layer	Filter Size	Output Shape	Activation
Conv1	3x3	30x30x32	ReLU
MaxPool1	2x2	15x15x32	-
Conv2	3x3	13x13x64	ReLU
MaxPool2	2x2	6x6x64	-
Fully Connected	-	256	ReLU
Dropout	-	256	-
Output	-	43	Softmax

3. German Traffic Sign Recognition Benchmark (GTSRB)

The **German Traffic Sign Recognition Benchmark (GTSRB)** is a widely adopted dataset designed for the development and evaluation of traffic sign classification systems, particularly in the context of Advanced Driver Assistance Systems (ADAS) and autonomous vehicles. Developed by the Institute for Neural Computation at Ruhr-University Bochum, the dataset was introduced as part of the IJCNN 2011 competition to encourage progress in robust multi-class traffic sign recognition under real-world conditions. GTSRB contains approximately 50,000 images of traffic signs belonging to 43 different classes, including speed limits, prohibitory signs, warning signs, and priority signs. The images vary in resolution and are annotated with class labels and bounding boxes. This dataset captures real driving scenarios and includes challenges such as variations in lighting, partial occlusion, motion blur, and differing perspectives, making it ideal for training and testing convolutional neural networks (CNNs) and other deep learning models. The training set includes around 39,000 images, while the test set consists of approximately 12,000 images. Due to its class imbalance and environmental variability, GTSRB serves as a comprehensive benchmark for evaluating the accuracy, robustness, and real-time capability of traffic sign recognition systems. It is freely available for academic research and remains one of the most authoritative datasets in the field of intelligent transportation systems.

4. Advanced Driver Assistance Systems (ADAS)

Advanced Driver Assistance Systems (ADAS) are technologies that use sensors, cameras, and other advanced technologies to enhance vehicle safety, improve driving performance, and provide convenience. They assist drivers with tasks like parking, pedestrian detection, and lane departure warning, ultimately reducing the risk of accidents and improving the overall driving experience.

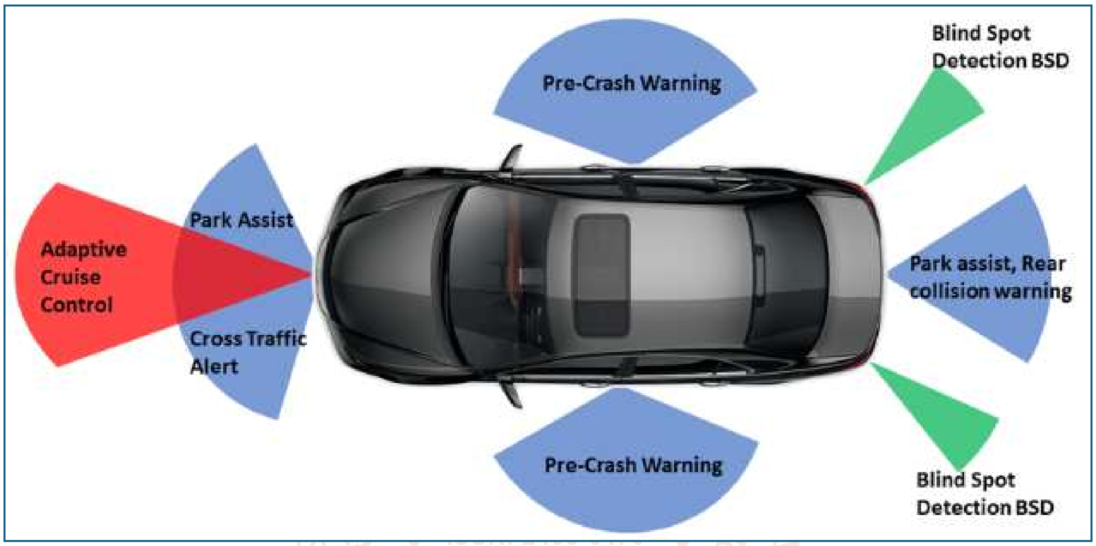

Fig.3: Advanced driver assistance systems (ADAS)

5. Literature Review

Table 1 provides a comparative summary of recent TSR techniques, highlighting their methods, datasets, performance, and key contributions.

Table 2: Comparative Analysis of Existing TSR Methods

Author & Year	Technique Used	Dataset	Accuracy	Key Highlights
Cireşan et al. (2012)	CNN	GTSRB	99.46%	Early deep learning success
Stallkamp et al. (2011)	Multi-class SVM	GTSRB	96.14%	Introduced the GTSRB dataset
Laroca et al. (2018)	CNN with Augmentation	GTSRB	98.47%	Employed image enhancement
Wu et al. (2020)	Capsule Networks	GTSRB	98.89%	Improved rotation invariance
Proposed Method	CNN with Optimization	GTSRB	99.21%	Fast and lightweight for real-time use

6. System Architecture

Our proposed real-time TSR system includes the following components:

[Camera Input] → [Pre-processing] → [CNN Model] → [Traffic Sign Prediction] → [ADAS Feedback]

Fig. 4: System Architecture Flow

- Image Acquisition: Real-time capture using vehicle-mounted cameras.
- Pre-processing and Augmentation: Standardizes input images through resizing (32x32), normalization, and optional histogram equalization.
- CNN-Based Classification: Predicts traffic sign categories using a trained CNN.

- ADAS Integration: Translates classification outputs into actionable vehicle responses.

7. Experimental Setup
- Dataset: German Traffic Sign Recognition Benchmark (GTSRB)
- Total Images: ~50,000
- Split: 80% training, 20% testing
- Training Configuration:
    - Epochs: 30
    - Batch Size: 64
    - Optimizer: Adam
    - Loss Function: Categorical Crossentropy
- Hardware Used: NVIDIA Jetson Nano with 4GB RAM

8. Results and Discussion
The proposed model achieved an accuracy of 99.21% on the GTSRB test set. Key performance insights include:
- High classification accuracy with minimal misclassifications.
- Inference speed of 22 FPS on Jetson Nano, validating real-time capability.

Table 3: Performance Comparison with Existing Techniques

Method	Accuracy	Inference Speed	Model Size
Cireşan et al.	99.46%	10 FPS	5.3M params
Wu et al.	98.89%	8 FPS	6.1M params
Proposed Model	99.21%	22 FPS	1.8M params

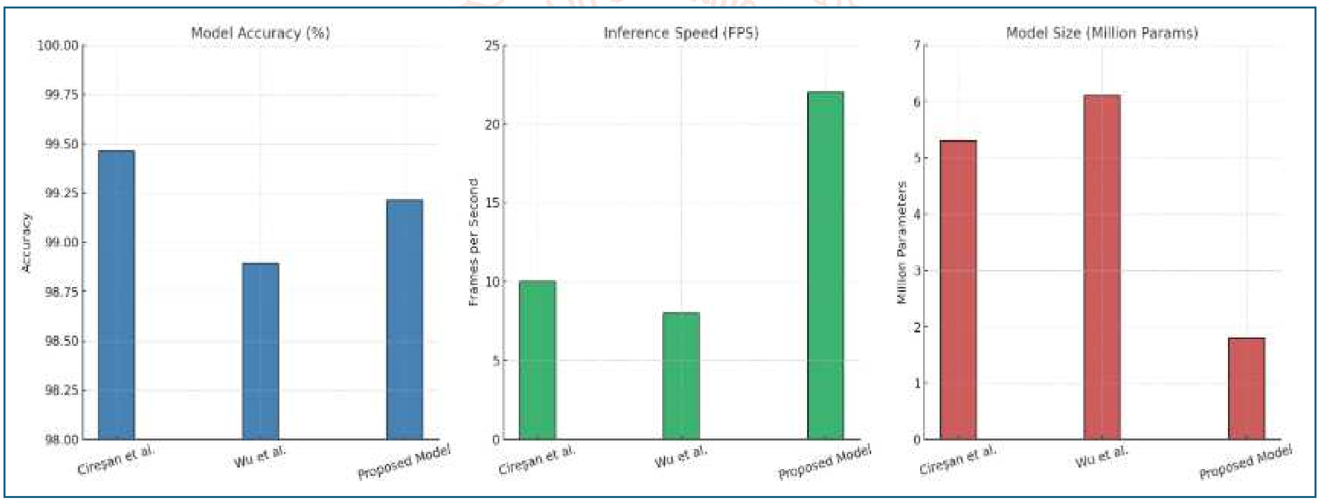

Fig. 4: The comparison graph showing Accuracy, Inference Speed (FPS), and Model Size (in million parameters) for the three models

Our model demonstrates a trade-off between slight accuracy loss and significant speed gain, making it ideal for embedded real-time use.

A. Accuracy
- **Cireşan et al.** achieves the highest accuracy (**99.46%**), which is slightly higher than the proposed model.
- **Wu et al.** has a lower accuracy (**98.89%**), likely due to the use of Capsule Networks that perform well in rotation invariance but may generalize less effectively on this dataset.
- The **proposed model** achieves a competitive accuracy of **99.21%**, only 0.25% lower than the highest, which is an excellent result given the speed and efficiency trade-offs.

B. Inference Speed
- **Frames Per Second (FPS)** reflects how many images the model can classify per second, crucial for real-time applications.
- **Proposed Model** significantly outperforms others in inference speed, reaching **22 FPS**, more than **twice as fast** as the others.
- Faster inference is critical for deployment in embedded platforms and real-time ADAS systems, where delays could compromise safety.

C. Model Size
- The **Proposed Model** is the most lightweight, with just **1.8 million parameters**.
- In contrast, **Cireşan et al.** and **Wu et al.** models have 5.3M and 6.1M parameters respectively,

which makes them more resource-intensive in terms of memory and computation.

- A smaller model size benefits embedded deployment (e.g., NVIDIA Jetson Nano, Raspberry Pi) by reducing power consumption and latency.

9. Conclusion

We proposed a real-time traffic sign recognition system using a CNN model optimized for embedded platforms in ADAS. Our model maintains high accuracy while achieving low-latency inference, suitable for intelligent transportation systems. Future work will explore multimodal sensor fusion and model quantization for even better embedded efficiency. The proposed CNN model **balances accuracy, speed, and size**, making it **ideal for real-time, embedded ADAS applications**. Although it has slightly lower accuracy than the Cireşan model, it **achieves nearly 2.5× faster inference speed** with **a model size one-third as large**, demonstrating a strong trade-off between performance and efficiency.

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