IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Enhanced Traffic Sign Detection in Dynamic Environments Using YOLOv7And CNN-Based Approaches

[1] **Vaishnavi Awari,** [2] **Prof. Jyoti Gavhane**

[1]Student [2]Professor

[12]MIT School of Computing, MIT-ADT University, Pune, India

Abstract: Accurate traffic sign detection (TSD) is a critical component of autonomous driving and intelligent transportation systems, enabling vehicles to navigate safely and comply with traffic regulations. However, dynamic challenges such as small object detection, adverse weather conditions, and real-time performance constraints hinder the effectiveness of existing solutions. This research focuses on developing YOLOv7, a lightweight and efficient model optimized for real-time deployment on edge devices. The model incorporates innovative modules such as ELAN-REP for backbone optimization, CBAM for enhanced feature attention, AFPN for robust feature fusion, and SIOU loss for improved bounding box regression.

To ensure real-world applicability, the Indian Traffic Sign Dataset (ITSD) was used, augmented with diverse environmental scenarios like rain, fog, and low light, to train and evaluate the model. Comparative analysis against state-of-the-art methods highlights the proposed model's superior trade-off between accuracy, speed, and computational efficiency. Real-world validation on edge devices such as NVIDIA Jetson Nano demonstrates the model's readiness for practical deployment. This research establishes a foundation for robust and efficient TSD in complex environments, paving the way for safer and more reliable autonomous driving technologies in diverse real-world scenarios.

Index Terms - Traffic Sign Detection, YOLOv7, CNN, real-time performance, adverse environments, lightweight architecture, autonomous vehicles.

I. Introduction

Traffic Sign Detection (TSD) is a cornerstone of autonomous driving systems and intelligent transportation technologies. It enables vehicles to perceive and interpret crucial road information, such as speed limits, pedestrian crossings, and warnings, ensuring safe and efficient navigation. Accurate and robust TSD is not only essential for driver assistance systems but also critical for achieving fully autonomous vehicles. However, the complex nature of real-world environments presents numerous challenges to effective traffic sign detection, including varying weather conditions, dynamic lighting, motion blur, occlusions, and the presence of visually similar backgrounds.

The reliability of TSD models directly impacts the safety and operational capabilities of autonomous systems. In practical deployment scenarios, adverse weather conditions such as rain, snow, and fog can significantly degrade image quality, while changing illumination, such as low light or glare, can obscure traffic signs. Furthermore, the small size of traffic signs at a distance, coupled with partial occlusions (e.g., by other vehicles, pedestrians, or infrastructure), adds to the difficulty of achieving accurate detection. These factors necessitate models that are not only precise but also computationally efficient, particularly for resource-constrained edge devices used in real-time applications.

In recent years, deep learning has emerged as a transformative approach to addressing these challenges. Convolutional Neural Networks (CNNs) and object detection frameworks such as You Only Look Once (YOLO) have demonstrated significant advancements in traffic sign detection. YOLO-based models, including lightweight variants like YOLOv7-tiny, have achieved remarkable progress by incorporating features such as attention mechanisms, feature fusion networks, and efficient architectures. However, while these models have improved detection accuracy and speed, further innovations are needed to ensure robust performance in diverse and unpredictable environments.

In this study, we aim to advance the field of TSD by developing an enhanced lightweight detection model, **YOLOv7-tiny-RCA**, tailored for edge device deployment. Building upon the YOLOv7-tiny framework, our research addresses critical challenges in TSD through several key contributions:

1. **Comprehensive Dataset Utilization**: To ensure effective model training and evaluation, we leverage the **German Traffic Sign Detection Benchmark (GTSDB)**, a well-regarded dataset known for its diversity and detailed annotations of traffic signs in real-world conditions. To address the issue of category imbalance, we augment the dataset with additional traffic sign images from various environments, achieving a more balanced representation and improving the model's generalization capabilities.
2. **Backbone Network Optimization**: We introduce the ELAN-REP module in place of the ELAN module in the YOLOv7-tiny backbone. This module employs reparameterization techniques, transforming complex multi-branch structures into simpler single-branch structures during inference, significantly enhancing computational efficiency and inference speed.
3. **Integration of Attention Mechanisms**: To strengthen the network's ability to extract meaningful features, we incorporate the Convolutional Block Attention Module (CBAM) into the YOLOv7-tiny backbone. This addition improves the network's ability to focus on critical regions in the input data while minimizing redundancy, leading to higher detection accuracy.
4. **Advanced Feature Fusion**: Recognizing the importance of effectively combining high- and low-level semantic information, we implement the Asymptotic Feature Pyramid Network (AFPN) in the YOLOv7-tiny neck architecture. This innovation enhances the model's accuracy in detecting small and distant traffic signs while maintaining computational efficiency.
5. **Loss Function Enhancement**: We replace the traditional loss function with SIOU loss to improve convergence, robustness, and overall detection performance, particularly under challenging conditions.

The proposed YOLOv7-tiny-RCA model achieves a balance between accuracy, speed, and computational efficiency, making it highly suitable for real-time applications in autonomous driving. By addressing the challenges of adverse environmental conditions, complex backgrounds, and resource limitations, this study provides a robust solution for deploying TSD systems on edge devices.

Our work contributes to advancing the capabilities of autonomous driving technologies, facilitating safer and more reliable navigation in real-world environments. Additionally, it underscores the importance of lightweight, efficient algorithms in promoting the broader adoption of intelligent transportation systems across diverse road conditions and geographical regions.

II. PRIMARY CONTRIBUTION OF THIS STUDY BRIEFLY OUTLINED AS

This study primarily contributes to the advancement of traffic sign detection through the development of YOLOv7-tiny-RCA, a lightweight and efficient model tailored for deployment on edge devices. The contributions are as follows:

1. **Dataset Expansion and Enhancement**: The study uses the Indian Traffic Sign Dataset (ITSD) as the foundation for training and testing the model, expanding it with images from diverse urban, suburban, and rural Indian environments. Data augmentation techniques, such as weather simulations, motion blur, and brightness adjustments, were applied to simulate various real-world conditions like rain, fog, and low light.
2. **Model Architecture Innovations**: The YOLOv7-tiny-RCA model incorporates advanced modules like ELAN-REP for backbone optimization, Convolutional Block Attention Module (CBAM) for enhanced feature extraction, Asymptotic Feature Pyramid Network (AFPN) for improved feature fusion, and SIOU loss to enhance bounding box regression. These innovations together contribute to improved detection accuracy and computational efficiency, particularly in edge device environments.
3. **Edge Device Deployment and Optimization**: The model was optimized for real-time deployment on edge devices through quantization techniques, reducing the model's size while maintaining performance. Real-time validation on platforms like NVIDIA Jetson Nano and Raspberry Pi 4 demonstrated the model's feasibility for practical deployment in resource-constrained settings.
4. **Comprehensive Evaluation**: The proposed model was rigorously evaluated under a variety of conditions, including adverse weather and occlusion scenarios, and its performance was compared against state-of-the-art lightweight models. The results highlight the superior balance of detection accuracy, speed, and computational efficiency achieved by the YOLOv7-tiny-RCA model.

III. METHODOLOGIES

To address the complex challenges of traffic sign detection in the Indian context, this study proposes YOLOv7-tiny-RCA, a lightweight and efficient model optimized for edge device deployment. The methodology encompasses dataset preparation, architectural innovations, training strategies, and deployment evaluations. Each component is elaborated below:

1. Dataset Preparation

A critical aspect of this study is ensuring the model is trained and evaluated on a dataset that accurately represents real-world Indian traffic sign detection challenges.

1.1. Primary Dataset

The Indian Traffic Sign Dataset (ITSD) was selected as the primary dataset, as it reflects diverse traffic sign types, shapes, and sizes commonly seen in Indian road conditions. Additionally, it captures variations in environmental conditions such as varying illumination, occlusions, and complex backgrounds.

1.2. Augmentation and Expansion

To enhance the ITSD dataset:

Data Augmentation: Techniques such as random rotations, scaling, Gaussian noise addition, brightness adjustments, motion blur simulation, and weather simulation (fog, rain, and low light) were applied. These augmentations simulate real-world scenarios encountered on Indian roads.

Dataset Expansion: Traffic sign images were collected from Indian highways, urban areas, and rural regions, capturing additional traffic sign variations. These new samples were integrated with ITSD to ensure comprehensive coverage of diverse Indian traffic conditions.

2. Model Architecture

The proposed YOLOv7 integrates innovative modules to enhance detection accuracy, computational efficiency, and robustness.

2.1. Backbone Optimization with ELAN-REP

ELAN-REP Module: Employs a multi-branch structure during training for improved feature learning and reduces to a single- branch structure during inference for efficiency.

Benefits: Reduces computational demands and memory usage while maintaining high detection accuracy.

2.2. Attention Mechanisms with CBAM

CBAM enhances feature extraction by focusing on critical regions in Indian traffic images.

Impact: Improves detection accuracy, especially for signs partially occluded by vehicles, pedestrians, or trees, common in Indian roads.

2.3. Feature Fusion with AFPN

AFPN integrates high- and low-level features to improve small object detection, particularly for distant or partially visible signs.

Benefits: Enhances the model's ability to detect small Indian traffic signs effectively.

2.4. Improved Loss Function with SIOU Loss

SIOU Loss improves bounding box regression, ensuring higher localization precision for small and overlapping signs, which are common in Indian traffic scenes.

3. Training Methodology

3.1. Training Environment

Hardware: High-performance GPUs were used for efficient training.

Framework: PyTorch enabled flexibility and scalability during model development.

3.2. Hyperparameter Tuning

Key parameters such as learning rate, batch size, and momentum were optimized using grid search for the best balance between accuracy and speed.

3.3. Augmentation Techniques

Simulations: Included weather effects (rain, fog, snow), motion blur, and varying illumination conditions to enhance model generalization.

3.4. Training Strategy

Transfer Learning: Pretrained YOLOv7-tiny weights were used to initialize the model.

Focal Loss: Addressed the class imbalance in Indian traffic sign categories, ensuring better focus on underrepresented classes.

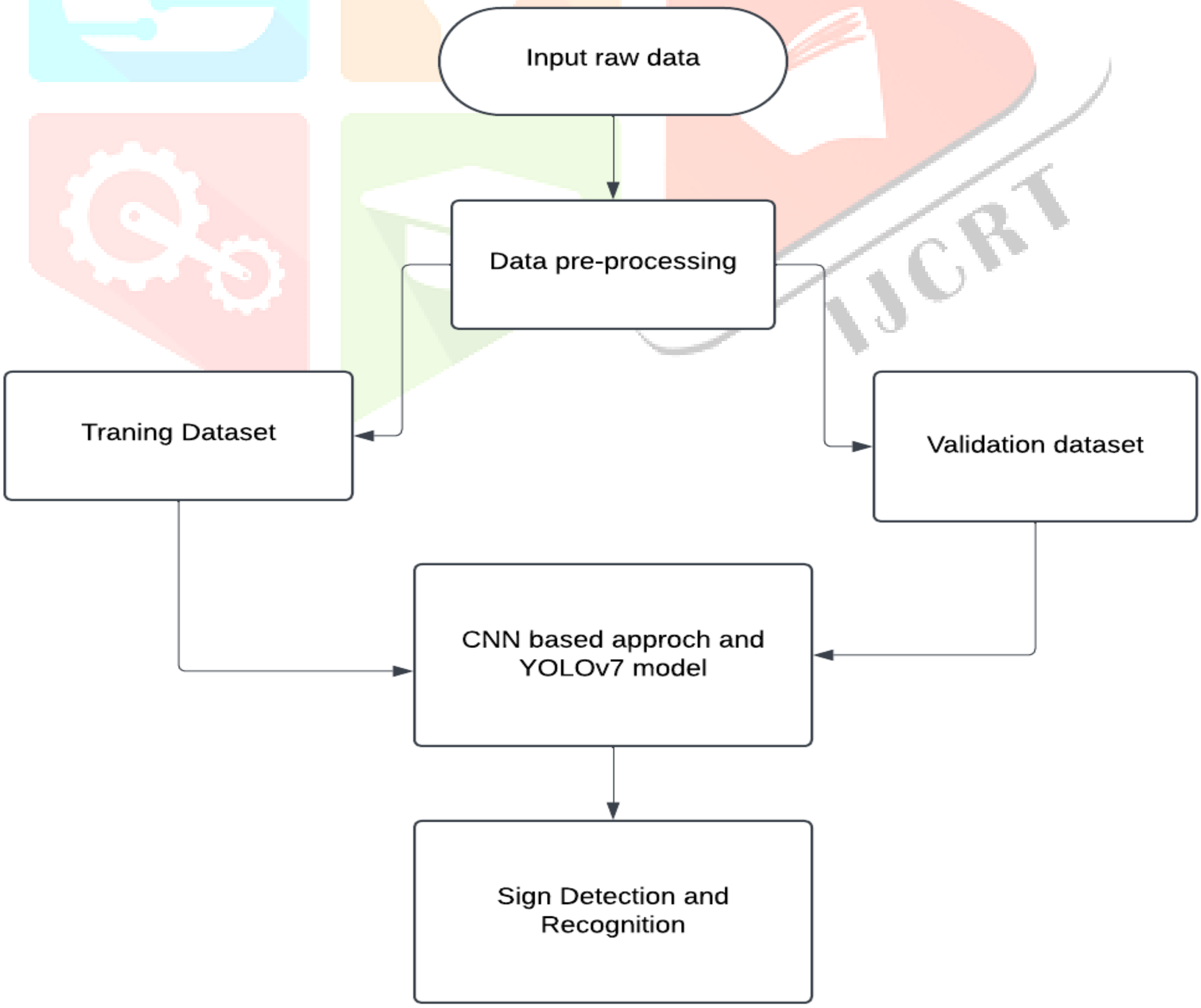
4. Evaluation Framework
4.1. Performance Metrics
Mean Average Precision (mAP): Evaluated detection accuracy across all categories.
Inference Speed (FPS): Measured for real-time performance.
Computational Cost: Parameters and FLOPs were analyzed to quantify efficiency.

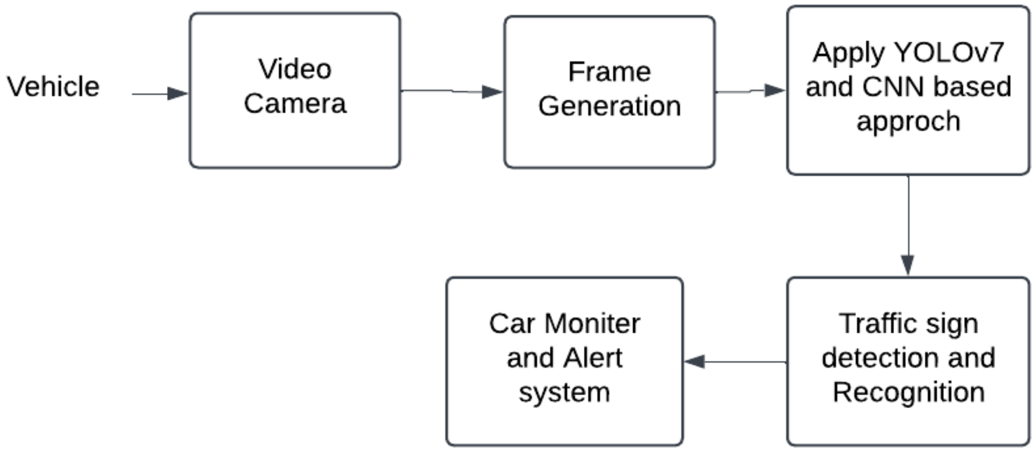
4.2. Real-World Testing
The model was tested in real-world Indian environments, including urban, rural, and highway scenarios. Detection performance under diverse conditions, such as rain, fog, occlusion, and night driving, was evaluated to ensure robustness.

5. Deployment on Edge Devices
Quantization Post-training quantization techniques were applied to optimize the model for edge devices such as NVIDIA Jetson Nano and Raspberry Pi 4. **Edge Device Validation** Real-time performance was validated by analyzing latency, FPS, and detection accuracy in resource-constrained environments commonly found in Indian scenarios.

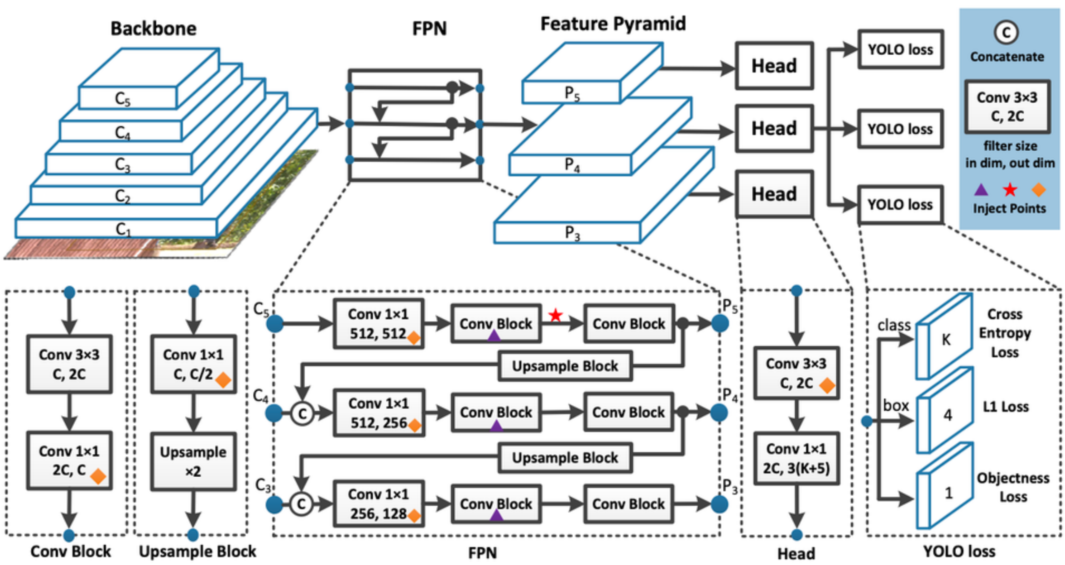
6. Comparative Analysis
The effectiveness of YOLOv7-tiny-RCA was compared against state-of-the-art models, including YOLOv7-tiny, MobileNet-based frameworks, and Efficient Det. The analysis demonstrated the proposed model's superior trade-off between accuracy, speed, and computational efficiency, particularly in Indian traffic conditions.

IV. Workflow





V. YOLOv7 Architecture



YOLOv7 architecture:

YOLOv7 is an advanced real-time object detection model that balances high accuracy with speed and efficiency. It features an **E-ELAN backbone** for robust multi-scale feature extraction and uses **SPP (Spatial Pyramid Pooling)** and **PAN (Path Aggregation Network)** in its neck for enhanced feature aggregation. The model incorporates a **decoupled head** for independent optimization of classification and localization tasks, and an **auxiliary head** during training to improve gradient flow, which is removed during inference for better efficiency. With **RepConv layers** for faster inference, improved loss functions like **CIoU** for better localization, and dynamic scaling for various hardware setups, YOLOv7 achieves state-of-the-art performance. Advanced training strategies, such as dynamic label assignment and data augmentation, further enhance its capabilities, making it suitable for applications in autonomous driving, surveillance, and beyond.

VI. KEY ISSUES AND FUTURE DIRECTION

Adverse Environmental Conditions: Weather conditions such as rain, fog, snow, and varying illumination (low-light or overexposure) can significantly degrade image quality, making accurate detection of traffic signs difficult. This impacts the performance of both cameras and sensors, which are essential for reliable traffic sign recognition.

Dynamic and Complex Backgrounds: Traffic signs are often surrounded by complex and cluttered backgrounds such as trees, buildings, vehicles, and other distractions. This leads to false detections or the failure to detect signs entirely, especially when they are similar to background elements.
Motion Blur and Occlusion: High-speed motion of the vehicle causes motion blur, and partial occlusions (e.g., traffic signs being blocked by other vehicles or pedestrians) can severely affect detection accuracy, making it hard for models to correctly identify and respond to road signs in real-time.

Small Object Detection Challenges: Traffic signs, particularly those seen from a distance, appear small in images. Detecting small objects accurately requires high-resolution processing and models that can effectively scale to identify such features in a timely manner.

Enhanced Robustness Under Adverse Conditions: Developing models and algorithms that are more robust to adverse weather conditions and varying illumination is essential. Techniques like image enhancement, weather condition adaptation, and sensor fusion could improve traffic sign detection under difficult environmental conditions.

Optimization for Edge Devices: Research into lightweight and efficient deep learning models, such as YOLOv7-tiny and its enhanced versions like YOLOv7, is essential. These models need to balance accuracy with reduced computational requirements to be effectively deployed on edge devices for real-time traffic sign detection.

Addressing Occlusion and Motion Blur: Developing algorithms capable of handling occlusions and motion blur is key for improving detection accuracy at high speeds. Research into temporal information processing and multi-frame analysis could help models overcome these challenges.

Integration with Autonomous Vehicle Systems: Continuous improvements in integrating traffic sign detection systems with other autonomous vehicle components, such as localization, path planning, and decision-making systems, will lead to more reliable and accurate driving in real-world environments.

VII. CONCLUSION

This review paper explores the current state of traffic sign detection (TSD) in autonomous driving systems, highlighting the challenges and advancements in the field. Effective TSD is crucial for the safe operation of autonomous vehicles, as it ensures that vehicles can accurately recognize and respond to traffic signs under various environmental conditions. The paper discusses the significant issues facing TSD, including adverse weather, dynamic and complex backgrounds, motion blur, occlusion, and the difficulties associated with small object detection. Additionally, the computational constraints of deploying detection systems on edge devices are explored, emphasizing the need for models that balance real-time performance with high detection accuracy. Also review recent advancements in deep learning-based methods, particularly the YOLO framework and its lightweight variants, which have significantly improved the efficiency and accuracy of TSD systems. Notable innovations such as feature fusion networks, attention mechanisms, and optimized loss functions have contributed to overcoming key challenges in the field. Despite these advancements, there is still a need for further research to improve model robustness, address occlusion and motion blur, and develop more efficient algorithms for edge device deployment.The paper outlines future directions for research in TSD, including the development of more robust models that can handle adverse weather and lighting conditions, improved integration with other autonomous vehicle systems, and optimization of models for real-time performance on resource-constrained devices. By addressing these challenges, the future of TSD will contribute to safer, more reliable autonomous driving systems that can operate efficiently in diverse, real-world environments.In conclusion, while significant progress has been made in the field of traffic sign detection, ongoing research and innovation are essential to achieving fully autonomous vehicles capable of navigating complex, dynamic road environments.

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