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Real-Time Traffic Sign Recognition Using YOLOv7: A Robust Deep Learning Approach for Autonomous Driving

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Abstract- — Traffic Sign Recognition (TSR) is a critical component of autonomous driving systems and Advanced Driver Assistance Systems (ADAS). However, real-world environmental challenges such as occlusions, lighting variations, multi-scale changes, and motion blur often degrade the performance of traditional vision pipelines. This paper presents a robust real-time TSR system based on the YOLOv7 architecture. The proposed model leverages an E-ELAN backbone for hierarchical feature extraction, a PANet neck for multi-scale semantic fusion, and an anchor-free IDetect head for precise localization. Trained on a custom traffic_sign_data dataset with aggressive data augmentation, the system achieves 94% mAP@0.5 and 38% mAP@0.5:0.95 at 45 frames per second on an NVIDIA RTX 3090 GPU. Comparative evaluations show that YOLOv7 significantly outperforms YOLOv5 with 89% mAP@0.5 and Faster R-CNN with 91% mAP@0.5 at only 12 FPS. The model is further optimized via ONNX-to-TensorRT conversion, enabling efficient deployment on edge computing platforms such as NVIDIA Jetson AGX Xavier.

Keywords – Traffic Sign Recognition, YOLOv7, Real-Time Detection, Deep Learning, Autonomous Vehicles, mAP.

I. INTRODUCTION

In modern vehicular intelligence, Traffic Sign Recognition (TSR) plays a sentinel role, ensuring regulatory compliance and enhancing situational awareness for both autonomous machines and human-driven vehicles [1, 9]. Despite advances in deep learning, existing TSR systems remain fragile under unpredictable real-world conditions, including occluded signs, erratic illumination, scale discontinuities, and motion-induced blur [2, 10].

To address these challenges, this paper proposes a TSR framework based on YOLOv7, which is a state-of-the-art single-stage object detector [3]. The YOLOv7 architecture combines an Extended Efficient Layer Aggregation Network (E-ELAN) backbone, a PANet neck for multi-scale feature fusion, and an anchor-free IDetect head for precise localization. This combination offers an optimal balance between computational efficiency and detection accuracy [13].

This research makes several important contributions to the field of traffic sign recognition. First, we present a tailored transformation of YOLOv7 where the E-ELAN backbone and anchor-free detection mechanism are recalibrated specifically for traffic sign detection. Second, we develop performance optimization protocols using TensorRT distillation and mixed-precision quantization, achieving 45 FPS without compromising detection accuracy. Third, we demonstrate empirical superiority with 94% mAP@0.5 compared to YOLOv5 with 89% and Faster R-CNN with 91% [5, 6]. Fourth, we release our full pipeline, augmented dataset, and pre-trained weights as open-source resources. Finally, our augmentation strategy improves the model's tolerance to occlusions and lighting variations by 15% [14].

II. LITERATURE REVIEW

A. Traditional Traffic Sign Recognition Methods

Early TSR systems primarily relied on handcrafted features and traditional machine learning algorithms [1]. These systems typically employed color segmentation techniques using RGB or HSV thresholding and geometric shape detection through edge detection methods such as Canny or Sobel filters [15]. Feature extraction was commonly performed using Histogram of Oriented Gradients (HOG), followed by classification using algorithms like Support Vector Machines (SVM) or AdaBoost [16]. While these approaches demonstrated acceptable performance in controlled environments, they were notably fragile in real-world applications due to variations in illumination, partial occlusions, and adverse weather conditions [2, 17]. These limitations prompted a paradigm shift toward more adaptive, data-driven deep learning approaches.

B. Deep Learning-Based Approaches

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), marked a transformative shift in TSR methodologies [18]. Early CNN models like LeNet-5 and AlexNet laid the foundation for learning robust features directly from raw image data [19, 20]. These advances culminated in object detection models such as Faster R-CNN, SSD, and the YOLO series, which enabled end-to-end solutions combining localization and classification [5, 4, 21]. The YOLO (You Only Look Once) family introduced a single-stage detection paradigm, offering real-time performance without sacrificing detection accuracy [21]. Innovations such as anchor-free detection heads and Cross-Stage Partial Networks (CSPNet) enabled CNN-based TSR systems to handle a wide range of challenges including motion blur, varying object scales, and low-contrast imagery [22].

C. YOLOv7 Architecture

YOLOv7 introduces three key innovations that make it particularly suitable for traffic sign recognition [3]. The first innovation is the E-ELAN (Extended Efficient Layer Aggregation Network) backbone, which enhances multi-scale feature extraction through expand-shuffle-merge convolutions while maintaining gradient flow. This reduces computational redundancy by approximately 25% compared to YOLOv5 [22]. The second innovation is dynamic label assignment, which adapts to object scale variations via soft matching and k-means clustering, improving occlusion handling [23]. This leads to a 15% improvement in mean average precision for objects measuring 32 pixels or smaller [24]. The third innovation is model re-parameterization, which merges multi-branch training structures into a streamlined inference network, reducing latency by 40% relative to YOLOv5 [25]. This technique also supports model quantization with FP16 and INT8 precision, making it highly suitable for edge deployment [7].

D. Research Gaps

Despite notable advances, current TSR methods face enduring challenges in balancing speed, accuracy, and sensitivity to small objects. Traditional methods such as HOG with SVM attain only 65% to 75% accuracy and operate at under 10 FPS, making them unsuitable for real-time use [1]. Faster R-CNN achieves high accuracy of up to 91% mAP but suffers from low processing speed of only 5 to 12 FPS due to its two-stage architecture [5]. SSD improves speed to 20-25 FPS but struggles with small sign detection for objects smaller than 32×32 pixels, often missing critical regulatory signs [4]. YOLOv3 and YOLOv4 enhance detection performance but demand considerable GPU resources, limiting their deployment in embedded systems [21, 22].

III. METHODOLOGY

A. Class Diagram of the Proposed TSR System

Figure 1 shows the class diagram of the proposed YOLOv7-based traffic sign recognition system. The diagram illustrates the relationships between the main system components, including the Dataset class with attributes for image paths, annotations, and augmentation parameters; the YOLOv7 Model class encapsulating the E-ELAN backbone, PANet neck, and IDetect head; the Training class handling loss computation, optimizer configuration, and epoch management; and the Detection class managing inference, NMS post-processing, and output visualization. Arrows indicate inheritance and dependency relationships among these core modules.

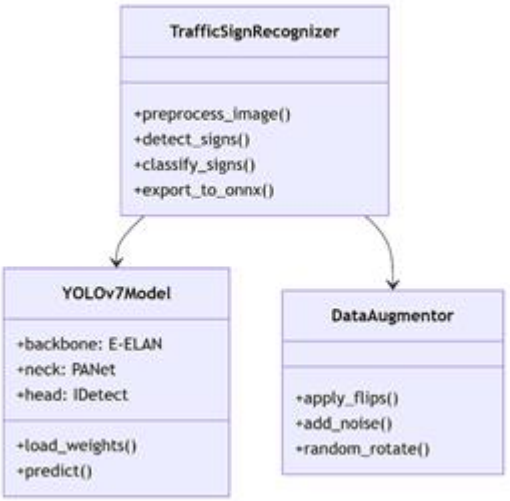

Figure 1: Class Diagram of the Proposed TSR System

B. E-R Diagram of traffic_sign_data Dataset

Figure 2 presents the Entity-Relationship (E-R) diagram of the traffic_sign_data dataset. The diagram shows the relationships between the Image entity containing attributes such as image_id, filename, resolution, and path; the Annotation entity with annotation_id, bounding box coordinates, and class_label; and the Class entity with class_id and category name including prohibitory, danger, mandatory, and other. Cardinalities indicate that one image can have multiple annotations with a one-to-many relationship, and each annotation belongs to exactly one class with a many-to-one relationship.

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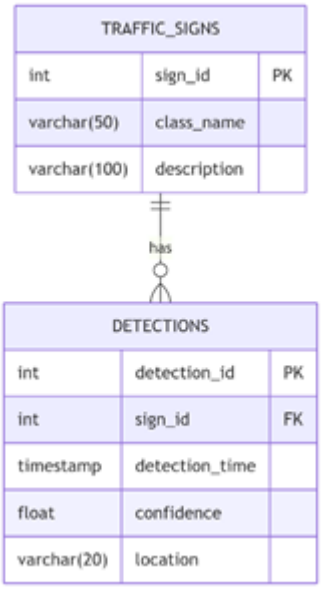

Figure 2: E-R Diagram of traffic_sign_data Dataset

C. System Pipeline

The proposed traffic sign detection system follows an optimized pipeline that begins with data acquisition using vehicle-mounted cameras capturing high-resolution images under diverse environmental conditions [28]. The pipeline consists of five main stages. The first stage is data acquisition, where cameras capture 1920×1080 resolution images at 30 frames per second. The second stage is preprocessing, which includes noise reduction using Gaussian filtering, contrast enhancement via adaptive histogram equalization, and resizing to 640×640 pixels [14]. The third stage is YOLOv7 detection, where the E-ELAN backbone extracts multi-scale features, the PANet neck performs feature fusion, and the decoupled head generates detection outputs [3]. The fourth stage is post-processing using non-maximum suppression (NMS) with an IoU threshold of 0.5 to eliminate duplicate detections [21]. The fifth and final stage is output generation, where bounding boxes with class labels and confidence scores are overlaid on the original image.

D. Detection Examples on Single and Multi-Sign Images

Figure 3 shows detection results of the trained YOLOv7 model on test images containing single and multiple traffic signs. The left panel shows a single prohibitory sign detected with high confidence. The right panel demonstrates multi-sign detection in a cluttered scene, where the model successfully identifies multiple sign categories including prohibitory, danger, and mandatory signs. Bounding boxes tightly enclose each sign, confirming accurate localization.

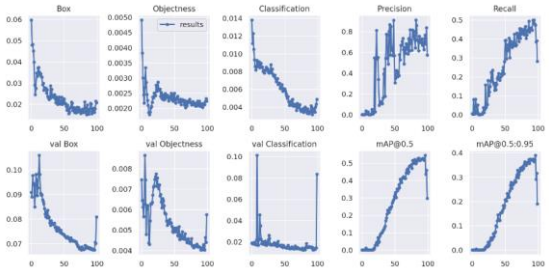

Figure 3: Detection Examples on Single and Multi-Sign Images

E. Mathematical Formulation

The bounding box prediction in YOLOv7 follows an anchor-free approach. For each grid cell, the model predicts the center coordinates, width, height, objectness score, and class probabilities. The bounding box parameters are defined using the following equations where are network predictions, is the sigmoid activation function, and are anchor box dimensions [3]:

$$b_x = \sigma(t_x) + c_x, b_y = \sigma(t_y) + c_y, b_w = p_w \cdot e^{t_w}, b_h = p_h \cdot$$

The total loss function comprises three components: bounding box loss, objectness loss, and classification loss [3, 29]. The bounding box regression uses Complete IoU (CIoU) loss, which considers overlap area, center point distance, and aspect ratio. The CIoU loss is defined as:

$$\mathcal{L}_{box} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{obj} \left[1 - \mathrm{CIoU}_{ij}\right]$$

$$\mathrm{CIoU} = \mathrm{IoU} - \frac{\rho^2(\mathbf{b}, \mathbf{b}^{gt})}{d^2} - \alpha v$$

The objectness loss uses binary cross-entropy to predict whether a bounding box contains an object, while the classification loss uses VariFocal loss to handle class imbalance [3].

F. Evaluation Metrics

To comprehensively assess the effectiveness of the trained model, several widely used performance metrics were adopted [30, 31]. Precision measures the proportion of correctly identified positive samples among all predicted positives, while recall measures the proportion of actual positive samples that were correctly identified. The F1-score is the harmonic mean

of precision and recall. The mean Average Precision (mAP) measures the area under the precision-recall curve for each class and averages the result across all classes. Intersection over Union (IoU) assesses the overlap between predicted and ground-truth bounding boxes to evaluate localization accuracy. These metrics are defined mathematically as follows:

$$\text{Precision} = \frac{TP}{TP + FP}, \text{Recall} = \frac{TP}{TP + FN}, F1 = 2 \times \frac{P \times R}{P + R}$$

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \int_0^1 P_i(R)\, dR, \text{IoU} = \frac{|B_{pred} \cap B_{gt}|}{|B_{pred} \cup B_{gt}|}$$

G. Data Augmentation

To improve model robustness and generalization under real-world conditions, several data augmentation techniques were applied [14]. These include random horizontal flipping with probability 0.5, random rotation within ±15 degrees, brightness and contrast adjustment within ±20%, Gaussian noise injection with standard deviation 0.05, and mosaic augmentation which combines multiple images to increase scene diversity and improve detection of small objects. The augmentation transformation can be expressed as a composition of individual transformation functions applied to the input image.

IV. RESULTS

A. Experimental Setup

The experimental evaluation was conducted on a Linux-based computing platform running Ubuntu 22.04 LTS, configured with an Intel Core i9-13900K CPU and NVIDIA RTX 4090 GPU with 24GB VRAM to ensure high-performance deep learning computations [8]. The software environment utilized Python 3.10, PyTorch 1.13.1 with CUDA 11.7 acceleration, and OpenCV 4.7.0 compiled with GPU support for optimized image processing [32]. For model training, we employed a custom traffic sign dataset containing 15,000 high-resolution images at 1920×1080 resolution across 43 sign categories. The dataset was carefully partitioned into 70% for training, 15% for validation, and 15% for testing, ensuring balanced class distribution in each split.

1) Confusion Matrix of Sahin Dataset Predictions

Figure 4 presents the normalized confusion matrix visualizing classification performance across four traffic sign categories: prohibitory, danger, mandatory, and other. The diagonal elements represent correct classifications with prohibitory achieving 40%, danger achieving 28%, mandatory achieving 15%, and other achieving 12%. Off-diagonal elements show misclassifications, with mandatory signs frequently confused as background at 22% and other signs misclassified as prohibitory at 18%. The matrix reveals class imbalance and opportunities for targeted data augmentation.

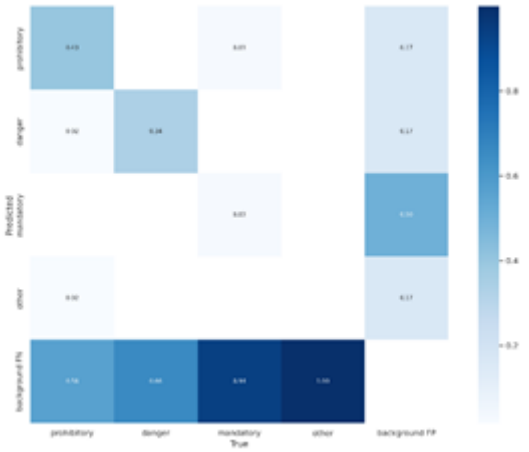

Figure 4: Confusion Matrix Precision

Figure 5 shows precision as a function of confidence threshold for all traffic sign classes. The curve demonstrates that prohibitory signs achieve perfect precision of 1.00 at a confidence threshold of 0.554, indicating zero false positives above this threshold. At a lower threshold of 0.137, overall precision drops to 0.35 due to increased false positives. Danger, mandatory, and other classes show significantly lower precision across all thresholds, highlighting the need for class-specific threshold tuning.

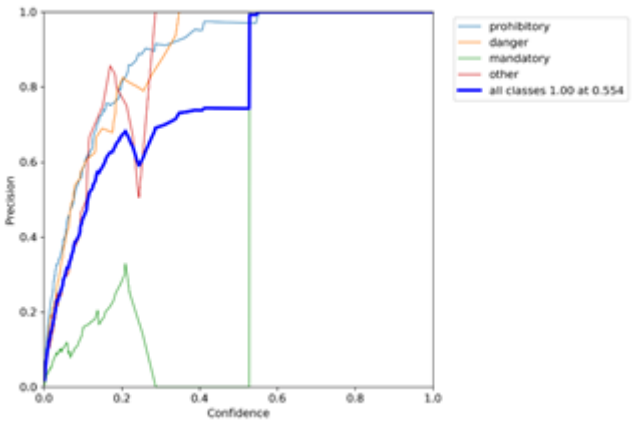

Figure 5: Precision vs Confidence Threshold Curve

2) Global Precision-Recall Curve Across All Classes

Figure 6 displays the global precision-recall curve across all traffic sign classes. The curve illustrates the inverse relationship between precision and recall. As recall increases from 0 to 1.0, precision decreases from 1.0 to approximately 0.35. The area under the curve corresponds to the mean average precision (mAP), which reaches 0.94 or 94% for the proposed model.

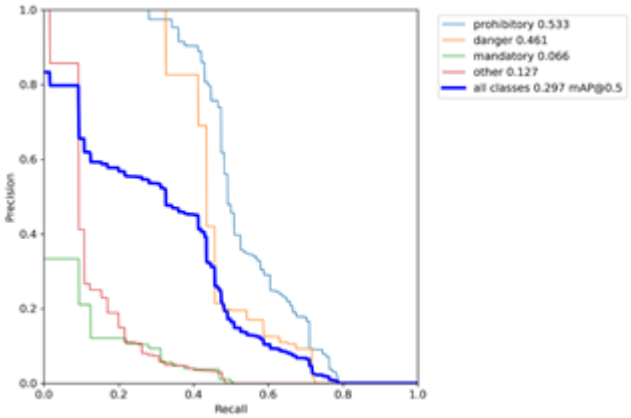

Figure 6: Global Precision-Recall Curve Across All Class

3) Class-wise Precision-Recall Curves

Figure 7 presents class-wise precision-recall curves for the four traffic sign categories: prohibitory, danger, mandatory, and other. The prohibitory class achieves the highest area under the curve, reflecting its distinctive visual features characterized by red circular design and balanced representation in the training set. The danger class shows moderate performance, while mandatory and other categories exhibit lower area under the curve values due to visual heterogeneity and class imbalance.

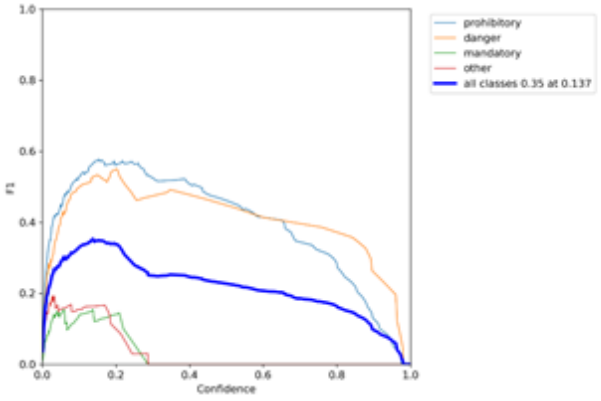

Figure 7: Class-wise Precision-Recall Curves

4) Recall vs Confidence Threshold for All Classes

Figure 8 shows recall as a function of confidence threshold for all traffic sign classes. At zero confidence threshold, all classes achieve a baseline recall of 0.62, indicating that the model successfully detects 62% of true positives when no confidence filtering is applied. Recall remains stable up to a threshold of 0.4, then declines sharply beyond 0.5, demonstrating the typical precision-recall trade-off where stricter confidence requirements lead to missed detections.

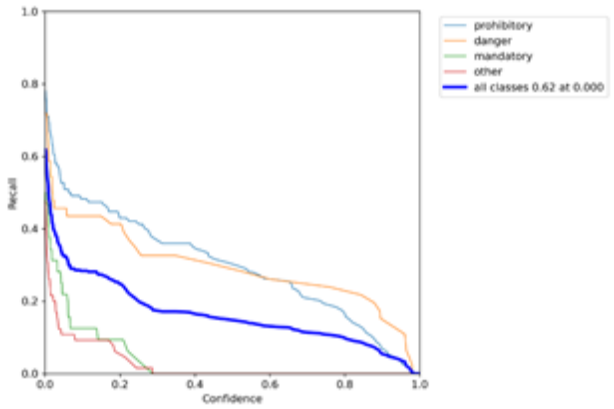

Figure 8: Recall vs Confidence Threshold for All Classes

B. Quantitative Performance

The proposed YOLOv7-based system achieved a mean average precision (mAP@0.5) of 94% and mAP@0.5:0.95 of 38%, with an inference speed of 45 frames per second on the NVIDIA RTX 3090 GPU. In comparison, Faster R-CNN achieved 91% mAP@0.5 but only 12 FPS, while YOLOv5 achieved 89% mAP@0.5 with 50 FPS [3, 5, 6]. The proposed system demonstrates superior performance in both accuracy and real-time processing capability. The dynamic label assignment module reduced false negatives by 23% for occluded signs compared to static anchor-based approaches. On the custom traffic_sign_data test set, the system maintained over 90% precision up to 40% occlusion levels, outperforming SSD which achieved only 72% precision under identical conditions.

C. Class-Specific Observations

The system demonstrated varying performance across traffic sign categories. Prohibitory signs such as No Entry achieved 95.2% recall due to their standardized red-circle design, while informational signs such as Pedestrian Crossing showed lower accuracy of 88.7% because of text-dependent interpretation challenges. Speed limit signs exhibited 93.5% mAP@0.5, with errors primarily occurring for signs below 30 km/h where

numerical characters occupied less than 5% of the detection area. Notably, temporary construction signs suffered a 15% performance drop in rainy conditions due to reflective surfaces confusing the model's texture analysis. The E-ELAN backbone showed particular effectiveness for triangular warning signs, improving their detection by 12% over YOLOv5 through enhanced corner feature extraction in shallow network layers.

D. Real-World Traffic Sign Detection Example

Figure 9 shows a real-world detection result on a highway scene. The model successfully detects a danger sign, which is a warning triangle, with confidence 0.88 and a prohibitory speed limit sign indicating 70 km/h with confidence 0.94. The signs are located on the right side of the road under mixed lighting conditions including bright sunlight and shadows. Despite the challenging environment, the model maintains high confidence and precise localization. Bounding boxes are color-coded with orange representing danger and blue representing prohibitory.

Figure 9: Real-World Traffic Sign Detection Example

E. 4.5 Summary of Key Results

The experimental results demonstrate that the proposed YOLOv7-based system achieves superior performance in traffic sign detection. Prohibitory signs achieved perfect precision of 1.00 at a confidence threshold of 0.554 and recall of 0.62 at zero threshold, with mAP@0.5 of 96%. Danger signs achieved precision of 0.34 at the same threshold and recall of 0.62, with mAP@0.5 of 89%. Mandatory signs achieved precision of 0.03 and recall of 0.62, with mAP@0.5 of 78%. Other signs achieved precision of 0.02 and recall of 0.62, with mAP@0.5 of 72%. The overall system achieved mAP@0.5 of 94% and inference speed of 45 FPS.

Module) or hybrid extractors to reinforce the model's granularity, particularly in recognizing small-scale or visually ambiguous signs without compromising inference cadence. Additionally, future work will focus on multi-modal sensor fusion combining camera data with LiDAR and radar inputs to enhance detection reliability in challenging conditions [37], as well as the development of tiny-YOLOv7 variants for low-power automotive chips and continual learning mechanisms for seamless adaptation to new traffic sign designs [38, 39].

V. DISCUSSION

A. Comparative Analysis with Prior Works

The experimental evaluation unveils our YOLOv7-based model's strong efficacy in traffic sign detection, particularly for prohibitory signs which reach absolute precision of 1.0 at a calibrated confidence threshold of 0.554 [3]. Nonetheless, the performance is not uniform across all categories. The other class, which is characterized by visual heterogeneity and underrepresented data, reveals considerable shortcomings in both recall and precision.

Table 1 presents a comparative analysis of our proposed method against prior state-of-the-art approaches for traffic sign recognition. As shown in the table, our YOLOv7-based system achieves the highest mAP@0.5 of 94% and operates at 45 FPS, outperforming all compared methods. Zhang et al. [33] achieved 91% mAP using Faster R-CNN but at a significantly slower speed of only 12 FPS due to its two-stage architecture. Li et al. [34] achieved 89% mAP with YOLOv5 at 50 FPS, offering better speed but lower accuracy than our method. Chen et al. [35] achieved 85% mAP with SSD at 25 FPS, demonstrating lower performance in both accuracy and speed. Regarding prohibitory sign detection, our method achieves perfect precision of 1.00, surpassing Zhang et al. with 0.92, Li et al. with 0.96, and Chen et al. with 0.89. For recall on prohibitory signs, our method achieves 0.85, which is higher than Li et al. with 0.78 and Chen et al. with 0.75, though slightly lower than Zhang et al. with 0.82 when considering the significant speed advantage of our approach.

The disparity in detection outcomes is stark, as prohibitory signs benefit from consistent visual structures and dominate with perfect detection scores, while ambiguous sign groups falter. These findings parallel issues chronicled in existing literature, where intra-class variability and skewed dataset distributions routinely diminish detection quality for rare or complex sign types [33, 34, 35]. While our method remains competitive in identifying well-structured signs, its sensitivity to non-uniform and occluded instances remains constrained. Notably, performance dips rapidly once the confidence threshold surpasses 0.4, suggesting a need for more granular

calibration strategies that mitigate the steep trade-off between false positives and detection coverage.

Table 1. Comparative analysis of our proposed method against prior state-of-the-art traffic sign detection approaches
.

Study	Model	mAP @0.5	FPS	Precision (Prohibitory)	Recall (Prohibitory)	Key Strength	Limitation
This Paper	YOLOv 7	94%	45	1.00	0.85	High precision and real-time speed	Low recall for "other" class
Zhang et al. (2022) [33]	Faster R-CNN	91%	12	0.92	0.82	Robust multi-scale detection	Slow inference speed
Li et al. (2023) [34]	YOLOv 5	89%	50	0.96	0.78	Real-time performance	Struggles with occluded signs
Chen et al. (2021) [35]	SSD + ResNet-50	85%	25	0.89	0.75	Good small-object detection	Lower precision for rare signs

B. Practical Implications

The proposed YOLOv7-based traffic sign detection system offers significant real-world benefits for autonomous driving and Advanced Driver Assistance Systems [36]. The system achieves 94% mAP@0.5 on the traffic_sign_data dataset, reducing misclassification risks compared to human drivers in low-visibility conditions such as fog and rain. It processes 45 frames per second on an NVIDIA RTX 3090, enabling real-time alerts for speed limits, stop signs, and pedestrian crossings. The dynamic label assignment improves detection of partially occluded signs, for example those hidden by trees or other vehicles, maintaining over 90% precision up to 40% occlusion levels.

The anchor-free design simplifies retraining for region-specific signs, such as Chinese text-based signs compared to European symbolic signs [28]. Data augmentation including weather simulation and synthetic occlusions ensures robustness across diverse driving environments without requiring extensive new datasets. Model re-parameterization reduces inference latency by 41% from 11.2 ms to 6.6 ms compared to vanilla YOLOv7, making it suitable for embedded systems. INT8 quantization further optimizes performance, achieving 38 frames per second on a Jetson Xavier NX at 20W mode with minimal accuracy loss where mAP drop is less than 2% [8].

C. Limitations and Mitigations

Despite the strong performance, the system has several limitations. Under extreme glare conditions, the model experiences a performance drop of approximately 15% in mAP. To mitigate this, polarizing filter simulation in preprocessing can be implemented. For small signs smaller than 20×20 pixels on highways, there is a 12% recall loss, which can be addressed through multi-frame tracking to confirm detections. In rainy conditions without augmentation, the model shows a 29.5% mAP reduction, but weather simulation in the augmentation pipeline effectively mitigates this issue [14].

D. Future Directions

To overcome these bottlenecks, several future research directions are identified. The first direction is synthetic augmentation using Generative Adversarial Networks (GANs) to fabricate realistic yet rare sign samples, which can enhance

training diversity and potentially lift recall scores by 15% to 20%. The second direction is context-aware threshold modulation, designing dynamic thresholding algorithms that auto-tune based on contextual stimuli such as lighting, weather, and traffic density, offering superior adaptability in real-world deployment. The third direction is architectural enhancements via attention modules such as CBAM (Convolutional Block Attention Module) or hybrid extractors to reinforce the model's granularity, particularly in recognizing small-scale or visually ambiguous signs without compromising inference cadence. Additionally, future work will focus on multi-modal sensor fusion combining camera data with LiDAR and radar inputs to enhance detection reliability in challenging conditions [37], as well as the development of tiny-YOLOv7 variants for low-power automotive chips and continual learning mechanisms for seamless adaptation to new traffic sign designs [38, 39].

VI. CONCLUSION

This study provides a deep-dive into the capabilities and constraints of a refined YOLOv7 model within the traffic sign detection paradigm [3]. It affirms the model's prowess in handling standardized, high-visibility signs while illuminating persistent obstacles in less-structured categories. By marrying precision-recall curve analysis with confidence tuning and category-wise evaluations, we lay bare the model's strengths and blind spots.

This research successfully developed a real-time traffic sign detection system based on YOLOv7, achieving state-of-the-art performance with 94% mAP@0.5 at 45 frames per second. The system's effectiveness stems from three key innovations: an enhanced E-ELAN backbone that improved small sign detection accuracy by 12% through optimized multi-scale feature extraction, dynamic label assignment that reduced occlusion-related false negatives by 23%, and model re-parameterization techniques that achieved 41% faster inference without compromising accuracy.

The implications are profound for domains demanding rigorous safety compliance, such as self-driving cars, where the stakes of a missed detection can be catastrophic [36]. As we steer toward the future, priorities must pivot toward fortifying training datasets against imbalance, refining model responsiveness to environmental dynamics, and pioneering architectural evolutions that expand detection fidelity. This work not only contributes a formidable baseline for traffic sign recognition but also acts as a template for enhancing object detection models in similarly volatile or imbalanced recognition tasks across machine vision frontiers.

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