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OPENING REMARKS

Fundamental And Applied IT Research (referred to as FAIR) is organized to contribute to promoting fundamental and applied research in Information Technology in Vietnam. This conference is under the chairmanship of the Vietnam Union of Science and Technology Associations, in collaboration with the Vietnam Academy of Science and Technology, Vietnam National University, Hanoi, and leading scientific institutions and researchers from research institutes and universities nationwide.

In 2025, the Conference Steering Committee, in partnership with the Hanoi University of Industry, organized the 18th National Scientific Conference (FAIR'2025) with the theme "Digital Transformation and Future Trends" on August 21–22, 2025, in Hanoi.

This conference serves as a forum for researchers in the field of Information Technology (IT), particularly faculty members from universities and research institutes across the country, to present their latest findings and exchange experiences in IT research and applications.

Currently, Vietnam is advancing its scientific and technological development, innovation, and digital transformation to become a high-income, developed nation. In this process, Information Technology, particularly Artificial Intelligence and communications plays a crucial role. We are building an economy based on high technology, with Vietnam actively undergoing digital transformation across all sectors. This process is unfolding dynamically and vigorously. With the theme "Digital Transformation and Future Trends", the conference acknowledges the substantial benefits of AI and digital transformation. We recognize that data has become an invaluable resource, yet the world is increasingly flooded with fake data and misinformation, largely generated by AI. As the IT community, we must actively engage in developing measures to mitigate these negative impacts, safeguarding users and ensuring societal safety.

The conference received over 170 submitted scientific reports addressing all current issues in Information Technology and Communications. The Program Committee conducted rigorous peer review and selection, accepting 112 papers for presentation in the conference's specialized sessions, 107 of which were selected for inclusion in the Conference Proceedings.

This year, the conference also hosted the FAIR PhD Forum 2025, attracting numerous doctoral candidates, graduate students, and young researchers. The Program Committee also selected the Best Paper Award for both research groups and young authors.

On behalf of the Organizing Committee and Program Committee, we extend our sincere gratitude to all authors who submitted their work to the conference and to the scientists who provided objective and valuable reviews of the submitted papers. We express our appreciation to the scientists who chaired the sessions in the specialized sessions and to all colleagues who participated in discussions. We are especially grateful to the Publishing House for Science and Technology, Vietnam Academy of Science and Technology, for their support in publishing the Conference Proceedings.

Finally, we extend our deepest gratitude to the Vietnam Union of Science and Technology Associations and the Hanoi University of Industry, the host institution for their significant efforts and time in organizing FAIR'2025. We also thank all sponsors whose multifaceted support and financial contributions were instrumental in ensuring the success of this conference.

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Traffic Sign Detection in Vietnam: An Experimental Study

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***Abstract*—Traffic Sign Recognition (TSR) is an important problem in the field of computer vision, particularly in the context of intelligent driving assistance and improving traffic safety. In this study, we apply YOLOv10—a novel real-time object detection architecture—to address the task of traffic sign recognition in Vietnam. The model was trained on a dataset of over 57,000 images, which were carefully preprocessed using sliding window and ROI cropping techniques to enhance the detection of small objects. Experimental results show that YOLOv10 achieved mAP@0.5 = 88.2%, outperforming YOLOv8 and YOLOv5 under the same training conditions, while maintaining an average inference speed of 48 FPS on an RTX 3090 GPU. These findings demonstrate the practical effectiveness of YOLOv10 in intelligent driving assistance systems and smart traffic monitoring.**

***Index Terms*—Traffic Sign Recognition (TSR), Computer Vision, Real-time Object Detection, YOLO**

I. Introduction

In Vietnam, road transport plays a crucial role in the national transportation system, with the number of vehicles increasing rapidly. As of 2024, approximately 82 million vehicles, including cars and motorcycles, had been registered nationwide [1]. Alongside the socio-economic benefits, the current traffic situation also reveals many concerning issues, particularly frequent violations of traffic safety regulations and accidents caused by driver errors.

One of the common causes is drivers failing to recognize or ignoring traffic signs in time due to adverse environmental conditions (poor lighting, backlight, rain), obstructed or damaged signs, or driver distraction. Therefore, driver assistance systems, especially those enabling **real-time automatic traffic sign recognition**, are increasingly being emphasized to reduce risks and enhance vehicle safety.

The **Traffic Sign Recognition (TSR)** problem is a highly applicable task in computer vision, typically consisting of two main steps:

- **Detection**: Locating the position of traffic signs in images through bounding boxes.
- **Classification**: Assigning the correct label to the corresponding sign.

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This task poses numerous challenges in real-world environments: small or deformed signs, non-fixed positions, partial occlusions, and influences from lighting and weather conditions. Moreover, for practical deployment, the system must ensure **real-time processing with low latency**.

Traditional approaches such as **HOG + SVM** [2], [3] or classifiers based on handcrafted features (**SIFT, KNN,...**) [4] are no longer effective in complex environments. The advancement of deep learning, particularly **Convolutional Neural Networks (CNNs)** [5], has significantly transformed the problem-solving approach. Among these, the **YOLO (You Only Look Once)** family of models [6]–[15] stands out for its ability to achieve fast and accurate object detection in a single forward pass. The latest version, **YOLOv10** [15], introduced in 2024, inherits and improves both efficiency and architecture by eliminating the **Non-Maximum Suppression (NMS)** step while maintaining high accuracy, making it highly suitable for real-time object detection tasks.

This paper aims to achieve the following objectives:

- Conduct an in-depth study of the **YOLOv10 architecture**, including its working principles, key components, and training strategies such as *Dual Label Assignment*, *Partial Self-Attention*, and *Compact Inverted Block*.
- Build a high-quality dataset of Vietnamese traffic signs through collection, analysis, preprocessing, and annotation.
- Design and implement a training and evaluation pipeline for YOLOv10 on real-world data, thereby assessing its effectiveness in practical applications within the Vietnamese context.

The scope of this research focuses on recognizing a subset of common traffic signs in Vietnam's traffic environment. The experimental application is limited to image-based recognition (without integration with mapping or vehicle control). Extensions such as dataset expansion or deployment on embedded devices will be considered in future developments.

The remainder of this paper is organized as follows:

- Section 2 presents a review of related studies in object detection and traffic sign recognition.
- Section 3 describes the dataset, preprocessing strategies, and model training setup.

- Section 4 reports the experimental results and evaluates model performance.
- Section 5 provides conclusions and directions for future work.

II. Related Work

A. Object Detection and Approaches

Object detection is one of the fundamental tasks in computer vision, aiming to localize and classify objects appearing in an image. This task serves as a foundation for various applications such as security surveillance, autonomous driving, behavior analysis, and especially intelligent driving assistance.

The main approaches include:

- **Two-stage detectors**: A representative example is Faster R-CNN [16], in which the first stage generates region proposals and the second stage performs classification and bounding box regression. While achieving high accuracy, this approach is slower and less suitable for real-time applications.
- **One-stage detectors**: Models such as SSD [17], RetinaNet [18], and especially the YOLO family [6]–[15] perform detection and classification in a single forward pass, significantly improving speed. From YOLOv1 to YOLOv10, continuous improvements in speed and accuracy have made YOLO one of the most popular choices for real-time applications.

B. Traffic Sign Detection

1) Previous Studies: The traffic sign recognition (TSR) problem has been extensively studied for many years. Models are often trained on benchmark datasets such as GTSRB [19], TT100K [20], and CCTSDB [21]. YOLO models, ranging from YOLOv3 to YOLOv8 [8]–[13], have been widely applied due to their fast and accurate performance.

According to Flores-Calero et al. (2024) [**?**], in a survey of multiple YOLO-based TSR systems, most achieved mean average precision (mAP) above 90%. However, challenges remain in detecting small signs, partially occluded signs, and signs under poor lighting conditions. Recently, improved models such as MSGC-YOLOv8 [22] and LLE-STD [23] have integrated attention mechanisms or low-light image enhancement modules to improve detection capability.

Nevertheless, most studies rely on international benchmark datasets, paying little attention to the unique characteristics of traffic signs in countries with complex traffic systems such as Vietnam.

2) Proposed Study: Unlike the aforementioned works, this study focuses on:

- Applying **YOLOv10**, one of the latest versions of the YOLO family, with architectural innovations such as the elimination of NMS, the use of *Dual Label Assignment*, *Partial Self-Attention*, and *Compact Inverted Blocks (CIB)*.
- Constructing a large-scale dataset of over 57,000 Vietnamese traffic sign images collected from various real-world locations, diverse in size, viewpoint, lighting, and context.
- Employing *ROI cropping* and *sliding window* techniques to improve detection of small or occluded traffic signs.
- Ultimately, evaluating the effectiveness of YOLOv10 in the TSR problem in Vietnam, aiming for real-time applications in driver assistance systems.

III. Proposed Method

A. System Overview

The traffic sign recognition system in this study is designed with a modular architecture to ensure flexible, efficient training, testing, and deployment of the YOLOv10 model. The overall system consists of the following main components:

1) **Data Preprocessing Module**
   - Input: raw images from dashcams, surveillance videos, or captured photos.
   - Applied techniques: ROI cropping, sliding window, and various augmentations (Mosaic, rotation, blurring, color adjustment, etc.).
   - Output: normalized input images ready for training or inference.
2) **Traffic Sign Detection Model**
   - Input: preprocessed images.
   - Detection performed directly using the YOLOv10n model.
   - Output: bounding boxes, traffic sign class labels, and confidence scores.
3) **Post-processing and Visualization Module**
   - Filtering detections below the configured confidence threshold.
   - Displaying detection results directly on the output image or video.
   - Sending warning notifications (if integrated with driver assistance systems).

The overall system architecture is illustrated in Fig. 1.

B. Dataset

To train and evaluate YOLOv10, we constructed a dataset of Vietnamese traffic sign images. The data were collected from multiple sources: field photographs, dashcams, surveillance cameras, and open datasets with labels reformatted to match local traffic signs. The distribution of object instances for each class is shown in Fig. 2.

Traffic signs are categorized into three main groups: *prohibitory signs*, *mandatory signs*, and *warning signs*. All images were annotated in the COCO format, including bounding boxes and class labels.

A spatial heatmap analysis (Fig. 3) shows that traffic signs tend to appear at the top and sides of images, usually small in size, and easily affected by environmental noise such as trees, vehicles, strong light, or rainy weather. Brighter regions on the heatmap indicate higher densities of occurrence.

The bounding box width–height distribution (Fig. 3) indicates that most bounding boxes concentrate within the width range of 70–130 pixels and height range of 80–160 pixels. This reflects the fact that most traffic signs in the dataset are of medium size and do not occupy a large portion of the image frame.

Example images from the dataset are shown in Fig. 4.

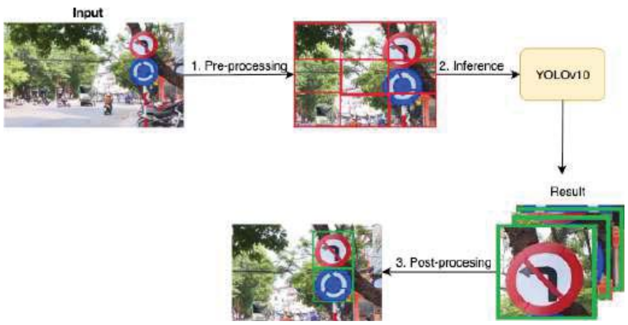

Fig. 1: Overall system architecture for traffic sign recognition.

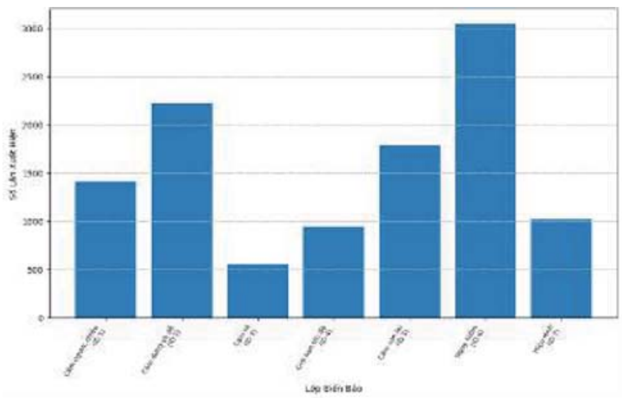

Fig. 2: Class-wise distribution of traffic signs in the dataset.

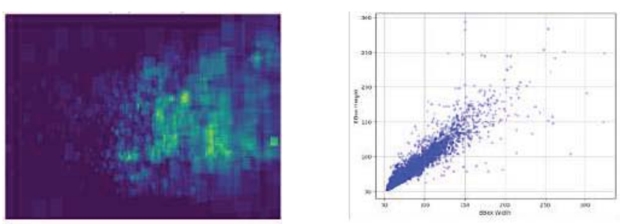

Fig. 3: Overview of spatial heatmap and bounding box size distribution

Fig. 4: Sample images from the dataset.

C. Data Preprocessing Strategy

To improve the detection capability for small objects and enhance input quality for the model, we designed a three-step preprocessing pipeline, illustrated in Fig. 5:

1) **ROI Cropping**: Based on the spatial analysis of common traffic sign locations, the input image is cropped to the region of interest (ROI). Most target traffic signs appear within approximately 70% of the image width (from the right edge) and 70% of the image height (from the top). This region is selected as the ROI.
2) **Sliding Window**: The cropped image is divided into tiles using a sliding window with a stride of 80 pixels. Each tile has a size of 320×320 pixels and is resized to 640×640 pixels to match the YOLOv10 model input.
3) **Data Augmentation**: Several augmentation techniques are applied to increase dataset diversity and model robustness under varying conditions of lighting and weather. These include Mosaic, Rotation, HSV Adjustment, Contrast/Brightness modification, and Blur.

D. Training Configuration

After preprocessing, we obtained a refined dataset consisting of 57,240 images. We split the dataset with an 80:20 ratio for training and validation, respectively. We selected the YOLOv10n model — the lightest variant of YOLOv10 — as it is suitable for real-time tasks and deployment on resource-constrained devices. The training parameters are summarized in Table I.

TABLE I: Training Configuration

Parameter	Value
Epoch	50
Batch size	16
Image size	640×640
Optimizer	SGD
Learning rate	0.001
Environment	NVIDIA RTX 3090, CUDA 12.1

E. YOLOv10 Architecture

YOLOv10 is the first YOLO architecture that completely removes the Non-Maximum Suppression (NMS) post-processing step by adopting a dual label assignment training strategy, while maintaining high accuracy. The model is optimized for real-time applications, with several key improvements in its main components:

- **Backbone:** Utilizes the Compact Inverted Bottleneck (CIB) block, inspired by [24], [25], which reduces the number of parameters, accelerates inference, and preserves strong feature extraction capability.
- **Neck:** Integrates Partial Self-Attention (PSA) at deeper layers, allowing the model to focus on critical regions, especially small traffic signs in complex backgrounds.
- **Head:** Enables NMS-free inference through an optimized one-to-one matching structure, reducing duplication and system latency.

Additional improvements of YOLOv10 are summarized in Table II.

With these characteristics, YOLOv10 fully meets the requirements of traffic sign recognition in Vietnam, particularly

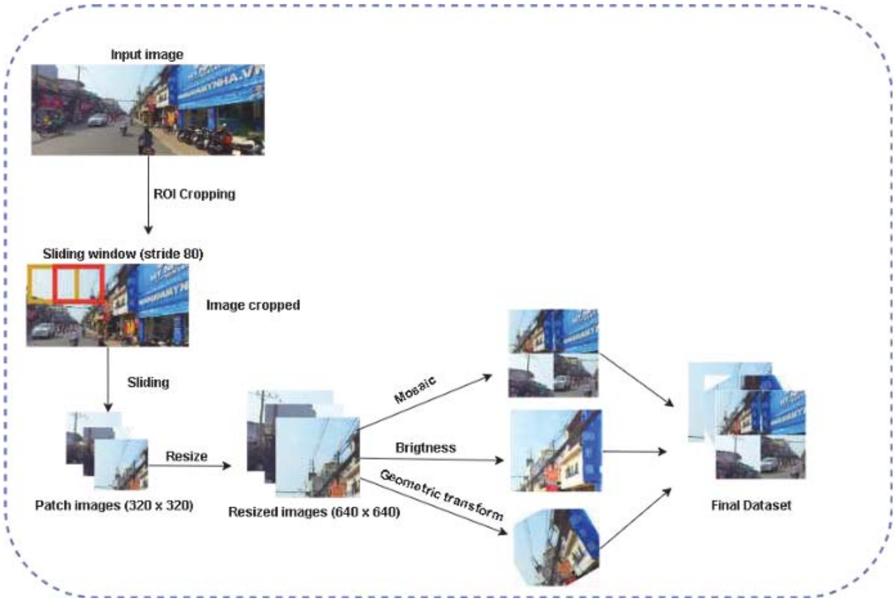

Fig. 5: Illustration of the three-step data preprocessing strategy

TABLE II: Key Improvements in YOLOv10

Component	Role
CIB (Compact Inverted Block)	Reduces parameters while maintaining feature extraction efficiency
Large Kernel Depthwise Conv	Expands receptive field, improving detection of small signs
Partial Self-Attention (PSA)	Enhances focus on informative regions
Dual Label Assignment	Combines one-to-many and one-to-one strategies for stable training and eliminates NMS
Anchor-Free Detection	Simplifies pipeline and increases flexibility for multi-scale objects

in terms of handling small objects, achieving fast inference speed, and enabling deployment on embedded systems.

IV. Results and Evaluation

A. Training and Evaluation Results

After 50 training epochs, the YOLOv10n model achieved promising results on the test dataset. Table III presents the performance metrics obtained after training. Fig. 6 illustrates the training metrics across epochs.

TABLE III: Training results at Epoch 50

Metric	Value
mAP@0.5	88.2%
Precision	90.4%
Recall	86.7%
F1-score	88.5%
FPS (RTX 3090)	∼48

Key observations:

- **Precision (90.4%):** The model correctly predicted most detected objects as traffic signs.
- **Recall (86.7%):** Demonstrates strong capability in detecting the majority of signs present in images, including small-scale ones.
- **F1-score (88.5%):** Indicates a well-balanced trade-off between precision and recall.

The Precision–Recall (P–R) curve shown in Fig. 7 highlights the model's stable performance across various confidence thresholds, with a high Area Under Curve (AUC) and low fluctuation, reflecting robust feature learning ability.

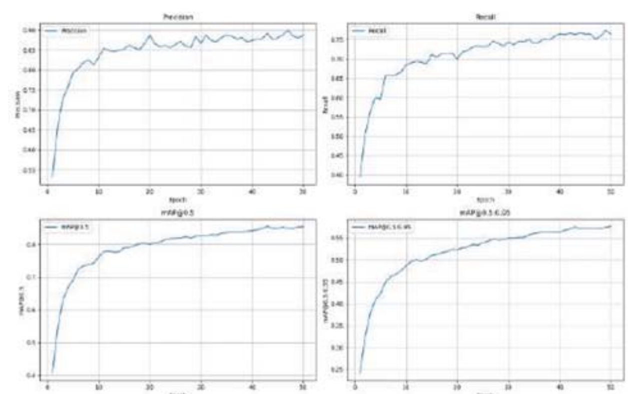

Fig. 6: Training metrics of YOLOv10n across 50 epochs

B. Comparison with Other Models

We conducted a comparison between YOLOv10n and other YOLO versions trained on the same dataset and with equivalent configurations. The results are summarized in Table IV.

TABLE IV: Comparison of YOLO models on the traffic sign dataset

Model	mAP@0.5	FPS	Parameters
YOLOv5s	84.6%	42	7.2M
YOLOv8n	86.9%	45	3.2M
YOLOv10n	**88.2%**	**48**	**2.3M**

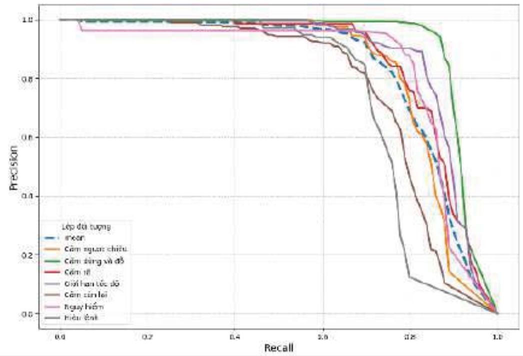

Fig. 7: Precision–Recall (P–R) curve of YOLOv10n on test dataset

YOLOv10n not only achieves superior accuracy but also improves inference speed while reducing the number of parameters, making it well-suited for real-world deployment.

Fig. 8 illustrates the mAP@0.5 progression of the models across training epochs.

Fig. 8: mAP@0.5 comparison of YOLOv5s, YOLOv8n, and YOLOv10n across epochs

C. Error Analysis

We further analyzed the failure cases of the model, which can be grouped into the following categories:

- **False Negatives (missed detections):**
  - Frequently observed in images where traffic signs are very small ($< 20 \times 20$ pixels) or located near the image boundary.
  - Signs that are partially occluded by trees, vehicles, or degraded/faded signs also posed challenges for the model.
- **False Positives (incorrect detections):**
  - The model occasionally confuses visually similar traffic signs, such as "No Left Turn" and "No U-Turn" signs.

The use of sliding window and Region of Interest (ROI) cropping significantly improved the detection of small signs, which previous YOLO versions struggled with. The remaining errors mainly stem from dataset quality or extreme environmental conditions.

Representative examples of common failure cases are illustrated in Fig. 9.

Fig. 9: Examples of frequent error cases in YOLOv10n predictions

V. Conclusion and Future Work

In this paper, we presented a traffic sign detection approach for Vietnam using YOLOv10, the latest model in the YOLO family. With its lightweight architecture, Non-Maximum Suppression (NMS)-free inference, and Dual Label Assignment training strategy, YOLOv10n demonstrated effective detection performance under real-world conditions.

We also proposed a preprocessing pipeline that integrates Region of Interest (ROI) cropping and sliding window to improve the detection of small traffic signs — a common challenge in the Vietnamese traffic environment. The real-world dataset, consisting of over 57,000 traffic sign images, allowed the model to learn rich features and better reflect deployment conditions.

Experimental results showed that the model achieved an mAP@0.5 of 88.2% and a processing speed of ∼48 FPS, outperforming YOLOv5s and YOLOv8n under the same dataset and training configuration. The model not only achieved high accuracy but also satisfied real-time requirements, making it suitable for applications in driver assistance systems or intelligent traffic monitoring.

For future work, we plan to focus on:

1) Expanding the dataset with rare traffic signs, damaged signs, and challenging weather conditions such as rain and fog.
2) Integrating the model into real-time driver assistance systems with direct feedback, e.g., audio alerts or Head-Up Display (HUD) visualization.
3) Deploying and evaluating the model on embedded platforms such as Jetson Nano and Raspberry Pi to assess performance under resource-constrained environments.
4) Combining detection with object tracking or segmentation for continuous video-based traffic sign recognition and enhanced stability.

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