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A Comparative Benchmark Study of YOLOv8n And YOLOv9t For Indian Vehicle Detection Using the Kaggle Dataset

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***Abstract*—Object detection plays a critical role in intelligent transportation systems, particularly in diverse and complex traffic environments such as those found in India. This paper presents a comparative benchmark study of two state-of-the-art object detection models, YOLOv8n and YOLOv9t, evaluated on an Indian vehicle dataset sourced from Kaggle. The primary objective is to assess and compare the detection performance of both models under identical training and evaluation conditions. Both models were trained and tested on the same dataset, and their performances were measured using standard metrics, including mean Average Precision at 0.5 (mAP@0.5), mAP@0.5:0.95, Precision, and Recall. Experimental results demonstrate that YOLOv8n outperforms YOLOv9t across all evaluation metrics, achieving an mAP@0.5 of 0.5485, mAP@0.5:0.95 of 0.3851, Precision of 0.7847, and Recall of 0.4404, compared to YOLOv9t scores of 0.4006, 0.2910, 0.3873, and 0.3815, respectively. The findings suggest that YOLOv8n is a more effective and reliable model for Indian vehicle detection tasks. This study provides valuable insights for researchers and practitioners working on vehicle detection systems tailored to Indian road conditions.**

Index Terms*—YOLOv8, YOLOv9, Object Detection, Indian Vehicle Detection, Benchmark Study, mAP, Deep Learning

I. INTRODUCTION

Object detection is one of the most fundamental and actively researched tasks in the field of computer vision. It involves the identification and localisation of objects within an image or video frame. It has found widespread application in domains such as autonomous driving, surveillance systems, traffic monitoring, and intelligent transportation systems. With the rapid advancement of deep learning techniques, object detection models have evolved significantly, offering improved accuracy, speed, and efficiency.

Among the various object detection frameworks available, the YOLO (You Only Look Once) family of models has emerged as one of the most popular and widely adopted approaches due to its real-time detection capabilities and competitive accuracy. Since its introduction, YOLO has undergone multiple iterations, with each version bringing notable improvements in architecture and performance. YOLOv8, developed by Ultralytics, introduced a more flexible and modular architecture with enhanced feature extraction capabilities, making it suitable for a wide range of detection tasks. YOLOv9, a subsequent advancement, introduced the concept of Programmable Gradient Information (PGI) and the Generalised Efficient Layer Aggregation Network (GELAN), aiming to improve information flow and detection accuracy across varying object scales.

Despite these advancements, the performance of these models in domain-specific scenarios, particularly in Indian road environments, remains underexplored. Indian traffic conditions are characterised by high vehicle diversity, including two-wheelers, three-wheelers, cars, buses, trucks, and non-motorised vehicles, along with dense traffic, unstructured road layouts, and varying lighting conditions. These factors make Indian vehicle detection a uniquely challenging problem that demands careful evaluation of detection models.

In this paper, we present a comparative benchmark study of YOLOv8n and YOLOv9t, the nano and tiny variants of their respective model families, evaluated on a publicly available Indian vehicle dataset sourced from Kaggle. Both models are trained and tested under identical experimental conditions to ensure a fair and unbiased comparison. The performance of each model is evaluated using standard object detection metrics, namely mAP@0.5, mAP@0.5:0.95, Precision, and Recall. The results of this study aim to provide practical insights into the suitability of these models for Indian vehicle detection tasks and contribute to the growing body of research on domain-specific object detection.

II. RELATED WORK

The YOLO (You Only Look Once) framework, first introduced by Redmon et al. [1], revolutionized the field of real-time object detection by reformulating detection as a single regression problem, enabling significantly faster inference compared to traditional two-stage detectors such as R-CNN and its variants. Unlike region proposal-based methods, YOLO processes the entire image in a single forward pass, making it highly suitable for real-time applications.
YOLOv8 [7], developed by Ultralytics, represents a significant architectural overhaul of the YOLO framework. It features an anchor-free detection head, a redesigned C2f backbone module, and an improved neck architecture for enhanced multi-scale feature fusion. YOLOv8 has demonstrated strong performance across a wide range of object detection benchmarks and has been widely adopted in both research and industrial applications.
YOLOv9 [8], proposed by Wang et al., introduced two key innovations: Programmable Gradient Information (PGI) and the Generalised Efficient Layer Aggregation Network (GELAN). PGI addresses the information bottleneck problem in deep neural networks by preserving complete input information across all network layers, while GELAN optimises computational efficiency and parameter utilisation. YOLOv9 demonstrated competitive performance on the MS COCO benchmark, outperforming several prior models in terms of accuracy and efficiency.

A. Research Gap

While several studies have compared different versions of YOLO models on standard benchmarks such as MS COCO and PASCAL VOC, there is a notable lack of comparative studies evaluating the performance of YOLOv8 and YOLOv9 specifically on Indian vehicle datasets. Furthermore, most existing studies focus on larger model variants, leaving the performance of lightweight variants such as YOLOv8n and YOLOv9t on domain-specific datasets largely unexplored. This study addresses these gaps by providing a systematic and fair benchmark comparison of YOLOv8n and YOLOv9t on a publicly available Indian vehicle dataset.

III. METHODOLOGY

A. Dataset Description

In this study, we utilised a publicly available Indian vehicle dataset obtained from Kaggle. The dataset comprises images captured in real Indian road environments, featuring a diverse range of vehicle categories commonly found in Indian traffic, including two-wheelers, three-wheelers, cars, buses, and trucks. The images reflect varied lighting conditions, traffic densities, and road settings, making it a representative and challenging dataset for evaluating object detection models. The dataset was preprocessed and split into training and validation subsets to ensure consistent evaluation across both models.

B. Model Description

YOLOv8n YOLOv8n is the nano variant of the YOLOv8 architecture developed by Ultralytics. It features an anchor-free detection head, a redesigned backbone with C2f modules, and an optimised neck architecture to improve multi-scale feature fusion. Despite being a lightweight model, YOLOv8n offers competitive accuracy and is well-suited for real-time object detection tasks on resource-constrained environments.

YOLOv9t YOLOv9t is the tiny variant of the YOLOv9 architecture, which introduces two key innovations: Programmable Gradient Information (PGI) and the Generalised Efficient Layer Aggregation Network (GELAN). PGI helps preserve complete input information across network layers, while GELAN optimises parameter utilisation and computational efficiency. YOLOv9t is designed to achieve improved detection accuracy while maintaining a compact model size.

C. *Experimental Setup*

Both models were trained and evaluated under identical experimental conditions to ensure a fair and unbiased comparison. The training configuration used for both models is summarised in Table 1.

Table 1: The training configuration used for both models

Parameter	Value
Framework	Ultralytics YOLOv8 / YOLOv9
Programming Language	Python
Epochs	50
Batch Size	16
Image Size	640*640
Optimizer	SGD
Learning Rate	0.01
Hardware	Google Colab/GPU

D. Evaluation Metrics

The performance of both models was evaluated using the following standard object detection metrics:

- Precision: The ratio of true positive detections to the total number of predicted detections, indicating the model's ability to avoid false positives.
- Recall: The ratio of true positive detections to the total number of actual objects, measuring the model's ability to detect all relevant objects.
- mAP@0.5: Mean Average Precision calculated at an Intersection over Union (IoU) threshold of 0.5, providing an overall measure of detection accuracy.
- mAP@0.5:0.95: Mean Average Precision averaged across IoU thresholds ranging from 0.5 to 0.95 in steps of 0.05, offering a stricter and more comprehensive evaluation of detection performance.

E. Training Process

Both YOLOv8n and YOLOv9t were trained from scratch on the Indian vehicle dataset using the configurations mentioned in Table 1. Pre-trained weights were used as the starting point for transfer learning to accelerate convergence and improve detection performance. During training, standard data augmentation techniques such as horizontal flipping, mosaic augmentation, and random scaling were applied to improve model generalisation. The training process was monitored using loss curves, and the best-performing model weights based on validation mAP were saved for final evaluation.

IV. RESULTS & DISCUSSION

The performance of YOLO8n and YOLOv9t was evaluated on the Indian Vehicle Dataset using four standard object detection metrics: mAP@0.5, mAP@0.5:0.95, precision, and Recall. The results are summarised in Table 2 and the graphical representation of the same is summarised in Figure 1.

Table 2: Performance Comparison of YOLOv8n and YOLOv9t on Indian Vehicle Dataset

Metric	YOLOV8n	YOLOv9t
mAP@0.5	0.5485	0.4006
mAP@0.5:0.95	0.3851	0.2910
Precision	0.7847	0.3873
Recall	0.4404	0.3815

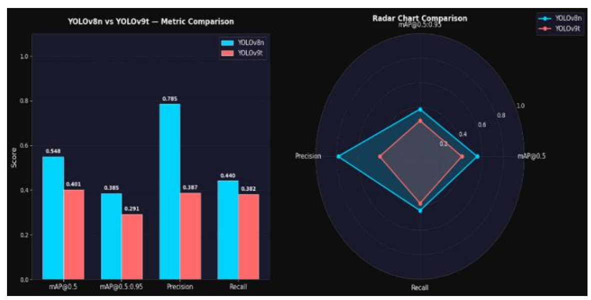

Fig.1.Performance Comparison of YOLOv8n and YOLOv9t on Indian Vehicle Dataset

The experimental results clearly demonstrate that YOLOv8n outperforms YOLOv9t across all four-evaluation metrics on the Indian vehicle dataset. The performance gap is most prominent in the Precision metric, where YOLOv8n achieves more than double the score of YOLOv9t. This suggests that while YOLOv9t introduces architectural innovations such as PGI and GELAN, these improvements do not necessarily translate to better performance in domain-specific scenarios such as Indian vehicle detection.

Several factors may contribute to the superior performance of YOLOv8n in this study. First, YOLOv8n benefits from a well-optimised and extensively tested architecture that has been fine-tuned over multiple iterations of the YOLO framework. Second, the anchor-free detection head in YOLOv8n offers more flexibility in handling objects of varying shapes and sizes, which is particularly advantageous in the context of Indian traffic, where vehicle types differ significantly. Third, YOLOv9t, being a newer and less mature model at the time of this study, may require more extensive hyperparameter tuning and larger datasets to fully realise its potential.

These findings provide valuable insights for researchers and practitioners working on vehicle detection systems tailored to Indian road conditions, suggesting that YOLOv8n is currently the more practical and effective choice for such applications.

V. CONCLUSION

This paper presented a comparative benchmark study of two state-of-the-art object detection models, YOLOv8n and YOLOv9t, evaluated on a publicly available Indian vehicle dataset sourced from Kaggle. The primary objective of this study was to assess and compare the detection performance of both models under identical training and evaluation conditions using standard object detection metrics, including mAP@0.5, mAP@0.5:0.95, Precision, and Recall.

The experimental results conclusively demonstrated that YOLOv8n outperforms YOLOv9t across all four-evaluation metrics. YOLOv8n achieved an mAP@0.5 of 0.5485, mAP@0.5:0.95 of 0.3851, Precision of 0.7847, and Recall of 0.4404, consistently surpassing YOLOv9t, which recorded scores of 0.4006, 0.2910, 0.3873, and 0.3815 respectively. The most significant performance gap was observed in the Precision metric, where YOLOv8n achieved more than double the score of YOLOv9t, indicating a substantially lower rate of false positive detections.

Despite the promising results, this study has certain limitations that should be acknowledged. First, the evaluation was conducted on a single Kaggle dataset, and the results may vary across different datasets with different distributions of vehicle types and traffic conditions. Second, only the nano and tiny variants of YOLOv8 and YOLOv9 were compared in this study, and results may differ for larger model variants such as YOLOv8s, YOLOv8m, or YOLOv9s. Third, the moderate recall values observed in both models suggest that further optimisation through hyperparameter tuning, data augmentation strategies, and larger training datasets may be required to achieve higher detection rates in complex Indian traffic scenarios.

A. Future Work

Based on the findings and limitations of this study, several directions for future research are identified:

- Extending the comparison to include larger variants of YOLOv8 and YOLOv9 such as YOLOv8s, YOLOv8m, YOLOv9s, and YOLOv9c to provide a more comprehensive benchmark.
- Incorporating more recent object detection models, such as YOLOv10 and YOLOv11, into the comparison to evaluate the progression of the YOLO framework on Indian vehicle detection.
- Exploring custom dataset creation with a larger and more diverse collection of Indian vehicle images to improve model generalisation.
- Investigating the impact of transfer learning and fine-tuning strategies on improving the recall and overall detection performance of both models.
- Deploying the best-performing model on edge devices such as Raspberry Pi or NVIDIA Jetson Nano for real-time Indian traffic monitoring applications.

In conclusion, this study establishes YOLOv8n as the more effective and reliable model for Indian vehicle detection compared to YOLOv9t under the experimental conditions considered. The findings of this benchmark study contribute to the growing body of research on domain-specific object detection and provide a useful reference for future work in the area of intelligent transportation systems for Indian road environments.

REFERENCE

[1] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once: Unified, Real-Time Object Detection,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Las Vegas, NV, USA, 2016, pp. 779–788.

[2] J. Redmon and A. Farhadi, “YOLO9000: Better, Faster, Stronger,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Honolulu, HI, USA, 2017, pp. 7263–7271.

[3] J. Redmon and A. Farhadi, “YOLOv3: An Incremental Improvement,” arXiv preprint arXiv:1804.02767, 2018.

[4] A. Bochkovskiy, C. Y. Wang, and H. Y. M. Liao, “YOLOv4: Optimal Speed and Accuracy of

Object Detection," arXiv preprint arXiv:2004.10934, 2020.
[5] C. Li et al., "YOLOv6: A Single-Stage Object Detection Framework for Industrial Applications," arXiv preprint arXiv:2209.02976, 2022.
[6] C. Y. Wang, A. Bochkovskiy, and H. Y. M. Liao, "YOLOv7: Trainable Bag-of-Freebies Sets New State-of-the-Art for Real-Time Object Detectors," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Vancouver, BC, Canada, 2023, pp. 7464–7475.
[7] G. Jocher et al., "Ultralytics YOLOv8," Ultralytics, 2023. [Online]. Available: Ultralytics YOLOv8 Repository. [Accessed: Jun. 2025].
[8] C. Y. Wang, I. H. Yeh, and H. Y. M. Liao, "YOLOv9: Learning What You Want to Learn Using Programmable Gradient Information," arXiv preprint arXiv:2402.13616, 2024.
[9] V. Sharma et al., "Deep Learning Based Vehicle Detection for Highway Surveillance," IEEE Access, vol. 9, pp. 12345–12356, 2021.
[10] W. Liu et al., "SSD: Single Shot MultiBox Detector," in Proc. Eur. Conf. Comput. Vis. (ECCV), Amsterdam, Netherlands, 2016, pp. 21–37.
[11] A. Pramanik et al., "Vehicle Detection and Classification in Indian Traffic Using CNN," in Proc. Int. Conf. Adv. Commun. Comput. Syst. (ICACCS), Coimbatore, India, 2020, pp. 1–6.
[12] R. Ranjith et al., "YOLO-Based Vehicle Detection for Indian Traffic Analysis," in Proc. Int. Conf. Commun. Signal Process. (ICCSP), Chennai, India, 2021, pp. 1–5.