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A Comparative Analysis of Accuracy–Computational Efficiency Trade-offs in YOLOv8, YOLOv9, and YOLOv11 for Underbody Vehicle Component Detection

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ABSTRACT

Traffic accidents are often caused by vehicle technical failures, making periodic inspections crucial. This study aims to implement YOLOv8, YOLOv9, and YOLOv11 algorithms on a camera-equipped robotic platform to detect powertrain system components located underneath vehicles. A quantitative experimental method was employed by comparing the performance of the three YOLO versions in detecting components such as the transmission, universal joint, and propeller shaft. The dataset consisted of 1,000 images collected from pick-up vehicles, processed using the Roboflow platform, and divided into training, validation, and testing sets. The results indicate that YOLOv9 achieved the highest classification accuracy, with an mAP@50 of 96.6%, while YOLOv11 demonstrated superior computational efficiency with an inference speed of 13.5 ms per image. An optimal dataset size of 500 images was found to provide a balance between accuracy and efficiency. This study contributes to the development of transparent and real-time AI-based vehicle inspection systems.

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1. INTRODUCTION

Transportation plays an essential role in supporting the mobility of people, goods, and services. However, the high number of traffic accidents in Indonesia highlights the need to improve vehicle safety and roadworthiness. According to the Indonesian National Police Traffic Corps (Korlantas Polri, 2024), 220,647 traffic accidents were recorded within a 10-month period. In addition to human factors, technical failures in vehicle systems such as braking, suspension, and powertrain components also contribute to accident risk, particularly under demanding road conditions (Roza et al., 2024; Abdurrois, 2025). These issues emphasize the importance of periodic vehicle inspection as a preventive measure.

In Indonesia, periodic vehicle inspection is regulated under the Ministry of Transportation Regulation No. PM 19 of 2021, which requires technical and roadworthiness testing of vehicles operating on public roads (Ministry of Transportation of the Republic of Indonesia, 2021). However, inspection of underbody components remains challenging because it often relies on manual visual observation under limited lighting, restricted viewing angles, and inadequate supporting tools. This condition may reduce inspection efficiency, increase subjectivity, and limit transparency for vehicle owners during the inspection process (Fiatri, 2023; Novianto et al., 2022).

Recent advances in robotics and artificial intelligence (AI) provide promising opportunities to improve vehicle inspection systems. In particular, deep learning–based object detection can support automated recognition of vehicle components in a fast and consistent manner (Wibowo & Hakim, 2022). Among available methods, the YOLO (You Only Look Once) family has become widely used for real-time object detection because of its balance between accuracy and computational efficiency (Adi Permana et al., 2024; Akyas Hifdzi Rahman et al., 2024). Several studies have applied YOLO-based approaches for automotive inspection, including the detection of suspension-related components using camera-equipped robotic systems (Jegham et al., 2025; Rasjid et al., 2024; Setiawan et al., 2024). However, comparative studies on multiple recent YOLO versions for detecting underbody powertrain components remain limited.

Therefore, this study implements YOLOv8, YOLOv9, and YOLOv11 on a camera-equipped robotic platform to detect powertrain system components underneath vehicles, including the transmission, universal joint, and propeller shaft. The study evaluates the detection accuracy and computational efficiency of the three models to identify the most suitable approach for real-time underbody vehicle inspection. The results are expected to contribute to the development of transparent, efficient, and AI-based vehicle inspection systems.

2. METHOD

The study was conducted at UPUBKB Jagakarsa, South Jakarta, an A-accredited motor vehicle testing facility. The research was carried out over a period of three months (February–April 2025) in accordance with the operational schedule of UPUBKB, namely Monday to Friday from 08:00 to 16:00 WIB and Saturday from 08:30 to 12:00 WIB.

2.1. Research Design

This study employed a quantitative experimental method by comparing the performance of three YOLO algorithm versions YOLOv8, YOLOv9, and YOLOv11 in detecting powertrain

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system components of pick-up vehicles (Ali et al., 2022; Waruwu et al., 2025). The research focused on object detection accuracy through image dataset analysis using different dataset sizes.

The data sources in this study consisted of both primary and secondary data. Primary data were obtained through direct observation of underbody vehicle components conducted in the underbody inspection lane using a digital camera or smartphone as the image acquisition device (Romdona et al., 2025). Secondary data were collected from relevant literature, including scientific journals, academic articles, and other supporting documents (Ariyanti et al., 2024; Ridwan et al., 2021). Data collection techniques included field observation for recording vehicle identification and capturing visual images of powertrain system components, as well as documentation-based observation through the visual recording of these components in the underbody inspection area.

2.2. Prosedur Penelitian

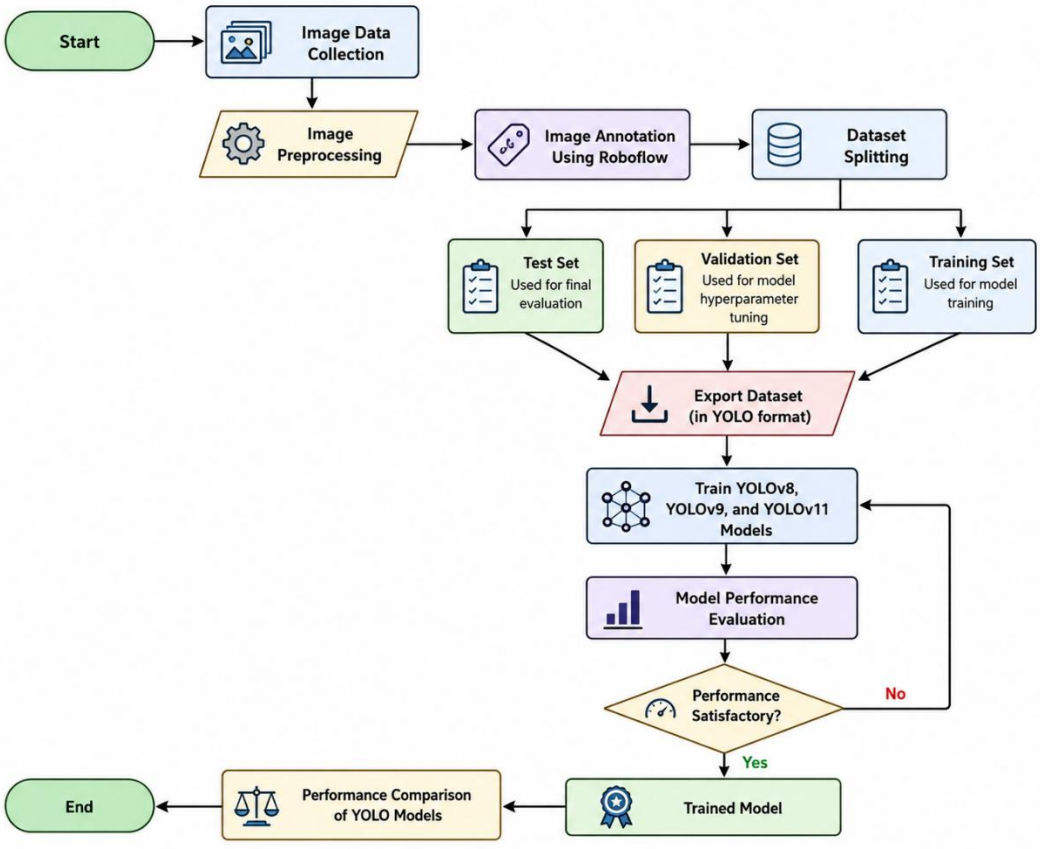

Figure 1. Research Flowchart

The study began with a data collection stage through field observation using a digital camera or smartphone, resulting in ten datasets containing between 100 and 1,000 images of vehicle powertrain system components, along with documentation of the test vehicle identities. The collected data then underwent a preprocessing stage, including manual annotation using bounding boxes on the Roboflow platform and dataset partitioning into training (80%), validation (10%), and testing (10%) sets (Kukartsev et al., 2024). Model training

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was conducted in Google Colab by implementing YOLO versions 8, 9, and 11, using training parameters of 100 epochs, a batch size of 16, and a learning rate of 0.001. Model performance was evaluated using metrics such as Precision, Recall, and F1-score, as well as confusion matrix analysis to comprehensively assess the effectiveness of object detection (Lonang et al., 2023; Palupi et al., 2023).

2.3. Research Instruments

The instruments used in this study included pick-up vehicles as the primary test objects, imaging devices in the form of a 12-megapixel digital camera and a smartphone for visual documentation, as well as complete personal protective equipment (PPE), such as a helmet, safety glasses, gloves, and safety shoes, to ensure safety during the observation process. In addition, the study utilized a high-performance laptop, particularly one equipped with an NVIDIA RTX 3060 GPU, to support the training process of YOLO-based models efficiently.

2.4. Teknik Analisis Data

This study employed two data analysis approaches, namely performance analysis and comparative analysis (Hadinata & Stianingsih, 2024; Khairunisa et al., 2024). Performance analysis was conducted to evaluate the effectiveness of the YOLOv8, YOLOv9, and YOLOv11 algorithms in detecting vehicle powertrain system components. This process involved performing inference on the evaluation data, calculating performance metrics such as accuracy, precision, recall, and F1-score, and interpreting the results to determine the level of object detection success underneath the vehicle. Meanwhile, comparative analysis was carried out by comparing the trained datasets, which consisted of image sets in increments of 100 for each algorithm version. The evaluation was performed graphically based on performance metrics and was followed by validation of model implementation under real-world conditions using various platforms, including desktop, server, and mobile devices.

3. RESULTS AND DISCUSSION

3.1. Dataset

The initial stage in developing the object detection system was carried out through the collection of images of powertrain components from motor vehicles with a gross vehicle weight (GVW) of ≤ 3.5 tons. The data were collected from various types of pick-up vehicles in the underbody inspection lane using a smartphone and LED auxiliary lighting to ensure optimal visual quality. A total of 1,000 images were successfully collected and categorized based on vehicle brand, type, and quantity.

Tabel 1. Vehicle Distribution and Number of Images

No	Brand	Type	Number of Vehicles	Number of Images
1	SUZUKI	SL 415	14	126
2	DAIHATSU	S403 RP	10	90
3	ISUZU	TBR 54	7	63

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No	Brand	Type	Number of Vehicles	Number of Images
4	DAIHATSU	S402 RP	21	168
5	MITSUBISHI	L 300 PU STD	18	162
6	SUZUKI	AEV415W CL	6	54
7	MITSUBISHI	T 120 SS	14	126
8	SUZUKI	ST 150	12	108
9	SUZUKI	ST 130	9	103

A total of 1,000 images were successfully collected, covering five main components of the vehicle powertrain system, namely the transmission, universal joint, propeller shaft, differential, and axle shaft. All images were processed using the Roboflow platform through several stages, including manual annotation with bounding boxes, grouping into 10 dataset versions containing 100 images each, and data augmentation through image flipping and rotation to increase data diversity. The dataset was then divided into training, validation, and testing subsets with a ratio of 70%, 20%, and 10%, respectively. Although this partitioning strategy is commonly used in object detection studies, the resulting testing subset consisted of only approximately 100 images, making it relatively limited for evaluating six object classes. Consequently, the testing data may not have fully represented variations in object appearance across vehicle types, image acquisition angles, and lighting conditions. Therefore, the evaluation results obtained in this study should be interpreted as an initial experimental benchmark, and future studies should consider using a larger and more balanced testing set to improve the robustness and generalizability of the model evaluation.

Table 2. Number of Annotated Data per Component Category

Dataset Version	Component Category				
	Transmission	*Universal joint*	*Propeller shaft*	*Differential*	*Axle shaft*
	58	69	44	39	71
Version 2	102	155	87	96	180
Version 3	152	261	182	139	250
Version 4	195	381	266	195	355
Version 5	238	475	341	241	457
Version 6	306	570	407	288	531
Version 7	351	680	445	340	593
Version 8	395	713	495	404	646
Version 9	432	727	541	451	658
Version 10	474	734	563	514	677

The component distribution included the transmission, universal joint, propeller shaft, differential, and axle shaft. The universal joint and axle shaft accounted for the highest

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number of images due to vehicle characteristics. Higher dataset versions showed an increase in both the number of images and annotation quality, which played an important role in reducing overfitting and improving model accuracy.

3.2. Model Training

The training process was conducted using three YOLO algorithm variants—YOLOv8, YOLOv9, and YOLOv11—with a consistent hyperparameter configuration.

Table 3. Hyperparameter Configuration

No	Hyperparameter Configuration	Description
1	Model Type	*YOLOv8*m.pt
		*YOLOv9*c.pt
		*YOLOv11*n.pt
2	Image Size	640
3	Batch Size	16
4	Number of Epochs	100

The training was conducted using three YOLO model versions through notebooks on the Google Colab platform, with an image size of 640 pixels, a batch size of 16, and 100 epochs for each dataset. Each model was trained under a consistent configuration to ensure that the evaluation results could be analyzed objectively and comparably across versions. The training process was carried out in Google Colab using a Roboflow notebook. The model variants selected in this study—YOLOv8m, YOLOv9c, and YOLOv11n—were chosen to represent different computational profiles within recent YOLO generations for deployment-oriented evaluation in a robotic underbody vehicle inspection system. Rather than performing a strictly size-matched benchmark, this study aimed to assess how representative YOLO models with different capacities balance detection accuracy and computational efficiency under practical inspection constraints. In this configuration, YOLOv8m served as a higher-capacity baseline, YOLOv9c represented a compact intermediate model, and YOLOv11n represented a lightweight model optimized for faster inference.

A limitation of this study lies in the use of YOLO variants with different model scales, namely YOLOv8m, YOLOv9c, and YOLOv11n. Because these variants do not represent equivalent model capacities across YOLO generations, the comparison should not be interpreted as a strictly controlled architecture-to-architecture benchmark. Part of the observed differences in detection accuracy and inference time may have been influenced by model size and computational complexity rather than by architectural improvements alone. Therefore, the findings of this study should be understood as a deployment-oriented comparative evaluation of representative YOLO models under practical inspection constraints. Future studies are recommended to perform size-matched comparisons, such as nano-to-nano, small-to-small, or medium-to-medium configurations, in order to isolate the

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effect of architectural differences more rigorously. The training results showed significant variations in computational time among the YOLO versions:

Table 4. Training Time for Each YOLO Version (1,000-Image Dataset)

Model	Time/*Epoch*	Total Waktu (100 *epoch*)
YOLOv8	29.16 detik	48.6 menit
YOLOv9	42.76 detik	71.28 menit
YOLOv11	14.10 detik	23.52 menit

YOLOv11 recorded the shortest training duration at 23.52 minutes, making it 51.6% more efficient than YOLOv9, which is consistent with the architectural optimization for edge computing reported by Jegham et al. (2024). Meanwhile, YOLOv9 demonstrated the highest classification accuracy, achieving the lowest classification loss (cls_loss) of 0.39787, thereby supporting the findings of Sapkota et al. (2025) regarding the integration of the GELAN mechanism. The use of a dataset containing 500 images produced the best performance across all models, indicating an optimal balance between data volume and training effectiveness, in line with the optimal data ratio reported by Muzaki (2024). The convergence pattern observed after 60 epochs also reflected the effectiveness of the applied learning rate configuration.

3.3. Model Training Metrics Evaluation

Training metrics represent the evaluation results used during the training process to monitor how the model learned from the training data. The following section presents a summary of the training results obtained from Dataset 1 to Dataset 10 using YOLOv8, YOLOv9, and YOLOv11.

Table 5. Comparison of Loss Values Across Models

Metrik	*YOLOv8*	*YOLOv9*	*YOLOv11*	Description
box_loss	0.64581	0.6376	0.68389	Lower is better
cls_loss	0.54229	0.39787	0.48476	*YOLOv9 outperformed the comparison model by 26.6%*
dfl_loss	1.0736	1.1025	1.03589	*YOLOv11 outperformed the comparison model by 3.5%*

YOLOv9 demonstrated superior classification performance, achieving a cls_loss value of 0.39787, which was 26.6% lower than that of YOLOv8. This result suggested the effectiveness of the GELAN architecture in extracting complex object features, as reported by Jegham et al. (2024). In contrast, YOLOv11 recorded the lowest dfl_loss value of 1.03589, indicating the reliability of the C2PSA mechanism in predicting bounding boxes with high precision, thereby supporting the findings of Nugroho and Cahyono (2022) regarding multi-scale object detection. Training optimization was achieved with the fifth dataset version containing 500

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images, which was consistent with the learning saturation concept described by Sapkota et al. (2025), where increasing the amount of data no longer provided a significant contribution to the quality of model training.

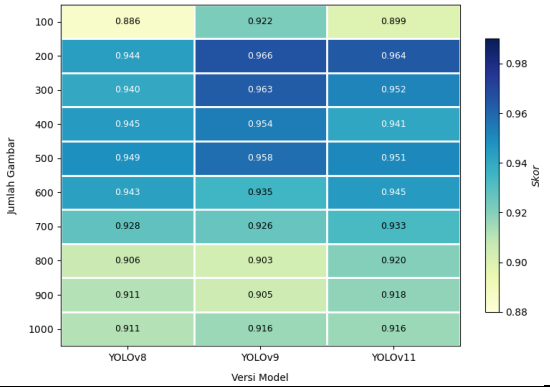
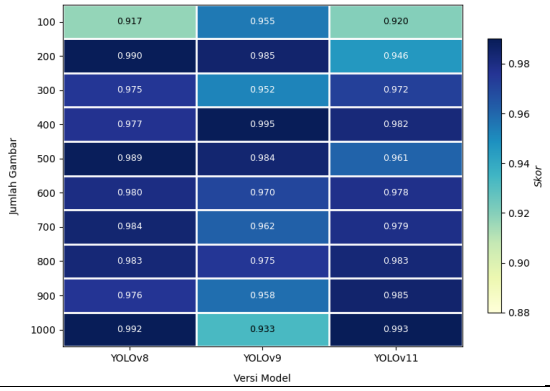
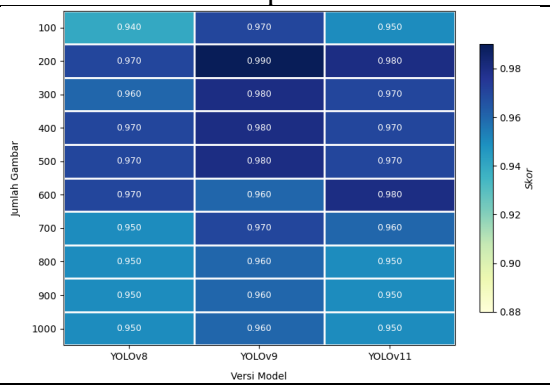
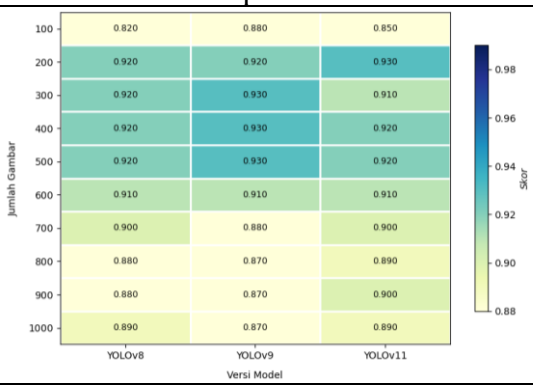
3.4. Model Performance Metrics Evaluation

Performance evaluation using the confusion matrix played a crucial role in assessing the effectiveness of the YOLOv8, YOLOv9, and YOLOv11 algorithms in identifying objects within the motor vehicle powertrain system. The models were evaluated using four main performance metrics, namely mAP@50, precision, recall, and F1-score. The best performance achieved by each model is presented as follows:

Table 6. Peak Performance of Each Model

Metrik	*YOLOv8*	*YOLOv9*	*YOLOv11*	Optimal Dataset Size
mAP@50 (%)	94.9	96.6	96.4	200-500 images
Precision	99.2	99.5	99.3	400-1000 images
Recall	95.0	99.0	97.0	200 images
F1-score	93.0	93.0	93.0	300-500 images

Table 7. Heatmap

Heatmap *mAP*	Heatmap *Precision*
	
Heatmap *Recall*	Heatmap *F1-Score*
	

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YOLOv9 demonstrates superior accuracy, achieving a mAP@50 of 96.6%, which reflects the effectiveness of the PGI (Programmable Gradient Information) mechanism in handling variations in component size, consistent with the study by Aloufi et al. (2023) on multi-scale object detection. Meanwhile, YOLOv11 exhibits high inference efficiency, with a processing time of 13.5 milliseconds per image, satisfying real-time processing standards and making it suitable for deployment on edge devices due to its lightweight architecture, as described by Padilla et al. (2020). In terms of object characteristics, the precision rate for universal joints reaches 99.1%, higher than that of transmission components at 98.7%, indicating that consistent shape contributes to improved detection accuracy, in line with the findings of Muzaki (2024) regarding the visual identification of automotive components.

3.5. Model Implementation

MThe object detection models were first tested using static images to evaluate performance under conditions free from motion interference. The images used were documentation of power transmission system components that were not included in the training data, making the testing independent and designed to measure the model's generalization capability in recognizing objects under conditions resembling real-world scenarios. Testing was conducted using the YOLOv8, YOLOv9, and YOLOv11 algorithms, each evaluated based on confidence score levels across various components of the vehicle's power transmission system.

Tabel 8. Confidence Score Rata-rata per Komponen

Komponen	*YOLOv8*	*YOLOv9*	*YOLOv11*
Transmisi	0.83	0.86	0.89
Universal joint	0.93	0.92	0.92
Propeller shaft	0.905	0.93	0.92

YOLOv9 demonstrates high performance in detecting elongated objects such as propeller shafts, achieving a confidence score of 0.93, which illustrates the effectiveness of the GELAN architecture, as supported by the study of Sapkota et al. (2025) on axial component identification. Meanwhile, YOLOv11 recorded the highest Intersection over Union (IoU) value of 0.83 for transmission components, reflecting the advantage of the C2PSA mechanism in complex object classification and supporting the findings of Jegham et al. (2024) regarding bounding box accuracy. In terms of efficiency, YOLOv11 achieved 74 frames per second (FPS) on a mid-range GPU, exceeding the real-time inspection system threshold required by industry standards (>30 FPS).

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Tabel 9. Comparison Between Algorithms

Parameter	*YOLOv8*	*YOLOv9*	*YOLOv11*
Model Architecture	Lightweight and efficient, suitable for large-scale data development	Utilizes GELAN and PGI for detection optimization	Optimized architecture with C2PSA for small object detection and high real-time accuracy
mAP	0.949	0.966	0.964
Inference Time	23 ms per image	54.2 ms per image	13.5 ms per image
Training Time	Fastest compared to other versions	Longest due to the complexity of the model architecture	Faster than YOLOv9, but slower than YOLOv8
Object Detection Efficiency	Good for real-time applications with limited computational resources	High accuracy, excels in detecting small and complex objects	Balanced between inference speed and accuracy
Optimal Use Case	Object detection in resource-constrained environments	Applications requiring high accuracy despite slower inference speed	Real-time applications balancing accuracy and speed

Table 9 presents a recapitulation of the training metric evaluation results for the YOLOv9 model based on ten dataset versions used during the learning process. This evaluation employs three key metrics val/box_loss, val/cls_loss, and val/dfl_loss which respectively represent the model's accuracy in predicting object location, classifying categories, and estimating bounding box shape distribution. In general, a lower loss value for each metric indicates better model performance. Based on the presented data, the fifth dataset version yielded the best results, with a val/box_loss of 0.6376, a val/cls_loss of 0.39787, and a val/dfl_loss of 1.1025. This indicates that a dataset with a moderate number of images provides an optimal balance between information complexity and training efficiency. Conversely, both the initial dataset with a limited amount of data and the final, very large dataset tended to produce higher loss values, indicating that performance does not always increase proportionally with data volume. Thus, the evaluation presented in Table 8 serves as an important reference in determining the most appropriate dataset configuration for implementing a YOLOv9-based detection system for motor vehicle inspection.

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3.5. Discussion

The YOLO algorithm exhibits distinct strengths across its versions, each suited to specific requirements in the technical inspection of motor vehicles. YOLOv9 stands out in the classification of complex objects owing to its GELAN architecture, which produced the lowest cls_loss value and effectively extracted visual features, as evidenced by the detection of propeller shafts with a confidence score of 0.93. In contrast, YOLOv11 excels in object localization due to its C2PSA mechanism and lightweight design, resulting in the lowest dfl_loss value and the highest IoU for transmission components. An inference speed of 74 FPS on a mid-range GPU makes it an ideal choice for real-time inspection implementation on resource-constrained devices.

In terms of performance evaluation, YOLOv9 recorded the highest mAP@50 at 96.6%, demonstrating precision in detecting objects of various shapes and sizes. The highest precision was obtained for the universal joint, whose consistent morphology contributed to classification stability. The fifth dataset version, comprising 500 images, delivered the best performance across all models, indicating a balance between data volume and training effectiveness. A decline in accuracy began to appear with larger datasets, signaling saturation. The evaluation graphs indicate stable convergence at the 60th epoch, supporting the reliability of the hyperparameter configuration. The synergy between architectural design, detection precision, and computational efficiency positions the YOLO algorithm as a strategic solution for adaptive and transparent AI-based visual inspection systems.

4. CONCLUSION

Based on the overall research findings, the implementation of the YOLO algorithm versions v8, v9, and v11 in a visual inspection system for vehicle power transmission components demonstrates complementary effectiveness according to specific technical requirements. YOLOv9 excels in the classification of complex objects owing to its GELAN architecture, while YOLOv11 exhibits high efficiency in position detection and real-time inference speed through its C2PSA mechanism. The fifth dataset version, consisting of 500 images, delivered optimal performance, marking an ideal balance point between data volume and training efficiency. Evaluation metrics such as mAP@50, Precision, Recall, and F1-score confirm that all three models are viable for implementation in an AI-based vehicle undercarriage inspection system, with significant potential to enhance the safety, transparency, and efficiency of motor vehicle technical inspection.

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