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Object Detection of Motor Vehicle Suspension Systems Based on the YOLOv8 Algorithm: Supporting Sustainable Industry and Innovation (SDG 9)

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ABSTRACT

Objective: *To develop an object detection system for identifying motor vehicle suspension system components using the YOLOv8 algorithm. Specifically, this study focused on improving the efficiency and accuracy of undercarriage inspection processes, which are commonly conducted manually and require technical knowledge to recognize suspension components and detect potential damage. This research contributes to automotive inspection innovation and supports the development of sustainable industrial technology in accordance with Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure).* ***Method:*** *The study employed a computer vision-based approach using the YOLOv8 object detection algorithm for recognizing suspension system components in motor vehicles. The dataset consisted of 1000 suspension system images collected from mandatory vehicle inspection activities at motor vehicle testing facilities.* ***Results:*** *The results showed that the YOLOv8-based detection model could identify suspension system components with an accuracy of up to 95%. Furthermore, the trained model successfully detected oil leakage damage on shock absorber components with an accuracy of 92%. The evaluation results indicate that the proposed system can effectively recognize suspension components under different inspection conditions and provide reliable assistance for vehicle undercarriage inspection processes.* ***Novelty:*** *The study provides a novel implementation of the YOLOv8 deep learning algorithm for automated suspension system inspection in motor vehicles by integrating computer vision technology into the vehicle testing process. The developed system contributes to automotive technology innovation and supports the advancement of smart inspection infrastructure in line with SDG 9 (Industry, Innovation, and Infrastructure).*

INTRODUCTION

Transportation is a means used by the community to support daily mobility needs, which continues to grow along with technological advances (Ceder, 2021; Paiva et al., 2021; Ribeiro et al., 2021). The increase in the number of vehicles should require every road user to ensure that the vehicle is roadworthy, prioritized safety and security when drove to reduce the risk of traffic accidents (Abebe, 2022; Ehsani et al., 2023; Organization, 2019). Therefore, to ensure drove safety and security, every road user is required to carry out periodic motor vehicle test (Blomquist, 2012; Feng et al., 2024; Gu et al., 2024). The role of motor vehicle test is carried out to ensure safety, provide a level of comfort, and assess the strength and safety of the vehicle. One of the components of a motor vehicle that has the most significant influence on vehicle comfort and safety is the suspension system (He et al., 2019). The suspension system was an important component in every vehicle that functioned to absorb shocks and vibrations from the road, thereby increased comfort for the driver and passengers (Dogruer, 2022). Damage to the suspension system can disrupt the comfort of the driver and passengers and increase the risk of accidents when the vehicle is being driven (Hou et al., 2022).

One example of a single accident involved a container truck experienced a broken rear wheel suspension on Friday, July 29, 2022 on the Cangkir highway, Gresik district. The accident occurred when the truck avoided a motorbike that turned suddenly. As a result of sudden brake, the truck's rear wheel suspension broke and the tire came off (Drozd et al., 2022; Giapponi, 2008; Waluś & Warszczyński, 2022). A major factor in the damage to the suspension system was the lack of regular motor vehicle test. However, currently, the undercarriage inspection process is still mostly done manually. If there is damage to the component, the driver will be asked to go down to the undercarriage test tunnel in order to find out and immediately repair the damage. Many drivers do not know about the components on the undercarriage of motor vehicles, so when component damage occurs, officers need to inform the undercarriage components along with the damage. So far, there has been no breakthrough by officers to provide information (Ochella et al., 2022; Widyastuti & Utami, 2018).

Research related to the use of robots in undercarriage inspections, the test officers and vehicle owners can directly see the condition of the underside of the vehicle on the monitor screen (Amador et al., 2022; Rempel et al., 2024; Smit et al., 2025; Wibowo & Hakim, 2022; Yu & Lee, 2022). With this problem, as even though vehicle owners can see directly, there are still many drivers who do not recognize the components of the lower part of the vehicle along with their damage. So this study provides an innovation in the form of used robots as intermediaries in check suspension system components with the YOLO (You Only Look Once) algorithm approach (Kang et al., 2022; Zhan, 2021; Hamadi et al., 2023). Where the robot is designed to be able to move along the track rail used a joystick, and is equipped with a camera that functions as the main link with the YOLOv8 algorithm. This camera captures objects from under the vehicle and transmits them to the YOLOv8 algorithm to identify components and at the same time check for damage to the bottom of the vehicle (Hu et al., 2022; Munteanu et al., 2022; Seraj et al., 2021). This study proposes the detection of suspension system objects on motor vehicles based on the YOLOv8 algorithm. The results of this study are expected to provide contributions and solutions to facilitate the process of public service for accurate undercarriage inspection of motor vehicles.

RESEARCH METHOD

This study employed an experimental research approach based on computer vision and deep learning methods to develop an object detection system for motor vehicle suspension components. This research implemented the YOLOv8 (You Only Look Once version 8) algorithm to train, test, and validate a detection model capable of recognizing suspension system components in vehicle undercarriage inspections. The fundamental concept of this research involved several stages, including data collection, dataset preparation, model training, model testing, and performance evaluation. The overall research workflow is presented in Figure 1.

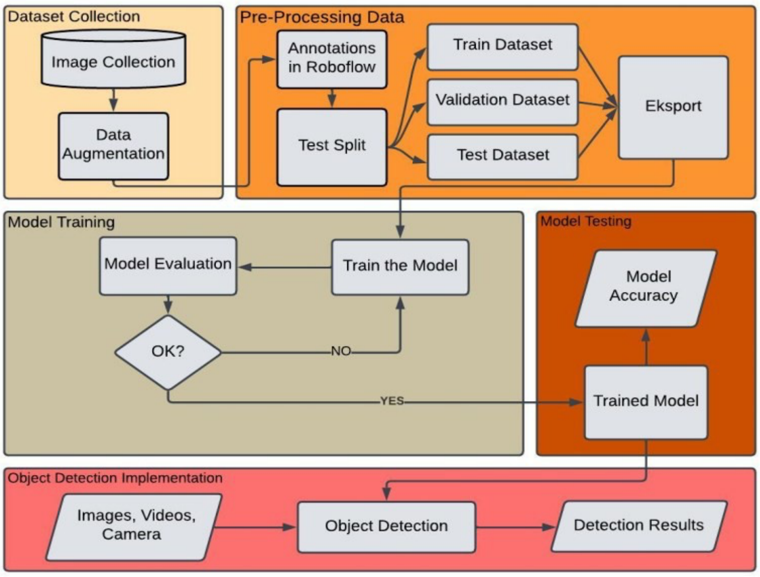


Figure 1. Research stages

The data used in this study consisted of images and video recordings of motor vehicle suspension system components. Data collection was conducted through direct observation at a Motor Vehicle Testing Facility in East Java. A total of 1000 images of suspension system components were collected and used as the dataset for training the YOLOv8 model. The collected images represented various inspection conditions, including different object orientations, lighting conditions, and distances between the camera and the detected objects. These variations were considered to improve the ability of the model to recognize suspension components under different operating conditions.

The collected dataset was then processed using the Roboflow web platform for data management and preparation. The processing stage included image annotation, bounding box labeling, dataset organization, and data division into training, validation, and testing datasets. The annotation process was performed by identifying the location of suspension system components within each image to provide object position information required for the YOLOv8 detection model. After the dataset preparation process was completed, the dataset was exported in a YOLOv8-compatible format for further training.

The prepared dataset was subsequently imported into the Google Colab platform as a computational environment for model training using Python programming code. The YOLOv8 algorithm was trained to recognize object patterns and characteristics of motor vehicle suspension system components. The training process was conducted progressively using different dataset quantities, starting from 100 images, 200 images, and increasing until 1000 images. Each training stage was evaluated based on the confidence level and detection performance generated by the model to determine the effect of dataset quantity on detection accuracy.

After the training process was completed, the trained YOLOv8 model was tested to evaluate its capability in detecting suspension system components. The model evaluation was conducted by analyzing detection accuracy and confidence values under different conditions, including variations in viewing angle, lighting intensity, and object distance from the camera. In addition, the capability of the model to identify oil leakage damage on shock absorber components was also evaluated as an indicator of suspension failure detection performance.

The final trained model was implemented for object detection using image input, video input, and real-time camera detection. The ability of the YOLOv8 model to perform real-time detection demonstrates its potential application as an intelligent assistance system for motor vehicle undercarriage inspection. This approach provides an innovative solution to support automated vehicle testing processes by reducing dependence on manual identification and improving inspection efficiency through artificial intelligence technology.

RESULTS AND DISCUSSION

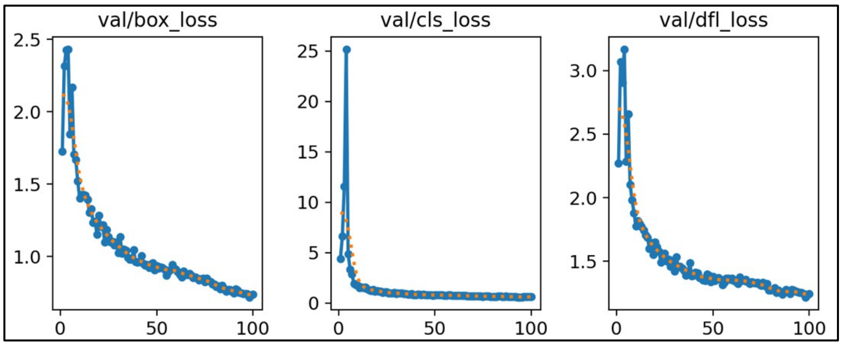
Results

The stages in designed an object detection system collected data in the form of photos and videos of suspension system components on motor vehicles. Data collection covers various types of vehicles with the number of annotations for each component in the suspension system in table 1.

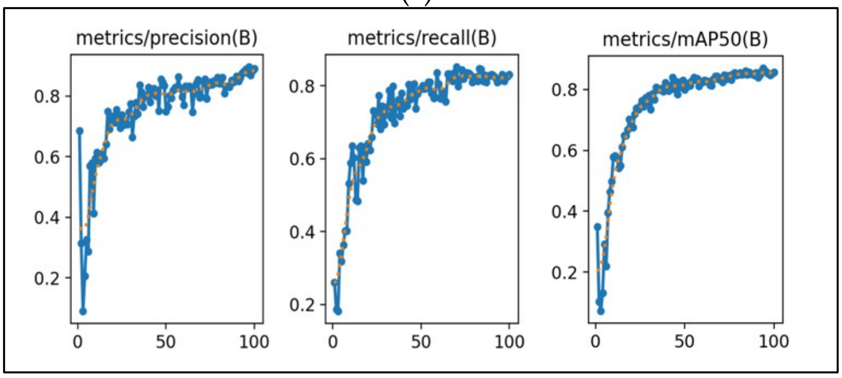
Table 1. Component category annotation data count

Group Data	Component Category				
	Leaf Spring	Shock Absorber	Coil Spring	Stopper	Ball Joint
Data 1	88	55	14	36	10
Data 2	143	109	42	51	56
Data 3	210	160	58	79	99
Data 4	292	238	84	112	99
Data 5	375	317	106	127	110
Data 6	460	401	121	138	121
Data 7	530	464	153	150	136
Data 8	627	552	159	171	142
Data 9	711	640	175	179	134
Data 10	765	697	219	197	183

Each group that has gone through the annotation process will undergo the next stage, namely the test split, to avoid overfitted on the latest dataset when predict object accuracy. This data test will be divided into three subsets. First, the train set is the data used as a sample to train the model with a ratio of 80%. Second, the valid set is the data used to test how well the model performs during train with a ratio of 15%. Third, the test set with a ratio of 5% is used to see how well the model performs on images that have never been used during model training. Training the Yolov8 Algorithm model by attention to hyperparameters include the type of yolov8m.pt model with a batch size of 16 and an epoch size of 100. Train metrics are the evaluation results used during the train process to monitor how the model learns from the train data (Carneiro et al., 2023; Naidu et al., 2023; Varoquaux & Colliot, 2023).



(a)



(b)

Figure 2. (a) Model train matrix evaluation results overview and (b) model performance matrix evaluation results overview

Figure 2a is an evaluation of the error calculation (Loss), which is an indicator of the measurement value of the error in predict the model during train. From the graph, there has been a stable and consistent decline. This shows that the model can make predictions with an increasingly good level of accuracy. While the higher loss value indicates that there are quite a lot of errors when predicted objects in the model. So further improvements are needed in the model train process. Figure 2b is a description of how well the model detects objects in new images. Such as accuracy, precision, recall, and F1-score are used to evaluate metrics, to obtain the value of the model's performance results. The figure above is an example of a metric graph measured from epoch 1 to 100. Each epoch, this graph shows a consistent and significant increase.

Table 2. Model performance evaluation results

Dataset	mAP	Precision	Recall	F1-Score
Dataset 1	61.6%	100%	70.0%	58%
Dataset 2	80.7%	100%	86.0%	73%
Dataset 3	80.1%	95.0%	92.0%	75%
Dataset 4	85.9%	100%	92.0%	82%
Dataset 5	79.5%	100%	87.0%	78%
Dataset 6	83.0%	100%	90.0%	81%
Dataset 7	81.1%	98.0%	89.0%	80%
Dataset 8	85.2%	99.0%	91.0%	84%
Dataset 9	85.5%	97.4%	91.0%	82%
Dataset 10	87.1%	98.0%	92.0%	84%

In Table 2, dataset 1 is an dataset with 100 images, dataset 2 with 200 images, dataset 3 with 300 images to dataset 10 with 1,000 images. Table 2 shows the results of model evaluation based on mAP (mean Average Precision), Precision, Recall, and F1-Score for 10 model datasets. From dataset 10 is the best value in all metrics with mAP 87.1%, precision 98.0%, recall 92.0%, and F1-Score 84%. This indicates that the performance of dataset 10 is very superior in detect objects, produced a good balance between precision and recall. In contrast, dataset 1 has the lowest performance with mAP 61.6%, precision 100%, recall 70.0%, and F1-Score 58%.

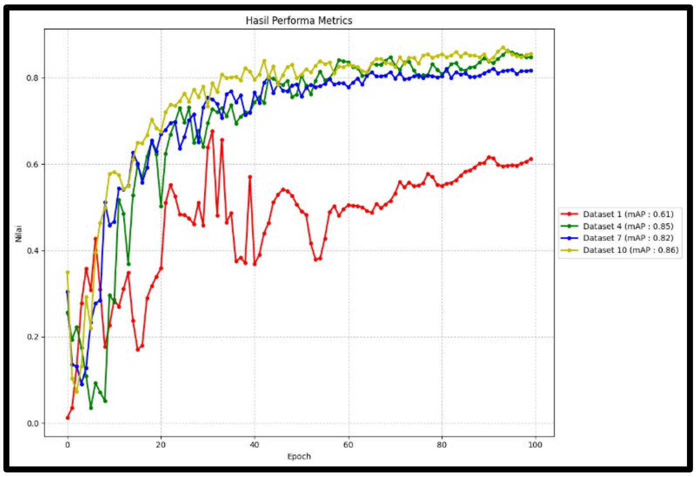
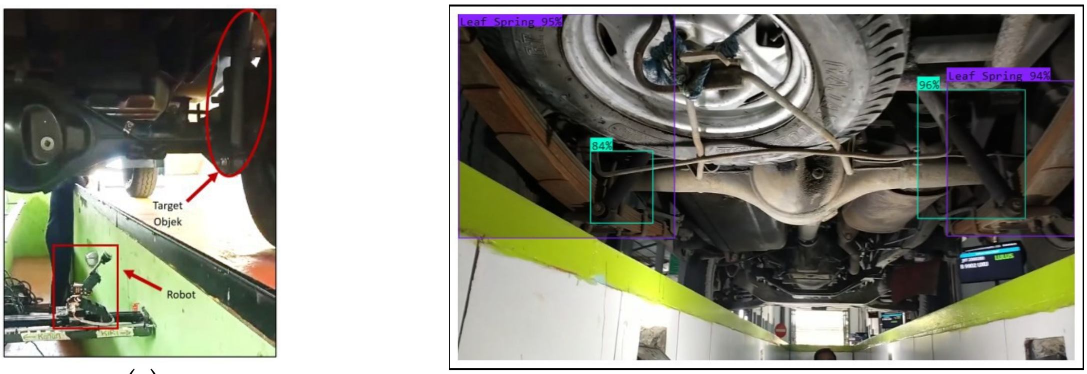


Figure 3. Comparison of model performance graphs

Figure 3 is a graphical analysis of the model performance evaluated used the mAP (mean Average Precision) metric show that the model trained on dataset 10 with an mAP value of 86%, this overall dataset has better performance compared to the model trained on the previous version of the dataset. However, even though dataset 10 gives better final results, there is a phase during train where the model from the previous version shows better performance on mAP. This phenomenon can occur due to fluctuations in the train process which causes the model to experience a temporary increase in performance such as there are underexposed images, unbalanced data weights, target objects not reached by the camera or the main object is blocked by other objects.

To support the implementation of the YOLOv8 algorithm, namely by utilize a robot intermediary designed with two hardware components, namely the Arduino Nano microcontroller and the ESP32 microcontroller. Arduino nano is responsible for robot movement and camera positioned via servo (Aziz et al., 2025; Karunakaran et al., 2025; Lahoti et al., 2024). While ESP32 manages data from the camera and transfers detection results to the monitor screen, in manage object detection used Jetson Nano. The robot is controlled used a joystick, which allows manual adjustment of the camera to obtain the optimal view angle during inspection of the undercarriage of motor vehicles.



(a) (b)

FIGURE 4. (a) The process of check the underside of the vehicle in motor vehicle test and (b) model tested on suspensian system components

Figure 4 is the result of model test on the suspension system components of motor vehicles. In the figure, the YOLOv8 model is able to detect leaf spring and shock absorber components with an accuracy value of 84% to 95%. These results indicate that the trained YOLOv8 model has a very good ability to recognize and identify the components of the suspension system of motor vehicles.

Discussion

The development of the object detection system for motor vehicle suspension components began with the collection of image and video data obtained from vehicle undercarriage inspection activities. The data collection process was conducted through direct observation at a Motor Vehicle Testing Facility in East Java. The collected dataset represented various types of vehicles and suspension component conditions to improve the ability of the YOLOv8 model in recognizing object variations during the inspection process.

The collected data were subsequently annotated based on five main suspension system categories, including leaf spring, shock absorber, coil spring, stopper, and ball joint. The annotation process was conducted progressively by increasing the amount of training data from Dataset 1 to Dataset 10. Dataset 1 consisted of 100 images with a total annotation distribution of 88 leaf spring objects, 55 shock absorber objects, 14 coil spring objects, 36 stopper objects, and 10 ball joint objects. As the dataset quantity increased, the number of annotated objects also increased. Dataset 10, which consisted of 1000 images, contained the highest number of annotations, including 765 leaf spring objects, 697 shock absorber objects, 219 coil spring objects, 197 stopper objects, and 183 ball joint objects.

The increase in annotation quantity provided more diverse visual information for the YOLOv8 model during the learning process. A larger dataset allows the model to recognize more variations in object shape, position, lighting conditions, and viewing angles. This condition is important in vehicle undercarriage inspection because suspension components are located in areas with limited accessibility and may appear differently depending on the camera position and environmental conditions.

After the annotation process, each dataset was divided into training, validation, and testing subsets using the test split method to minimize overfitting during model prediction. The training dataset accounted for 80% of the total data and was used to optimize the model parameters. The validation dataset accounted for 15% and was used to monitor the learning performance during training, while the testing dataset accounted for 5% and was used to evaluate the model performance using images that were not previously involved in the training process.

The YOLOv8 model training process was conducted using the YOLOv8m.pt pretrained model with a batch size of 16 and an epoch value of 100. The model performance was monitored using training loss and evaluation metrics, including mean Average Precision (mAP), precision, recall, and F1-score. These metrics were used to determine the capability of the model in learning suspension component characteristics and generating accurate object predictions (Carneiro et al., 2023; Naidu et al., 2023; Varoquaux & Colliot, 2023).

The training evaluation results showed that the YOLOv8 model experienced a consistent reduction in loss value from the beginning until the end of the training process. The decreasing loss trend indicates that the model was able to optimize its parameters and reduce prediction errors during object recognition. A lower loss value represents improved prediction accuracy because the difference between the predicted bounding box and the actual object position becomes smaller. This result demonstrates that the YOLOv8 architecture was capable of effectively learning the visual characteristics of motor vehicle suspension components.

The evaluation results of different dataset quantities showed that increasing the number of training images generally improved model performance. The model trained using Dataset 1 with 100 images achieved an mAP value of 61.6%, precision of 100%, recall of 70%, and F1-score of 58%. Although Dataset 1 produced a high precision value, the lower recall value indicates that the model was unable to detect all suspension components due to limited training information. This condition shows that a small dataset can produce accurate predictions for detected objects but may have limitations in recognizing object variations that were not sufficiently represented during training.

Dataset 2, which consisted of 200 images, improved the model performance with an mAP value of 80.7%, precision of 100%, recall of 86%, and F1-score of 73%. The improvement indicates that additional training samples allowed the model to learn more representative object patterns. However, some fluctuations occurred in the subsequent datasets due to differences in image characteristics, object distribution, and environmental conditions.

The best performance was achieved by Dataset 10, which consisted of 1000 images. This dataset produced an mAP value of 87.1%, precision of 98%, recall of 92%, and F1-score of 84%. The high mAP value indicates that the model achieved strong detection performance across different suspension components. The precision value of 98% demonstrates that the model generated very few false detections, while the recall value of 92% indicates that most suspension components within the test images were successfully identified. The balance between precision and recall resulted in an F1-score of 84%, confirming that Dataset 10 provided the most stable and reliable detection performance.

The comparison of model performance among different dataset quantities shows that increasing training data improves the generalization capability of the YOLOv8 model. However, the improvement does not occur linearly because model performance can be influenced by several factors, including image quality, object scale variation, lighting conditions, and object occlusion. During the training process, several fluctuations in mAP values were observed, where some smaller datasets temporarily achieved higher performance compared with larger datasets. This phenomenon can occur because certain datasets may contain images with clearer object features, while larger datasets may introduce more complex variations that require additional training optimization.

To support the practical implementation of the YOLOv8 algorithm, the trained model was integrated with a robotic inspection system consisting of Arduino Nano, ESP32 microcontroller, and Jetson Nano. Arduino Nano was used to control robot movement and adjust camera positioning through a servo mechanism, while ESP32 managed camera data communication and transmission to the monitoring system. The object detection computation was performed using Jetson Nano to enable real-time processing. The robot was controlled using a joystick, allowing operators to adjust the camera position and obtain optimal viewing angles during vehicle undercarriage inspection (Aziz et al., 2025; Karunakaran et al., 2025; Lahoti et al., 2024).

The implementation test showed that the YOLOv8 model was able to detect suspension system components, particularly leaf spring and shock absorber components, with detection accuracy ranging from 84% to 95%. These results demonstrate that the trained model has good capability in recognizing suspension components under practical inspection conditions. In addition, the model was also capable of identifying oil leakage damage on shock absorber components with an accuracy value of 92%, indicating its potential for supporting early detection of suspension failures.

The developed system provides an innovative approach for improving vehicle inspection processes by combining artificial intelligence, computer vision, and robotic technology. Compared with conventional manual inspection methods, the proposed YOLOv8-based system can assist inspectors in identifying suspension components more efficiently and consistently. Therefore, this research contributes to the advancement of intelligent automotive inspection technology and supports Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure) through the implementation of digital innovation in industrial inspection systems.

CONCLUSION

Fundamental Finding: This study developed an object detection system for motor vehicle suspension components using the YOLOv8 algorithm. The dataset consisted of 1,000 suspension system images covering five main components: leaf spring, shock absorber, coil spring, stopper, and ball joint. The results showed that the model performance improved as the training data increased. The best model (Dataset 10) achieved an mAP value of 87.1%, precision of 98%, recall of 92%, and F1-score of 84%. The model was able to detect suspension components under different conditions and identify oil leakage damage on shock absorber components with an accuracy of 92%. These results indicate that YOLOv8 can be effectively applied for automated vehicle suspension inspection. **Implication:** The findings show that the YOLOv8-based detection system can improve the efficiency of vehicle undercarriage inspection by assisting the identification of suspension components and potential damage. The integration of artificial intelligence, computer vision, and robotic systems provides a potential solution for developing smart automotive inspection technology. This research supports Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure) through the application of intelligent technology in automotive inspection systems. **Limitation:** This study was limited to 1,000 images and five suspension component categories, which may not represent all vehicle types and inspection conditions. The model evaluation was also limited to component detection and shock absorber oil leakage detection, while other types of damage were not analyzed. In addition, real-time detection performance may be affected by camera quality, lighting conditions, computing capability, and robot positioning accuracy. **Future Research:** Future studies should expand the dataset with more vehicle types, component variations, and inspection conditions to improve model generalization. The application of newer YOLO architectures, such as YOLOv9 and YOLOv10, can also be investigated to improve detection accuracy and processing speed. Further research may extend the system to other vehicle undercarriage components, including power transfer systems, braking systems, and exhaust emission systems, to develop a more comprehensive intelligent vehicle inspection platform.

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AUTHOR CONTRIBUTIONS

Helmi Wibowo: Conceptualization, methodology, investigation, data curation, formal analysis, writing original draft preparation, and visualization. **Nurul Muzakki Rihhadatul:** Data collection, software implementation, dataset preparation, annotation process, and validation. **Aisy:** Methodology support, data analysis, model evaluation, and visualization. **Muhammad Iman Nur Hakim:** Software development, machine learning implementation, algorithm training, and performance evaluation.**Mokhammad Rifqi Tsani:** Investigation, experimental testing, data interpretation, and validation. **Setya Wijayanta:** Supervision, conceptualization, writing review and editing, project administration, resources, and research support.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

STATEMENT ON THE USE OF AI OR DIGITAL TOOLS IN WRITING

AI tools were used only for language editing, grammar improvement, and discussion support. The authors take full responsibility for all aspects of the research and the final content of the manuscript.

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