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# Artificial Intelligence Based Detection of Over Dimension and Overload (ODOL) Vehicles Using the YOLO Algorithm for Sustainable Transportation Infrastructure (SDG 9)

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**ABSTRACT**

***Objective:*** *To develop an artificial intelligence-based detection system for identifying Over-Dimension and Overload (ODOL) vehicles using the YOLO algorithm. Specifically, this study focused on improving the efficiency of ODOL vehicle monitoring, which is important for maintaining road safety, reducing infrastructure damage, and supporting effective transportation regulation. This research contributes to the development of smart transportation systems and sustainable infrastructure innovation in accordance with Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure).* ***Method:*** *The study employed a computer vision-based approach using YOLOv8m and YOLOv10n algorithms for ODOL vehicle detection. The dataset consisted of vehicle images containing over-dimension vehicles, normal vehicles, and trucks collected from digital image sources.* ***Results:*** *The experimental results showed that YOLOv8m achieved better performance compared with YOLOv10n in detecting ODOL vehicles. YOLOv8m obtained a confusion matrix value of 78%, a precision-recall curve value of 81.7%, precision of 91.6%, and recall of 90%. Although YOLOv10n achieved a higher recall value of 93%, its overall detection performance was lower, with a confusion matrix value of 59%, precision-recall curve value of 72.3%, and precision of 89.9%. The implementation of YOLOv8m into an IoT-based detection system successfully enabled real-time data transmission and storage in a database, demonstrating its capability for practical ODOL vehicle monitoring applications.* ***Novelty:*** *The study provides a novel implementation of YOLO-based artificial intelligence technology for real-time ODOL vehicle detection by integrating deep learning, computer vision, and IoT infrastructure. The developed system supports the advancement of intelligent transportation infrastructure and contributes to sustainable innovation in transportation management in line with SDG 9 (Industry, Innovation, and Infrastructure).*

## INTRODUCTION

Along with increasing population, manufacturer's goods distribution requirements to consumers increases (Alverhed et al., 2024; Chandan et al., 2023; Chopra et al., 2022). Rapid and safe distribution demands become challenges by logistic companies (Ogedengbe et al., 2024; Rushton et al., 2026; van Beusekom–Thoolen et al., 2024). Logistic efficiency is crucial to intensify people purchase power and it is crucial for a nation to compete on international trading (Akter et al., 2022; Ding et al., 2022; Y. Zhao et al., 2023). In the logistics and goods distributions, trucks take an important role as main transportation and become the backbone of logistics system (Ali, 2026; Sarder, 2025; Skiba, 2024). Therefore, logistics companies should have strategies to achieve their defined target. To facilitate Indonesia's logistics delivery fluently, the government focusing on sustainable infrastructure construction, including road constructions those connect among villages, cities, and provinces. However, not long after those road constructions completed, several sections of the road were found to be in a damaged condition. According to Transportation Observer, Djoko Setijowarno from Indonesian Transportation Society (Masyarakat Transportasi Indonesia / MTI) said that in 2023 road infrastructure construction was imbalance, with 52% of the roads are in an unfit condition. One of the main factors which causes road damage is the overload vehicle which known as Over Dimension Over Loading (ODOL) (Nurkhowati et al., 2023; Tampubolon et al., 2025; Widyanti et al., 2025).

Over Dimension Over Loading (ODOL) truk cause a number of hazards, including physical, economic, and environmental impacts (Harun et al., 2024; Widyanti et al., 2025). The physical impact includes road structural damage, such as to the pavement and foundation. In terms of economic impact, ODOL trucks increase the cost of road infrastructure maintenance, fuel consumption, and truck maintenance costs (Chen & Xue, 2025; Pinkaew et al., 2025). ODOL trucks also cause significant environmental impact, particularly by increasing greenhouse gas emissions, which contribute to climate change (Arifuddin et al., 2024; Johansson et al., 2024; Pino et al., 2025). Moreover, ODOL trucks raise the risk of traffic accidents. Police Chief Commissioner Made Agus Prasatya, Head of the Enforcement and Violations Sub-Directorate, Law Enforcement Directorate, Indonesian National Police Traffic Corps, stated that traffic accidents caused by ODOL trucks increased by 29 cases. In 2020, there were 30 recorded traffic accident cases, which rose to 59 cases in 2021.

Overloaded vehicles have a very low safety rate, which increases the likelihood of fatal accidents. Overloaded vehicles are more prone to brake failure and tire blowouts, which can lead to serious accidents (Doecke et al., 2024; Huang et al., 2025; Kesuma et al., 2022).

The Over Dimension Over Loading (ODOL) problem has become a topic of attention in society (Hendrawan et al., 2024; Suprayitno et al., 2024; Wiramukti et al., 2025). However, most ODOL cases often focus on overload, while vehicle over-dimension violations are often ignored by several drivers. Carrying goods that exceed the vehicle's dimensional limits can endanger other road users and lead to traffic accidents. One such accident, caused by an over-dimension loaded vehicle, was reported by Kompas and took place on Wednesday, March 27th, 2024, at the Halim Utama Toll Gate. The chronology is as follows: a truck with license plate number BG 8420, driven by MI, which was carrying sofas, hit vehicles with license plate numbers B 2780 TYB and E 1505 MR at a distance of 300 meters before the toll gate. The truck was driven at high speed, passing cars named Brio and Xpander, and eventually hit an Isuzu pick-up truck with license plate number Z 8445 AH, which flung into Depot 5. Next, the truck hit a white Hyundai with license plate number B 1061 SPW and a pick-up box truck with license plate number D 8633 YR. As a result of this accident, four people had difficulty breathing, and the truck ended up upside down. According to CCTV footage at the Halim Utama Toll Gate, the truck appeared to have lost its balance due to being overloaded, making it difficult to control and eventually causing it to roll over.

Zero ODOL was implemented by the Indonesian Government in 2023 (Rossa et al., 2025). To address the ODOL issue, coordination is needed among shipping companies, drivers, freight forwarders, and the government. The government has taken several bold actions against over-dimension and overloading violations by trucks operating on toll roads and arterial roads. Several sanctions were imposed, including recording violations, transferring 50% of the load to other vehicles, and cutting the truck boxes. Additionally, the government has utilized technologies to address the ODOL problem, such as Weight In Motion (WIM). The aim of WIM is to expedite the detection of vehicles that potentially violate over-dimension and overloading regulations. However, it is still facing several challenges today, so innovative solutions are needed to ensure road safety and prolong infrastructure life. One innovative approach is the utilization of artificial intelligence (AI), which allow real-time data gathering and analysis from AI cameras installed on road infrastructure. Artificial intelligence (AI) is a field of computer science devoted to solving cognitive problems commonly associated with human intelligence, such as learning, creating, and recognizing images (Jaboob et al., 2024; J. Zhao et al., 2022).

The previous research conducted by Telegraph & Kyrkou, (2024) achieved vehicle detection accuracy results based on YoloV4, with the lowest accuracy of 21.23% for buses and the highest accuracy of 98.24% for trucks, leading to an average accuracy of 70.75%. The system was able to detect several types of vehicles, including Big SUVs, Buses, City Cars, Low MPVs, Medium Boxes, Medium MPVs, Medium SUVs, Mini Boxes, Minibuses, Pick-ups, Premium MPVs, Sedans, and Trucks. Based on the problems and research previously outlined, this study aims to develop and test an Over Dimension Over Loading (ODOL) detection system based on the YOLO algorithm, as well as evaluate its performance and effectiveness in real transportation environments. Thus, it is expected that this system can contribute to improving traffic safety and reducing road infrastructure damage caused by ODOL vehicles. The YOLOv8 algorithm is supported by the principles of real-time performance, high classification, fast detection and high accuracy and the YOLOv10 series generation for real-time end-to-end object detection. In this research experiment, it will be compared using the over-dimensional dataset (ODOL) of truck vehicles.

## RESEARCH METHOD

This research is an experiment on the YOLO algorithm using an over-dimension truck dataset, and it is implemented on tools so that the tools can detect over-dimension vehicles. Dataset management is conducted using Google Colaboratory.

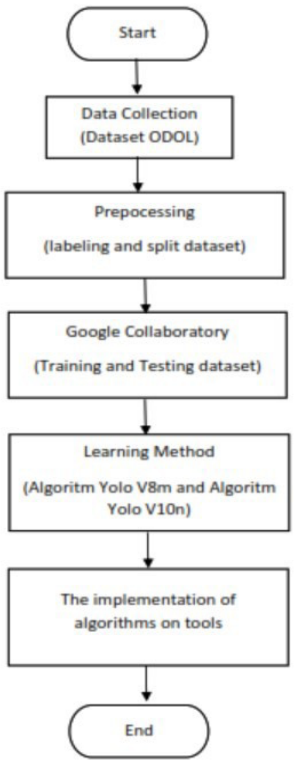


**Figure 1.** Research design model

Figure 1 illustrates the research design model used to observe artificial intelligence for detecting over-dimension vehicles (ODOL). The process consists of several steps: The first step is Dataset Collection, where images of ODOL vehicles were gathered from Google's search engine. The next phase involves Preprocessing, during which the dataset is annotated by labeling the ODOL vehicle objects in the collected images. The dataset is then split into training, validation, and test sets. For the Training Dataset, the dataset was fetched from Roboflow by inserting an API key or snippet code into Google Colaboratory. The training process included tuning hyperparameters, selecting appropriate datasets, and executing model training. Model Evaluation followed, where various evaluation metrics such as Confusion Matrix, Precision, Recall, and Precision-Recall were used to measure the model's accuracy in classifying new datasets. A detection threshold of 0.5 was applied, and models with accuracy above 50% were considered suitable for implementation. Finally, the Algorithm Implementation and Tools Assembling stage involved embedding the trained algorithm into a tool. Using Pycharm as the Python IDE, the algorithm was connected to a webcam and integrated with IoT technology for database storage of ODOL vehicle data.


**Figure 2.** Ca HowtheToolsWork

In figure 2 is the design of how the tool works, where there is a camera as a tool to capture over-dimensional objects and a laptop to carry out the YOLO algorithm process which is then stored in the website database.

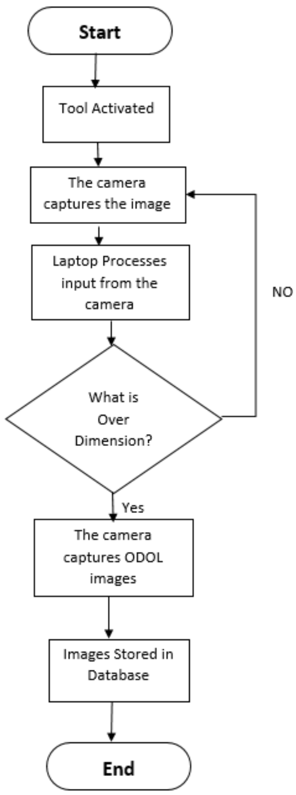


**Figure 3.** Flowchart of how the tools work

Figure 3 illustrates the workflow of the artificial intelligence tools used to detect over-dimension vehicles. The process begins by running a detection program in PyCharm, which automatically activates the camera to capture images and send them to the laptop. The laptop then processes the received images using a trained detection model, labeling the detected vehicles with bounding boxes according to their classes: car, over-dimension, and truck. If a vehicle is identified as over-dimension, the laptop sends a command to capture additional images of that vehicle. Finally, the captured images are uploaded to a database for further analysis.

## RESULTS AND DISCUSSION

### *Results*

This artificial intelligent vehicle over-dimensional detection research uses 100 datasets, with 70 training datasets, 20 validation datasets and 10 testing datasets. For tools, use Google Collaboration, by comparing the Yolov8 and Yolov10 algorithms.

### *Algorithm training*

In the algorithm construction step that was conducted in this research result ODOL vehicle detection algorithm. The dataset collection involved gathering images of over-dimension (ODOL) vehicles, cars, and trucks from Google. In the dataset annotation phase, each class of vehicles was annotated, and preprocessing was performed by resizing all images to a pixel dimension of 640x640 and auto-orienting them. This process resulted in a total of 100 images, which were split into 70 training datasets, 20 validation datasets, and 10 test datasets. For dataset training, the dataset was fetched from Roboflow by inserting an API key/snippet code into Google Colaboratory. The training process involved several phases, including tuning the appropriate hyperparameters, selecting the training and validation datasets, and training the model using the YOLOv8m architecture. The training was conducted for 100 epochs with an image size of 800 pixels.

### *Algorithm comparison*

The development that used were train and compare ODOL vehicle detection model algorithm between YOLOv8 and YOLOv10 with same dataset and hyperparameter setup and evaluate their comparison later.

YOLOv8 is iteration of YOLO (You Only Look Once) algorithm, which known by its object detection ability. It was launched at January 10$^{th}$ 2023 by Ultralytics, which signs a significant advancement in YOLO series. This version was developed after extensive research by Ultralytics, which aimed to exceed its predecessor's performance by presenting some modifications. This research was used YOLOv8m or the medium version of YOLOv8 algorithm. YOLOv10 was released at May 23$^{th}$ 2024, it is real-time object detection model which developed by researchers from Tsinghua University. YOLOv10 follows YOLO model series which have been going on for a long time, it was created by authors from a number of researchers and organizations. This research was used YOLO v10n or the nano version of YOLOv8 algorithm. The evaluations of training results between YOLOv8 and YOLOv10 are as Table 1.

**Table 1.** The comparison of confusion matrix and precision-recall between YOLOv8m

| Algoritma | Conf Matrix (Over Dimension) | Precission Recall (Over Dimension) |
|---|---|---|
| **YOLOv8** | 78% | 81.7% |
| **YOLOv10** | 59% | 72.3% |

**Table 2.** The comparison of precision and recall between YOLOv8m and YOLOv10n

| Algoritma | Precission | Recall |
|---|---|---|
| YOLO v8 | 91.6%% | 90% |
| YOLO v10 | 89.9% | 93% |

Tables 1 and 2 are the results of experiments using over-dimensional datasets, YOLOv8m shows superior performance in detecting over-dimension vehicles with a Confusion Matrix value of 78%, a precision-recall curve of 81.7%, precision of 91.6%, and recall of 90%, indicating a balance between accuracy and detection. Although YOLO v10n has a higher recall of 93%, its performance in the Confusion Matrix (59%) and precision-recall curve (72.3%) is lower, and its precision of 89.9% is slightly lower than that of YOLOv8m. Therefore, YOLOv8m will be implemented in the tools because it is more accurate and consistent in detecting over-dimension vehicles. In figures 4, 5 and 6 are graphs of the performance results of the YOLOv8 algorithm with the ODOL dataset of truck vehicles.

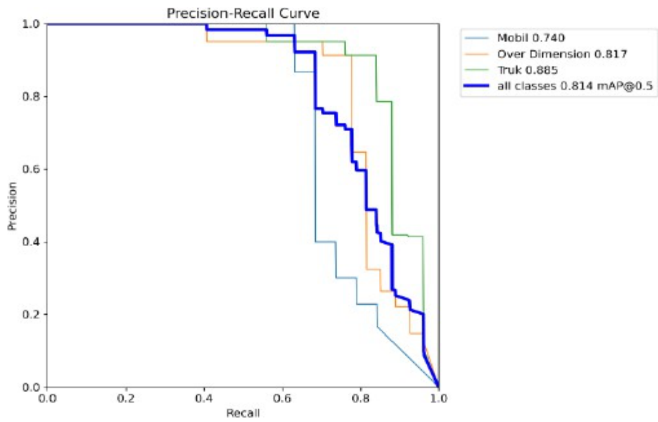


**Figure 4.** Precision-recall curve

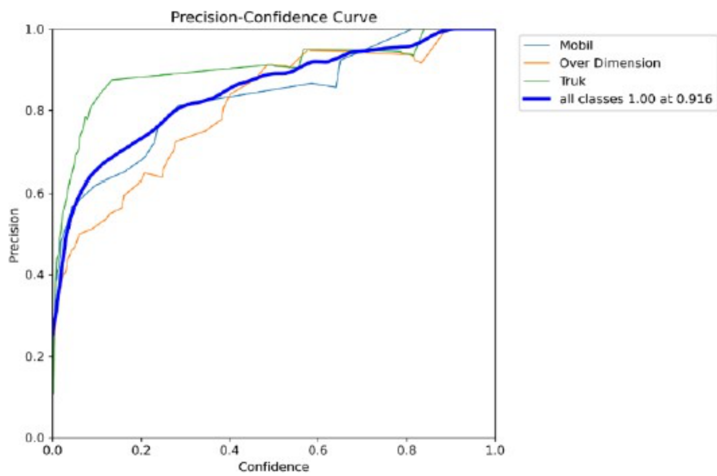


**Figure 5**. Precision-confidence curve

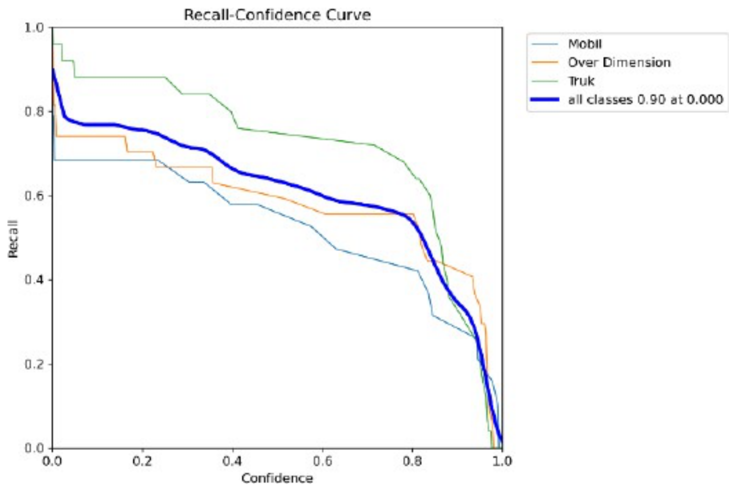


**FIGURE 6**. Recall-confidence curve

***Algorithm implementation and IoT integrated tools assembling***

The YOLOv8m algorithm was implemented into the tools using Visual Studio as the Python IDE (Integrated Development Environment) so that the data could be connected to the database by creating a database connection, API code, and index, and connecting the YOLO program to the database. This allows the images resulting from ODOL vehicle detection to be stored in the database. The results from the detection tools that are stored in the database are as Figure 7.

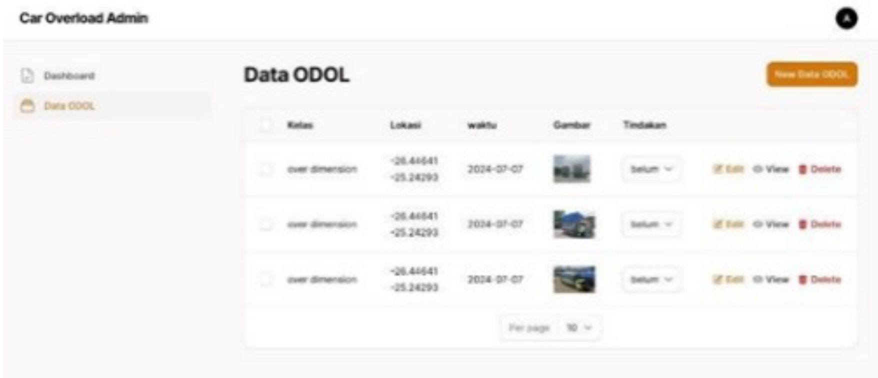


**Figure 7.** Website interface

In figure 5 is the display of the over-dimensional detection website, the data on this website will increase automatically from the results of camera input data which detects over-dimensional objects which are then processed by the YOLO algorithm, then stored in the database and the results can be seen on the website display.

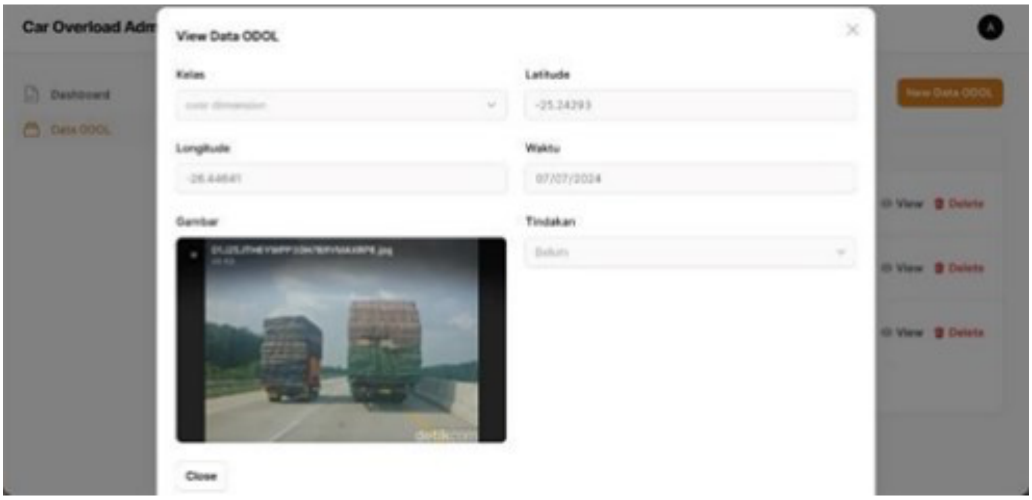


**Figure 8.** Website data which resulting from detection

In Figure 6 is the website display of the detection data results, on this website display you can check the status of the action whether it has been acted upon or not. In this trial, it was still carried out using images of trucks that were over dimensional and had not been tested directly on the highway or toll road.

***Discussion***

The development of the artificial intelligence-based ODOL vehicle detection system was conducted using a dataset consisting of 100 vehicle images, including over-dimension vehicles, normal vehicles, and trucks. The dataset was divided into three subsets, consisting of 70% training data, 20% validation data, and 10% testing data. The collected images were annotated based on vehicle categories and preprocessed through image resizing to 640 × 640 pixels and automatic image orientation adjustment. The prepared dataset was subsequently used for training the YOLOv8m and YOLOv10n models using Google Colaboratory as the computational platform.

The training process was performed using the YOLOv8m architecture with optimized hyperparameters. The model was trained for 100 epochs with an image size of 800 pixels. The training process aimed to improve the ability of the model to recognize visual patterns associated with ODOL vehicles, particularly differences in vehicle dimensions and body characteristics. The use of sufficient training iterations allowed the model to optimize object feature extraction and improve detection performance.

The comparison between YOLOv8m and YOLOv10n was conducted using the same dataset and training parameters to determine the most suitable model for ODOL vehicle detection. The evaluation was performed using several performance indicators, including confusion matrix, precision-recall curve, precision, and recall. These metrics provide information regarding the accuracy, consistency, and ability of the model to detect ODOL vehicles correctly.

The experimental results showed that YOLOv8m achieved better overall performance compared with YOLOv10n. YOLOv8m obtained a confusion matrix value of 78%, while YOLOv10n only achieved 59%. The higher confusion matrix value indicates that YOLOv8m was more capable of distinguishing ODOL vehicles from other vehicle categories. In addition, YOLOv8m achieved a precision-recall curve value of 81.7%, which was higher than YOLOv10n with a value of 72.3%. This result demonstrates that YOLOv8m provided better balance between detection accuracy and object recognition capability.

The precision and recall evaluation also showed different characteristics between the two algorithms. YOLOv8m achieved a precision value of 91.6% and recall value of 90%, while YOLOv10n achieved a precision value of 89.9% and recall value of 93%. The higher precision of YOLOv8m indicates that the model generated fewer false detections when identifying ODOL vehicles. Meanwhile, YOLOv10n obtained a slightly higher recall value, indicating that it was able to detect more potential ODOL objects. However, the lower precision and confusion matrix values indicate that YOLOv10n produced more incorrect detections compared with YOLOv8m.

The balance between precision and recall is an important factor in ODOL vehicle detection because incorrect identification can affect enforcement decisions. A model with high recall but lower precision may generate excessive false alarms, while a model with high precision can provide more reliable detection results. Based on these considerations, YOLOv8m was selected for implementation because it demonstrated more consistent detection performance with precision of 91.6%, recall of 90%, and a confusion matrix value of 78%.

The Precision-Recall curve, Precision-Confidence curve, and Recall-Confidence curve further support the evaluation results of YOLOv8m. The Precision-Recall curve demonstrates the relationship between detection precision and recall performance at different confidence thresholds. The achieved value of 81.7% indicates that the model maintained reliable detection performance across different prediction confidence levels. The Precision-Confidence curve shows that increasing confidence thresholds improved detection reliability by reducing false predictions. Meanwhile, the Recall-Confidence curve indicates that the model maintained sufficient object detection capability even when different confidence levels were applied.

The selected YOLOv8m model was subsequently implemented into an IoT-integrated ODOL detection system. The implementation was conducted using Visual Studio as a Python development environment, where the YOLO detection program was connected to a database through API integration. The system was designed to capture vehicle images through a camera, process the images using the trained YOLOv8m model, and store the detection results automatically in a database.

The developed web-based monitoring interface provides information regarding detected ODOL vehicles, including captured images and detection records. The automatic data transmission process allows detected vehicle information to be stored and monitored digitally. This implementation demonstrates that artificial intelligence-based detection can support real-time monitoring and improve the efficiency of ODOL enforcement processes.

Although the system successfully demonstrated the capability to detect ODOL vehicles, the current implementation was still evaluated using image-based testing and has not yet been fully tested under real highway or toll road conditions. Environmental factors such as lighting variation, vehicle speed, camera position, and traffic density may influence detection performance. Therefore, further field testing is required to validate the reliability of the system in real transportation environments.

Overall, the results indicate that the YOLOv8m-based detection system provides an effective approach for automated ODOL vehicle monitoring. The combination of deep learning, computer vision, and IoT technology enables faster identification and digital recording of ODOL violations. This system has the potential to support transportation authorities in improving road safety, reducing infrastructure damage caused by overloaded vehicles, and advancing smart transportation infrastructure in accordance with Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure).

## CONCLUSION

**Fundamental Finding:** This study developed an artificial intelligence-based detection system for identifying Over-Dimension and Overload (ODOL) vehicles using the YOLO algorithm. The dataset consisted of 100 vehicle images, divided into 70 training datasets, 20 validation datasets, and 10 testing datasets. The experimental results showed that YOLOv8m achieved better overall performance compared with YOLOv10n. YOLOv8m obtained a confusion matrix value of 78%, a precision-recall curve value of 81.7%, precision of 91.6%, and recall of 90%. Although YOLOv10n achieved a higher recall value of 93%, its confusion matrix value (59%), precision-recall curve (72.3%), and precision value (89.9%) were lower than YOLOv8m. These results indicate that YOLOv8m provides a more balanced and consistent performance for ODOL vehicle detection. The developed YOLOv8m model was successfully implemented into an IoT-integrated detection system capable of transmitting and storing detection data in real-time. **Implication:** The findings demonstrate that the YOLOv8m-based detection system can improve the efficiency of ODOL vehicle monitoring by providing automated identification and digital recording of potential violations. The integration of artificial intelligence, computer vision, and IoT technology provides a practical solution for supporting transportation monitoring systems. This research contributes to the development of smart transportation infrastructure and supports Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure) through the implementation of intelligent technology for improving road safety and reducing infrastructure damage caused by ODOL vehicles. **Limitation:** This study has several limitations that should be considered. First, the dataset used in this research consisted of only 100 images, which may not fully represent variations in vehicle types, environmental conditions, and real traffic situations. Second, the system evaluation was conducted using image-based testing, while real-time implementation under highway and toll road conditions has not yet been fully evaluated. Third, external factors such as lighting conditions, vehicle speed, camera position, and traffic density may affect the detection performance of the developed system. **Future Research:** Future studies should expand the dataset by including more vehicle types, diverse road environments, and various ODOL violation conditions to improve model generalization. Further research can also evaluate newer YOLO architectures, such as YOLOv9 and YOLOv10, to improve detection accuracy and processing speed. In addition, future development may integrate advanced sensors, wider IoT networks, and real-time enforcement systems to create a more comprehensive intelligent transportation monitoring platform for ODOL prevention and road safety improvement.

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## AUTHOR CONTRIBUTIONS

**Mokhammad Rifqi Tsani:** Conceptualization, methodology, investigation, data curation, formal analysis, writing original draft preparation, and visualization. **Humam Eka Saputra:** Data collection, dataset preparation, annotation process, software implementation, and validation. **Muh. Irhas Rafiqi:** Machine learning implementation, algorithm training, model evaluation, data analysis, and visualization. **Hafid Yusuf Ramadhan:** Supervision, methodology support, validation, 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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