Road Damage Detection and Reporting System Using YOLOv7: Enhancing Public Participation in Infrastructure Maintenance

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Abstract: Road damage in Lampung Province poses a serious threat to public safety and transportation, necessitating immediate government assistance. Despite the necessity for fast repair, there has been a lack of an appropriate platform for public reporting, making road inspections inefficient and error prone. This study makes two significant contributions: (1) the creation of a comprehensive dataset documenting road damage in Lampung, using samples collected in Pesawaran Regency, and (2) the development of an automated road damage identification and reporting system based on the YOLOv7 object detection model. The technology detects damage types such as alligator cracking, corrugation, depression, and potholes and provides real-time geolocation to improve reporting accuracy. Furthermore, it allows the public to report road damage. The model was trained on 1,200 pictures over 100 epochs, yielding a mean average precision (mAP) of 0.6. System performance was evaluated using precision and recall metrics, and compatibility testing confirmed that the system works reliably across various devices and browsers. This research enhances road maintenance by making inspections faster and more precise, while also promoting greater public involvement. Future work could integrate additional data sources, such as satellite imagery or IoT technology. to further increase the system's scalability and accuracy.

Keywords: Road Damage Detection, YOLOv7, Public Reporting System, Infrastructure Maintenance, Website

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Introduction

Road damage in Lampung Province has been a serious worry in recent years, prompting the central government to assess the status of highways that have suffered severe damage in Lampung Province (Jacinda Agsa Nova, 2023). This inspection seeks to discover and assess the issue of road surface deterioration, which is often produced by the cumulative effects of long-term road usage, increased traffic volume, and heavy loads (Mei et al., 2022). Road quality has a significant influence on a region's economic level, and strong road infrastructure boosts a region's competitiveness in building long-term enterprises that rely heavily on transportation (Syamsuddin et al., 2023). There is a significant link between road condition and accident rates, with better roads likely to minimize the probability of accidents (andryani et al., 2024). The degradation of highway standards not only increases the probability of accidents, but it also has an impact on inhabitants' income in comparison to other areas or nations with high-quality roads (Pandiangan, 2023). Furthermore, poor road quality incurs considerable expenditures for private automobile users. Having a car in one location with good roads is significantly cheaper than in another, reducing mobility and income in places with poor roads (Rahmawati & Pratama, 2023). According to the findings of the study (Warjiyono et al., 2020), a transparent, effective, and efficient complaint service application would make it simpler for the public to register their grievances, allowing them to indirectly contribute to the growth and improvement of public services. The objective of this study is to design a platform for reporting road surface damage, which is able to detect road surface damage, and the location of the report automatically, to increase community participation in highway maintenance which indirectly increases their income if highway maintenance is carried out quickly.

The first step in road maintenance is to identify the damage that exists on the road, to determine the necessary repair steps. Identification of road damage conditions carried out manually includes road tracing activities, taking photos of damage using a camera, measuring the area of damage, assessing the severity according to the type of damage, and compiling a report (Galang et al., 2023). This method is time-consuming, laborious, and expensive. Road tracing activities can endanger officers because they have to be in the middle of traffic (Hartono et al., 2017). Manual methods also tend to be susceptible to subjective assessments, so they can provide low accuracy in identifying highway damage (Aditya Rafi et al., 2023).

The issue statement in this study is "How to Design a Road Damage Detection Application using the YOLOv7 Model to Improve Infrastructure Sustainability and Green Economy in Lampung Province?" Automatic detection employs a tool capable of taking images of road conditions, automatically recognizing various forms of road damage, and determining the position of the damage in the image. This approach is expected to improve efficiency, objectivity, and safety in road repair activities (Wibowo & Setiyadi, 2023) . Redmon, Divvala, Girshick, and Farhadi initially developed YOLO in 2016 in a paper titled "You Only Look Once: Unified, Real-Time Object Detection." This paper demonstrates the benefits of the basic YOLO architecture, which can recognize objects relatively quickly. According to reports, YOLO achieved an average accuracy of 88% in the 2012 ImageNet validation, resulting in remarkable real-time object identification (Widjaja et al., 2022). Several prior studies related to this research have been conducted, such as the study by (Jakubec et al., 2023), titled "Comparison of CNN-Based Models for Pothole Detection in Real-World Adverse Conditions: Overview and Evaluation," which identified pothole damage in road images using CNNs (convolutional-neural-networks). Another study (Hu et al., 2024), titled "Road Surface Crack Detection Method Based on Improved YOLOv5 and Vehicle-Mounted Images," used YOLOv5 for detecting crack damage on roads. YOLOv7 has been utilized in (Yi et al., 2023) in the research titled “An Efficient Method of Pavement Distress Detection Based on Improved YOLOv7.” However, there has been limited research on road damage detection using the YOLOv7 model combined with a web-based application, especially when focusing on Lampung Province. This research aims to develop an automatic road damage reporting and detection application using the YOLOv7 Model based on a website-based application, allowing the application to be used anytime and anywhere.

Research Method

In this study, the researchers outline two main contributions: (1) the development of a dataset documenting road damage in Lampung, including samples taken from highways in Pesawaran Regency, and (2) the creation of a system for reporting and automatically detecting road damage in Lampung using YOLOv7. Figure 1 below depicts the overall methodology of the research.

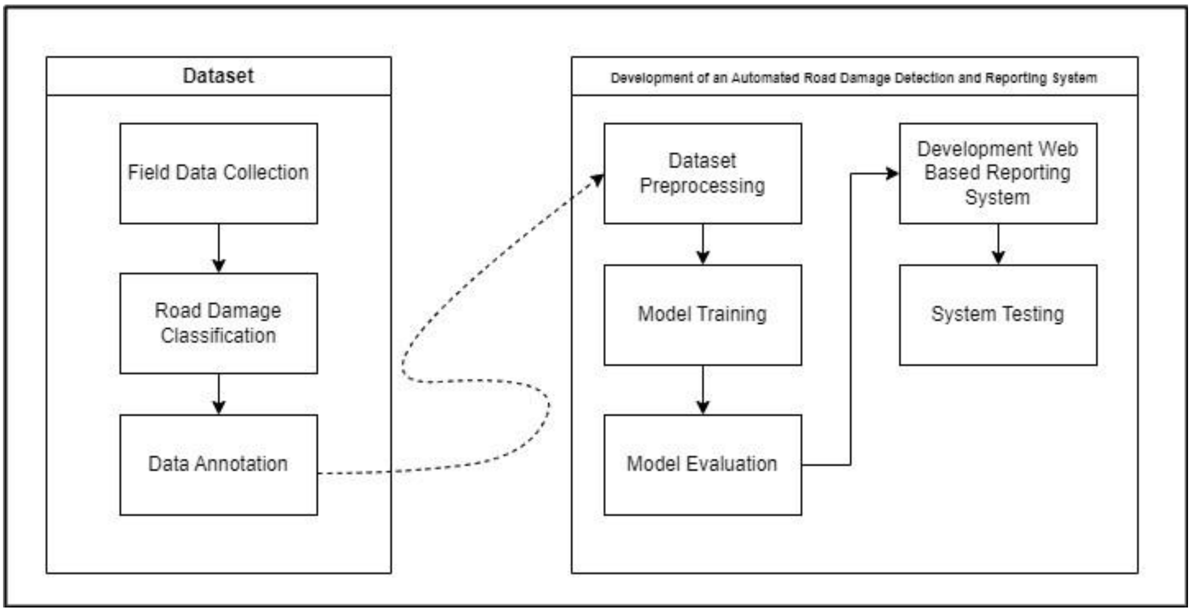

Figure 1 Research Process for Road Damage Dataset Development and Automated Detection System

A comprehensive explanation of each step in the both of research contribution is provided in the discussion below.

Field Data Collection

At this stage, data was collected on the highway in Pesawaran Regency, which was selected as an important area for the study due to its varied road conditions and frequent road damage. The data that was successfully collected was around 1,200 high-resolution photos using a camera. The photos were taken several times a day to accommodate changes in lighting conditions and perspectives, which ensured complete coverage of the road surface. The data collection process focused on the type of road damage, such as cracks caused by alligators, potholes, etc., to ensure that the data collected was in accordance with the type of road damage to be studied. At the time of data collection, the camera was positioned at a certain height and angle to capture clear and detailed images of road damage, which allowed for accurate labeling and annotation in the following steps.

Furthermore, data gathering was carried out by ensuring that photographs were captured from various spots along the roadway, including different road textures, climatic conditions, and the amount of damage. This stage ensures that the obtained data may be used to construct an automatic road damage detecting system for the research. Figure 2 displays an example of data collection during the field data collection procedure.

Figure 2 Example of Collected Road Damage Data from Highways in Pesawaran Regency

Figure 2 shows an example of the collected data results. Road damage image capture is focused on types of road damage such as alligator cracking, corrugation, depression, potholes. In figure 2 starting from left to right are examples of alligator cracking, pothole, depression highway damage.

Road Damage Classification

According to (Triyanto et al., 2019), potholes, depression, corrugation and alligator cracks are four types of road damage. Alligator cracks are often caused by high traffic and fragile road pavement infrastructure, the characteristics of alligator cracks are interconnected crack patterns resembling crocodile scales. Corrugation occurs as a series of ripples over the road surface and is mainly caused by inadequate road maintenance or vehicle wear. Depression happens when a piece of the road surface dips, leaving uneven surfaces that might cause more damage. Finally, potholes are depressions or holes in the road produced by water penetration and traffic stress, which can deteriorate over time if not fixed.

Data Annotation

In this stage, the road damage photos were labeled with the LabelImg program, a Python-based tool often used for image labeling. The application enables users to manually draw bounding boxes around areas of road damage, indicating the precise position of cracks, potholes, and other road faults. This technique was critical for successfully training the YOLO model since it taught the machine how to detect damage in a variety of forms and under varied settings.

Annotations are first stored in XML format, such as the annotations with the structure used in the PASCAL VOC dataset (Everingham et al., 2015). Many machine learning models are compatible with this format, and it is widely supported in various computer vision projects. In this study using YOLOv7, the annotation results are stored in TXT format; this file contains numbers that represent the class labels of road damage types. This format was specifically developed to operate with the YOLO architecture, allowing annotated data to be used in the model training process. Figure 3 shows an example of data annotation performed using the LabelImg application.

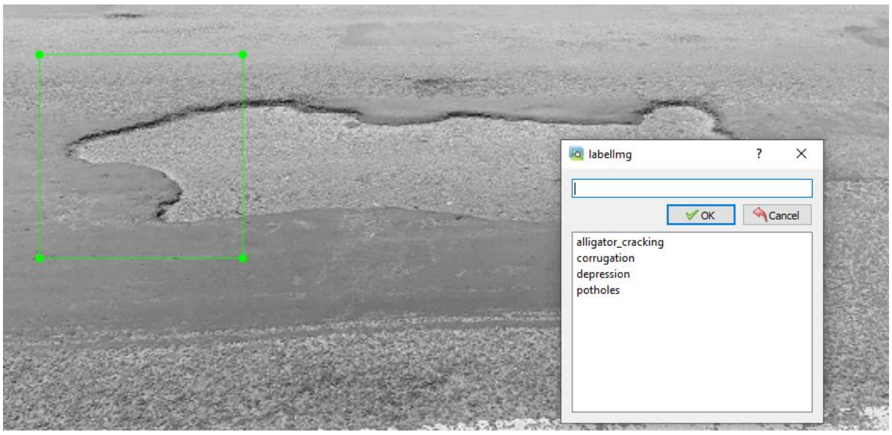

Figure 3 Example of Data Annotation Using LabelImg

Figure 3 shows the annotation process for images of road damage by providing boxes and labels according to the type of road damage. After annotation of the image is carried out, the annotation results are saved in TXT format for YOLO model training purposes.

Dataset Preprocessing

In the preprocessing stage, all road damage images are converted to a resolution of 640 x 640 pixels. This resizing step is very important to maintain consistency in the images from data collection, and ensure that all images have the same dimensions, this is intended for effective model training. By standardizing the image size, the YOLOv7 model can process and learn the data better, so that it can produce good performance and accuracy in detecting road damage.

Model Training and Evaluation

At the model training and model performance measurement stage, the performance of the YOLO model is represented by the calculation of Accuracy, Precision, Recall, and F1 Score, used to assess the performance of the resulting model.

Accuracy assesses the total accuracy of the model's predictions, taking into account both true positives (TP) and true negatives. It indicates the model's ability to categorize examples properly across all classes, as described in Formula 1:

$$Accuracy = \frac{TP + TN}{Total\ Observation\ (TP+FP+FN+TN)} \tag{1}$$

Where: TP = True Positive (Positive data sample, negative prediction), TN = True Negative (Negative data sample, positive prediction), FP = False Positive (Negative data sample, positive prediction), FN = False Negative (Positive data sample, negative prediction).

Precision is a measure of how accurate the model's favorable predictions are. This statistic is especially useful when the cost of false positives (FP) is significant since it compares the proportion of accurately detected positive occurrences to all instances anticipated as positive. Precision is calculated as follows:

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Positives\ (FP)} \tag{2}$$

Recall assesses the model's capacity to recognize all instances inside a given class (Formula 3). It becomes critical when the expenditure of false negatives (FN) is substantial, since it measures the ratio of correctly predicted the formula for Recall is:

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Negative\ (FN)} \tag{3}$$

F1-Score combines Precision and Recall into a single metric, offering a balanced assessment of the model's performance. It is particularly useful when dealing with uneven class distributions or when the importance of false positives and false negatives is not equal. The F1-Score is calculated as:

$$F1\text{-}Score = \frac{2\ x\ (Recall\ x\ Precision)}{(Recall + Precision)} \tag{4}$$

These performance metrics provide a thorough evaluation of the model's capabilities in detecting and classifying road damage, informing further improvements and refinements.

Development Web Based Reporting System

In this stage, the road damage reporting and detection system was built with CodeIgniter 3, a powerful PHP framework noted for its ease of use and efficiency in web application development. The system was created to make it easier to report and detect road damage using the YOLOv7 model.

System Testing

At this stage, testing is carried out on the road damage detection and reporting application to ensure its functionality, performance, and compatibility. The tests carried out include:

Blackbox testing and compatibility testing. Blackbox testing is used to evaluate the functionality of the system without considering the application coding. This testing approach focused on assessing the system's behavior and performance based on the inputs provided and the expected outputs (Putra et al., 2020). Test cases were designed to cover various user scenarios, such as submitting road damage reports, uploading images, and receiving detection results from the YOLOv7 model. The goal was to confirm that the system met its functional requirements and that all features worked appropriately from the end user's perspective. By evaluating the system as a whole, any differences between predicted and actual outcomes were recognized and remedied, assuring the system's dependability and accuracy.

Compatibility Testing: Compatibility Testing was conducted to verify that the web-based reporting system functions correctly across different environments and devices. This included testing the system's performance on various web browsers (e.g., Chrome, Firefox, Safari) and operating systems (e.g., Windows, macOS, Linux). Additionally, the system was evaluated on different screen sizes and resolutions to ensure a consistent and user-friendly experience. Compatibility Testing aimed to identify and resolve any issues related to browser or platform-specific behavior, ensuring that all users, regardless of their device or environment, could access and use the system effectively.

Result and Discussion

In this step, we show and discuss the findings on road damage identification and classification using the YOLOv7 model. The data used to train the YOLO model consists of around 1,200 annotated photos classified into four kinds of road damage. The model is trained using 100 epochs with an Intersection over Union (IoU) threshold of 0.5, and 4 workers are utilized to optimize the training process. This parameter is intended to maximize the YOLO model training process. The talk below describes the findings obtained throughout the research process of developing an application for automatically reporting and identifying road damage.

Number of Instances per Class

The dataset is annotated with the type of road damage and stored in TXT format, which allows detailed analysis of each class used for training the Yolo model. The images are categorized into four main classes: crocodile cracks, wrinkles, depressions, and potholes. Understanding the distribution of each of these road damage classes is critical to assessing how well the model can detect and classify each type of road damage. Figure 6 shows the distribution of each road damage class in the road damage dataset.

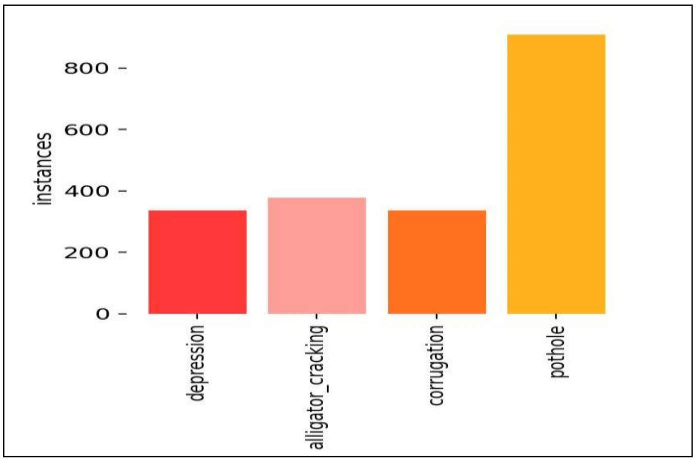

Figure 4 Distribution of Road Damage Instances

Figure 4 shows the estimated number of classes from the road damage dataset used for YOLO model training. The largest number of classes is the potholes road damage type. More than 800 images in the dataset have potholes road damage annotations. While for the other three types of road damage such as alligator cracking, depression, corrugation, the average annotation in the dataset is around 300 road damage images.

Model Performance Evaluation

The YOLOv7 model's performance is assessed using a variety of essential metrics to determine its ability to recognize and categorize road issues. Precision, recall, and the F1 Score are three measurements that offer information about the model's performance in several domains. The training results are provided as a series of graphs to assist visualize the model's performance. These graphs demonstrate how well the YOLOv7 model performs in terms of accuracy, precision, recall, and F1 Score for various types of road faults.

Precision: Figure 5 shows the precision-confidence curve. Users may understand the trade-off between the model's accuracy and confidence levels by analyzing the accuracy-Confidence Curve and choosing the appropriate threshold to meet the specific requirements of a certain application or use case.

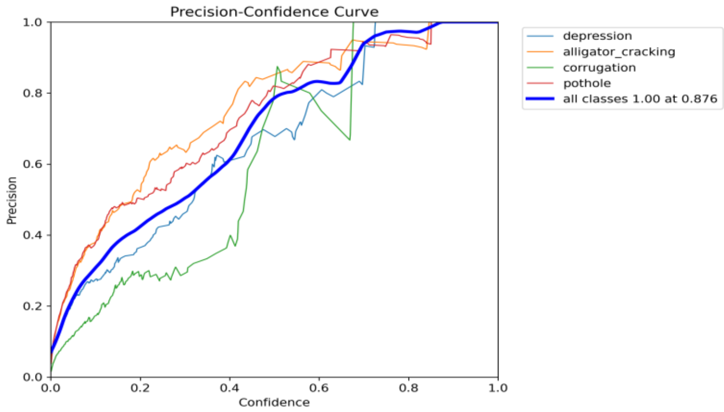

Figure 5 Precision-Confidence Curve

The precision-confidence curve compares the precision value to the confidence value. The training results showed that the accuracy value reached a maximum average of 1.00 with a confidence level of 0.876. This means that, at that confidence level, the model has the highest level of precision, with all predictions correct and no false positives.

Recall: Recall-Confidence Curve illustrates the correlation between the classification model's confidence level and recall rate, or the percentage of all positive classifications the model correctly predicts. This curve aids in understanding how the model's recall rate varies with the confidence level. Users can determine a suitable threshold to obtain the required recall rate depending on the particular requirements of the application or use case by studying the Recall-Confidence Curve, which allows them to assess how effectively the model can identify the positive class at various confidence levels. Figure 6 depicts the findings of this recall-confidence curve.

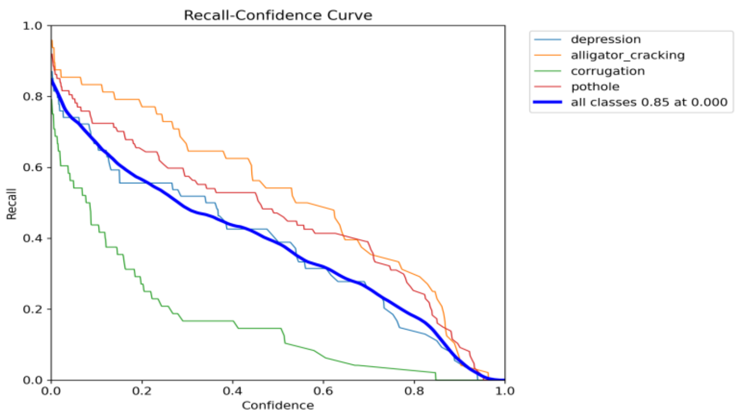

Figure 6 Recall-Confidence Curve

The graph in Figure 6 shows the recall value against the confidence value. From the training results obtained, it was found that the recall value reached a maximum average of 0.85 at a confidence value of 0.00. This shows that at a very low confidence level (0.00), the model successfully recalled most of the actual positive instances.

F1-Score: The F1-Confidence Curve is a graphical illustration of the relationship between the F1-score (a statistic that evaluates the trade-off between accuracy and recall) and the classification model's confidence level. This curve shows how well the model balances accuracy and recall at different degrees of confidence. With F1-Confidence Curve, users may select the appropriate threshold to alter the trade-off between precision and recall based on the specific requirements of a certain application or usage situation. Figure 7 displays the findings of this F1-Confidence Curve.

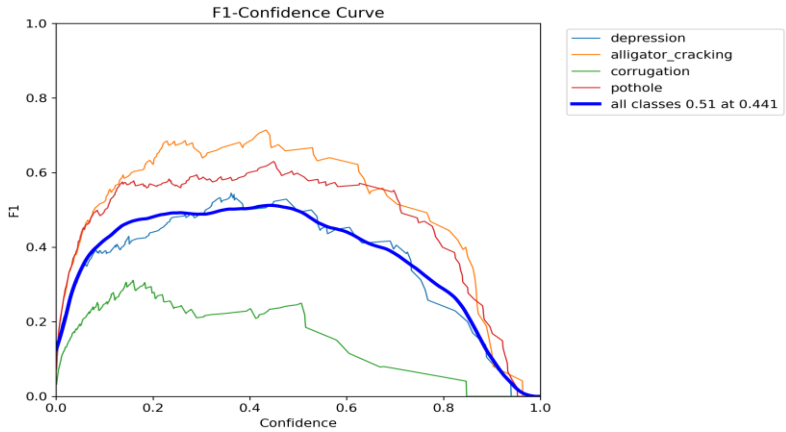

Figure 7 F1-Confidence Curve

The F1 graph from the YOLO v7 model training procedure with 100 epochs reveals that the F1 score has the greatest average value of 0.51 at a confidence level of 0.441. This graph depicts the link between the confidence value and the F1 score, which demonstrates the model's ability to balance precision and recall at different degrees of confidence in predictions. At a confidence rating of 0.441, the model achieves an ideal balance of precision and recall, resulting in the greatest F1 score.

In addition to the graphical representations, Table 1 provides a detailed evaluation of the model's performance metrics. The table includes the mean Average Precision (mAP), Precision, and Recall for the model overall, as well as for each class.

Table 1 Model Evaluation

Class	**Precision**	**Recall**	**mAP 0,5**
ALL	0,626	0,538	0,6
Depression	0,634	0,513	0,581
Alligator cracking	0,611	0,635	0,68
Corrugation	0,619	0,444	0,446
Pothole	0,641	0,59	0,69

The evaluation results of the YOLO V7 algorithm-based road damage detection model are shown in this table. Three primary measures were employed in the study: mean Average Accuracy (mAP) at a threshold of 0.5, accuracy, and recall. Precision assesses the accuracy of the model's predictions, and the highest value in the Pothole class is 0.641, suggesting that potholes are successfully identified. The Alligator Cracking class gets the highest value of 0.635 in the recall section, which assesses the model's capacity to identify all positive examples that have been seen. This suggests that the model can identify the majority of this kind of damage. In the mAP segment, the Pothole class had the best performance with a value of 0.69. Overall, the model was effective in detecting various forms of road damage, with an average mAP of 0.6. However, performance varied between damage kinds, showing that there is still space for improvement, particularly in the Corrugation class, which had the lowest mAP (0.446).

After this model evaluation stage, we proceed to test the trained model to detect road damage types using some images taken randomly from the internet. The purpose of this test is to assess the ability of the model to generalize and work in real-world scenarios. Based on the damage classes in the dataset, the photos utilized depict different sorts of road damage scenarios. We hope to establish the model's capabilities and efficacy in recognizing various forms of road damage by analyzing it on these photographs. Figure 7 shows the results of a road damage identification test using the trained YOLOv7 model. This graphic displays the results of road damage recognition from randomly selected photographs. The trial results may be used to explain the model's performance and capacity to detect various forms of road damage under varied road conditions.

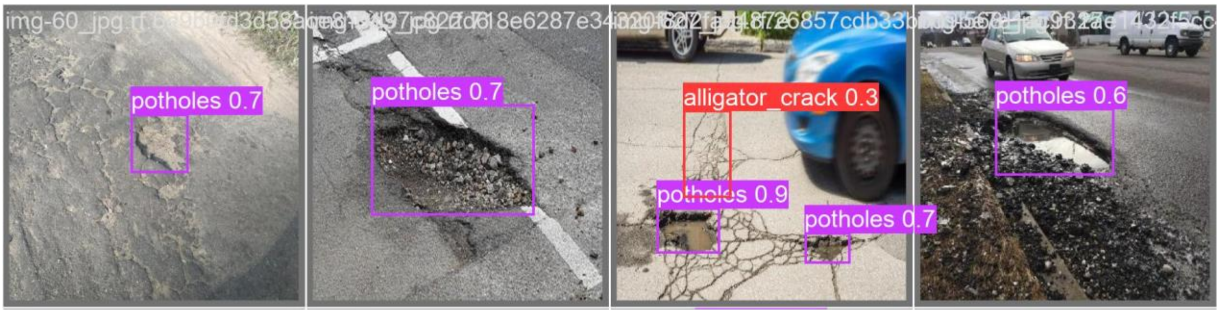

Figure 7 Detection of road damage using the trained model

The results of the road damage identification experiment, which employed a trained model capable of detecting the type of road damage present in the image under test. The model correctly identified the types of damage potholes and alligator cracks.

Web-Based Reporting and Detection System

This web-based reporting and detection application was developed to simplify the process of identifying and reporting road damage using camera detection and location tracking. This application is expected to increase community participation in highway maintenance, as well as a forum for the community to report road damage in their area. This system integrates the YOLOv7 model that has been trained to detect road damage automatically. The key features of the application include:

1. **User Registration with Google Account**: To use this road damage reporting and detection system, users can register as a reporting user with an active Google email address.
2. **Real-Time Detection Using Camera**: This application for automatic reporting and detection of road damage, uses the device's camera directly in the process of reporting and detecting road damage.
3. **Instant Display of Detection Results**: After capturing an image with the camera, the system displays the captured image alongside the detection results. Users can immediately view the type of road damage identified by the model, providing instant feedback.
4. **Automatic Location Tracking**: The system provides automatic location access when a user reports road damage. Using GPS on the device used to report road damage.
5. **Report Submission**: After reporting and detecting road damage, users can view the history of reporting and detecting road damage that they have done while using this highway damage reporting and detection application.

Figure 8 below shows the interface of a web-based road damage reporting and detection application. This system integrates cameras and GPS in the process of reporting and detecting road damage. The application was developed with CodeIgniter 3 and utilizes the YOLOv7 model as a model to automatically detect road damage.

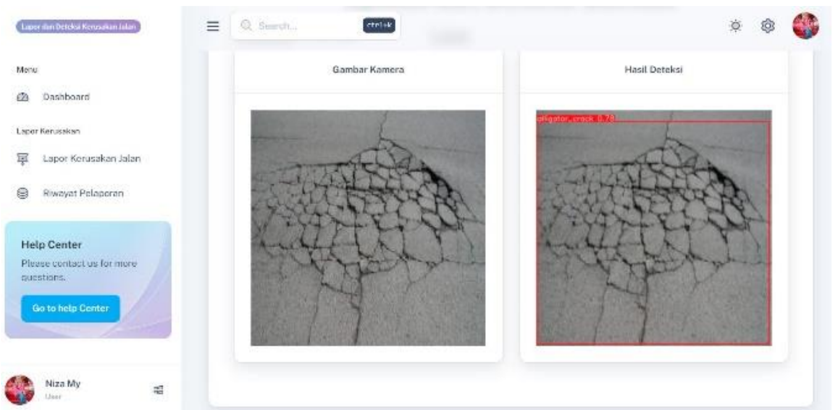

Figure 8 User interface of the web-based road damage reporting application.

Figure 8 shows the results of reporting and detecting road damage. In the image, the detection results can be seen in the form of a red box and there is a caption of the detection results. The image on the left is the result of the camera capture and the right is the result of detection by the system.

System Evaluation

At this stage, a system functioning test was performed on the road damage detection and reporting form. This test focuses on the camera and GPS access scenario on the gadget that detects and reports road damage. Table 2 below presents the results of black box testing on the road damage detection and reporting form.

Table 2 Black-Box Testing Results for Road Damage Reporting Form

Test Scenario	Input Data	Expected Result	Observed Result
Camera Access	Captured image via camera	The system should detect if camera access is granted and display a notification asking for permission	Camera permission notification displayed
Location Access	GPS location enabled by browser	The system should detect if location access is granted and display a notification asking for permission	Location permission notification displayed

This table presents the results of black box testing for the road damage reporting and damage detection forms, with two test scenarios: camera access and location access. In the first scenario, input data in the form of images taken through the camera is expected so that the system can detect whether camera access has been granted, and display a notification requesting permission. In the second case, the system is supposed to identify location access and display a message seeking permission. The browser has enabled input data in the form of a GPS position. The test results also reveal that the location authorization notification is presented correctly, showing that the system meets the criteria. These findings suggest that the system is capable of effectively controlling the access rights required to facilitate the reporting of road damage.

Compatibility testing is the next stage after black-box testing, which verifies system performance across browsers and devices. To make sure the program functions properly on whichever device or browser the user chooses, this testing is done. Table 3 highlights the compatibility testing findings for a road collision reporting app. The purpose of this table is to provide users with consistent functionality and interface quality by highlighting system performance across devices and browsers.

Table 3 Compatibility Testing Results

No	Device Type	Browser Type	Status
1	Computer	Google Chrome	Good
2	Computer	Mozilla Firefox	Good
3	Samsung A55	UC Browser	Good
4	iPhone 13	Safari	Good

Table 6 showing the results of compatibility testing for the road crash reporting application, covering various types of devices and browsers. In this test all tested combinations showed a status of "Good" indicating that the application works well on all tested platforms. On a computer device, the application was tested using two popular browsers, namely Google Chrome and Mozilla Firefox, both of which gave satisfactory results. In addition, the application was also tested on a Samsung A55 mobile device using UC Browser, as well as on an iPhone 13 with Safari, and both also showed good performance. These results indicate that the application has been optimized to provide a consistent and responsive user experience, regardless of the device or browser used.

Conclusions

The YOLOv7 model was used in this study to effectively construct and assess a web-based road damage reporting system. This technology is intended to identify and report road damage in real time. The algorithm was trained on a dataset including around 1,200 annotated road damage photographs. The YOLOv7 model was trained using numerous parameters, including 100 epochs, IoU 0.5, and 4 workers, and it performed well with a mean Average Precision (mAP) of 0.6, Precision of 0.626, and recall of 0.538. This model effectively recognized and categorized road deterioration into four categories: alligator cracking, corrugation, depression, and potholes. In this study the researcher has not tried to change the model training parameters due to time and device limitations. Based on the results of blackbox testing the application has good functionality. This application successfully reports and detects road damage using the device's camera and GPS. Compatibility testing demonstrates that the program works consistently on a variety of devices and browsers, including Google Chrome, Mozilla Firefox, UC Browser, and Safari. Overall, this system offers a reliable solution for real-time road damage reporting and identification. This study is designed to contribute and increase public engagement in the upkeep of public facilities and serve as a platform for citizens to report road problems in their communities. Suggestions for future study include doing model training with several training parameters and increasing the amount of road damage picture datasets utilized to develop a model with improved model performance.

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