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Article

iRodd (intelligent-road damage detection) for real-time infrastructure preservation in detection, classification, calculation, and visualization

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Abstract: Preserving roads involves regularly evaluating government policy through advanced assessments using vehicles with specialized capabilities and high-resolution scanning technology. However, the cost is often not affordable due to a limited budget. Road surface surveys are highly expected to use low-cost tools and methods capable of being carried out comprehensively. This research aims to create a road damage detection application system by identifying and qualifying precisely the type of damage that occurs using a single CNN to detect objects in real time. Especially for the type of pothole, further analysis is to measure the volume or dimensions of the hole with a LiDAR smartphone. The study area is 38 province's representative area in Indonesia. This research resulted in the iRodd (intelligent-road damage detection) for detection and classification per type of road damage in real-time object detection. Especially for the type of pothole damage, further analysis is carried out to obtain a damage volume calculation model and 3D visualization. The resulting iRodd model contributes in terms of completion (analyzing the parameters needed to be related to the road damage detection process), accuracy (precision), reliability (the level of reliability has high precision and is still within the limits of cost-effective), correct prediction (four-fifths of all positive objects that should be identified), efficient (object detection models strike a good balance between being able to recognize objects with high precision and being able to capture most objects that would otherwise be detected-high sensitivity), meanwhile, in the calculation of pothole volume, where the precision level is established according to the volume error value, comparing the derived data to the reference data with an average error of 5.35% with an RMSE value of 6.47 mm. The advanced iRodd model with LiDAR smartphone devices can present visualization and precision in efficiently calculating the volume of asphalt damage (potholes).

Keywords: 3D visualization; accuracy; efficiency; object detection; prediction; precision; reliability

1. Introduction

Identifying and quantifying road, bridge, and building infrastructure damage has been conducted over the past decade. Some research determines current equipment and solutions that can be adapted to infrastructure conditions (Coenen and Golroo, 2017). Related research seeks low-cost, automated solutions to handle large amounts of data.

Methods of identifying road damage conditions can be evaluated manually, semi-automatically, or fully automatically. In the manual method, appraisers visually inspect pavement surfaces by walking over road surfaces or observing the windshields of slow-moving vehicles (Liang et al., 2022; P. Wang et al., 2023). Manual methods may include direct observation in the field, interviews with relevant agencies, and traffic volume and speed surveys (Choiri et al., 2024; Pebrianto, 2023).

The old concept, which uses manual and visual surveying methods, involves a high workforce and poses numerous hazards for inspectors and road users. Conducting surveys with large and many road networks is impractical, and it is easy to deploy surveyors to obtain dynamic data (Benmhahe and Chentoufi, 2021). In addition, the manual inspection method is very subjective, entails substantial labor and time expenses, particularly in highway zones or extreme weather conditions, and endangers surveyors (Majidifard et al., 2020; P. Wang et al., 2023).

Identifying physical damage to road infrastructure applied by the Indonesian government involves a survey to identify and classify the extent of road damage in the form of estimated percentages (Pebrianto, 2023). The highways method provides a systematic way to assess the condition of road pavements and prioritize preservation efforts (Choiri et al., 2024). Once the type and extent of damage are identified, road infrastructure maintenance methods are classified by decision tree analysis (Choiri et al., 2024; Pebrianto et al., 2023). This analysis gives an order of priority to routine maintenance programs and special repair methods. Such priority can be recommended based on the type of damage and its severity.

Devices for road damage detection by semi-automatically methods are expensive in terms of the initial investment and cost of carrying out the operation, about USD 1.180 million and USD 70 thousand, respectively (Majidifard et al., 2020). Meanwhile, according to research from Sattar et al. (2021), semi-automated systems cost about $541 to $933 per mile in the United States. Manually and semi-automatically, procedures are appropriate for monitoring road conditions. However, they present risks to safety, are lengthy, and are costly. Advanced technology allows fully automated vehicle and equipment monitoring of road damage conditions (Ruseruka et al., 2023).

During the review (Benmhahe and Chentoufi, 2021), compared to cutting-edge methods, it was observed that most studies are restricted to detecting and measuring the specific damage to roads with a small scope. The damage is also difficult to analyze and requires extensive training. This remains a genuine issue that requires attention in the case of smart cities with extensive road networks. Several sensors are needed to improve the performance of the evaluation of the condition of the road surface. Sensors allow flexibility while working with extracted images from videos that convey significant data rather than basic images.

Automated road damage identification is the most effective (N. Wang et al., 2023), but heavily dependent on expensive automated survey vehicles. In contrast, low-cost options are less efficient time-wise. Conventional techniques are usually used to identify and evaluate road damage; nevertheless, they are not entirely precise. Automated methods in the form of artificial intelligence approaches are expected to enhance the precision of identification results. several research projects applying artificial intelligence (AI) technology to road inspections have been published (Thuyet et al., 2022).

Spatial information with 2D pixels to overcome spatial constraints that can capture complex visual layouts (Liu et al., 2023). Liang et al. (2022) detect and categorize various types of road damage with precision, quickness, and automation using lightweight attentional CNN. An effective model was recently developed to automatically identify and categorize road damage from end to end. N. Wang et al. (2023) created an automated system for identifying pavement cracks using digital photos that primarily focuses on individual cracks. The same is done by Zhang et al. (2022), named Automatic Road Damage Detection Algorithm, which automatically detect damaged components that can enhance maintenance efficiency. However, Huang et al. (2023) perform real-time identification of road deterioration for practical use in intelligent transportation systems using light category crack and road damage detection methods. This detection method reduces computational complexity and increases efficiency while maintaining detection accuracy (Wan et al., 2022). Al Duhayyim et al. (2022) classify road damage using deep learning models.

Penallal and Amb (2023) use local damage image or video databases and produce special automatic road damage detection devices. The UAV survey device is not optimal for scanning on road surfaces. This is constrained by the reliability of damage detection algorithms and the need for more efficient methods to merge single images into continuous road images to perform machine-learning damage detection (Zhao et al., 2023). Yan et al. (2022) created an advanced software system for detecting and categorizing cracks beneath bridges, but automated visual inspection is challenging to perform efficiently. Song et al. (2020) labelled a multisource road damage category dataset to reflect the overall situation of road damage in China. Joykishore et al. (2022) conducted YOLO (You Only Look One) training with labeling formats.

On the other hand, when utilizing images to detect holes, there are still limitations regarding the coordinates and scale. It is difficult to determine the exact size and location of the detected holes (Chaithavee and Chayakul, 2022). Various sensors are utilized for data collection (Bhatt et al., 2017; Ramesh et al., 2022; Ruseruka et al., 2023; Vogt et al., 2023; Xin et al., 2023) for the process of identifying damage to road surfaces. However, visual-based methods are more accessible to apply. Some of the advantages are that it can scan the entire area with weather limitations (Benmhahe and Chentoufi, 2021), can extract and categorize the type of damage through images or videos (Abbas and Ismael, 2021), can be combined with detection algorithms (Chaithavee and Chayakul, 2022), can identify or find cracks using complex image processing (Utaminingrum et al., 2023), can use the integrated sensors of mobile devices and in-vehicle cameras extensively (Maeda et al., 2016; Xin et al., 2023).

The importance of the infrastructure damage estimation process, which led to forecasting the cost of road infrastructure projects, is inaccurate. Delays have been linked to this estimation, including inadequate road condition data and limited budget (Majidifard et al., 2020). Variance in construction costs between predicted and actual costs due to the lack of adequate, cost-effective predictive models. Before entering the cost prediction model stage, it is necessary first to determine cost drivers automatically and in real-time based on infrastructure condition data collected based on a quantitative approach without relying on qualitative estimates, percentage conditions, or expert opinions (Elmousalami, 2019).

Road conditions must be monitored periodically to minimize maintenance costs with appropriate and timely preservation measures. Delays in identifying road damage lead to accelerated road deterioration, enhanced maintenance costs, and decreased safety for road users (Majidifard et al., 2020). The frequency of road condition surveys might vary based on the particular requirements and resources of an organization responsible for road maintenance. In Amelia Setiaputri et al.'s (2021) research shows that Indonesia's national roads are surveyed annually to determine the extent of road damage following prevailing government policies. Due to high survey costs, maintenance, and restoration decision-making are frequently based on outdated data. In addition, surveys should be conducted more frequently in areas with high traffic volumes or adverse weather conditions.

Smartphone usage has grown significantly in recent years (Tsuboki et al., 2023; Xin et al., 2023; Yang et al., 2020). Smartphones have advanced computational capabilities and various sensors, including GPS, cameras, accelerometers, gyroscopes, and magnetometers (Shan et al., 2023). Numerous individuals carry cell phones in vehicles (Ramesh et al., 2022). This method reduces computational complexity and increases efficiency while maintaining detection accuracy (Pebrianto et al., 2023). Light detection and ranging (LiDAR) is a technique that has proven useful in depth monitoring based on remote sensing. LiDAR sensor is built on the smartphone device to correctly observe changes in depth (King et al., 2022). The LiDAR-based depth sensor 2020 was introduced by Apple as the first LiDAR smartphone (Luetzenburg et al., 2021; Xhimitiku et al., 2022) with an improved application programming interface (augmented reality) for iPad Pro and iPhone Pro Max devices (Costantino et al., 2022; Gollob et al., 2021).

High accuracy in the detection and classification of types and quantities and presentation of data in visual 3D about road surface conditions can provide more accurate information about damage in digital image-based details (Bera et al., 2023; Xhimitiku et al., 2022). Furthermore, the results of identifying damage to the road can improve the accuracy of forecasting the cost of road infrastructure projects. More accurate information about road damage can help strategic decision-making regarding road maintenance and repair. Essential models capable of continuously monitoring road damage in terms of safety and driving comfort (Ramesh et al., 2022).

This research aims to create a road damage detection application system by identifying and qualifying precisely the type of damage that occurs using a single CNN to detect objects in real time. The application discussed in this study is called iRodd (intelligent road damage detection). Especially for the type of pothole damage, further analysis can be done by measuring the volume or dimensions of the hole with a LiDAR smartphone. The study intends to enhance resource allocation and cost accuracy in road preservation by improving precision and efficiency by improving detection, classification, and damage volume calculation.

2. Research methods

The scope of this study is flexible pavement; the minimum length of road sections detected for damage is 5 km, which can be divided into several road length intervals depending on video capabilities during the recording process. The image or video data of road conditions used for the presented research was collected from government databases of road data of the 38 province's plain areas in Indonesia for one representative area. Section road and survey schedules vary by accessibility, climate, and traffic conditions with various conditions and situations.

The first stage in the study is the collection of appropriate and sufficient data for simulation. The data should reflect the variation in the problem the deep learning model is trying to solve. Data was obtained through procedures focusing on a specific type of road damage, specifically asphalt roads.

This study considers the viewpoint of monitoring road conditions with damage categories, especially in the form of cracks and potholes, which are prevalent in most countries. This category consists of two categories of damage: asphalt damage (crocodile crack, pothole, elongated crack, transverse crack) and marking damage. This study's category of damage types is more or less in line with previous studies (Benallal and Tayeb, 2023; Eslami and Yun, 2023; Tang et al., 2022; Zhang et al., 2022).

2.1. Dataset collection, labeling, and training process

The process flow is divided into the data collection process, data labeling process, and dataset training. This study used images of flexible pavement roads that contain road damage. Primary data retrieval is performed when the sky conditions are clear and the position is straight facing the road-damaged surface. The mode of transport used can be a motorcycle or car. The picture capture process can use a regular camera, while secondary data is collected using existing datasets. The object caption for each image needs to be built first. The information in question is information about the location of the object and the class of objects to be detected and classified. This information serves as a target or reference to obtain weight during the data training process and to compare output values during the testing process.

The dataset labeling stage is the stage of annotating each data. The description is the confidence level of the boundaries and damaged type from every damaged thing depicted in the picture. This information will be used for the training and testing process. The data label process stores information on the location of bounding boxes and object classes. The information will be used to form the target class of the object. The output for each image is an image with bounding boxes and classes on each object in the image. The annotation results are used for data containing individual text files for each image.

This process begins with classifying cracks to be detected. Labelling uses a polygon tool to follow irregular crack patterns and produce crack precision better than bounding box tools. This polygon tool starts from one point and ends at the same point surrounding the crack shape that occurs. When the polygon has been closed (back to its original point), an automatic crack class will appear and be selected according to the type of crack. This process is carried out as accurately and consistently as possible. The resulting value from the formation of polygons will later be used as a target for the training process. This will facilitate the training process, although minimal data is utilized. The total number of cracks that can be detected is about five thousand datasets. The 9290 datasets were collected, and the total number of damages that can be detected is 5317 datasets. Datasets were obtained with details for training as much as 60%, for validation 20%, and for testing as much as 20%.

After all, the data is labelled, inputted into the database, and divided into three sets. (1) The training dataset looks for relationships between desired features and labels. The number of data trains in this study was 60%. (2) The validation dataset optimizes the model parameters generated during training and avoids overfitting. Model performance will be evaluated using valid data, and parameters that give the best results will be selected. The amount of valid data in this study is 20%. (3) A test dataset is used to test the performance of models that have been trained and optimized. The test datasets should not be used in training or model optimization. Testing datasets objectively depict a model's performance on never-before-seen data. The evaluation results on the test data are used to measure the general ability of the model to make accurate predictions; the number of test data in this study is 20%. Preprocessing and augmentation are not performed due to time constraints and large amounts of data.

The training process produces models that detect objects quickly, accurately, and reliably in various situations and image resolutions. This process first determines the number of epochs used during model training. The number of epochs affects the degree to which models converge or achieve optimal performance levels (Alamgeer et al., 2023). Models can learn better patterns in training data and improve their performance. However, more epochs can also affect the risk of overfitting. If the epoch quantity is too low, the model may underfit the data, resulting in poor performance. On the other hand, if the quantity of epochs is too high, the model may memorize the training data, resulting in overfitting and limited generalization to new data. Prevention can be done using independent datasets (Gavilán et al., 2011). Overfitting occurs when a model learns training data so well that it cannot generalize to never-before-seen data. On the other hand, too many epochs can increase the risk of overfitting.

The results of the training dataset process obtained curves that help to understand how the model behaves. The four curves are accuracy, precision, sensitivity, and F-1-score of each type of detection. A further explanation of the process of analyzing accuracy performance measurement is provided in the next section. At the model training stage, the amount of damage detected in the dataset in the form of instances can also be generated. This process is obtained after the entire running epoch is completed and the detection of the number of cracks of each type of crack appears.

2.2. Road damage detection and classification analysis method

The process analysis evaluates the image results using threshold values, selecting threshold values for bounding box emergence, examining test output results, including test images and model performance measurements, and assessing bounding boxes and classification accuracy against datasets.

This detection phase aims to identify and localize the position of road damage in images or videos. Furthermore, the classification phase assigns a specific category or type of damage to the detected agency. The level of classification accuracy can be quantified using parameters like accuracy, precision, sensitivity, and F-1 score. Finally, the quantification phase involves estimating the severity by classifying the amount of damage per type of road damage detected. When detecting the location of objects, object detection algorithms must be considered. The trained model's performance is evaluated based on accuracy and sensitivity. Accuracy is the measure of accurately anticipated features as a percentage. Sensitivity is the proportion of accurately predicted features.

Precision and sensitivity evaluated with IoU indicate the division of the region that overlaps between the expected border and the actual boundary on the ground's surface. If one increases, it decreases the other; a popular way to establish a balance between these matrices is by using an F-1 score to measure the model's overall accuracy. The maximum F-1 score ensures considerable precision. An IoU threshold of 0.5 is frequently used in assessing object detection algorithms to determine the precision of the detection (Dollár and Zitnick, 2015; Everingham et al., 2010).

According to Zhang et al. (2022), if the algorithm achieves >90%, bringing improved detection accuracy and processing speed in real-time into the detection system, providing scalability for the detection system will bring The results indicate that the proposed technology provides high precision in detection and significantly improves field monitoring processes. Real-time detection error factors are light intensity, traffic crowds, processor specifications, and resolution used. The epoch value influences the model's performance in this framework. These values are assigned to the entire test dataset. The method's performance depends on object classification accuracy and the effectiveness of boundary box detection.

2.3. Road damage calculation and visualization analysis method

Information collected by smartphone LiDAR and low-cost GNSS devices utilizing georeferenced 3D modeling and GNSS data to compare volume. The study analyzed data to assess device volume deviation outcomes using volume benchmarks. The local coordinate data is converted to global coordinates using tools and at least four reference locations. Such references can create layouts, contours, transverse profiles, longitudinal profiles, and volume calculations. In this section, the accuracy of measuring the dimensions of road damage will be compared. To reference (benchmark) the volume of road damage, manual measurements of the volume of road damage are carried out. Measurements are made using a thin plastic base placed in a pothole; then, sand is inserted to cover the hole. Based on data on sand weight (kg) and sand specific gravity (kg/cm^3), the volume of road damage holes (cm^3) is obtained.

The accuracy of estimating pothole volume using the spot scan data collection method depends on the type of pothole damage and precision determined by the volume error value of the acquired data compared to the reference data. Meanwhile, it is done with root-mean-square error (RMSE) analysis to give more weight to significant errors (Elwahsh et al., 2023). RMSE was used in tree mapping studies based on diameters from five different modeling approaches. RMSE is also used to measure connectivity levels in forest vegetation using LiDAR devices and GNSS receivers (Zimbelman and Keefe, 2022).

Data processing for potholes using Cloud Compare and Global Mapper applications. Cloud Compare binds the data point cloud with the GCP point. A global mapper models cross and long sections, makes contours, and generates volumes.

The application process of the iRodd advanced (volume calculation and pothole visualization) is divided into the following stages (**Figure 1**):

a) Preparation. The preparation phase includes integrating LiDAR smartphone devices and low-cost GNSS to obtain ground control point (GCP) information. The process continues to connect the receiver to a low-cost GNSS antenna and the receiver to a LiDAR smartphone by tagging over GCP.

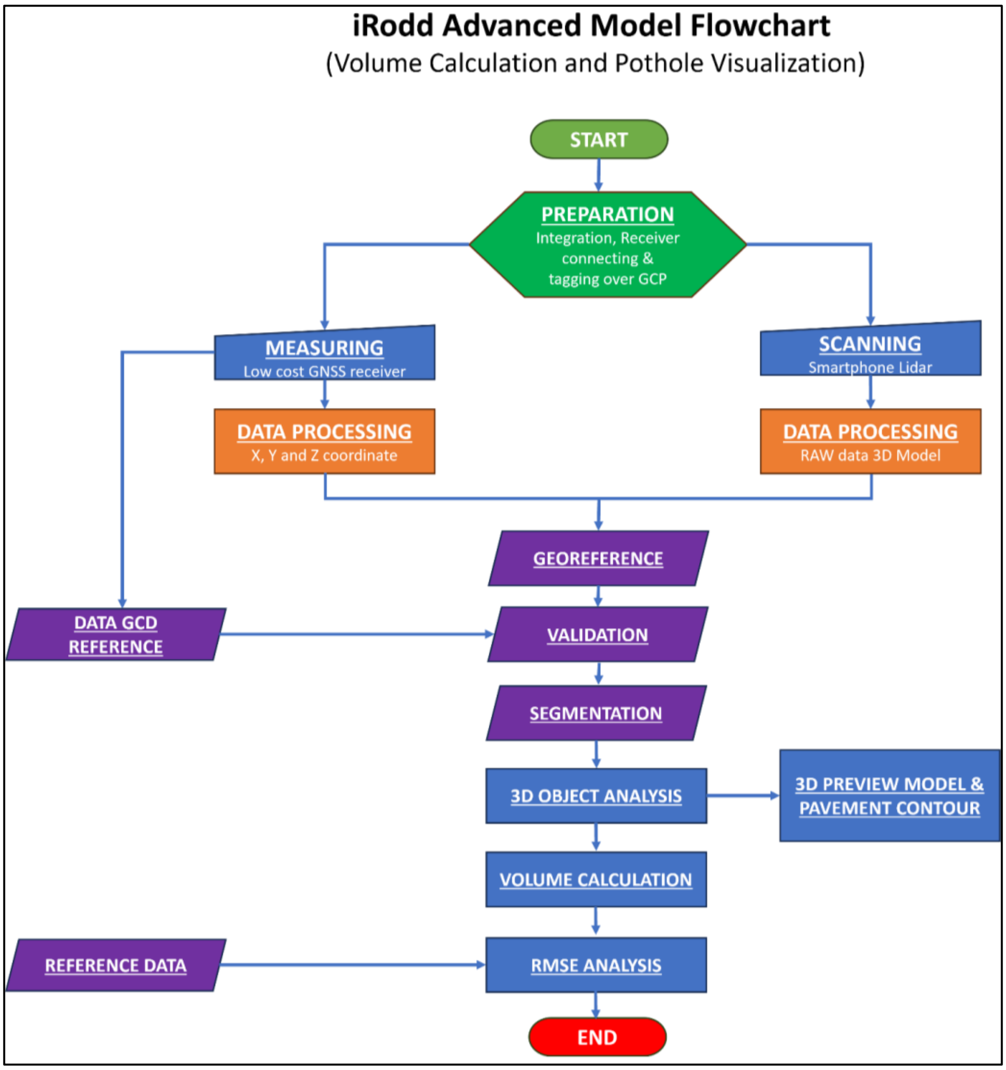

Figure 1. iRodd advanced model flowchart.

b) The GNSS measurement process uses a low-cost GNSS receiver. Data is carried out on top of the ground control point (GCP) determination required to cover the object to be measured. The GNSS receiver device obtains position data for usage as georeferenced data.

c) LiDAR data retrieval process. Data is collected by focusing on damaged roads and the established ground control points (GCP). iPad Pro LiDAR devices are equipped with devices that sharpen objects and estimate their distance.

d) Data processing. This process uses freeware applications such as 3D Scanner Apps™ and Cloud Compare™. Input data and coordinates using the file toolbar in the open-source software Cloud Compare™. The output is processed using a 3D Scanner application (high resolution & low resolution) to produce 3D Raw Data (obj, ascii, ply, photos) and coordinate data from GNSS. The 3D Scanner Apps™ offers the highest possible accuracy in RMSE compared to Polycam and SiteScape (Gollob et al., 2021).

e) Georeferencing. The subsequent step involves georeferencing after acquiring 3D data in the previous phase. Georeferencing assigns spatial references to items depicted through visuals that lack a defined coordinate system to assign ground control information to the observed area (Shan et al., 2023). For image georeferencing purposes, multiple control point coordinates are required. The data utilized are local coordinates acquired during measurement with a LiDAR smartphone. The following procedure transforms local coordinates to global coordinates utilizing observation data from inexpensive GNSS sensors.

f) Validation. This process determines georeferenced results post-processing data utilizing three or four ground control points (GCP) as reference data for comparing it with GNSS georeferenced data coordinates. This study utilizes several modifications in the number of ground control points (GCP) as ground control points and independent control points (ICP) as test points for precise image geometry accuracy in the coordinate transformation process.

g) Segmentation. Segmentation activities are carried out in data collection treatment, namely spot and continuous scans (extending along the road). This is done because the characteristics of lidar will be able to retrieve data on the objects it sees.

h) 3D object analysis. The test occurred utilizing georeferenced modeling (3D) and GNSS data. Data analysis was performed in this investigation to determine the volume and area of road damage. Some analyses that might be conducted include classification depending on the form or type of damage, differences in the distance of objects, structure and material objects, and others.

i) Volume estimation. LiDAR smartphone data collection outcomes were analyzed through volume analysis using georeferenced 3D modeling data acquired from GNSS data. The investigation analyzed data to identify volume differences among devices using volume references. Free Applications Cloud Compare™ or Global Mapper may transform local coordinate data to global coordinates by using at least four reference locations for calculations such as grinding, contours, profiles, and volume measurements.

3. Results

Intelligent detection and classification are divided into two main stages: data retrieval and data processing. In the data retrieval stage, with moving video, video capture is carried out through the ground control point (GCP). The mode of transport used can be a motorcycle or car. The video capture process can use a regular camera. The data processing stage based on images or video resulting from data retrieval in real time is inputted to the iRodd to produce output in the form of damage detection results and categorization of types of damage.

The system installation process is generally divided into two stages: database installation and iRodd user system installation. After installing the system, users can take advantage of the main menu, which consists of administration, road section data, asphalt road condition data, a system trained using YOLOv5, identifying, analyzing, and categorizing damage for each specific type of damage, and reports. The iRodd model initiation steps begin with an input picture or video, load model, result of road damage detection, export file, and road management information system. The graphical user interface (GUI) of iRodd software developed by the author can be seen in **Figure 2**.

Figure 2. iRodd model initiation steps.

3.1. iRodd model performance measurement results

Real-time performance in the detection system, providing scalability for the detection system. These results indicate that the proposed algorithm provides high precision in detection and significantly improves field monitoring processes. The trial epoch was applied to more than nine thousand data with damage categories: crocodile cracks, longitudinal cracks, transverse cracks, potholes, and damaged paint.

The detection for the model generated from this training is based on four curves: 1) precision curve, 2) sensitivity curve, 3) precision-recall curve (mAP), and 4) precision and sensitivity curve. The iteration process uses 100 epochs, 150 epochs, and 200 epochs. **Figures 2–5** show the curves of precision, sensitivity, average precision, and *F*-1 scores on training datasets to become models. Precision, sensitivity, mAP, and *F*-1 scores are shown in **Table 1**.

Table 1. Summary of test results on each iteration of epochs.

Number of epochs	Precision	Sensitivity	mAP	*F*-1 score
100	94%	85%	61%	61%
150	95%	80%	60%	62%
200	93%	84%	60%	61%

The graph in **Figures 3–6** shows the test results divided into 3 exercises (100 epochs, 150 epochs, and 200 epochs). The blue bold line in each graph shows the mean results of all damage classes. **Table 1** shows that after 100 epochs, the precision reached 94%, the sensitivity reached 85%, the mAP score at 61%, and the *F*1 score at 61%. Running processes with a higher number of epochs does not provide better results. So, these 100 epochs will be used to model detection, identify, and localize objects in an image or video. These high-precision scores indicate that the iRodd provides effective results in identification and classification. The iRodd model can learn from images without going through the preprocessing process, and the resulting output is very satisfying. Using three types of datasets and several types of training and testing data sharing, several test results were obtained along with the following explanation.

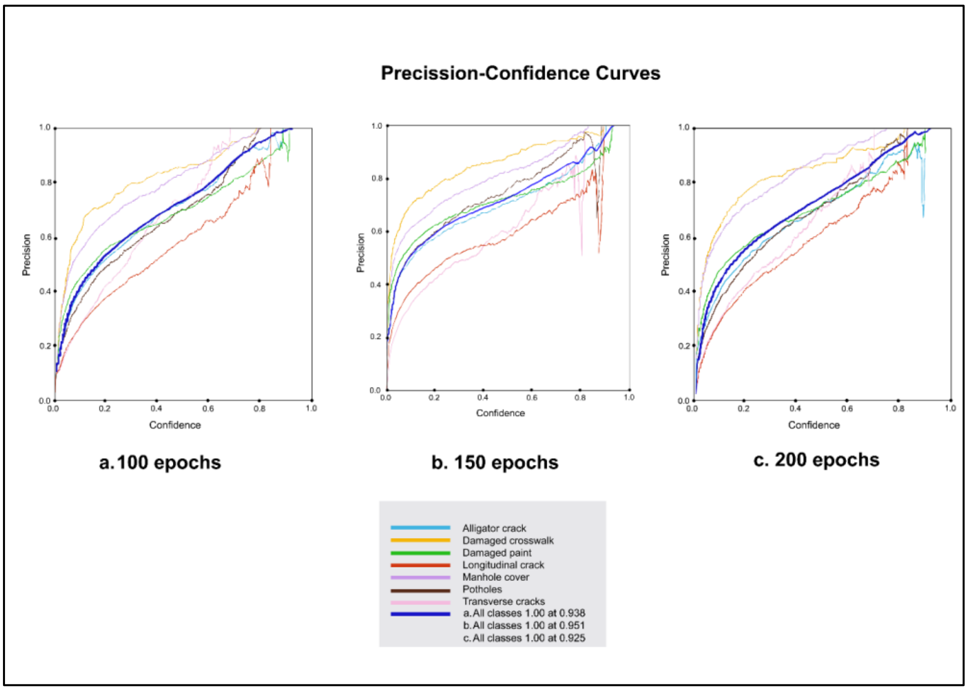

Figure 3. Precision curve.

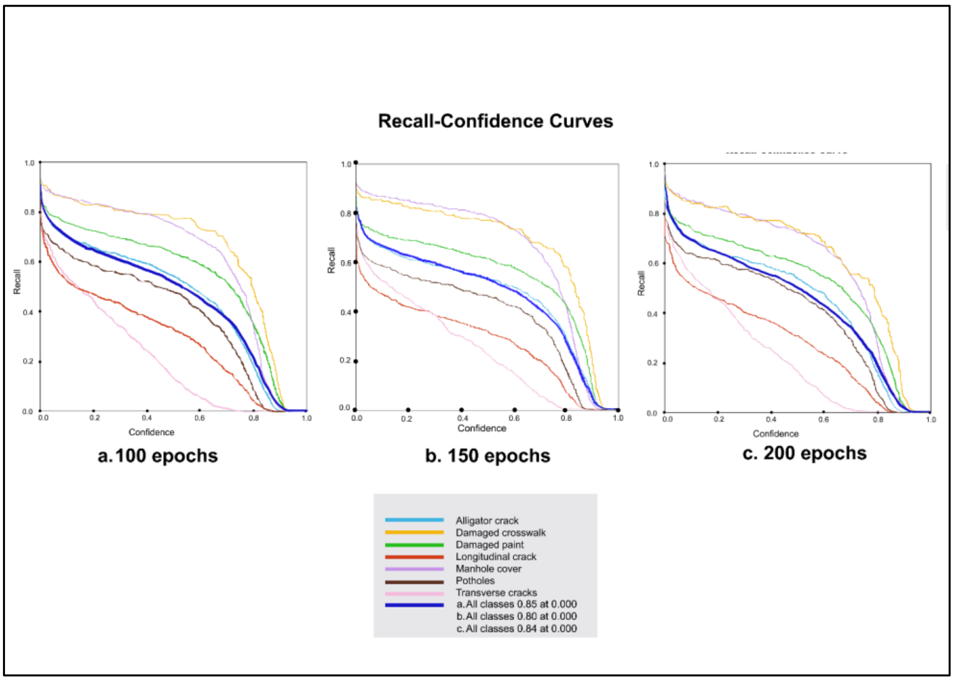

Figure 4. Sensitivity curve.

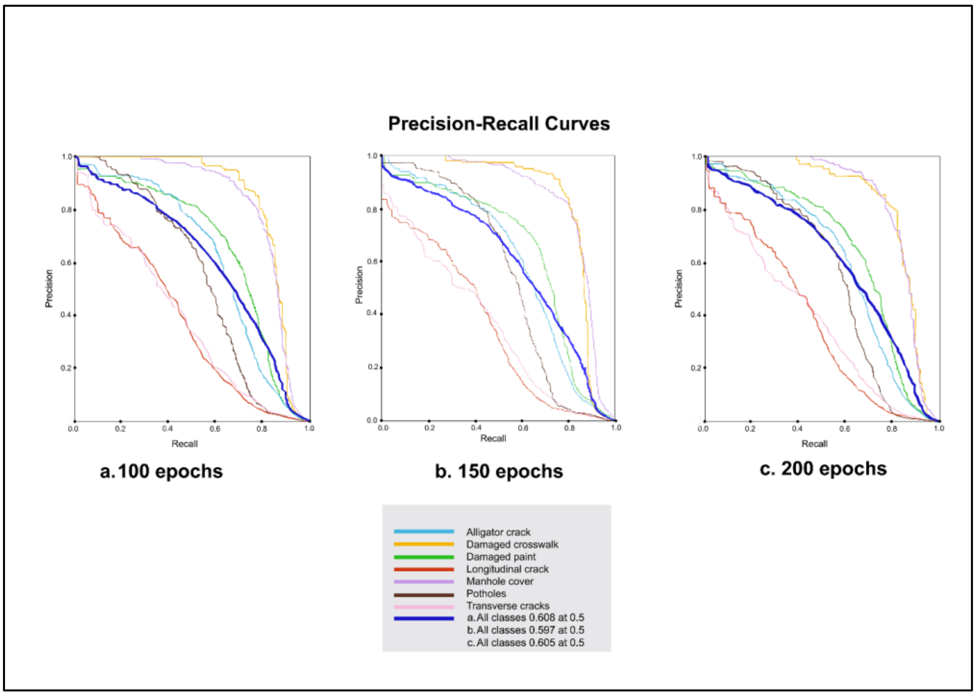

Figure 5. mAP curve.

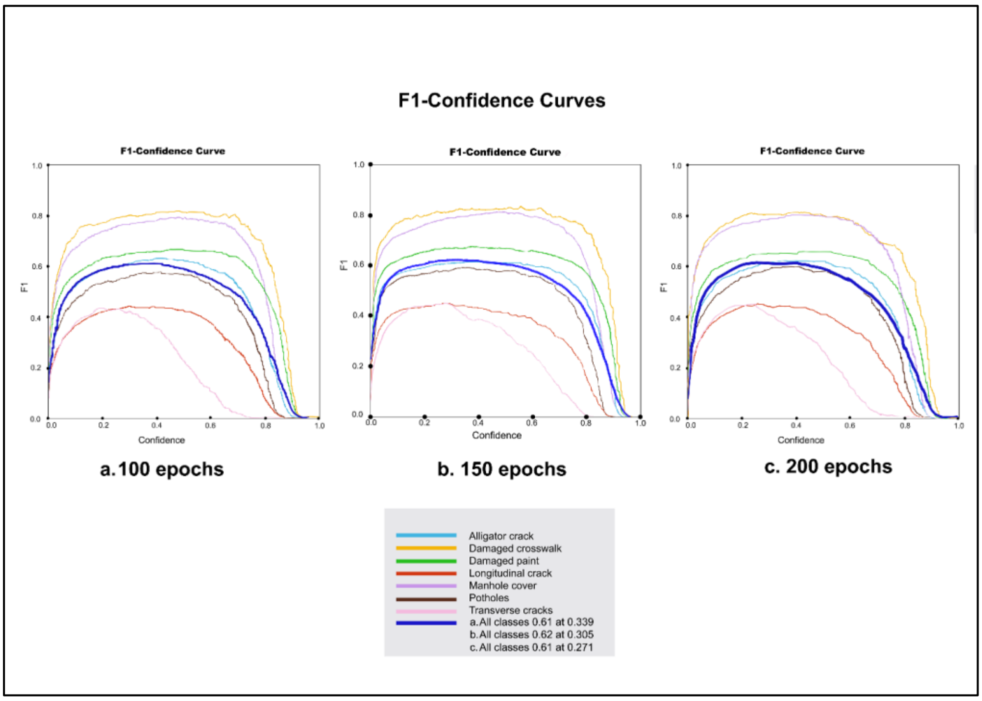

Figure 6. Precision and sensitivity curve.

The precision test results produce different accuracies from the three epochs above. The precision test measures whether the model's predictions are correct. This is the ratio of positive things with the total number of objects predicted as positive. The model obtained a precision of 94% at 100 epochs. This indicates that 94% of the positive predictions provided by the model were true positive results, while the remaining 6% were untrue positives. This is due to the high precision value, so the model can more correctly detect objects. If the model produced several incorrectly identified objects, the overall accuracy could remain high, but the precision remains low, indicating that many irrelevant items have been identified.

The sensitivity test results (recall), comparing positive predictions, are correct, and the actual amount of positive data indicates sensitivities. At 100 epochs, the model detected 85% of all true positive objects and missed 15% of positive objects.

Mean average precision (mAP) results at different sensitivity levels indicate the model's performance in object-detecting tasks. Thus, each calculated accuracy average will be combined to produce a result. mAP@0.5 was highest at 61%, indicating that the object detection model had achieved excellent performance.

In the final test, the $F1$ score is determined as the average of accuracy and sensitivity. The maximum achievable $F1$ score is 1.0, and the minimum is 0. A substantial F-1-score suggests that the classification model exhibits accuracy and sensitivity. F-1 test results can show a model confidence level of 61% for all models. That should be considered a pretty good value. This suggests that the object detection model performs well in recognizing exact objects and capturing most objects that would otherwise be detected.

3.2. iRodd model performance measurement results

3.2.1. Volume calculation accuracy performance

The graph in **Figure 7** describes the results of trials in this study on 25 (twenty five) pothole damage object observation. The accuracy level is set according to the volume error value of the calculated data compared to reference data, with an average

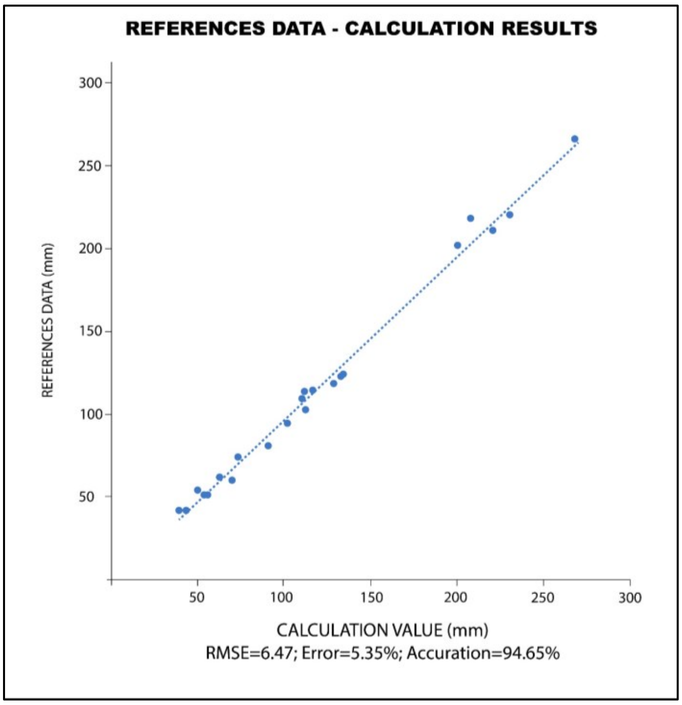

Figure 7. Comparison graphs of reference data vs. calculation value in error, accuracy, and RMSE.

error of 5.35%. The resulting error analysis can be calculated using the RMSE method. RMSE quantitatively describes the approximate average distance of objects and reference points (Desai et al., 2021). This method gives more weight to significant errors (Elwahsh et al., 2023). The RMSE value on the model yields a value of 6.47 mm, indicating a sufficient and acceptable level of accuracy for forensic studies of road damage.

3.2.2. Three-dimension object analysis

Visualization of the smartphone LiDAR data survey device consistently displays the surface scan. A total of 15 min is required for preparation, scanning, data transfer, and data processing on an area of pavement 10 m in length and 5 m in width. Texturing enhances the point cloud by displaying the distinct shapes of road surfaces and 2D objects. The trial was carried out at several points on roads constructed from asphalt. The scanning technique generates a point cloud that is subsequently utilized to generate a pavement profile in a 3D model. The scan results, including the spot and continuous scans, in a 3D model, as illustrated in **Figure 8**.

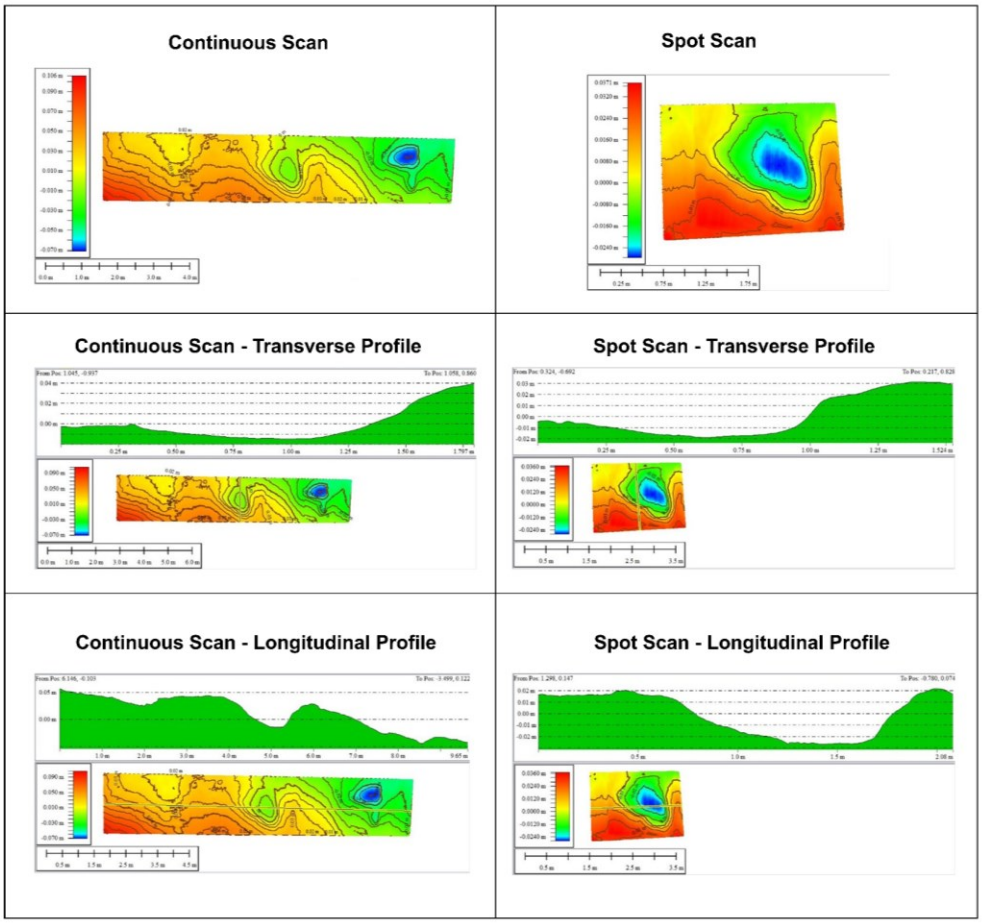

Figure 8. 3D model and profile.

Data acquisition from sampling locations shows that LiDAR smartphones are already proficient in creating high-quality 3D model visualizations. The continuous scan sample is scanned by walking 10 m along the measurement of the measured object. Conversely, the spot sample is directly scanned above the object (Waliulu et al., 2023). The equipment has sensor capabilities to collect numerous data points. The data is interpolated to generate a 3D visual model; however, the final model of the continuous scan method remains more grainy than the spot scan. Devices provide comparable data on elevation variances through contour color gradations.

4. Discussion

Preserving roads remains crucial for a country's socio-economic growth. The government periodically performs periodic assessments of road conditions simultaneously. Consultants use advanced survey vehicles with several sensors to assess road conditions during condition surveys. Imaging equipment is typically connected to specialized and costly vehicles. Frequently, the expense is not affordable for regional institutions with limited budgets.

Road surface surveys are highly expected to use low-cost devices and methods that can be carried out comprehensively, such as methods that can be applied using smartphones. Japanese cities have initiated the use of smartphone-based apps (Ruseruka et al., 2023). Nevertheless, numerous other countries have insufficient related studies (Alqethami et al., 2022; Kulambayev et al., 2022; Pham et al., 2022; Ramesh et al., 2022; Thuyet et al., 2022; Zhang et al., 2022).

Automatic identification in real-time in the form of deep learning approaches can be used more efficiently and effectively than conventional and semi-automated methods. In the field measurement stage of the model, video capture is carried out with points through the ground control point (GCP). This suggests that the system can be adapted to detect road damage in real time by taking video as the vehicle moves.

The iRodd (intelligent-road damage detection) model uses artificial intelligence (AI) technology to detect road damage instantly while data is being received through cameras or sensors installed on the vehicle. It works because the camera or sensor attached to the vehicle takes visual data from the road surface. The detection results are then displayed instantly, allowing immediate action if needed. Using video as input to detect road damage shows that the proposed system can logically be used according to the needs and facilities available in the field.

The iRodd is designed for real-time object detection. The same method is carried out by Huang et al. (2023); Wan et al. (2022) with mild category crack and road damage detection using YOLOv5s. CNN Method was also used by Liang et al. (2022) using the Lightweight Attentional Convolutional Neural Network method, R-CNN Model Mask (P. Wang et al., 2023)—Zhang et al. (2022) using automatic road damage detection algorithms.

The iRodd can accurately label datasets using the polygon tool, which makes it possible to follow irregular crack patterns. With this capability, the system can detect road damage with high precision in real time. The iRodd model uses a system trained using YOLOv5 with plenty of datasets. It has been trained with rich and diverse datasets, allowing it to detect road damage in various conditions and situations.

Performance model iRodd is used for detection accuracy to classify the type and amount of road damage with four high assessment parameters. Model accuracy is assessed based on four curves: 1) precision curve, 2) precision-recall curve (mAP), 3) F-1-confidence curve (precision and sensitivity) and 4) recall-confidence curve (sensitivity). Of all the positive predictions made by the model, 95% were correct predictions, while the remaining 5% were incorrect predictions. This precision score is higher than the detection performance of road damage objects with an accuracy of

91.4% (Ma et al., 2020) and 91.60% (N. Wang et al., 2023) of road cracks, and in line with the correct damage detection level carried out by Guerrieri and Parla (2022) which ranges from 91.0% to 97.3%. With the high precision value, the model can more correctly detect objects.

Another result is that eighty-five percent of the positive objects in the recall results were correctly identified, but the model failed to find the remaining 15% of positive objects. Meanwhile, the average test results of the highest precision (mAP@0.5) reached 60%. This indicates that the object detection model has achieved excellent performance. Moreover, the F-1 test results can show a model confidence level of 62% of the entire model. This indicates that the object detection model has a good balance between recognizing objects with high precision and capturing most objects that would otherwise be detected (high sensitivity).

Further analysis has been carried out in the form of volume or dimension measurement of pothole damage with high accuracy as a compliment. The accuracy rate is determined based on the volume error value of the calculated data compared to the reference data, with an average error of 5.35%. Another research (Vogt et al., 2023) analyzed infrastructure damages quantitatively and found average misperceptions of dimension error value: 3.53% (height-X), 4.43% (width-Y), and 10.57% (depth-Z) directions. Root mean square error (RMSE) quantitatively describes the approximate average distance of objects and reference points, and this method gives more weight to significant errors (Elwahsh et al., 2023). The RMSE value on the model yields a value of 6.47 mm. The RMSE value of the model is close to the RMSE value of King et al.'s (2022) research, which is 6.00 mm, while the depth accuracy of the sensor described by Apple on LiDAR smartphone devices is 5 mm. In another study, the RMSE value acquired for feature profile proximity using an iPad was 3 cm (Desai et al., 2021) and 3.13 cm with scanning using iPad Pro devices (Gollob et al., 2021). So, the model produces a sufficient and acceptable accuracy for forensic studies of road damage.

Lang et al. (2020) developed clustering models utilizing 3D pavement surface images. The models can detect and classify cracks in 3D pavements and can be used for pavement preservation to extend road life, but the model has not gained depth as one of the resulting variables. This research demonstrates that despite some limitations of the LiDAR sensor, the iPad Pro, as one of the LiDAR smartphones, effectively illustrates the capability to present 3D visualization and accurately calculate the volume of road damage. This aligns with Desai et al. (2021) statement that smartphone LiDAR can perform 3D scans of vehicles with equivalent precision to survey-grade LiDAR equipment in a shorter duration. LiDAR technology directly measures the range between the camera and the target. Apple's ARKit can create 3D models from close-up environments without prior preparation (Xhimitiku et al., 2022). Creating 3D models in a close-up setting provides the benefit of quick and efficient data collection. The 3D models obtained are analyzed to evaluate the accuracy of the respective reconstructions (Gollob et al., 2021).

In this study, the iRodd support with LiDAR equipment used an iPad Pro device. Costantino et al. (2022) initially assessed iPad Pro devices to generate 3D point clouds. Their performance is acknowledged for accurately collecting 3D point cloud data using affordable devices. Luetzenburg et al. (2021) developed clustering models utilizing 3D pavement surface images. The models have high accuracy in detecting and classifying cracks in 3D pavements and can be used for pavement preservation to extend road life.

The iRodd offers device accessibility, user-friendly operation, simplicity of use, and time efficiency. This paradigm is anticipated to decrease time, reduce survey expenses, and offer ease of application throughout fieldwork and post-processing. The advanced model is an improved method for evaluating road pavement conditions using LiDAR smartphones, which produce three-dimensional visuals and damage volume. The LiDAR smartphone device offers cost-effective, efficient, reliable, and user-friendly benefits.

In the future, the iRodd model can be used as a foundation. The prototype can be extended to suggest a universal standard model implemented worldwide or in regions with similar road conditions. Adding the type of damage and the amount of data can increase the model's generalization, as shown by the appearance of several other countries, such as India and Japan (Liu et al., 2023; Pham et al., 2022). To enhance the general resilience of the identifying system for every type of damage, the experiment can be performed by gathering more images from various locations and seasonal conditions to improve the representation of each damage class.

Community participation through a smartphone app used by communities to take pictures with geotags of deteriorating road sections can offer additional information on the present condition of the local infrastructure. Model performance can be trained using different data sets; this is necessary to improve model performance. Future research can focus on improving model performance, leading to improved accuracy in model design.

5. Conclusion

This research produced an Artificial Intelligence-based iRodd (intelligent road damage detection) to develop a model for real-time object recognition to identify, classify, and quantify different types of road damage. Especially for pothole damage, further analysis is carried out to obtain a damage volume calculation model and 3D visualization. The resulting iRodd model contributes to identifying road damage in terms of CARE (compliance, accuracy, reliability, and efficiency).

Complete—The model analyzes the characteristics needed for road damage detection. The output produced can all be used for the following analysis process, especially the determination of steps to handle road damage repairs to be carried out and budgeting analysis. The model can accurately label datasets using the polygon tool, which makes it possible to follow irregular crack patterns. With this capability, the system can detect road damage with high precision in real time. In addition, LiDAR smartphones are capable of producing 3D visualizations and calculations of the volume of road damage. The complete system provides benefits in accessibility, usability, and integrated data processing.

Accurate—A precision value of 95% is a correct prediction. Eighty percent of the positive objects were correctly detected in the sensitivity study. Meanwhile, based on mean average precision (mAP), the object detection model has achieved excellent performance. The score on the $F1$ score analysis indicates that the object detection model strikes a good balance between being able to recognize objects with high precision and being able to capture most of the objects that would otherwise be detected (high sensitivity). The calculation of damage volume is where the level of accuracy is determined based on the volume error value of the calculated data compared to reference data, which has an average error of 5.35% and an RMSE value of 6.47 mm. So, the advanced iRodd model can provide 3D images and accurately calculate the volume of a pothole.

Reliable—A model is considered trustworthy when a program consistently delivers the intended functionality without errors within a specific timeframe. The reliability level of the iRodd Model has high precision and is still within cost-effective limits. The model can learn from the image without going through the preprocessing process, and the resulting output is very satisfying. The system can be adapted to detect road damage in real-time by taking video as the vehicle moves.

Efficient—The model can perform real-time analysis using video data capture that is directly processed into an output as a report in a short time (within minutes). The system was trained using a CNN network with a large number of datasets, demonstrating that it has been trained with a rich and diverse dataset, allowing it to detect road damage in a variety of conditions and situations. Meanwhile, pothole volume quantification and 3D visualization of road conditions using LiDAR smartphone devices are expected to accelerate the process, cut survey expenses, and simplify implementation during fieldwork and post-processing.

This research is essential for the planning of road infrastructure. By improving the accuracy of the type and volume of road damage detection, relevant stakeholders can allocate resources more efficiently and reduce the costs associated with handling road repairs. In addition, more accurate information about road damage can help make strategic decisions related to road maintenance and repair to improve safety riding. In the future, it can display road conditions and be equipped with coordinate measurements, which can be added to a road condition map.

The benefit of this research is that it is an application of digital image-based road damage condition assessment, which can later be used to determine alternatives and handling costs based on detailed damage conditions based on digital imagery. This research can be used as a tool in road maintenance for relevant stakeholders. It can encourage innovation and utilization of artificial intelligence (AI) technology in infrastructure forensic detection more efficiently and accurately.

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