Pothole Detection and Dimension Estimation via Image Transformation and Scaling with Thai Road Data Integration

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Abstract

Potholes on roads affect traffic safety and the overall quality of infrastructure. If left unrepaired, they can lead to increased maintenance costs and broader community impacts. Traditional inspection methods, such as visual surveys by human observers, still have limitations in terms of efficiency, accuracy, and safety. To facilitate manual inspection process, a pothole detection and dimension estimation technique combining deep learning and image processing techniques is presented in this study. The method employs the YOLOv8n-seg model, which performs instance segmentation to outline pothole boundaries. Model training was conducted using a combination of open-source and Thai roads pothole dataset to enhance contextual relevance. Inverse Perspective Mapping (IPM) was applied to estimate pothole dimensions and convert front-view images into bird's-eye views. The segmentation masks predicted by the model were then used to calculate the real size of each pothole. The presented method requires single camera calibration for each camera installation. The results highlight the potential of integrating deep learning with image processing techniques to support road condition monitoring, as evidenced by a precision of 0.745, mAP@0.5 of 0.708 and an average dimension estimation error of 11.30%.

1. Introduction

Road networks are one of the most crucial components of road infrastructure that facilitate economic development by enabling resource mobility, increased productivity, and connecting social activities at the local and regional levels. A sufficiently efficient road network contributes to better access to essential services, including education, public health, and employment opportunities, and additionally helps decrease time and transport-related expenses. In economic research, road length is frequently used as a proxy for transportation capacity and regional connectivity, key factors influencing economic growth (Ng et al., 2019; Xueliang, 2013).

Nevertheless, road infrastructure can deteriorate due to cracks and potholes without proper maintenance. These problems may result from the erosion of surface materials (Khan et al., 2024) or extreme weather conditions, such as heavy rainfall, cyclones, or the excessive use of de-icing chemicals in winter (Liu et al., 2021; Yang et al., 2021). Such factors significantly accelerate the deterioration of road surfaces, compromise road safety, and increase long-term maintenance costs.

Potholes are among the most common and hazardous forms of road surface damage. They contribute to traffic accidents, congestion, and the accumulation of stagnant water, which can encourage the spread of mosquito-borne diseases such as dengue fever and malaria (Gupta et al., 2020; Kombe, 2025; Yang et al., 2021). These road defects pose a direct threat to drivers. They may also have broader consequences for nearby communities, especially when encountered at night or under poor weather conditions that impair visibility (Setyawan and Sari, 2024). In addition, potholes can cause significant damage to vehicles, increasing repair and maintenance costs. Therefore, regular inspection and maintenance of road infrastructure are essential to ensure travel quality, public safety, and sustainable economic development.

Transportation authorities in many countries have traditionally used manual inspection techniques to address road surface deterioration, such as visual surveys conducted by field personnel using standardized reporting forms (Federal Highway Administration, 2003). Although this method can observe certain surface conditions with the naked eye, it presents several limitations. These include high labor intensity, safety risks for on-site inspectors, operational delays, and elevated inspection costs (Radopoulou and Brilakis, 2016). Visual inspection is inappropriate for long-term proactive road maintenance planning (Asad et al., 2022). Due to these constraints, many countries are now emphasizing the application of technology to improve road conditions and efficiency and reduce labor burdens.

Due to the limitations of traditional road inspection methods, transportation departments and researchers in many countries are currently developing real-time detection systems for monitoring road surface conditions. A common approach involves equipping vehicles with sensors or cameras to collect real-time surface data while in motion. For instance, GPS or accelerometers can automatically identify road deterioration indications (Ranyal et al., 2022). These approaches represent an initial step toward replacing manual inspections with automated systems, saving labor expenses and enabling continuous monitoring without disrupting traffic flow. Nonetheless, these techniques have limitations in terms of accuracy, particularly in distinguishing between different types of road damage, highlighting the ongoing need for more precise detection methods.

Deep learning is one of the most recent developments in road condition monitoring, particularly Convolutional Neural Networks (CNNs). These models have presented high accuracy in detecting and categorizing road surface damage, even in cases with diversity in damage types and lighting intensity (Asad et al., 2022; Safyari et al., 2024). These approaches have been practically implemented in automated road inspection systems to support real-time processing and reduce the reliance on manual inspection methods.

Although these methods show great potential in pothole detection, they are still limited in estimating the size of the damage which is an essential factor in pavement deterioration analysis. Therefore, this study presents the process of pothole detection and size estimation using deep learning and image processing techniques to facilitate manual inspection process.

2. Literature Review

2.1 Deep Learning Approaches for Pothole Detection

In recent years, deep learning has become a vital technique for road surface damage detection, particularly when damage must be identified from image or video data, which often exhibit complexity and lighting variability. The convolutional neural network (CNN) is a widely used model that can autonomously learn and recognize image features without the need for manual feature extraction. Furthermore, a variety of CNN architectures have been developed, such as

1. R-CNN (Region-based CNN): divides the image into multiple regions before performing classification.
2. Faster R-CNN: developed to improve processing speed by using a Region Proposal Network (RPN) to generate regions of interest more efficiently, replacing the slower Selective Search method.

Although these models provide high accuracy, they are challenging to deploy on systems with limited resources due to their high computational load on lightweight devices. Therefore, to overcome these limitations, the Single Shot MultiBox Detector (SSD) was offered as a single-stage detection model that performs object localization and classification in a single forward pass, enabling fast and efficient object detection. In addition, the YOLO model (You Only Look Once) has also gained significant popularity due to its ability to perform real-time object detection while maintaining high accuracy. In addition, Arya (2021) developed an automatic damage detection system optimized for devices with limited computational capacity, such as smartphones.

Deep learning-based approaches to pothole detection have been more thoroughly studied regarding detection accuracy, computational efficiency, and their practicality in real-time system applications. As reported in Dhanreeshkar et al. (2020), a comparative analysis of YOLOv2, YOLOv3, and YOLOv3-tiny was conducted based on 1,500 images captured using an iPhone 7 in India. The results showed that YOLOv3-tiny offered the most appropriate in a real-time context. This point is attributed to its balance between fast inference time and reliable pothole detection performance.

Another study (Safyari et al., 2024) presented a comparative inspection of road damage detection techniques classified into four main categories. With traditional 2D image processing, 3D point cloud analysis, machine learning, and deep learning approaches. Additionally, the hybrid approach integrates multiple techniques mentioned above. The study concluded that hybrid methods demonstrated performance in terms of accuracy, efficiency, and practical flexibility in real scenarios.

Meanwhile, the study presented by Asad et al. (2022) emphasized the development of a pothole detection system on compact, low-cost hardware platforms such as the Raspberry Pi to attempt to reduce reliance on large-scale servers or cloud-based systems while maintaining real-time processing efficiency. This reflects the pothole detection technology's development toward edge computing solutions that are practical for real deployment.

2.2 Pothole Size Estimation Using Image Processing

Recent research has focused on achieving high-accuracy pothole detection; estimating the actual size of the damage remains a significant challenge. Various approaches have been proposed to address this issue, involving differences in both the models used and the techniques for area computation.

Arjapure (2021) proposes Mask R-CNN for detecting and estimating the area of potholes from road surface images. This model performs object detection and instance segmentation, allowing it to generate masks for individual potholes. Then, the actual pothole dimension is estimated using road width as a reference.

In another approach, Chitale (2020) employed YOLOv3 and YOLOv4 models to develop a pothole detection system with the triangular similarity technique, a geometric method used to convert pixel dimensions in images into real-world dimensions. However, this method requires the camera to be positioned at a fixed height and tilt angle, as these parameters directly affect the accuracy of the pre-calibrated values.

In another line of research, Putri (2024) proposed a hybrid system that integrates pothole detection using the YOLOv5 model with a smartphone equipped with a LiDAR sensor to obtain 3D information of the potholes and includes a GNSS system to geotag each pothole location for mapping and analysis purposes.

Additionally, Ruseruka (2024) has focused on using images from built-in vehicle cameras implemented with YOLOv5 to develop a pothole detection system based on a front-view perspective, which is subsequently transformed into a bird's-eye view using the camera's intrinsic parameters as part of the Inverse Perspective Mapping (IPM) technique. As a result, the actual size of a pothole can be estimated from its pixel dimensions by referencing the real lane width obtained from a Lane Keeping Assistance (LKA) system. Nevertheless, this method is subject to a key limitation: the camera must be installed in a fixed position, and the accuracy of the estimated pothole size depends largely on the precision of the lane detection process.

This study emphasizes estimating pothole dimensions on road surfaces, primarily based on camera images. A recent lightweight instance segmentation model, YOLOv8n-seg, is applied to detect potholes of roads in Thailand. The detected images are further processed using the Inverse Perspective Mapping (IPM) technique by applying the Four-Point Perspective Transformation method to convert the image perspective into a top-down view to estimate the potholes size. This combination, to our knowledge, has not yet been applied in this domain, especially in the context of Thailand roads. Subsequently, the pothole dimensions are estimated through pre-calibration using a reference object with a clear scale to approximate the actual size. These estimations are intended to support the assessment of damage severity and facilitate planning for future road maintenance.

3. Methodology

3.1 Overview

This study framework is structured into two main stages: (1) pothole detection model training and (2) pothole dimension estimation method. The overall workflow of the proposed methodology is presented in the flow chart in Figure 1.

In pothole detection, the process begins with collecting images from two sources: images collected in the context of Thailand and images from publicly available datasets to serve as training data for the YOLOv8n-seg model, which is an instance segmentation model.

The trained model is used to detect and apply mask to the potholes from videos recorded by a smartphone mounted on the vehicle dashboard. Appropriate frames are selected (see section 3.3.2) to estimate the dimension of detected potholes using the Inverse Perspective Mapping (IPM) technique which transform images into a bird's-eye view. A pre-calibrated homography matrix is used in IPM method (see section 3.3.1).

In the final stage, the transformed images with segmentation mask obtained are used to estimate the real-world dimensions of the potholes using the pixel-to-millimeter ratio obtained during the initial calibration (see section 3.3.3).

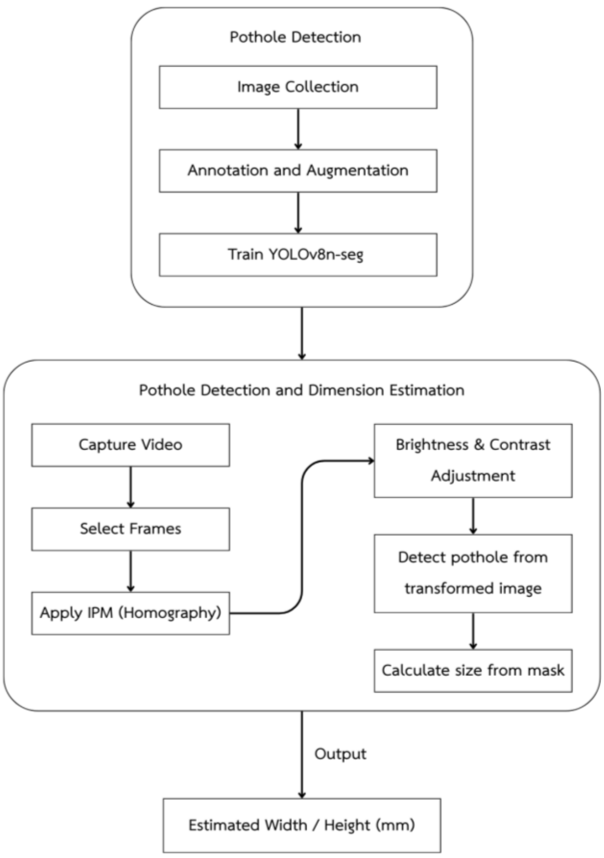

Figure 1. The overall workflow of the proposed.

3.2 Pothole detection model training

3.2.1 Data Sources: Acquisition of pothole image the datasets of pothole detection in this study were collected from two sources: (1) self-collected datasets and (2) publicly available open-source datasets.

Pothole images were captured using an iPhone 14 Pro Max smartphone camera, which has a resolution of 12 MP (4032×3024 pixels). The data was collected on roads within Chiang Mai University and surrounding urban areas in Chiang Mai, Thailand, covering concrete and asphalt surfaces. All images were taken during the daytime under sunny and clear weather conditions. A total of 22 images were collected, with no augmentation.

The primary dataset used for model training was obtained from an open-source resource (Nekouei, 2024) containing 780 pothole images. These images were augmented through rotation, flipping, brightness adjustment, and resizing to 640×640 pixels to increase data diversity and reduce the risk of overfitting during the training process.

3.2.2 Data preparation: Raw pothole images collected from Thailand were uploaded to the Roboflow platform for annotation using the polygon tool. The annotation format applied was instance segmentation, which enables the identification of individual object locations. However, one drawback of the polygon tool in Roboflow is its dependence on manual annotation, which can be particularly time-consuming for large datasets. The original 22 annotated images were further augmented using flipping, blurring, rotation, and resizing to 640 × 640 pixels to enhance data diversity and improve model training efficiency. As a result, the dataset was expanded to 127 images. These annotated and augmented images were combined with an open-source dataset containing 780 pothole images, resulting in 907 images. The complete dataset was exported in YOLO format to train the object detection model.

3.2.3 Pothole Detection training: In this study, the YOLOv8n-seg model was selected for pothole detection due to its support segmentation and precise object boundary detection at the pixel level. This technique is appropriate for potholes, which often have irregular and undefined shapes. Therefore, the use of segmentation enables more accurate size estimation than using bounding boxes. This study adopted the full implementation from the publicly available (Nekouei, 2024), including model configuration, training pipeline, and 780 road images dataset. The original codebase and dataset were modified to fit the objectives of this study.

The final dataset of 907 images was split into 837 images for training and 70 for validation. The model was trained for 150 epochs with an initial learning rate 0.0001 and a batch size of 16. An automatic optimizer was used, with a dropout rate of 0.25. Early stopping was not applied to allow the model to learn through all specified training epochs.

The intersection over union (IoU) was used to assess the overlap between the predicted segmentation mask and the ground truth annotation to evaluate the performance of pothole detection. For the calculation of mean Average Precision (mAP), an IoU threshold of 0.5 was applied, meaning that detection is deemed correct if the IoU reaches 0.5 or higher. The model accuracy presented in the following sections is based on mAP@0.5, a widely used benchmark for evaluating model performance in object detection and instance segmentation.

3.3 Pothole Dimension Estimation

3.3.1 Inverse Perspective Mapping (IPM): Images captured by a smartphone camera mounted on the vehicle dashboard are in a perspective view, where objects closer to the camera appear larger than those farther away, as the object dimensions in the image do not correspond proportionally to real-world distances. To correct this distortion, the inverse Perspective Mapping (IPM) technique can be implemented using two approaches: (1) utilizing the intrinsic parameters of the camera, which is suitable for moving cameras where detailed knowledge of the camera's internal properties is required; and (2) applying a four-point perspective transformation, which is more appropriate for static images or fixed camera setups (Ahmed and Kharel, 2021). This study adopts the second approach by computing a homography matrix for image calibration using the four-point method from a standard reference image captured before recording the video. In this image, a clearly scaled object was placed to assist in selecting the four points and to serve as a reference for converting pixel values into real-world measurements in millimeters. This approach is consistent with the homography principle described in (Vazquez Guevara, 2021), where the relationship between corresponding points in two planes is modeled as a projective transformation using a 3×3 homography matrix, which is estimated by solving the set of linear equations derived from these four point correspondences, such that:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = H \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{1}$$

where (x, y) are coordinates in the source image, (x′, y′) are the corresponding points in the destination, and H is the homography matrix. This transformation assumes a fixed camera position and a flat scene geometry, which ensures that it remains valid throughout the process.

This method remains accurate in practice and offers a straightforward way to convert perspective images into a bird's-eye view, without requiring camera calibration. It is particularly suitable for field applications where intrinsic camera parameters are unavailable or where full camera calibration is impractical.

3.3.2 Frame Selection and Preprocessing: To ensure accurate size estimation, potholes in the recorded video consistently appear near a fixed region of the frame, close to a red reference line, which helps maintain a constant distance between the camera and the object (Figure 2). This setup enables a fairly accurate pixel-to-millimeter conversion and minimizes perspective distortion.

A pre-trained detection model is used to identify suitable frames in which potholes align with the reference line. The selection process is semi-automated and manually verified. Each selected frame is then transformed using a calibrated homography matrix, followed by brightness and contrast enhancement to improve the visibility of pothole features for accurate size estimation.

This method is practical for field use; however, it requires that both the reference image and the video frames be captured using the same camera, with consistent resolution and viewing angle.

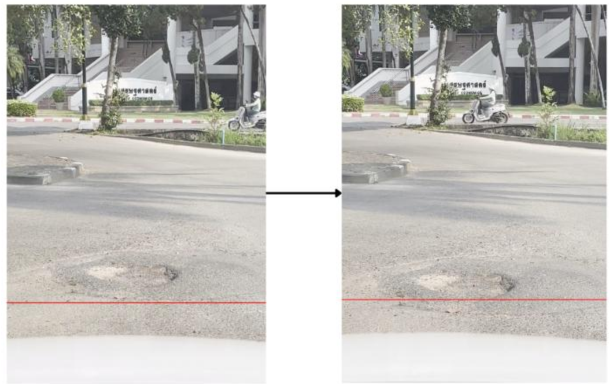

Figure 2. Pothole Approaching Reference Line.

3.3.3 Size Calculation from Segmentation Masks: Following transformation and contrast adjustment, each image is subsequently processed by the pre-trained YOLOv8n-seg model, which segments pothole areas from the background. The resulting segmentation mask is then used to estimate each pothole's area, width, and length in pixel units. These measurements are converted into millimeters using the pixel-to-millimeter ratio obtained during the initial calibration. This method enables pothole size estimation directly from images, eliminating the need for field measurements.

4. Result

4.1 Pothole Detection Results

The model achieved a mAP@0.5 of 0.694 for bounding box detection and 0.708 for segmentation mask detection (Table 1), which can be considered satisfactory, particularly given that YOLOv8n-seg is a lightweight model designed for speed and efficiency. Additionally, model behavior during training was analyzed using training plots, which visualize the loss and evaluation metrics across epochs. From the Precision-Recall curves (Figures 3 and 4), it was observed that the model maintained high precision at high confidence levels and achieved good recall at mid-range confidence levels. The F1–Confidence curves (Figures 5 and 6) further revealed that the optimal confidence threshold was approximately 0.48, at which point the F1-score peaked at around 0.70 for both bounding box and segmentation mask results. Based on the analysis, it can be concluded that the model demonstrates reasonably accurate and consistent pothole detection performance, making it suitable for application in the subsequent step of size estimation.

Metric	Bounding Box	Segmentation Mask
Precision	0.725	0.745
Recall	0.601	0.610
mAP@0.5	0.694	0.708
mAP@0.5–0.95	0.397	0.396

Table 1. Performance comparison between bounding box and segmentation mask using standard evaluation metrics.

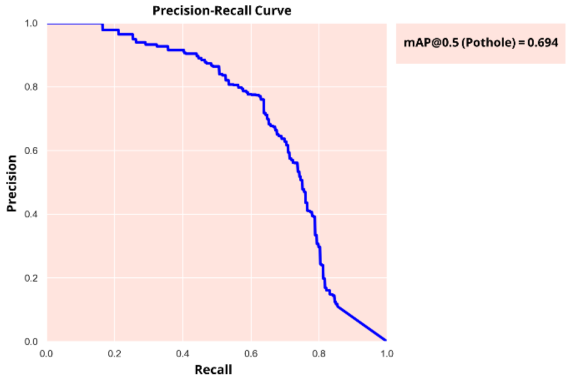

Figure 3. Precision-Recall curve for bounding box prediction.

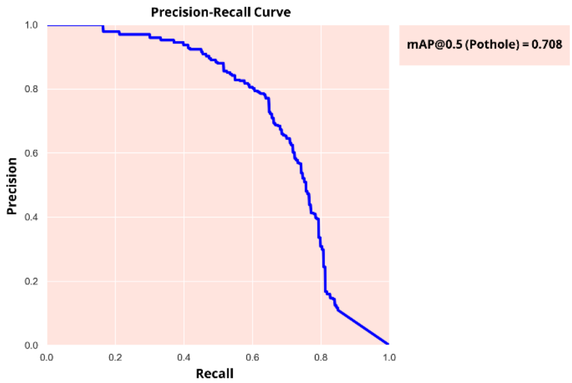

Figure 4. Precision-Recall curve for segmentation mask.

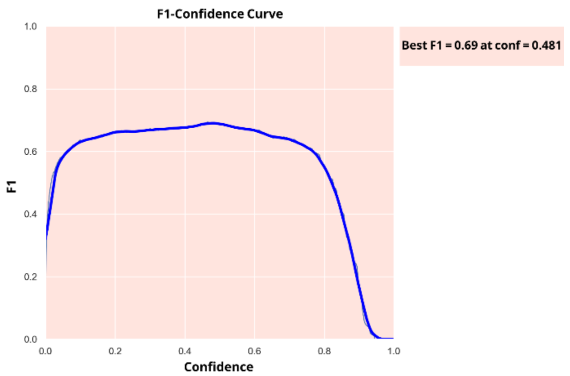

Figure 5. F1-Confidence Curve (Bounding Box)

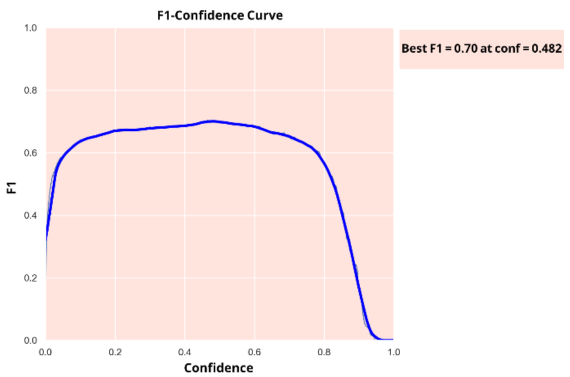

Figure 6. F1-Confidence Curve (segmentation mask).

4.2 Pothole Dimension Estimation Results

Following pothole detection using the YOLOv8n-seg model, the segmentation masks were used to estimate their dimensions in millimeters via the IPM process. This point was achieved using a homography matrix because the camera position remained fixed, and the viewpoint did not change throughout the data collection process. As a result, the same matrix could be applied to other images captured by the same camera setup without recalculation. The potholes' dimensions (width and height) were estimated from segmentation masks in six images and compared with the actual measured values. The percentage error in the results is shown in Table 2.

Image name	% Error (Width)	% Error (Height)
Image1	7.79	7.83
Image2	0.20	3.90
Image3	3.33	4.10
Image4	23.54	20.13
Image5	16.53	21.01
Image6	19.05	8.16

Table 2. Percentage error of estimated vs. actual pothole

The comparison results indicate that the average overall error in width and height estimation was approximately 11.30%, which is considered acceptable in field applications. Various factors, such as shadows, road surface conditions, the irregular shapes of potholes, instability of the camera mount during driving, the selection of four reference points in the IPM process, and the calibration reference equipment, may contribute to these deviations. Examples of pothole detection and real-size estimation are illustrated in Figure 7 and Figure 8. Each example shows the detection results from a video frame (left) and the image after inverse perspective transformation (right), where the segmentation mask was applied to estimate the pothole size in pixel units. It is also observed that in the last three samples, the percentage error increases noticeably. A potential cause is the minor displacement of the camera caused by vehicle-induced vibration, which affects the consistency of the viewing angle during video recording. Consequently, the dimension estimation from these frames may introduce greater error due to geometric distortion.

Detected Pothole Image

Image after IPM process

Figure 7. Example of Pothole No.1 (Image1).

Detected Pothole Image   Image after IPM process

Figure 8. Example of Pothole No.4 (Image4).

5. Conclusion

This study aims to develop an approach for detecting and estimating the dimensions of potholes on road surfaces by integrating image processing techniques with deep learning. The proposed method employs the YOLOv8n-seg model, which enables efficient instance segmentation for accurate pothole localization and size estimation.

The results indicate that the model can detect potholes with a reliable level of accuracy. The mAP@0.5 for segmentation masks was 0.708, and the precision was 0.745, which is sufficient for implementation in preliminary road surface condition assessment systems.

Segmentation masks were combined with the Inverse Perspective Mapping (IPM) technique to estimate pothole dimensions based on a homography matrix. The results show that the estimated dimensions were reasonably accurate compared to the actual measurements, with an average percentage error is 11.30%. This level of accuracy is considered sufficient for practical use in field applications, enabling automated assessment of road conditions, which can significantly aid in prioritizing repairs and allocating resources for maintenance.

6. Study Limitations and Suggestions for Future Improvements

6.1 Research Limitations

Although the results of this study are promising, several limitations remain, as outlined below:

1. In some cases, the segmentation output from the model did not fully cover the damaged area, particularly when the pothole edges were indistinct or affected by shadows and surface irregularities. The mask produced in these cases was unreliable for accurate size estimation.
2. The effectiveness of the Inverse Perspective Mapping (IPM) process depends on the quality of the reference image used for calibration. In this study, the image contained areas that were not clearly defined due to the limitations of the mobile phone camera. This point may have led to errors in selecting reference points for constructing the homography matrix, affecting the precision of converting pixel values into real measurements.
3. Data collection was conducted using a fixed camera position, which limited the method's adaptability to camera angle or height changes. Any change in camera setup requires repeating the same calibration procedure.
4. The pothole image data collected from Thailand for training the model remains limited. If a larger and more diverse dataset representing various road conditions were available, the model could potentially be trained more effectively and achieve improved performance.

6.2 Recommendations for Future Research

1. Increasing the quantity and diversity of the dataset, particularly by including images from various locations with different road surface conditions. This point would help reduce bias and improve the model's generalization capability.
2. Develop the system to be applicable in real-world settings, such as deploying it for real-time road monitoring and integrating it with GIS platforms to automatically generate road condition maps, enabling future pothole localization.

7. References

Ahmed, K.R., Kharel, S., 2021: *Potholes Detection Using Deep Learning and Area Estimation Using Image Processing*. doi.org/10.1007/978-3-030-82199-9_24.

Arjapure, S., Kalbande, D.R., 2021: Deep Learning Model for Pothole Detection and Area Computation. 2021 International Conference on Communication Information and Computing Technology (ICCICT).

Arya, D., Maeda, H., Ghosh, S.K., Toshniwal, D., Mraz, A., Kashiyama, T., Sekimoto, Y., 2021. Deep learning-based road damage detection and classification for multiple countries. *Automation in Construction* 132, 103935. doi.org/10.1016/j.autcon.2021.103935.

Asad, M., Khaliq, S., Yousaf, M.H., Ullah, M., Ahmad, A., 2022. Pothole Detection Using Deep Learning: A Real-Time and AI-on-the-Edge Perspective. *Advances in Civil Engineering* 2022. doi.org/10.1155/2022/9221211.

Chitale, P., Kekre, K., Shenai, H., Karani, R., Gala, J., 2020. *Pothole Detection and Dimension Estimation System using Deep Learning (YOLO) and Image Processing*. doi.org/10.1109/IVCNZ51579.2020.9290547.

Dhanreeshkar, J., Dhakshana, V.S., Aniruthan, S.A., Karthika, R., Parameswaran, L., 2020. Deep Learning based Detection of potholes in Indian roads using YOLO. 2020 International Conference on Inventive Computation Technologies (ICICT).

Federal Highway Administration., 2003. *Distress Identification Manual for the Long-Term Pavement Performance Program*. U.S. Department of Transportation.

Gupta, S., Sharma, P., Sharma, D., Gupta, V., Sambyal, N., 2020. Detection and localization of potholes in thermal images using deep neural networks. *Multimedia Tools and Applications* 79(35), 26265-26284. doi.org/10.1007/s11042-020-09293-8.

Khan, Z.H., Altamimi, A.B., Imran, W., Alsaffar, M., Khattak, K.S., Alfaisal, F.F., 2024. Macroscopic Traffic Modelling on the

Impact of Road Surface Potholes: Development and Numerical Solution. *IEEE Access* 12, 81718-81735. doi.org/10.1109/ACCESS.2024.3411303.

Kombe, G.G., 2025. A sustainable approach for road pothole repair using waste plastic bottles and aggregates. *Frontiers in Engineering and Built Environment* 5(1), 52-67. doi.org/10.1108/FEBE-05-2024-0020.

Liu, S.S., Budiwirawan, A., Arifin, M., Chen, W.T., Huang, Y.H. 2021. Optimization Model for the Pavement Pothole Repair Problem Considering Consumable Resources. *Symmetry* 13. doi.org/10.3390/sym13030364.

Nekouei, F., 2024. Pothole Segmentation for Road Damage Assessment. kaggle.com/code/farzadnekouei/pothole-segmentation-for-road-damage-assessment (10 January 2025).

Ng, C.P., Law, T.H., Jakarni, F.M., Kulanthayan, S., 2019. Road infrastructure development and economic growth. *IOP Conference Series: Materials Science and Engineering* 512(1), 012045. doi.org/10.1088/1757-899X/512/1/012045.

Putri, Y., Suprobo, P., Adi, T., 2024. Accuracy of Hybrid Models of Detection, Classification, and Quantification for Automatic Road Damage Evaluation. *Civil Engineering and Architecture* 12, 2648-2660. doi.org/10.13189/cea.2024.120412.

Radopoulou, S.C., Brilakis, I., 2016: Improving Road Asset Condition Monitoring. *Transportation Research Procedia* 14, 3004-3012. doi.org/10.1016/j.trpro.2016.05.436.

Ranyal, E., Sadhu, A., Jain, K., 2022. Road Condition Monitoring Using Smart Sensing and Artificial Intelligence: A Review. *Sensors* 22, 3044. doi.org/10.3390/s22083044.

Ruseruka, C., Mwakalonge, J., Comert, G., Siuhi, S., Ngeni, F., Anderson, Q., 2024. Augmenting roadway safety with machine learning and deep learning: Pothole detection and dimension estimation using in-vehicle technologies. *Machine Learning with Applications* 16, 100547. doi.org/10.1016/j.mlwa.2024.100547.

Safyari, Y., Mahdianpari, M., Shiri, H., 2024. A Review of Vision-Based Pothole Detection Methods Using Computer Vision and Machine Learning. *Sensors* 24(17).

Setyawan, Y., Sari, Y.A., 2024: Analysis of safety issue of potholes and lighting: case a jalan beber – jatiwangi, majalengka. doi.org/10.37253/leader.v2i1.9502.

Vazquez Guevara, D., 2021. CS194-26 Project 5AB: Autostitching Photo Mosaics. dvazquezg.github.io/cs194-26-repo/proj5/index.html (1 April 2025).

Xueliang, Z., 2013. Has Transport Infrastructure Promoted Regional Economic Growth?— With an Analysis of the Spatial Spillover Effects of Transport Infrastructure. *Social Sciences in China* 34(2), 24-47. doi.org/10.1080/02529203.2013.787222.

Yang, C.H., Kim, J., Shin, S., 2021. Road Hazard Assessment Using Pothole and Traffic Data in South Korea. *Journal of Advanced Transportation* 2021, 1-10. doi.org/10.1155/2021/5901203.