Contents lists available at IdNNS
Journal of Intelligent Systems for Community Development
Volume 1 ; Issue 1
journal homepage: https://journal.idnns.org/index.php/jiscode

Road Damage Segmentation Using U-Net and FCN Based on Digital Imagery

Sultan Ahmad Rizki Badani[a], Herlawati[a,*] and Sugiyatno[a]

[a]*Informatics, Faculty of Computer Science, Universitas Bhayangkara Jakarta Raya, Jl. Perjuangan No. 81, Marga Mulya, Bekasi Utara, Bekasi, 17143, West Java, Indonesia*

ARTICLE INFO

Keywords:
road damage segmentation
U-Net
Fully Convolutional Network
deep learning
semantic segmentation

ABSTRACT

Road damage is an infrastructure problem that affects public safety and transportation mobility. Manual road damage identification is considered less effective because it is time-consuming and subjective. This study aimed to implement semantic segmentation using the U-Net and Fully Convolutional Network (FCN) architectures for road damage detection based on digital images. The research used the Cross Industry Standard Process for Data Mining (CRISP-DM) method with datasets consisting of secondary Pothole Mix data and primary data collected in West Bekasi. Model training was conducted using 256×256 pixel images with evaluation metrics including Accuracy, Dice Score Coefficient, Intersection over Union (IoU), and Loss. The results showed that the U-Net model achieved better performance than FCN with an Accuracy of 0.9652, Dice Score Coefficient of 0.9596, IoU of 0.9267, and Loss of 0.0674. Furthermore, the model was successfully implemented into a Flutter-based mobile application for automatic road damage identification and monitoring.

1. Introduction

Road damage is an infrastructure problem that can affect the comfort, safety, and smoothness of public transportation. Road conditions in many regions of Indonesia are still frequently affected by damage such as cracks, potholes, and surface deformation caused by vehicle loads, weather conditions, and inadequate drainage systems (Hari et al., 2025). Based on 2024 data from the Directorate of Road and Bridge Engineering of the Indonesian Ministry of Public Works and Public Housing, some sections of national roads remain in lightly or severely damaged condition, so more optimal road monitoring and maintenance processes are required. This condition not only hinders transportation activities but also increases the risk of traffic accidents and vehicle operating costs (Yulianto and Wibowo, 2023).

Road damage identification has generally still been carried out manually through visual inspection by field officers. This method is considered less effective because it requires a long time, incurs high operational costs, and is subject to a level of subjectivity that varies between observers (Faritzie et al., 2022). Therefore, an automatic system is needed that is able to detect road damage quickly and accurately.

*Corresponding author
202210715237@mhs.ubharajaya.ac.id (S.A.R. Badani); herlawati@ubharajaya.ac.id (Herlawati)
ORCID(s):

The development of computer vision and deep learning technology offers new solutions for identifying road damage based on digital imagery. One widely used method is the Convolutional Neural Network (CNN), which has a strong capability to recognize patterns in digital images (Hari et al., 2025). Several previous studies have applied deep learning methods to detect road damage, such as the U-Net architecture, which obtained a mean Intersection over Union (mIoU) of 76.4% and an F1-score of 74.2% (Zhang et al., 2025), as well as the Fully Convolutional Network (FCN) model, which is able to produce high accuracy with fast execution time (Huang et al., 2025). In addition, other research shows that the CNN method is able to detect road damage with an accuracy of around 80% (Mulyana and Wahyudi, 2025).

However, most previous studies have still focused on object-detection processes and have not yet been able to identify damaged areas in detail down to the pixel level. The semantic segmentation approach is one solution because it is able to classify every pixel of an image. The U-Net architecture has an encoder-decoder structure with a skip-connection mechanism that is able to preserve spatial information and produce more detailed segmentation (Putra et al., 2023; Sadewa et al., 2024). In addition, FCN is also a deep-learning-based semantic segmentation method that is able to perform pixel classification directly through a fully convolutional network (Huang et al., 2022).

Based on the problems described above, this study applies the semantic segmentation method using the U-Net and

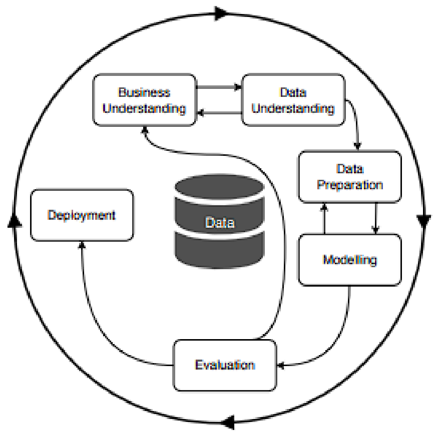


Figure 1: Stages of CRISP-DM. Source: Martinez-Plumed et al. (2021).

Fully Convolutional Network (FCN) architectures to detect road damage based on digital imagery more accurately down to the pixel level.

2. Research Method

This research uses the Cross Industry Standard Process for Data Mining (CRISP-DM) method to perform road damage segmentation using the U-Net and Fully Convolutional Network (FCN) architectures.

2.1. Cross Industry Standard Process for Data Mining (CRISP-DM)

Cross Industry Standard Process for Data Mining (CRISP-DM) is a methodology used as a systematic framework for the data analysis and model development process. This method consists of six main stages, namely Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment, which are carried out in stages and are interrelated (Dhewayani et al., 2022). In this study, CRISP-DM is used to support the data processing, model training, and evaluation of road damage segmentation in a structured manner.

2.2. U-Net Architecture

U-Net is one of the artificial neural network architectures widely used in image segmentation tasks, particularly for medical imagery. This architecture was developed based on the Fully Convolutional Network (FCN) concept, modified so that it is able to perform image segmentation more accurately while preserving the spatial information in the image (Putra et al., 2023).

The U-Net architecture consists of an encoder for extracting image features and a decoder for producing a segmentation map through an upsampling process. U-Net also uses skip connections to preserve detailed image information, resulting in more accurate segmentation (Putra et al., 2023; Sadewa et al., 2024).

2.3. Fully Convolutional Network (FCN) Architecture

Fully Convolutional Network (FCN) is a deep-learning architecture for semantic segmentation that replaces the fully connected layer with convolutional layers, so that it is able to perform classification at every image pixel and produce a segmentation map that preserves spatial information (Fatih et al., 2021).

The main difference between FCN and a traditional CNN lies in the use of the final layer, where FCN replaces the fully connected layer with a convolutional layer so that it is able to produce predictions for every image pixel directly. FCN also uses skip connections to preserve spatial information so that segmentation becomes more accurate (Huang et al., 2022).

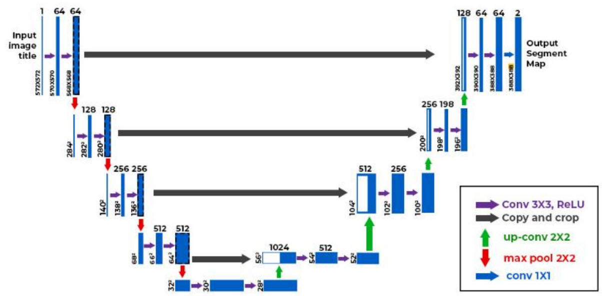


Figure 2: How U-Net works. Source: geeksforgeeks.org, U-Net Architecture Explained.

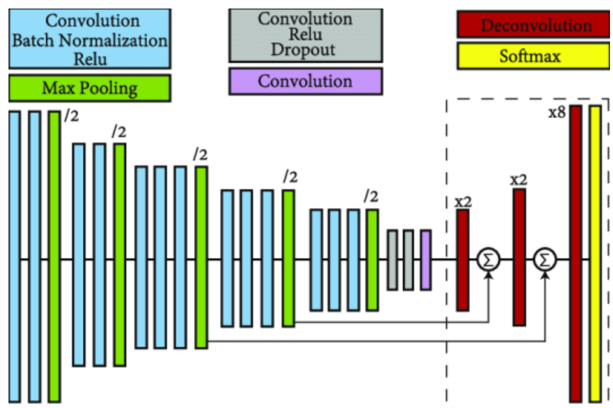


Figure 3: How FCN works. Source: researchgate.net, Fully Convolutional Network (FCN) Structure.

3. Results and Discussion

This research uses the Cross Industry Standard Process for Data Mining (CRISP-DM) method with the U-Net and Fully Convolutional Network (FCN) architectures to perform road damage segmentation based on digital imagery. The dataset used consists of primary and secondary data in the form of road damage images of the crack and pothole types.

The research process included data preprocessing, model training, and evaluation using the Accuracy, Intersection over Union (IoU), and Dice Score Coefficient metrics. The results show that both the U-Net and FCN models are able to perform road damage segmentation well, with U-Net producing more optimal performance compared to FCN.

3.1. Business Understanding

The Business Understanding stage was carried out by identifying road damage problems such as cracks and potholes that are still detected manually, making the process less effective. This study aims to develop a road damage segmentation system based on digital imagery using the U-Net and FCN architectures, implemented in a Flutter-based application.

3.2. Data Understanding

The dataset used in this study consists of the secondary Pothole Mix dataset from the Mendeley Data platform and a primary dataset obtained from field observations in the West Bekasi area, as shown in Figure 4. The secondary dataset was used as the main data for model training, while the primary dataset was used as testing data under real-world conditions.

The secondary Pothole Mix dataset (a) consists of approximately 4,288 road damage images of the crack and pothole types, complete with ground-truth masks obtained from segmentation annotation, while the primary dataset (b) consists of 136 images obtained from direct observation in the West Bekasi area using a smartphone camera under varying road and lighting conditions. The entire dataset was obtained in .zip format and subsequently extracted and annotated using the Labelme application to produce ground-truth masks representing the road damage area at the pixel level. The secondary dataset was used as the main training data, while the primary dataset was used as testing data to evaluate the model's ability to detect road damage under real-world conditions.

3.3. Data Preparation

The data preparation stage in this study included several steps, as follows:

3.3.1. Annotation and ground-truth mask validation

The annotation validation process was carried out by comparing the original image with the ground-truth mask to ensure that the road damage area had been correctly marked at the pixel level.

Figure 5 shows that the crack and pothole areas in the image correspond to the annotated ground-truth mask, so the data can be used in the model training process.

3.3.2. Resizing and image normalization

The resizing step was carried out to standardize the size of all images and segmentation masks to 256×256 pixels to match the model's input requirements.

Figure 6 shows that the resizing process successfully changed the size of the image and mask without losing information on the road damage area. Pixel-value normalization was then performed, rescaling values from the 0–255 range to the 0–1 range to improve stability and speed up the deep-learning model training process.

Figure 7 shows the change in the pixel-value range after normalization, so that the data becomes more consistent when processed by the model.

3.3.3. Dataset splitting

The processed dataset was then split into training, validation, and testing data with a ratio of 80%, 10%, and 10%, respectively, to support the model training and evaluation process.

Figure 8 shows that each image has a corresponding segmentation mask in each dataset category (3,430 training pairs, 429 validation pairs, and 429 testing pairs).

3.3.4. Data augmentation

The data-augmentation step was carried out to increase dataset variation using horizontal flip, vertical flip, and rotation techniques applied to the images and segmentation masks.

Figure 9 shows the augmentation results, which produce new image variations without changing the main information in the road damage area.

3.4. Modeling

The Modeling stage is the process of applying the deep-learning method using the U-Net and Fully Convolutional Network (FCN) architectures to perform road damage segmentation based on digital imagery. At this stage, the dataset resulting from data preparation, consisting of road images and ground-truth masks, was used as training and testing data.

3.4.1. Determination of the U-Net and FCN model architectures

This step covers the determination of the deep-learning model architectures used in the road damage segmentation process, namely U-Net and Fully Convolutional Network (FCN). The U-Net model was used because of its encoder-decoder structure and skip connections, which are able to preserve the spatial information of the image, while FCN was used as a comparison model for performing pixel-level segmentation. Both models were trained to learn road damage patterns such as cracks and potholes in digital images so that they could produce segmentation masks that match real-world conditions.

Table 1
Hyperparameter settings.

Hyperparameter	Value
Input image size	256 × 256
Batch size	8
Epochs	40
Learning rate	0.0001
Number of classes	3
Optimizer	Adam
Metrics	Accuracy, Dice Coefficient, IoU

Table 2
U-Net training results.

Epoch	Accuracy	Dice	IoU	Loss
1	0.9586	0.9270	0.8692	0.1154
10	0.9633	0.9541	0.9132	0.0774
20	0.9658	0.9573	0.9190	0.0705
30	0.9688	0.9610	0.9256	0.0636
40	0.9692	0.9614	0.9264	0.0628

3.4.2. Hyperparameter settings and model configuration

At this stage, hyperparameters and model configuration were set to obtain optimal segmentation performance. The models were trained using an input image size of 256×256 pixels, a batch size of 8, 40 epochs, and a learning rate of 0.0001 with the Adam optimizer. In addition, model evaluation used the Accuracy, Dice Coefficient, and Intersection over Union (IoU) metrics to measure segmentation performance at the pixel level. The hyperparameter settings used in this study are shown in Table 1.

After the configuration process was complete, the model was compiled using the Adam optimizer and a loss function to calculate the segmentation prediction error against the ground-truth mask. This configuration was used so that the model could learn road damage patterns in a more stable and accurate manner during the training process.

3.4.3. Model training

The model training stage was carried out using the training data and ground-truth masks prepared previously. In this process, the U-Net and Fully Convolutional Network (FCN) models were trained to learn road damage patterns such as cracks and potholes so as to produce segmentation matching real-world conditions. The training process was carried out incrementally at each epoch to improve the model's prediction capability.

Based on Table 2, the performance of the U-Net model improved during the training process, as indicated by the increasing Accuracy, Dice Coefficient, and IoU values, along with a decreasing loss value. At epoch 40, the U-Net model obtained an accuracy of 0.9692 and an IoU of 0.9264, indicating good segmentation performance.

Table 3
FCN training results.

Epoch	Accuracy	Dice	IoU	Loss
1	0.9583	0.9465	0.9014	0.0997
10	0.9621	0.9521	0.9098	0.0823
20	0.9636	0.9541	0.9133	0.0768
30	0.9637	0.9544	0.9137	0.0763
38	0.9638	0.9546	0.9141	0.0759

Based on Table 3, the FCN model also showed improved performance during training. The Accuracy, Dice Coefficient, and IoU values increased gradually, while the loss value decreased. At epoch 38, the FCN model obtained an accuracy of 0.9638 and an IoU of 0.9141, showing that the model was able to perform road damage segmentation reasonably well.

3.4.4. Model storage

After the training process was complete, the trained U-Net and Fully Convolutional Network (FCN) models were saved in .h5 format for use in the testing, evaluation, and deployment stages of the road damage segmentation application. The model-saving process was carried out so that the training results could be reused without needing to repeat the training process. The saved models included `unet_final_model.h5` and `fcn_final_model.h5` as the final models produced by the study.

3.5. Evaluation

The Evaluation stage was carried out to measure the performance of the road damage segmentation models using the U-Net and Fully Convolutional Network (FCN) architectures. The evaluation process used the Accuracy, Dice Score Coefficient, Intersection over Union (IoU), and Loss metrics to determine the level of correspondence between the model segmentation results and the ground-truth mask at the pixel level. The main metrics can be defined as follows.

3.5.1. Accuracy

Accuracy is an evaluation metric used to measure the level of precision of the model in performing image segmentation prediction. This metric shows the ratio between the number of correctly predicted pixels and the total number of pixels in the image (Pangestu and Putra, 2025). In this study, Accuracy was used to determine the ability of the U-Net and Fully Convolutional Network (FCN) models to perform road damage segmentation based on the correspondence between the prediction results and the ground-truth mask. The Accuracy formula used is shown as follows (Putra and Utomo, 2025):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \tag{1}$$

where TP is the True Positive value, TN is the True Negative value, FP is the False Positive value, and FN is the False Negative value. The higher the Accuracy value, the better the model's ability to perform road damage segmentation precisely at the pixel level.

3.5.2. Dice Score Coefficient

The Dice Score Coefficient (DSC) is an evaluation metric used to measure the degree of similarity between the model segmentation result and the ground truth based on the overlapping pixel area (Butt and Zaman, 2023; Putra and Utomo, 2025). In this study, DSC was used to determine the ability of the U-Net and Fully Convolutional Network (FCN) models to produce road damage segmentation that closely approximates real conditions. The Dice Score Coefficient formula used is shown as follows:

$$\text{DSC} = \frac{2TP}{2TP + FP + FN} \tag{2}$$

where TP is the True Positive value, FP is the False Positive value, and FN is the False Negative value. The DSC value ranges from 0 to 1, where a value closer to 1 indicates better model segmentation results with a higher degree of correspondence to the ground truth (Li and Liang, 2023).

3.5.3. Intersection over Union (IoU)

Intersection over Union (IoU) is an evaluation metric used to measure the degree of correspondence between the model's predicted area and the ground truth in the semantic segmentation process (Pangestu and Putra, 2025). The IoU value is obtained from the ratio between the overlapping area (intersection) and the total combined area (union) of the prediction result and the ground truth. In this study, IoU was used to evaluate the ability of the U-Net and Fully Convolutional Network (FCN) models to perform road damage segmentation at the pixel level. The Intersection over Union (IoU) formula is shown as follows:

$$\text{IoU} = \frac{A \cap B}{A \cup B} \tag{3}$$

where A is the model's predicted area, B is the ground-truth area, $A \cap B$ is the intersection area, and $A \cup B$ is the union area. The higher the IoU value, the better the correspondence between the model segmentation result and the ground truth, indicating more accurate segmentation performance (Pangestu and Putra, 2025).

3.5.4. Loss

Loss is used to measure the level of prediction error of the model during the training process. The smaller the loss value, the better the model's performance in producing segmentation. The evaluation results of the U-Net and FCN models are shown in Table 4.

Based on Table 4 and the evaluation results obtained, the U-Net model shows better performance than FCN based on higher Accuracy, Dice Score Coefficient, and Intersection over Union (IoU) values, as well as a lower Loss value.

Table 4
Model evaluation results.

Model	Accuracy	Dice	IoU	Loss
U-Net	0.9652	0.9596	0.9267	0.0674
FCN	0.9624	0.9561	0.9201	0.0759

These results indicate that the U-Net architecture is able to produce road damage segmentation that is more optimal and closer to the ground truth compared to FCN. In addition, the segmentation results on the testing data and primary data show that U-Net is able to produce more detailed road damage segmentation. This is influenced by the use of the skip-connection mechanism in the U-Net architecture, which is able to preserve the spatial information of the image better than FCN.

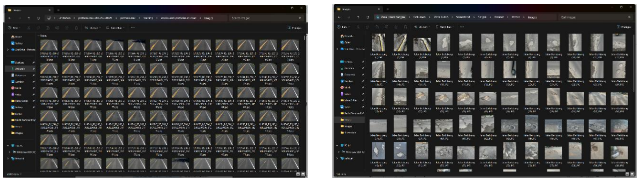
3.6. Deployment

The Deployment stage is the process of implementing the road damage segmentation system into a Flutter-based mobile application, integrating the U-Net and Fully Convolutional Network (FCN) models with Python as the backend. The application allows users to perform segmentation via the camera or image gallery, and displays the segmentation results and model comparison directly through an interactive and easy-to-use interface.

Based on Figure 10, the SiLapor AI application has a home page, a map page, and a statistics page that support the road damage segmentation and monitoring process. The home page is used for scanning road damage via the camera or image gallery, the map page displays the location of road damage on a digital map, while the statistics page displays a visualization of the road damage distribution in the form of a percentage chart. Overall, the application is designed with a simple and easy-to-use interface to help the road damage identification process become more effective.

Based on Figure 11, the SiLapor AI application is also equipped with a statistics detail page, a settings page, and an about-application page to support the use of the system in a more informative manner. The statistics detail page displays the number of road damage categories along with color indicators to make it easier for users to understand the analysis results. In addition, the settings page provides features for configuring the application display, notifications, and GPS tracking to support user convenience. Meanwhile, the about-application page displays general information about SiLapor AI, the application developer, the affiliated university, and the application version used.

Based on Figure 12, the SiLapor AI application successfully performed prediction and segmentation on various road conditions, namely potholed, normal, and cracked roads. The system was able to visually display the road damage area using segmentation masks and provide prediction results, confidence values, and a performance comparison between the U-Net and FCN models. In this testing, the U-Net model showed better results for potholed and normal road segmentation, while the FCN model showed better performance for crack segmentation. These results indicate that the system is able to perform automatic and informative road damage analysis based on digital imagery.



(a) (b)

Figure 4: (a) Secondary Pothole Mix dataset, (b) Primary dataset. Source: Research Results (2026).

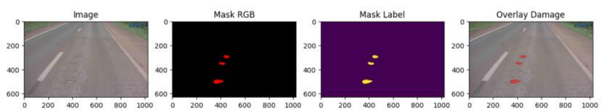


Figure 5: Validation of image and ground-truth mask correspondence. Source: Research Results (2026).

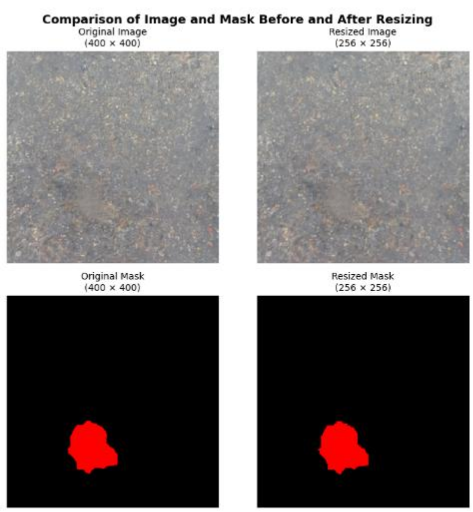


Figure 6: Comparison of image and mask before and after resizing. Source: Research Results (2026).

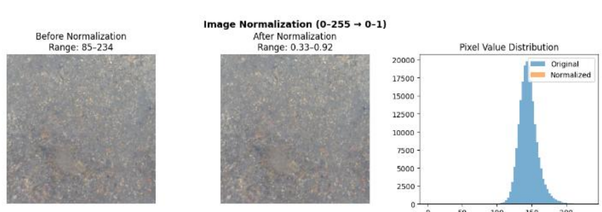


Figure 7: Pixel-value normalization process. Source: Research Results (2026).

```
Train → Gambar: 3430, Masks: 3430
Valid → Gambar: 429, Masks: 429
Test  → Gambar: 429, Masks: 429
```

Figure 8: Dataset and mask split results. Source: Research Results (2026).

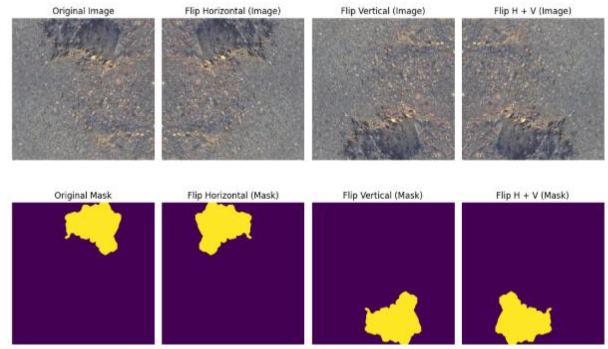
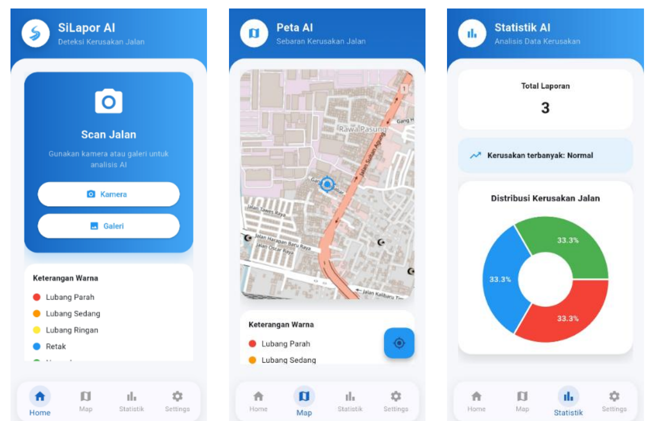
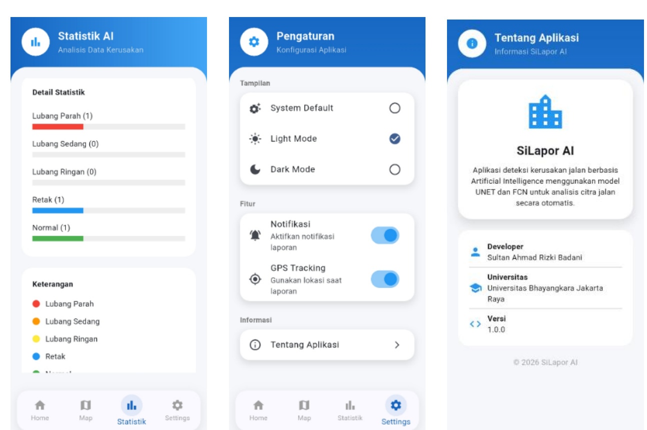


Figure 9: Results of data augmentation applied to the image and mask. Source: Research Results (2026).



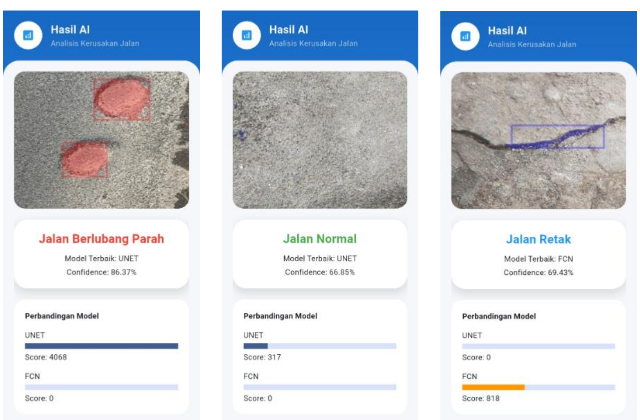
(a) (b) (c)

Figure 10: (a) Home page, (b) Map page, (c) Statistics (pie chart) page. Source: Research Results (2026).



(a) (b) (c)

Figure 11: (a) Statistics detail page, (b) Settings page, (c) About-application page. Source: Research Results (2026).



(a) (b) (c)

Figure 12: (a) Prediction result for a badly potholed road, (b) Prediction result for a normal road, (c) Prediction result for a cracked road. Source: Research Results (2026).

4. Conclusion

Based on the research results obtained, the semantic segmentation method using the U-Net and Fully Convolutional Network (FCN) architectures is able to perform road damage segmentation based on digital imagery reasonably well. The evaluation results show that the U-Net model has more optimal performance compared to FCN, with an Accuracy of 0.9652, a Dice Score Coefficient of 0.9596, an Intersection over Union (IoU) of 0.9267, and a lower Loss value. In addition, the implementation of the model into a Flutter-based mobile application successfully supported the process of automatic road damage identification and monitoring via the camera or image gallery. This research is therefore expected to serve as a supporting solution for road infrastructure monitoring and maintenance processes in a more effective and efficient manner. Future research can be developed by increasing the size of the dataset, incorporating more varied types of road damage, and applying more complex segmentation models so that segmentation results become more accurate and stable under various road conditions.

Credit authorship contribution statement

Sultan Ahmad Rizki Badani – Methodology, Software, Data Curation. Herlawati – Conceptualization, Resources, Draft Writing and Reviewing. Sugiyatno – Analysis, Draft Writing and Reviewing.

Funding: Not Applicable

Data Availability Statement: The secondary dataset (Pothole Mix) is publicly available via Mendeley Data. The primary dataset generated and analyzed during the current study is available from the corresponding author on reasonable request.

Acknowledgments: The researchers would like to express their appreciation and gratitude to the reviewers for their constructive criticism and suggestions, which helped improve the quality of this article. Gratitude is also extended to Universitas Bhayangkara Jakarta Raya for the support, facilities, and guidance provided throughout the research process. All of these contributions greatly helped support the smoothness and success of this research.

Conflicts of Interest: The authors declare no conflict of interest.

References

Butt, M. A. and Zaman, M. (2023). Attention Res-UNet: Attention residual UNet with focal tversky loss for skin lesion segmentation. *International Journal of Decision Support System Technology*, 15(1):1–17.

Dhewayani, F. N., Amelia, D., Alifah, D. N., Sari, B. N., and Jajuli, M. (2022). Implementasi k-means clustering untuk pengelompokkan daerah rawan bencana kebakaran menggunakan model CRISP-DM. *Jurnal Teknologi Dan Informasi (JATI)*, 12:64–77.

Faritzie, H. A., Firda, A., and Aprilyanti, S. (2022). Identifikasi dan analisis kerusakan jalan pada ruas jalan siaran sako kota palembang. *BEARING: Jurnal Penelitian Dan Kajian Teknik Sipil*, 7:223–229.

Fatih, M., Suciati, N., and Navastara, D. A. (2021). Deteksi kerumunan menggunakan metode Fully Convolutional Network pada kamera. *Jurnal Teknik ITS*, 10(2):339–344.

Hari, E., Prasetyo, A., and Rosyidah, A. N. (2025). Deteksi kerusakan jalan menggunakan model deep learning YOLOv8. *INOVATE: Jurnal Ilmiah Inovasi Teknologi Informasi*, 10(1):105–114.

Huang, H., Ho, G. T. S., Tang, V., Chow, E. W. H., Ip, W. H., and Yung, K. L. (2025). A lightweight fully convolutional neural network for efficient and accurate tunnel crack detection. *Journal of Advanced Research*.

Huang, S.-Y., Hsu, W.-L., Hsu, R.-J., and Liu, D.-W. (2022). Fully convolutional network for the semantic segmentation of medical images: A survey. *Diagnostics*, pages 1–21.

Li, H. and Liang, B. (2023). Liver tumor computed tomography image segmentation based on an improved U-Net model. *Applied Sciences*, 13(20):11283.

Martinez-Plumed, F., Contreras-Ochando, L., Ferri, C., Hernandez-Orallo, J., Kull, M., Lachiche, N., Ramirez-Quintana, M. J., and Flach, P. (2021). CRISP-DM twenty years later: From data mining processes to data science trajectories. *IEEE Transactions on Knowledge and Data Engineering*, 33(8):3048–3061.

Mulyana, D. I. and Wahyudi, I. (2025). Deteksi kerusakan jalan berdasarkan citra digital menggunakan Convolutional Neural Network (CNN). *Jurnal Indonesia: Manajemen Informatika Dan Komunikasi*, 6(1):294–302.

Pangestu, A. and Putra, M. P. K. (2025). YOLOV9-based traffic sign detection under varying lighting conditions. *Jurnal Teknik Informatika (JUTIF)*, 6(1):291–300.

Putra, I. M. A. D., Maysanjaya, I. M. D., and Kesiman, M. W. A. (2023). Pendekatan berbasis U-Net untuk segmentasi hard exudate dalam citra fundus retina. *Information System and Emerging Technology Journal*, 4(1):26–36.

Putra, Z. D. E. and Utomo, D. W. (2025). Penerapan deep learning dengan mekanisme attention untuk meningkatkan performa segmentasi liver dan tumor pada citra CT menggunakan ResUnet. *Jurnal Nasional Teknologi Dan Sistem Informasi*, 3:231–239.

Sadewa, D. R., Via, Y. V., and Nurlaili, L. A. (2024). Implementasi SSD-MobileNet dan U-Net untuk deteksi dan penilaian tingkat keparahan pada aplikasi pelaporan jalan berlubang. *JITET (Jurnal Informatika Dan Teknik Elektro Terapan)*, 12(3):4334–4344.

Yulianto, Y. and Wibowo, A. (2023). Deteksi keretakan jalan aspal menggunakan metode Convolutional Neural Network. *Jurnal Teknik Sipil Cendekia*, 4(2):581–594.

Zhang, Z., He, Y., Hu, D., Jin, Q., Zhou, M., Liu, Z., Chen, H., Wang, H., and Xiang, X. (2025). Algorithm for pixel-level concrete pavement crack segmentation based on an improved U-Net model. *Scientific Reports*, 15(1):1–17.