Electronic Journal of Education, Social Economics and Technology
Vol. 7, No. 1, (2026), e1428
ISSN 2723-6250 (online)
DOI: https://doi.org/10.33122/ejeset.v7i1.1428

SAINTIS publishing

Research Article

Road Condition Recognition Based on Object Classification Using YOLOv8

Nathaniel Putra Haryanto[1], and Mohammad Nasucha[2]*

[1] Department of Informatics, University Pembangunan Jaya, South Tangerang, Indonesia, 15413
[2] Center for Urban Studies, University Pembangunan Jaya, South Tangerang, Indonesia, 15413
*Corresponding Author: mohammad.nasucha@upj.ac.id | Phone Number: +628119740271

ABSTRACT

The quality of road infrastructure is one of the important factors in supporting the safety and comfort of road users as well as the smooth distribution of transportation. Road maintenance requires periodic monitoring by authorized institutions or agencies. Manual road condition monitoring tends to require considerable time, cost, and manpower, and is also prone to subjectivity. Therefore, a computational system capable of performing this task is needed. Based on this background, this study aims to develop a computer vision-based application for recognizing road conditions. Data consisting of road images with proper annotations (damaged or good) were used to train the YOLOv8 vision model. Our test found that the system accuracy, precision, recall, and F1-score is 0.96, 0.93, 1.00, and 0.96 respectively. The developed application allows users to input road images through a live camera and obtain real-time road condition classification results.

Keywords: YOLOv8; Road Condition Classification; Deep Learning; Computer Vision; Infrastructure Monitoring

1. INTRODUCTION

Roads are a crucial component of community activities. Roads facilitate transportation access from the point of origin to the destination. In addition, roads play an important role as land transportation infrastructure for both people and goods. However, inadequate road conditions can cause accidents (Sasmito et al., 2023). Road damage such as cracks and potholes has become an infrastructure problem that disrupts safety and traffic flow. The manual identification methods currently used are considered less efficient (Iza Sofiani et al., 2025). Damage to these road segments can disrupt road user activities and affect vehicle travel time, resulting in slower transportation movement (Kesuma Putra et al., 2022). Advances in science and technology, particularly in the fields of artificial intelligence and machine learning, have facilitated problem solving and improved human work efficiency (Djulyansyah et al., 2024). Since the discovery of Computer Vision in the 1950s, object detection and classification have attracted considerable attention from various sectors, including industry and healthcare. Since then, numerous studies have been conducted using various Deep Learning algorithms capable of detecting objects (Sakinah et al., 2025). One of these approaches is the implementation of intelligent system methods for detecting road damage using the Convolutional Neural Network (CNN) algorithm (Yulianto & Wibowo, 2023). Although this system still requires a computer to run YOLOv8, this research represents an important step toward the development of a more independent and accurate road pothole detection system (Royhan et al., 2025). Through this application, users can take appropriate follow-up or preventive actions to improve road conditions and effectively enhance traffic safety in Indonesia (Habibi & Wibowo, 2023).

Research on road damage classification and recognition has been widely developed using deep learning and computer vision methods to improve the ability to identify road conditions more quickly and accurately. Combining the strengths of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) can create a highly powerful hybrid algorithm for detecting and analyzing road cracks (Akbar Pradana et al., 2024). In addition. The innovation in this research uses CNN with the transfer learning method, which can be predicted to be more effective compared to the classical CNN method because its architecture has been proven to save computational time and resources. This study is expected to produce the best model with several conditioning techniques for classification in identifying types of road damage and can assist related parties in damaged road maintenance (Shodiq et al., 2024). Besides CNN methods, research related to object detection using the YOLO algorithm has also continued to develop. Mahmud et al. (2026) stated that YOLOv8 provides the best trade-off between accuracy and speed for real-time implementation. Based on these research results, YOLOv8 demonstrates good accuracy performance and therefore has the potential to be applied in real-time applications. Other studies have also discussed the use of image processing methods in the process of identifying road damage. The results of this study indicate that Canny edge detection is the best method compared to Sobel and Prewitt methods (Rafi et al., 2023). The study shows that edge detection methods are still widely used to assist the process of identifying road damage patterns based on line and edge patterns on road surfaces. In addition to detection methods, other studies have also discussed factors affecting the level of road damage based on soil conditions and pavement types. The level of road damage is directly proportional to the increasing values of the plasticity index, liquid limit, plastic limit, and soil expansion value. Conversely, the level of road damage on the Manulai-Tablolong road section is inversely proportional to the decrease in shrinkage limit values, maximum dry density, and CBR values (Hangge et al., 2022). Furthermore, research on pavement types also shows that rigid pavement has different characteristics compared to other pavement types. Rizaldi et al. (2023) stated that rigid pavement consists of slabs and foundation layers. Rigid pavement is generally used on roads with traffic conditions that may cause damage in a relatively short period. However, if rigid pavement is properly maintained and kept in good condition, rigid pavement will have a longer service life. In the process of road condition testing, several studies use the Pavement Condition Index (PCI) method. The PCI method is used as a condition rating reference ranging from failed for the lowest value of 0 to good for the best road condition value of 100 (Widiatmoko et al., 2022). This method is used to assist the process of evaluating road conditions based on the level of damage found on the road surface.

2. RESEARCH METHOD

Overall, this research was conducted by involving several methods and stages as described in the following subsections.

2.1 Research Method

This study uses a quantitative method because the entire data processing procedure is carried out using numerical calculations and number-based analysis. The data used consist of digital images of road conditions captured in real-time through a camera and processed by the computer in the form of pixel matrices and numerical vectors. Computer vision computation was performed using the YOLOv8 model to detect and classify road conditions into damaged road or good road categories. All research stages, including image preprocessing, YOLOv8 model training, real-time object detection and classification, and system performance testing, were conducted quantitatively. All computations were implemented using the Python programming language. System performance analysis was carried out using the parameters of accuracy, precision, recall, and F1-score, which were presented in percentage form. The results of this analysis are useful for evaluating the system's performance in classifying road conditions.

2.2 Pipeline of the System Development

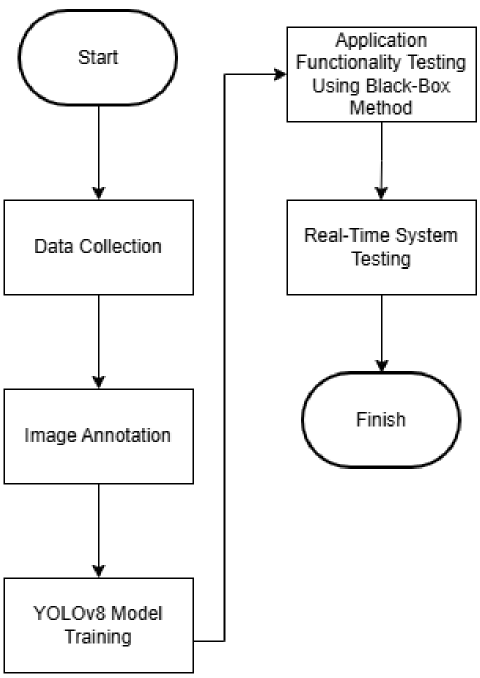

Figure 1. Pipeline of the System Development

The development begins with the data collection process in the form of road condition images consisting of damaged roads and good roads. After the data are collected, image annotation is performed by assigning labels to each image according to the road condition category so that the data can be used in the YOLOv8 model training process. Once the model training process is completed, the model is integrated into the developed application. After the application is ready, functional testing is conducted using the black-box method to ensure that all application features operate according to the designed functions. In this study, the evaluation is not specifically focused on the vision model itself, but rather on the overall system using real-time images. This represents the final stage, where the system is tested to evaluate the system's capability in recognizing and classifying road conditions directly.

3. RESULTS AND DISCUSSION

This section discusses the implementation and testing results of the YOLOv8-based road condition classification application. The discussion includes the application implementation results and system testing results using the confusion matrix method. This section also analyzes the values of accuracy, precision, recall, and F1-score to evaluate the system's capability in recognizing and classifying road conditions automatically.

3.1 Constructed Dataset

In this study, the dataset was successfully constructed consisting of 50 images of damaged roads and 50 images of good roads. The dataset was developed through preprocessing stages including resizing, data normalization, annotation, and augmentation. The augmentation process included rotation and lighting variation. **Figure 1** and **Figure 2** show examples of images from the constructed dataset.

Figure 2. Example of Good Road Images for the Dataset

Figure 3. Example of Damaged Road Images in the Dataset

3.2 Developed Application

The application displays recognition results in the form of bounding boxes, classification labels, confidence scores, and the number of damaged road recognitions. The system also provides application control features such as starting the recognition process, stopping the recognition process, and resetting road section data.

Figure 4. User Interface of the Road Condition Classification Application

Figure 5. Application Interface During Testing on Jl. Vila Pamulang Road Section

Figure 6. Application Interface During Testing on Jl. Pamulang Permai Road Section

Figure 7. Application Interface During Testing on Jl. Pamulang Raya Road Section

Figure 8. Application Interface During Testing on Jl. Alam Segar Road Section

Figure 9. Application Interface During Testing on Jl. Gria Jakarta Road Section

Figure 10. Application Interface During Testing on Jl. Vila Dago Road Section

Figure 11. Application Interface During Testing on Jl. Paradise Serpong Road Section

Figure 12. Application Interface During Testing on Jl. Nusa Loka Road Section

Figure 13. Application Interface During Testing on Jl. Nusa Indah Road Section

Figure 14. Application Interface During Testing on Jl. Vila Pamulang Mas Road Section

3.3 System Test Results

System testing was conducted using the confusion matrix method to evaluate the model's performance in classifying road conditions. The testing process used 100 test data consisting of 50 images of good roads and 50 images of damaged roads. Based on the testing results, the following values were obtained.

Table 1. Test results with confidence threshold of 0.1 and 0.9 for the damaged road class and the good road class.

	Road Condition	
Actual/Predicted	Damaged	Good
Damaged	50	4
Good	0	46

Table 2. Confusion Matrix of the Test

	Final Results
TP	50
FP	4
TN	46
FN	0

Table 3. Model Evaluation Results

Metrics	
Accuracy	0,96
Precision	0,93
Recall	1
Fl Score	0.96

3.4 Discussions

Using equation (1), the system accuracy is 0.96, the precision is 0.93, the recall is 1.00, and the F1-score is 0.96. It shows that the system is capable of performing road condition classification with good performance in real-time testing processes. The high accuracy value was influenced by the use of a training dataset containing several types of road damage such as potholes, cracks, and uneven road surfaces, allowing the vision model to learn damage patterns more effectively. The precision value of 0.93 indicates that most damaged road classification results corresponded to the actual conditions, resulting in a relatively low classification error rate. In addition, the recall value of 1 indicates that all damaged road data in the testing process were successfully recognized by the system without any missed data. The F1-score value of 0.96 also indicates that the model has a good balance between precision and recall in the real-time road condition classification process. Furthermore, the training process using a dataset with various road conditions helped the model recognize the differences between damaged roads and good roads under different testing conditions. The confidence threshold ranges from 0 to 1 and takes a significant role in determining the system's accuracy, precision, recall and F-1 score. In this study, the confidence thresholds for the damaged road class and the good road class were set to 0.1 and 0.9, respectively.

4. CONCLUSION

Based on the research that has been conducted, the YOLOv8-based road quality classification application was successfully developed and is capable of identifying road conditions in real-time using a webcam mounted on a four-wheeled vehicle. The system can classify road conditions into damaged road and good road categories based on road images captured by the camera. Based on the model evaluation results, the model achieved an accuracy value of 0.96, a precision value of 0.93, a recall value of 1, and an F1-score value of 0.96, indicating that the model has good performance in the road condition classification process. In addition, the developed application is capable of displaying classification results directly on the system interface, thereby facilitating the road condition monitoring process. This study also demonstrates that the implementation of computer vision and deep learning using YOLOv8 can be utilized as a solution to assist the road condition monitoring process compared to manual observation methods. The confidence threshold ranges from 0 to 1. In this study, the confidence thresholds for the damaged road class and the good road class were set to 0.1 and 0.9, respectively.

ACKNOWLEDGEMENTS

We would like to express our gratitude to Dr. Ida Nurhaida, Head of the Informatics Study Program, for providing access to laboratory facilities, and to Universitas Pembangunan Jaya for providing overall facilities and support.

REFERENCES

Akbar Pradana, I., Rahajoe, A. D., & Sihananto, A. N. (2024). Algoritma Hybrid CNN-LSTM. In Jurnal Informatika dan Sistem Informasi (JIFoSI) (Vol. 5, Number 2).

Djulyansyah, M. F., Laxmi, G. F., & Agustian, S. (2024). Model Deteksi Jalan Untuk Smart Glasses Menggunakan Algoritma Yolo. In Jurnal Mahasiswa Teknik Informatika (Vol. 8, Number 4).

Habibi, M. B., & Wibowo, S. (2023). Pengembangan Aplikasi Deteksi Kerusakan Lubang Jalan Berbasis Android. 2023.

Hangge, E. E., Karels, D. W., & Kapitan, A. O. (2022). PENGARUH Karakteristik Tanah Dasar Terhadap Kerusakan Perkerasan Jalan. In Jurnal Teknik Sipil (Vol. 11, Number 2).

Yulianto, Y., & Wibowo, A. (2023). Deteksi Keretakan Jalan Aspal Menggunakan Metode Convolutional Neural Network. Power Syst, 4(2), 581-594.

Iza Sofiani, A., Eka Hervy, N., Dwi Lestari, F., Rizky Ardiansyah Putra, M., Fadhila Putri, M., Khaira, U., & Eko Prasetyo Utomo, P. (2025). Tahun 2025 Penerapan Model Yolo Untuk Deteksi Kerusakan Jalan Berdasarkan Citra Visual.

Kesuma Putra, W., Nurdin, A., & Febriasti Bahar, F. (2022). Analisis Kerusakan Jalan Perkerasan Lentur menggunakan Metode Pavement Condition Index (PCI). In Jurnal Teknik (Vol. 16, Number 1).

Mahmud, Ysuandi, I. A., Amir, A. A., Sulaiman, M. A., & Humera, A. P. (2026). Sistem inventarisasi kerusakan perkerasan jalan deep learning dengan arsitektur Convolutional Neural Network (CNN) YOLOv8. DECODE: Jurnal Pendidikan Teknologi Informasi, 6(1), 213–222. http://dx.doi.org/10.51454/decode.v6i1.1511

Rafi, F. A., Fanggidae, A., & Polly, Y. T. (2023). ASPHALT ROAD DAMAGE DETECTION SYSTEM USING CANNY EDGE DETECTION. Jurnal Komputer Dan Informatika, 11(1), 85–90. https://doi.org/10.35508/jicon.v11i1.10100

Rizaldi Hermansyah, M. A. (2023). Science and Technology Menggunakan Metode Pci (Pavement Condition Index) (Vol. 7, Number 2). http://jurnal.uts.ac.id

Royhan, E., Beta, M., Sucipto, A., Regasari, R., Putri, M., & Setiawan, B. D. (2025). Pengembangan Sistem Deteksi Lubang

Pada Jalan Menggunakan Algoritma Yolo Berbasis ESP32-CAM (Vol. 9, Number 4). http://j-ptiik.ub.ac.id

Sakinah, L., Haryatmi, E., & Riyadi, T. A. (2025). Implementasi Algoritma Yolo Untuk Mendeteksi Jalan Berlubang dan Retak. JITSI : Jurnal Ilmiah Teknologi Sistem Informasi, 6(3). https://doi.org/10.62527/jitsi.6.3.488

Sasmito, B., Setiadji, B. H., & Isnanto, R. (2023). Deteksi Kerusakan Jalan Menggunakan Pengolahan Citra Deep Learning di Kota Semarang. TEKNIK, 44(1), 7–14. https://doi.org/10.14710/teknik.v44i1.51908

Shodiq, U., Hadi Avizenna, M., Teknik, F., Studi Teknik Informatika, P., Muhammadiyah Magelang, U., Mayjen Bambang Soegeng, J., Mertoyudan, K., & Magelang, K. (2024). JOISIE licensed under a Creative Commons Attribution-ShareAlike 4.0 International License (CC BY-SA 4.0) Klasifikasi Jalan Rusak Menggunakan Transfer Learning Arsitektur Vgg16. Journal Of Information Systems And Informatics Engineering, 8(1), 75–85. https://doi.org/10.35145/joisie.v8i1.4243

Wardono, H., Widiatmoko, L., & Widyawati, R. (2022). Kajian Kerusakan Jalan Dengan Menggunakan Metode Pavement Condition Index (Pci), Pada Ruas Jalan Sirah Pulau Padang – Pampangan Km. 17+800 – Km. 19+200, Kabupaten Ogan Komering Ilir. Jurnal Profesi Insinyur Universitas Lampung, 3(2), 85–90. https://doi.org/10.23960/jpi.v3n2.85