Pavement Distress Detection Using Artificial Intelligence Algorithm

Mahmuda[1], Didi Yuda Wiranata[2*], Revias[3], Lino Garda Denaro[4], Gamma Ade Pertiwi[5], M Farizki Budiman[6], Zaki AlHusin Al Basami[7], Nabila Rara Sapitri[8]

(1, 2*, 3, 5, 6, 7, 8) Civil Engineering Departement State Polytechnic of Sriwijaya, Jl. Srijaya Negara Bukit Besar Palembang 30139, Indonesia
4) Research Center for Geoinformatics, National Research and Innovation Agency (BRIN), Bandung 40135, Indonesia

*Corresponding Author: didi.yuda@polsri.ac.id

Abstract. Road infrastructure is a crucial component of modern transportation systems, and its maintenance is essential to ensure safety and efficiency. To avert road degradation from undermining safety and functionality, it is essential to detect road damage promptly. Pavement distress detection is a time-consuming and labor-intensive process that requires manual visual inspection. This study proposes the development of an artificial intelligence (AI) using YOLOVv8 algorithm for automated pavement distress detection. The proposed algorithm utilizes machine learning and computer vision techniques to analyze images of pavement surfaces and identify various types of distresses, including cracks, potholes, and roughness. The algorithm is trained on a large dataset of labeled images and evaluated using performance metrics such as accuracy, precision, and recall. The results show that the proposed algorithm achieves high accuracy and outperforms traditional manual inspection methods. The use of AI in pavement distress detection can significantly reduce maintenance costs, improve road safety, and enhance the overall efficiency of transportation infrastructure. This study contributes to the development of smart and sustainable infrastructure management systems.

Keywords: Pavement Distress Detection, Artificial Intelligence, Machine Learning, Computer Vision, Infrastructure Management.

1 Introduction

1.1 Background

Roads are essential components of infrastructure, facilitating transportation within cities, between regions, and across countries. According to Wiranata et al. in their book chapter, roads are the most essential need in transportation. Without roads, it would be impossible to provide transportation services for users. Roads are intended and provided as a base for means of transportation to move from a place of origin to their

N. L. Husni et al. (eds.), *Proceedings of the 8th FIRST 2024 International Conference on Global Innovations (FIRST-ESCSI 2024)*, Advances in Engineering Research 261,
https://doi.org/10.2991/978-94-6463-678-9_24

destination (Wiranata et al., 2023). However, road infrastructure is prone to structural degradation due to material damage mainly caused by heavy traffic, adverse weather conditions, aging, poor construction quality, and insufficient maintenance. Over time, this leads to a decline in road quality and serviceability, impacting their ability to provide smooth, safe, and efficient transportation. Key issues that arise from declining road quality include surface deterioration, structural failures, reduced safety, and decreased serviceability.

In order to prevent road deterioration from compromising safety and serviceability, it is crucial to identify damage sooner. Traditionally, human inspectors use a manual approach method to identify pavement distress, visually assessing road conditions by driving or walking on the road. They record signs of damage such as cracks, potholes, or surface deformation. This method has disadvantages such as being labor-intensive, inconsistent, and time-consuming. Numerous semi-automated methods have been developed to identify pavement distress, and technology assists human inspectors by partially automating the data collection or analysis process (Zalama et al., 2014). This approach bridges the gap between fully manual inspections and entirely automated systems but still needs expensive equipment and human involvement. Automatic road damage detection involves fully automating both the data collection and analysis processes using advanced technologies. This approach relies on cutting-edge tools like machine learning, artificial intelligence (AI), and sensors to detect and classify road damage without human intervention. The trend in road maintenance is moving toward more automated and intelligent systems due to their efficiency, cost-effectiveness, and ability to provide real-time monitoring.

Several automated criteria have been proposed to address these and other limitations, beginning with the evidence that applications of artificial intelligence (AI) are becoming increasingly prevalent in pavement engineering and transportation (Guan et al., 2021; D. Zhang et al., 2018). Deep learning (DL) algorithms were implemented in prior investigations (Liu et al., 2022; A.Zhang et al., 2019). Deep learning has recently demonstrated a variety of prospective applications in a variety of real-world domains, such as the detection of targets in pavement engineering (Sha et al., 2023). In deep learning, a computer model acquires the ability to perform classification tasks by analyzing various categories of information, including texts, audio, and images. Deep learning models are constructed from a substantial quantity of labeled data and neural network structures that incorporate various layers. The term "deep" denotes the quantity of concealed layers in the neural network. Deep learning models can be employed to evaluate the status of pavement conditions, including fissures, potholes, and other pavement distress, by analyzing pavement images and videos. This seems to be a beneficial method for prioritizing maintenance and repair projects.

To rectify the shortcomings of manual approaches, artificial intelligence techniques are being employed to identify pavement distress. Artificial intelligence surpasses manual approaches in identifying pavement damage owing to its capacity to handle extensive jobs with many problems, enhance detection accuracy, and exhibit high efficiency and robust scalability. Additionally, it detects defects in real time. However, AI detection methods can be costly to implement at the outset, necessitate technical expertise to operate and maintain, may necessitate frequent updates to accommodate new pavement distress, and may be susceptible to error if not properly trained or in unanticipated circumstances.

1.2 Objective

Furthermore, this research aims to provide a deep learning-based method for monitoring asphalt pavement conditions and minimizing the overall time needed for pavement assessment. The YOLOv8 algorithm is utilized for the detection of pavement deterioration. It utilizes a deep convolutional neural network (CNN) architecture akin to its predecessors, but with some alterations. The modifications encompass a novel backbone architecture termed CSPNet, an innovative neck architecture designated FPN+PAN, a fresh head architecture referred to as PANet, and a revised training procedure. Due to its recent introduction in 2023, there are only a limited number of YOLOv8 applications in pavement engineering.

2 Methodology

2.1 Dataset preparation

Pavement distress data was acquired by field surveys on national roads in Palembang city, initiated by designing and mapping routes to provide thorough coverage of diverse road conditions. A basic cell phone camera was employed to take detailed photos and movies of pavement deterioration in the field. The photos and videos are further annotated using labeling software to precisely identify various forms of pavement distress. A total of 200 photos were collected, with each image recorded three to four times to assure uniformity. The dataset was rigorously partitioned into two subsets: 70% of the photos were designated for model training, while the remaining 30% were reserved for testing. To strengthen the evaluation's integrity, the testing set was verified using suitable methodologies to confirm the model's performance reliability. This divide facilitated a thorough evaluation of the model's precision and applicability throughout the dataset.

2.2 Yolo v8 architecture

This research employed the YOLOv8 algorithm for the detection of pavement deterioration. The YOLO (You Only Look Once) algorithm was developed by Redmon et al. in 2016. It can identify and position things in a single step. YOLOv2 is an improved version of the original YOLO model. It applies the principle of anchor priors in single shot multibox detectors (SSD). YOLOv2 significantly varies by having a reduced number of layers, consisting of only 19 convolutional layers utilizing 3 x 3 and 1 x 1 filters.

YOLOv8 is the latest variant of the YOLO series, initially introduced in May 2023. It employs a deep convolutional neural network (CNN) architecture similar to its predecessor, but with modifications, including an innovative backbone architecture termed

PANet and a revised training methodology. YOLOv8 comprises five various model sizes: nano, small, medium, large, and extra-large. The Nano model has a parameter count of only 3.2 million, enabling implementation on mobile and GPU platforms. YOLOv8 consists of three elements: the backbone for feature extraction, the neck for multi-feature integration, and the head for prediction output. Figure 1 depicts the architecture of the YOLOv8 network.

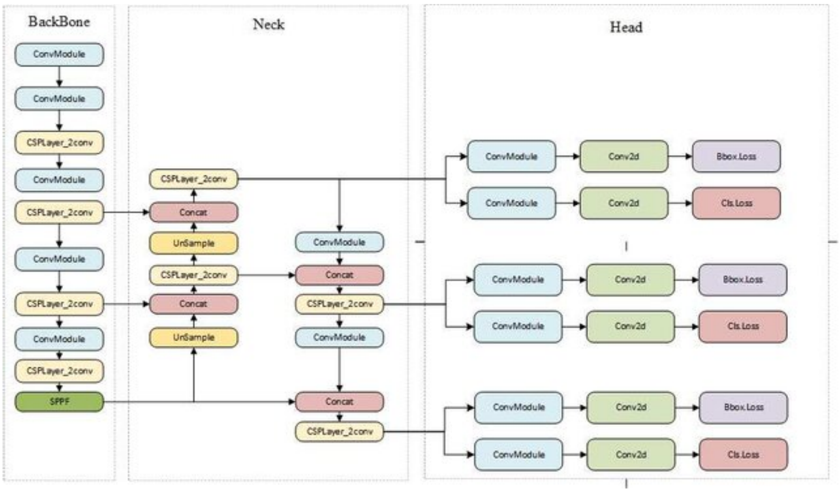

Fig. 1. The architecture of the YOLOv8 network (adapted from Yang et al., 2023).

3 Results and Discussions

3.1 Detection result

Figure 2 accurately depicts the efficacy of the YOLOv8 model in identifying different categories of road damage. Sixteen images were evaluated to assess the performance of YOLOv8 architecture. Each bounding box provides a clear visual reference for the model's confidence in detecting specific damage areas, showing that the YOLOv8 algorithm is well-suited for tasks like infrastructure maintenance and road condition monitoring. The diversity of road damage types detected in the images highlights the model's versatility, indicating it has been trained on a comprehensive dataset covering a wide range of potential defects that occur on roads.

In practical applications, the output provided by this model could be used by urban planners, road maintenance teams, or automated systems to identify and prioritize areas in need of repair. The model's ability to accurately identify road damage from different angles and in various lighting conditions suggests it can be reliably deployed in real-time road monitoring systems, including those using cameras mounted on vehicles for continuous road inspection. Overall, the consistent and accurate detection of road damage across various images demonstrates the potential of the YOLOv8 model to enhance the efficiency and accuracy of road maintenance operations.

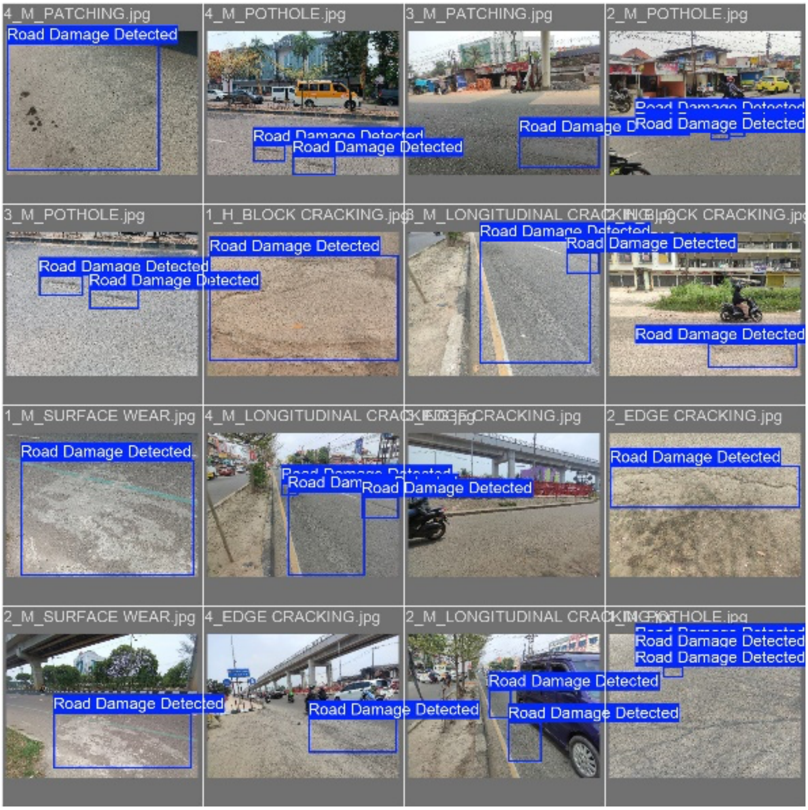

Fig. 2. Training dataset of road damage detection for 500 epochs.

3.2 Y-Net optimization

A number of performance indicators and loss curves produced by the YOLOv8 model during training and validation are shown in figure 3. The top row shows the model's progress in minimizing various training losses, including bounding box loss (train/box_loss), classification loss (train/cls_loss), and distribution focal loss (train/dfl_loss), all of which steadily decrease over time. This indicates that the model is improving in terms of accurately predicting both the location and classification of objects, such as road damage. The validation losses (val/box_loss, val/cls_loss, and val/dfl_loss) are shown in the bottom row. They all go down in the same way, showing that the model works well and consistently on new data that it hasn't seen before.

Additionally, the performance metrics precision, recall, and mean average precision (mAP) show significant improvement as training progresses. Precision and recall (metrics/precision(B) and metrics/recall(B)) increase, indicating the model is becoming more accurate at detecting road damage while reducing false positives and capturing more true positives. The model's overall better performance is shown by a sharp rise in the mean average precision at IoU thresholds of 50% and across 50–95% (mAP50(B) and mAP50–95(B)). This is true even when predicted and actual bounding boxes overlap to different degrees. Overall, these trends suggest that the YOLOv8 model is successfully learning to detect road damage with high accuracy and precision, ensuring reliable predictions on both the training and validation datasets.

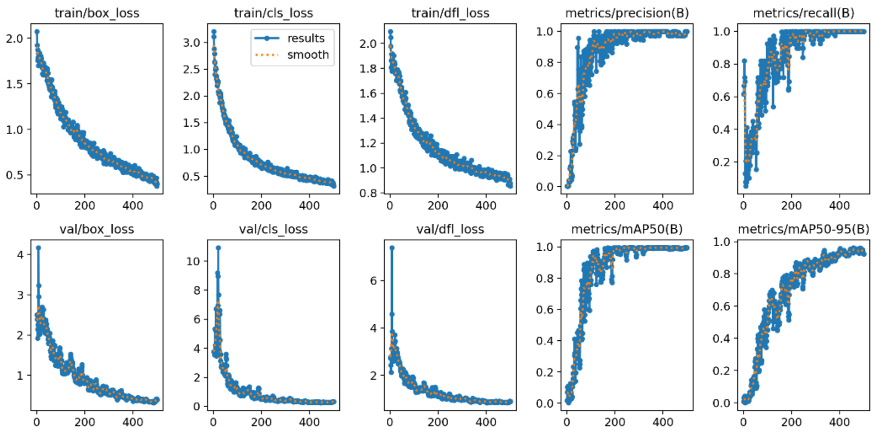

Fig. 3. Training dataset of road damage detection for 500 epochs.

3.3 Statistical analysis

In object detection tasks utilizing YOLOv8, the given correlogram graphically depicts the relationship between important variables usually linked to bounding boxes. The boxes' height, width, and bounding box center's x and y coordinates are among these variables. Histograms illustrate the distribution of data for distinct qualities, such as width and height, while diagonal graphs display the distribution of each variable. The offdiagonal heatmaps provide insights into pairwise relationships between these variables. For example, the relationship between the x and y coordinates of the bounding box centers suggests how the objects are positioned in the image, while the heatmap between width and height may reveal trends in object sizes, potentially indicating typical aspect ratios. This visualization is a useful tool for understanding the underlying structure and relationships in your dataset, offering a deeper exploration of how bounding boxes are distributed and correlated within the image data.

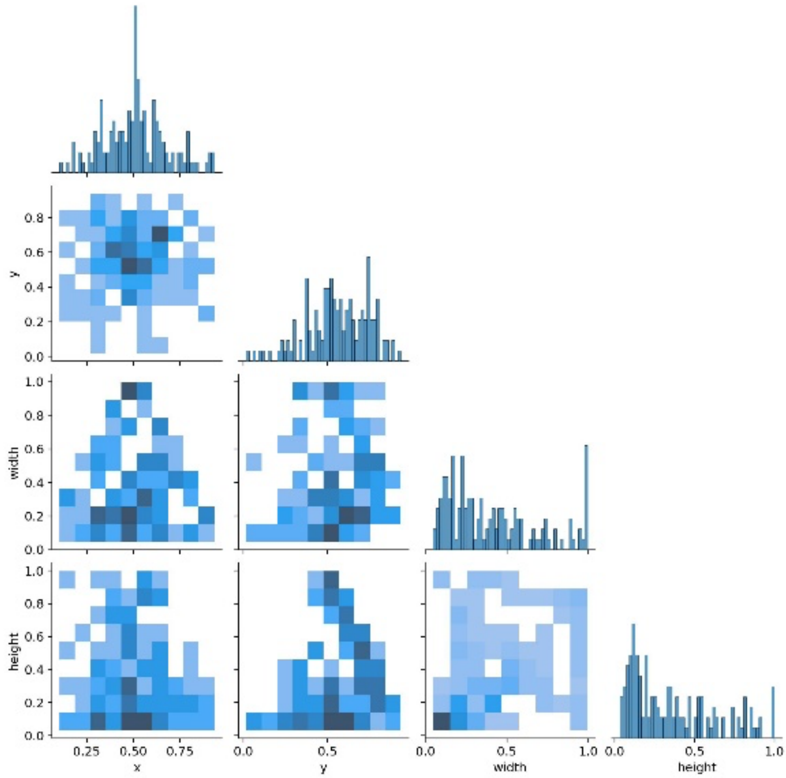

Fig. 4. Correlogram of Bounding Box Attributes (x, y, Width, Height) from YOLOv8 Object Detection Model.

A depiction of the Precision-Confidence Curve shows how well the YOLOv8 model detects damage to roads. The curve demonstrates a strong correlation between confidence levels and precision, with the model maintaining high precision across various confidence thresholds. Even at lower confidence levels, the precision remains close to 1.0, indicating that the model consistently produces few false positives. As confidence increases, the curve flattens, showing that the model achieves nearly perfect precision as it becomes more certain in its predictions. Notably, at a confidence level of approximately 0.929, the model reaches a precision of 1.00, which means that all predictions made at this confidence threshold are correct. This high precision across the board suggests that the YOLOv8 model is highly reliable and accurate in detecting road damage, reinforcing its effectiveness for automated road monitoring and maintenance tasks.

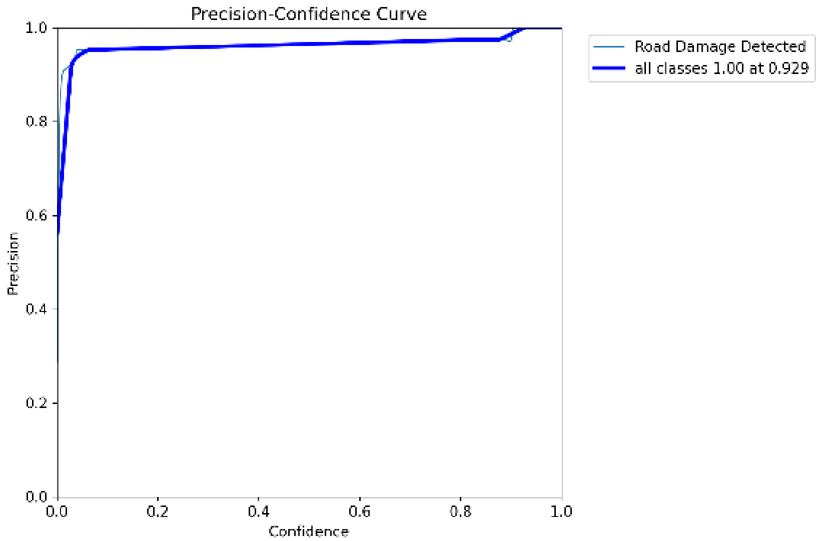

Fig. 5. Precision-Confidence Curve for Road Damage Detection Using YOLOv8.

4 Conclusion

There is a high degree of accuracy demonstrated by the findings of the road damage detection using the YOLOv8 model, with the forecasts obtaining a confidence level of 92%. This confidence indicates that the model is able to reliably identify and localize road damages, such as cracks and potholes, within the captured images. The high prediction confidence is likely due to the well-trained model on a diverse dataset, allowing it to effectively generalize across various road conditions and damage types. Additionally, the correlogram analysis of bounding box attributes (x, y coordinates, width, and height) reveals consistent patterns in the predictions, further validating the model's reliability. The distribution of the bounding boxes suggests that the model is effectively capturing and delineating road damage, providing precise localization of defects. This level of performance positions the YOLOv8 model as a highly suitable tool for automated road damage detection, offering a promising solution for maintenance and monitoring efforts.

References

1. Guan, J., Yang, X., Ding, L., Cheng, X., Lee, V. C. S., &Jin, C. (2021). Automated pixel-level pavement distress detection based on stereo vision and deep learning. *Automation in Construction*, *129*(March), 103788. https://doi.org/10.1016/j.autcon.2021.10378
2. Liu, Z., Gu, X., Yang, H., Wang, L., Chen, Y., &Wang, D. (2022). Novel YOLOv3 Model With Structure and Hyperparameter Optimization for Detection of Pavement

Concealed Cracks in GPR Images. *IEEE Transactions on Intelligent Transportation Systems*, *23*(11), 22258–22268. https://doi.org/10.1109/TITS.2022.3174626

3. Redmon, J., Divvala, S., Girshick, R., &Farhadi, A. (2016). You only look once: Unified, real-time object detection. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2016-Decem*, 779–788. https://doi.org/10.1109/CVPR.2016.91
4. Sha, J., Wang, J., Hu, H., Ye, Y., &Xu, G. (2023). Development of an Accurate and Automated Quality Inspection System for Solder Joints on Aviation Plugs Using Fine-Tuned YOLOv5 Models. *Applied Sciences (Switzerland)*, *13*(9). https://doi.org/10.3390/app13095290
5. Wiranata, D. Y., Agustin, T., Hakim, L., Kurnia, A. Y., Della, R. H., Satmoko, N. D., Jamilah, W., Agustien, M., Syafarina, P., Sari, N. M., &Pirdiansyah, H. (2023). MANAJEMEN TRANSPORTASI. In R. H.Della (Ed.), *Indie Press*. Indie Press. http://scioteca.caf.com/bitstream/handle/123456789/1091/RED2017-Eng-8ene.pdf?sequence=12&isAllowed=y%0Ahttp://dx.doi.org/10.1016/j.regsciurbeco.2008.06.005%0Ahttps://www.researchgate.net/publication/305320484_SISTEM_PEMBETUNGAN_TERPUSAT_STRATEGI_MELESTARI
6. Yang, Y., Hu, S., Zhang, J., Ren, X., &Ke, Y. (2023). Moving targets intelligent detection and tracking algorithm for that can restrain of local occlusion. *Research Square*, 0–12. https://doi.org/https://doi.org/10.21203/rs.3.rs-3462016/v1 License:
7. Zalama, E., Gómez-García-Bermejo, J., Medina, R., &Llamas, J. (2014). Road Crack Detection Using Visual Features Extracted by Gabor Filters. *Computer-Aided Civil and Infrastructure Engineering*, *29*(5), 342–358. https://doi.org/10.1111/mice.12042
8. Zhang, A., Wang, K. C. P., Fei, Y., Liu, Y., Chen, C., Yang, G., Li, J. Q., Yang, E., &Qiu, S. (2019). Automated Pixel-Level Pavement Crack Detection on 3D Asphalt Surfaces with a Recurrent Neural Network. *Computer-Aided Civil and Infrastructure Engineering*, *34*, 213–229.
9. Zhang, D., Zou, Q., Lin, H., Xu, X., He, L., Gui, R., &Li, Q. (2018). Automatic pavement defect detection using 3D laser profiling technology. *Automation in Construction*, *96*(May), 350–365. https://doi.org/10.1016/j.autcon.2018.09.019