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Implementation of Convolutional Neural Network for Road Damage Detection and Classification in Surabaya City

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Abstract

Road damage is a significant infrastructural problem that impacts the safety of road users and economic efficiency. The current road damage detection system, which relies on manual inspection, has limitations in speed and accuracy. Therefore, this study proposes the use of a conventional Convolutional Neural Network (CNN) to enhance accuracy and efficiency in the detection and classification of road damage in Surabaya City. The methods applied include data preprocessing and basic data augmentation techniques such as rotation and flipping. The dataset used comes from CV. Wastu Kencana Teknik, consisting of four road damage classes: potholes, surface delamination, cracks, and edge cracks. The implementation of the CNN model with standard configurations shows potential for application in an AI-based road infrastructure monitoring system. The model evaluation was performed using a confusion matrix and ROC-AUC, indicating that the model has stable and accurate classification performance. With these results, the model has the potential to enhance the effectiveness of detection and decision-making in road maintenance.

Keywords– *Nolam Siti Saripah, Oral Literature, Religion, Dimensions of Religiosity*

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1. Introduction

Road infrastructure is a vital component in the development and economic growth of an area, particularly in major cities like Surabaya, which has a high population mobility rate (Ahmad, 2022; Bhattacharyya & Kim, 2023; P et al., 2023). Over the last decade, the significant increase in vehicle volume, coupled with extreme weather conditions and excessive loads, has accelerated road infrastructure damage in various city areas (Siahay et al., 2023; Bharat et al., 2023; Deepa & Sivasangari, 2023)). In Surabaya, road damages of varying severity levels, ranging from minor cracks to dangerous potholes, pose a serious problem.

This issue of road damage impacts not only the safety aspects of road users but also has substantial economic implications (Rusli & Ridayati, 2024). Delays in identifying and addressing road damage can lead to wastage and an increase in repair costs by up to 40% compared to early intervention (Jasri et al., 2020). The conventional monitoring systems, which still rely on manual inspections, face several serious limitations, including time inefficiency, subjectivity in assessment, and challenges in systematic documentation and classification of damages (Susilo et al., 2024; Eslami & Yun, 2023; Vaz et al., 2023; Yamaguchi & Mizutani, 2024). his is exacerbated by limited human resources and budgetary constraints for regular inspections throughout the city’s road network (“keterbatasan dana sebabkan penanganan jalan tidak menyeluruh,” n.d.).

In addressing these challenges, the use of artificial intelligence technology, especially in the field of Computer Vision and Deep Learning, becomes crucial. This research implements Convolutional Neural Networks (CNNs) designed for the automatic identification and classification of road damages. Although previous studies have proposed the use of complex CNN architectures, this research aims to employ a standard configuration of CNN that is effective in detecting various types of road damage with good accuracy.

This study utilizes a dataset from CV. Wastu Kencana Teknik, consisting of four road damage classes: potholes, surface peeling, cracks, and edge cracks. The use of standard data preprocessing techniques and data augmentation such as rotation and flipping is expected to enhance the model's performance in diverse environmental conditions. With the implementation of this CNN, it is hoped to develop a more accurate and efficient road damage detection and classification system for the city of Surabaya.

2. Method

This research is designed by referring to five main stages that will be described systematically. Each stage in this process is structured, starting from data collection to the final evaluation of the model's performance.

a. Data Collection

The Data Collection stage in this research uses a dataset sourced from CV. Wastu Kencana Teknik, which contains images of road damages with a resolution of 300x300 pixels. This dataset encompasses four major types of road damages, as shown in Figure 1 regarding Data Distribution: potholes, surface peeling, cracks, and edge cracks. The number of images in each class varies, with the crack class having the most images, totaling 1752, followed by the edge crack class with 1709 images. The surface peeling class contains 1658 images, while the pothole class has the fewest, with 1651 images.

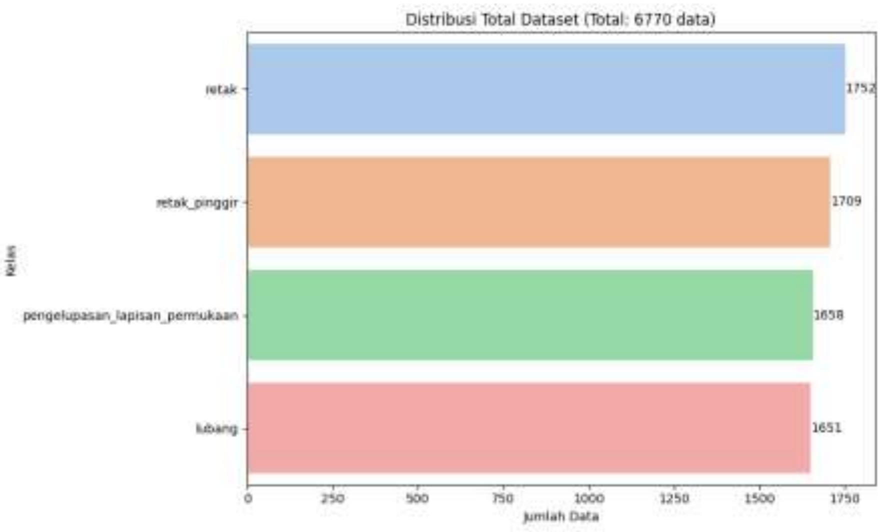

Figure 1. Total Dataset Distribution

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b. Data Preprocessing

The Preprocessing stage is the initial step in preparing image data to be effectively used in training a CNN model. This process is essential to ensure that the data has the format and quality needed for the model in use.

The first step in preprocessing is resizing all images to dimensions compatible with the input size of the chosen CNN model. For example, if the selected model requires an input size of 224x224 pixels, then all images will be resized to 224x224 pixels. Additionally, the images are converted to the float32 data type, which supports high-precision pixel value computations during processing.

Subsequently, a normalization process is conducted to standardize the pixel value scale across all images. Pixel values originally in the range of 0–255 (for RGB images) are transformed to a range of [0, 1]. The purpose of this normalization is to reduce large-scale value variations, which can help stabilize the model training process.

c. Data Augmentation

The Data Augmentation stage aims to enhance the diversity of the dataset by applying various transformations to the images. As a result, the model can learn from more varied data and become more robust in handling different real-world conditions. The augmentation techniques used include rotation, zoom, horizontal flip, and brightness adjustment. These augmentations are applied randomly to images in the training set, ensuring that each epoch presents a unique and different data combination.

d. Model Development

In this study, a Convolutional Neural Network (CNN) model was developed to classify various types of road damages in Surabaya City. CNN was chosen due to its proven capability in image analysis, efficiently extracting image features through convolutional operations.

The model is designed with several convolutional blocks, where each block consists of a convolutional layer followed by batch normalization and maximum pooling. The first block uses 32 filters of size 3x3 and the ReLU activation function, arranged to maintain the spatial dimensions of the image with 'same' padding. Batch normalization after convolution aims to accelerate convergence during training and reduce the problem of internal covariate shift. Each convolutional block is followed by a MaxPooling layer with a 2x2 pool size to reduce the output dimensions, thereby decreasing the number of parameters and computations in subsequent layers.

The complexity of the model is gradually increased by adding more filters in subsequent convolutional blocks—64, 128, and 256 filters. This approach is designed to allow the model to capture more complex features at higher levels of abstraction, crucial for a deeper understanding of various road damage patterns.

After feature extraction through the convolutional blocks, the data is flattened using a Flatten layer. This step transforms the two-dimensional data into a one-dimensional vector, which is then processed through fully connected layers. The first fully connected layer has 512 units with ReLU activation, equipped with a 0.5 Dropout to reduce the risk of overfitting by randomly turning off units during the training process. The same process is repeated in the second layer, which contains 256 units. The final layer, which is also the output layer, uses a softmax activation function to classify the output into appropriate road damage categories based on the number of classes.

With this architecture and strategy, the developed CNN model is expected to accurately identify and classify road damages, aiding in decision-making for road infrastructure repair and maintenance.

e. Model Training

The model training process uses the Adam optimizer with an initial learning rate of 0.001. Categorical Crossentropy is used as the loss function for its effectiveness in handling multi-class classification. The model is trained with a batch size of 32 and a maximum of 100 epochs, aiming for good convergence.

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During the training process, several basic techniques are applied to support the efficiency and effectiveness of learning. EarlyStopping with a patience of 10 is used to stop training early if there is no improvement in validation loss, helping to prevent overfitting. ModelCheckpoint is implemented to automatically save the best-performing version of the model during training. Additionally, ReduceLROnPlateau with a factor of 0.1 and a patience of 5 is implemented to dynamically adjust the learning rate based on the model's performance, helping to avoid stagnation in learning.

Although more complex strategies such as learning rate scheduling, cross-validation, and gradient clipping could be applied, in this study, we prioritize the use of simple and straightforward techniques to ensure stability and effectiveness without adding unnecessary complexity.

f. Evaluasi

The model evaluation is conducted comprehensively using various metrics to ensure accuracy and effectiveness of the classification. The primary metric used is accuracy, which measures the overall classification correctness. Precision and recall are also calculated to assess the accuracy of positive predictions and the model's ability to correctly detect positive cases, while the F1-Score, a harmonic mean of precision and recall, is used to provide a balance between these two metrics.

Further performance analysis is conducted through a confusion matrix, which offers an effective visualization to assess the classification ability of the model for each road damage category. Additionally, learning curves that include training accuracy and training loss graphs are presented to monitor the learning process and identify potential overfitting or underfitting throughout the training phase.

The results from these metrics provide a deep understanding of the model's performance in classifying road damages, aiding in decision-making related to future model improvements.

3. Result and Discussion

In this chapter, the results from training the developed Convolutional Neural Network (CNN) model for classifying road damage will be discussed. This analysis involves assessing the model's performance through evaluation metrics and visualizing the results with charts and a confusion matrix.

a. Analisis Learning Curves

As shown in Figure 2, the training and validation loss graphs exhibit interesting dynamics during the training process. There are significant fluctuations in the validation loss values, reflecting the model's challenge in generalizing to previously unseen data. Meanwhile, the training loss shows a consistent decrease, indicating that the model continues to effectively learn from the training data. Both graphs indicate points where the model might be experiencing overfitting, as marked by a sharp spike in validation loss around the 20th epoch.

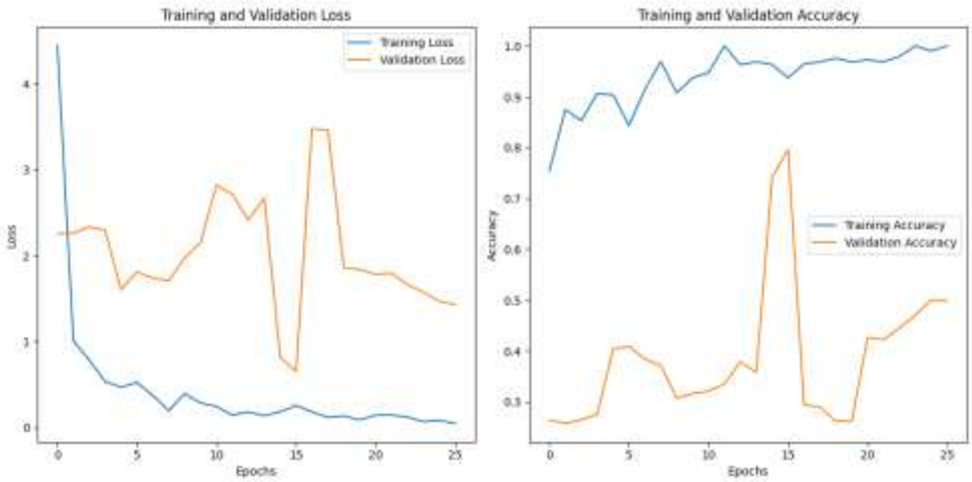

Figure 2. Graph Train Accuracy and GraphTrain Loss

The training and validation accuracy graphs, also shown in Figure 1, depict a similar trend where training accuracy is consistently higher than validation accuracy. This suggests that the model may be too specific to the training data and less flexible in responding to variations in validation data. Fluctuations in validation accuracy emphasize the need for strategies such as parameter adjustment or the use of more effective regularization techniques.

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b. Evaluasi Confusion Matrix

The confusion matrix presented in Figure 3 provides deep insights into the classification capabilities of the model across each category of road damage. The model shows a strong tendency to identify 'edge cracks' with high precision and recall, resulting in an F1-score of 0.90. However, the model is less effective in classifying 'surface peeling', with a recall of only 0.54, indicating the model's difficulty in accurately detecting this class.

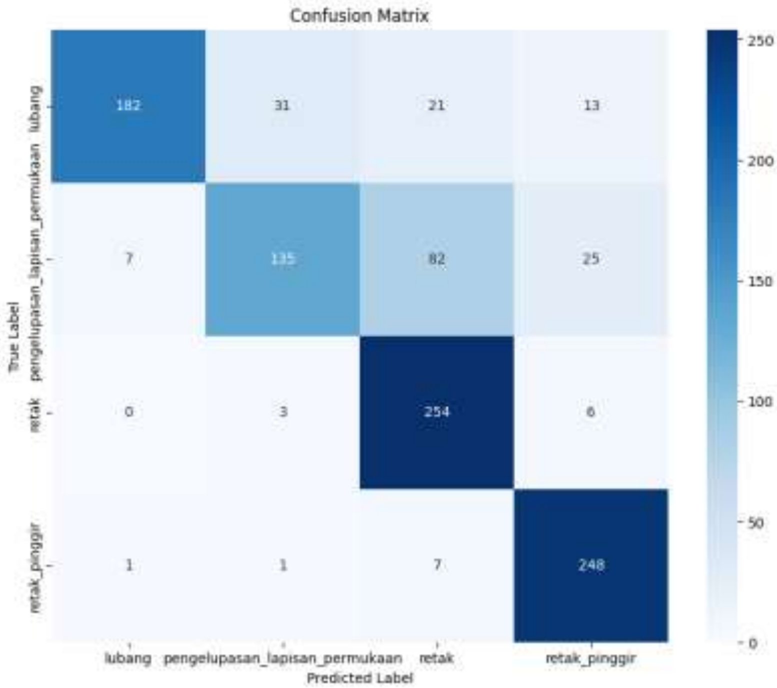

Figure 3. Confusion Matrix

c. Evaluasi Performance

Based on the Performance Evaluation illustrated in Figure 4, it is evident that the model has high precision for the classes 'pothole' and 'edge crack', but shows challenges in recall for 'surface peeling'. This indicates that although the model is quite accurate in identifying positive cases for some classes, there is still room for improvement, particularly in enhancing the model's sensitivity to classes with less distinct or more varied characteristics.

Classification Report:

	precision	recall	f1-score	support
lubang	0.96	0.74	0.83	247
pengelupasan_lapisan_permukaan	0.79	0.54	0.64	249
retak	0.70	0.97	0.81	263
retak_pinggir	0.85	0.96	0.90	257
accuracy			0.81	1016
macro avg	0.82	0.80	0.80	1016
weighted avg	0.82	0.81	0.80	1016

Figure 4. Evaluasi Performance

Based on the training results of the developed CNN model, several key findings emerged regarding the model’s performance in classifying road damage. The learning curve analysis reveals challenges in the model’s generalization process, as indicated by significant fluctuations in validation loss (Figure 2). This suggests that while the model effectively learns patterns from the training data, its ability to recognize new data still requires improvement. Overfitting is a crucial concern, particularly given the sharp spike in validation loss around the 20th epoch. One potential solution to address this issue is the implementation of regularization techniques such as dropout or data augmentation to enhance the model’s generalization capability.

Furthermore, the confusion matrix evaluation (Figure 3) demonstrates that the model performs well in classifying the ‘edge cracks’ category, achieving an F1-score of 0.90. However, the model struggles to accurately detect ‘surface peeling,’ as indicated by a recall score of only 0.54. The low recall suggests that the model frequently fails to identify positive cases for this category. One possible reason for this limitation is an imbalance in the training data or the inherently diverse visual characteristics of this damage type. To mitigate this issue, strategies such as increasing the sample size for the ‘surface peeling’ category or applying image augmentation techniques could help enrich the training data and improve classification accuracy (Bicbic et al., 2023; Parvathavarthini et al., 2023; Zhang et al., 2022).

From the overall performance evaluation (Figure 4), the model exhibits high precision for the ‘pothole’ and ‘edge crack’ classes but faces challenges in

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recall for ‘surface peeling.’ This indicates that while the model is effective in identifying well-defined patterns, its sensitivity to more complex damage types needs enhancement. Therefore, optimizing the model architecture, exploring hyperparameter tuning, and utilizing a more adaptive loss function could be potential steps to improve classification accuracy and balance across all categories (Chen et al., 2024; Makendran et al., 2024; Sanjai Siddharthan et al., 2024).

4. Conclusion

This study successfully developed an effective Convolutional Neural Network (CNN) model for classifying road damage in Surabaya City. Although the model demonstrates good accuracy in identifying certain types of damage, such as 'edge cracks', there is still room for improvement, particularly in addressing classes with less distinctive features like 'surface peeling'. Overfitting poses a major challenge, indicating the need for more effective regularization strategies to enhance the model's generalization capabilities.

As recommendations, future research could explore the application of advanced regularization techniques, the use of a more diverse dataset, and the exploration of alternative model architectures to improve the robustness and accuracy of the model. The implementation of this model is expected to aid in faster and more accurate decision-making for infrastructure repairs, enhancing road user safety, and reducing road maintenance costs.

References

Ahmad, F. salam. (2022). The Impact of Trans Java Toll Road Construction on Economic Growth in Central Java. JEKP, 11(1), 1–18. https://doi.org/10.29244/jekp.11.1.2022.1-18

Bharat, R., Ikotun, A. M., Ezugwu, A. E., Abualigah, L., Shehab, M., & Zitar, R. A. (2023). A real-time automatic pothole detection system using convolution neural networks. *Applied and Computational Engineering*, *6*(1). https://doi.org/10.54254/2755-2721/6/20230948

Bhattacharyya, C., & Kim, S. (2023). Black Ice Classification with Hyperspectral Imaging and Deep Learning. *Applied Sciences (Switzerland)*, *13*(21). https://doi.org/10.3390/app132111977

Bicbic, J., Gabriel MacAtangay, T. E., Miranda, M., Ocina, M., & Santos, A. (2023). Automated Pavement Distress Detection and Classification Using Convolutional Neural Network with Mapping. *IEEE Region 10 Annual International Conference, Proceedings/TENCON*. https://doi.org/10.1109/TENCON58879.2023.10322464

Chen, C., Wang, X., Zhu, J., Zhang, T., Yin, S., Wang, H., Wei, Q., & Qiao, F. (2024). Rock Slag Classification Algorithm Based on Convolutional Neural Network and Its FPGA Acceleration. *Chinese Journal of Sensors and Actuators*, *37*(1). https://doi.org/10.3969/j.issn.1004-1699.2024.01.012

Deepa, D., & Sivasangari, A. (2023). An effective detection and classification of road damages using hybrid deep learning framework. *Multimedia Tools and Applications*, *82*(12). https://doi.org/10.1007/s11042-022-14001-9

Eslami, E., & Yun, H. B. (2023). Comparison of deep convolutional neural network classifiers and the effect of scale encoding for automated pavement assessment. *Journal of Traffic and Transportation Engineering (English Edition)*, *10*(2). https://doi.org/10.1016/j.jtte.2022.08.002

Jasri, H., Anwardi, A., & Hamdy, M. I. (2020). Identifikasi Waste Proyek Konstruksi Jalan dengan Menggunakan Metode Lean Project Management. Jurnal Teknik Industri: Jurnal Hasil Penelitian Dan Karya Ilmiah Dalam Bidang Teknik Industri, 5(2), 115–124. https://doi.org/10.24014/jti.v5i2.8999

KETERBATASAN DANA SEBABKAN PENANGANAN JALAN TIDAK MENYELURUH. (n.d.). In Kementerian PUPR. https://pu.go.id/berita/keterbatasan-dana-sebabkan-penanganan-jalan-tidak-menyeluruh?utm_source=chatgpt.com

Makendran, C., Karthik, M., Hasan, S. M. J., Harivignesh, M., & Varun Raahul, G. (2024). Designing an Intelligent Pavement Maintenance and Management System using Drone Imagery and Artificial Intelligence. *MATEC Web of Conferences*, *393*. https://doi.org/10.1051/matecconf/202439302005

P, Dr. K., S, A., & Agarwal, A. (2023). Automated Asphalt Crack Detection Using Convolutional Neural Networks. *INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT*, *07*(03). https://doi.org/10.55041/ijsrem17974

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Parvathavarthini, S., Shreekanth, M., Vigneshkumar, S., & Santhosh, N. S. (2023). Road Damage Detection using Deep Learning. *Proceedings - 7th International Conference on Computing Methodologies and Communication, ICCMC 2023*. https://doi.org/10.1109/ICCMC56507.2023.10083795

Rusli, C. R., & Ridayati, R. (2024). Dampak Ekonomi Akibat Kerusakan Infrastruktur Jalan di Desa Wisata Srikeminut Imogiri Bantul. 5TH CEEDRIMS 2024, 5(1), 42–48. https://journal.itny.ac.id/index.php/CEEDRIMS/article/view/5046

Sanjai Siddharthan, M., Aravind, S., & Sountharrajan, S. (2024). Real-Time Road Hazard Classification Using Object Detection with Deep Learning. *Lecture Notes in Networks and Systems, 789 LNNS*. https://doi.org/10.1007/978-981-99-6586-1_33

Siahay, M. C., Ahmad, S. N., Supacua, H. A. I., Ampangallo, B. A., Rachman, R. M., Latupeirissa, J. E., Maitimu, A., & others. (2023). Pembangunan Infrastruktur di Indonesia. TOHAR MEDIA. https://books.google.co.id/books?id=IOvpEAAAQBAJ

Susilo, H., Bani, M. N., Aditya, M. T., Cahyani, E., & Kurniawan, A. M. (2024). ANALYSIS OF ROAD DAMAGE DETECTION USING ORTHOPHOTO MAP FROM UNMANNED AERIAL VEHICLE (UAV-PHOTOGRAMMETRY). Quateknika, 14(1), 53–65. https://doi.org/10.35457/quateknika.v14i1.3258

Vaz, E. da S., Gasparello, L. F., Gouveia, L. T. de, & Senger, L. J. (2023). Detecting Damage in Roads Using Convolutional Neural Networks. *Iberoamerican Journal of Applied Computing*, *11*(1).

Yamaguchi, T., & Mizutani, T. (2024). Road crack detection interpreting background images by convolutional neural networks and a self-organizing map. *Computer-Aided Civil and Infrastructure Engineering*, *39*(11). https://doi.org/10.1111/mice.13132

Zhang, C., Nateghinia, E., Miranda-Moreno, L. F., & Sun, L. (2022). Pavement distress detection using convolutional neural network (CNN): A case study in Montreal, Canada. *International Journal of Transportation Science and Technology*, *11*(2). https://doi.org/10.1016/j.ijtst.2021.04.008