Classification of Cracked Concrete Images Using Convolutional Neural Algorithm

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Classification of Cracked Concrete Images Using Convolutional Neural Algorithm

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Abstract. Concrete is the most widely used construction material in the construction industry. This concrete material is one of the important materials used in infrastructure development in Indonesia. Cracks in a building is something that is avoided in every infrastructure development. Cracking is a condition when water evaporation in concrete occurs very quickly due to changes in weather. Many traditional measures have been taken to determine if a building is cracked or not cracked, but it has resulted in inaccurate conclusions. Indonesia is a country that is doing a lot of significant infrastructure development to become a developed country and improve the country's internal situation. Therefore, one of the basic things in a construction that uses concrete in infrastructure development is very concerned about its condition. Based on these problems, this study uses one method of classifying an object using digital images, namely Convolutional Neural Network to classify cracks in concrete. This study aims to classify images of concrete cracks using the Convolutional Neural Network algorithm. The stages in this study are the preparation of secondary data research data collection which is stored in a file format (.jpg) with tens of thousands of data and the second stage is the pre-processing stage by selecting a class on the image, then compiling a design using the Convolutional Neural Network architecture, training and testing process will be carried out from the results obtained, and accuracy testing will be carried out. The results of this study are expected to provide benefits from seeing the results of the best level of accuracy of classifying concrete crack images using the Convolutional Neural Network algorithm.

INTRODUCTION

Indonesia is located in the trajectory of the Pacific Circum Line and the Indian Himalayan Line and is on the path of the subduction of the earth's plate, namely the subduction of the Indo-Australian Ocean Plate with the Eurasian Continental Plate. This subduction path is the path that causes regional tectonic earthquakes and causes very severe damage. If the path of the earthquake is on the seabed, it has the potential to cause a tsunami disaster[1]. From the earthquake incident, the loss of life that fell was not a direct impact of the earthquake itself, but cracks in the concrete and the collapse of a building were also affected by the earthquake [2]. Cracks in concrete are one of the most common impacts when there is an earthquake and other factors that cause cracks[3].

Detecting a crack early is very important in constructing a building structure because this is the main element in the construction of a building. This seems very simple and sometimes forgotten because conditions like this are difficult to detect properly[4]. The detection that is often done by most people is to see and detect cracks manually[5]. This manual detection has many weaknesses in analyzing because it requires a long observation process[6].

Based on these problems, one technique emerged, namely by classifying images of cracks in concrete. Image classification is a process commonly used to detect objects from existing images. Image classification is a part of Computer Vision[7]. Working in this field greatly facilitates work and interest in using this field is increasing rapidly[8]. One technique for image classification that is well known is Artificial Neural Network which can solve

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problems using internal and external information[9]. This technique has several layers called Multi Layer Perceptron , which is with the concept of fully connecting between neurons so that it has a strong classification ability. However, this technique still has shortcomings in classifying input in the form of images. This is because there are several processes that must be carried out and there are many free parameters or redundant information so that the classification results are less than optimal and take a long time[10]. One of the other technical solutions in solving this problem is to use the Deep Learning method, namely the Convolutional Neural Network method . Deep Learning methods, especially Convolutional Neural Networks, are one of the methods that make Computer Vision develop very rapidly at this time[11]. The Convolutional Neural Network method is very well known in Computer Vision problems because there is a competition for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) (olga R). In image classification, one of the CNN architectures, AlexNet, can increase the accuracy of other traditional methods by more than 10% , and it is also shared by other CNN architectures such as ResNet[12] and GoogLeNet[13].

In previous studies, crack classification in concrete has been developed using a Deep Neural Network with 6 convolutional layers for crack detection on highways and using ConvNet architecture with the highest precision gains reaching 0.8696 and 0.9251[2]. Visual inspection and crack detection are methods that are widely used to obtain information about the best conditions in construction structures and cracks. Meanwhile, if it is done manually, it will take a lot of time and evaluation subjectivity[4]. Based on the problems that have been described and previous research, therefore this study was conducted to see the results of the accuracy of the classification of concrete crack images using the Convolutional Neural Network.

LITERATURE REVIEW

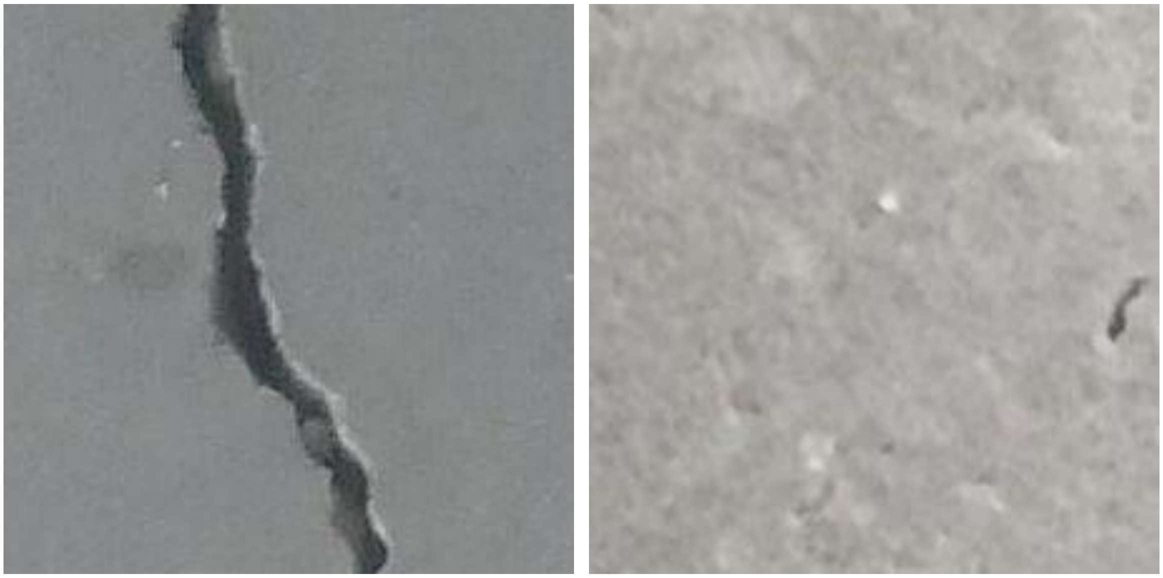
Previous Works

Several studies have been conducted using the Convolutional Neural Network Algorithm method which has been applied to research on the classification of concrete cracks. In a study[2] that discusses Road Deep Crack Detection Using Convolutional Neural Network. This research examines the concrete cracks of roads and sidewalks and uses the Deep Neural Network method with the architecture used is ConvNet. Accuracy results obtained using ConvNet architecture get high accuracy results compared to SVM and Boosting methods with precision acquisition accuracy results of 0.8696 and 0.9251. In a study[14] that discussed Concrete Crack Detection Using the Integration of Convolutional Neural Network and Support Vector Machine conducted research using the Support Vector Machine method. The accuracy results obtained using the SVM method are 0.9076. In a study[4] that discussed Performance Comparison of Pretrained Convolutional Neural Networks on Crack Detection in Buildings conducted research using the Convolutional Neural Network method . The data used are 600,000 training data and 200,000 testing data . The CNN architecture used is AlexNet, VGG 16 , VGG 19 , GoogLeNeeet, ResNet 50 , ResNet 101 , and ResNet 152. The highest and best accuracy results obtained are using the VGG 16 architecture with the best result of 0.96.

DATA AND METHODS

Data

The dataset is an image collection of concrete cracks which is secondary data and is obtained from the Mendeley data source . The data used in this study consists of three types of data, namely training data, data validation , and data testing. The data used consists of image data of concrete cracks with positive and negative class data. Each class data amounted to 20,000 image data, so that all image data used amounted to 40,000 image data in .JPG/JPEG (Joint Photographic Experts Group) format . Image data with dimensions of 224x224 pixels with a resolution of 4032x3024 pixels using RGB (Red , Green , Blue) color modeling which will then be stored in a folder with positive and negative names based on the data class of each data. Figure 1 shows a sample of the data used in this research.



(a) (b)

FIGURE 1. The Example of Cracked Concrate Dataset ((a) Positive Cracked Images and (b) Negative Cracked Images).

Methods

The method used in this study is the CNN (Covolutional Neural Network) method. At this research stage, the initial stage is to look for a literature study on the research conducted, after obtaining a literature study then collecting concrete crack image data obtained from the Mendeley data source. The next stage, namely the pre-processing stage to change the size of the image to be smaller and with the same size, then the data will be processed using the Convolutional Neural Network (CNN) design. The next stage is model training and model testing on image calculations obtained from CNN design. The final stage will get the final result, which is a classification evaluation from the classification that has been carried out at the model training stage and CNN design model testing. These stages are explained in Figure 2.

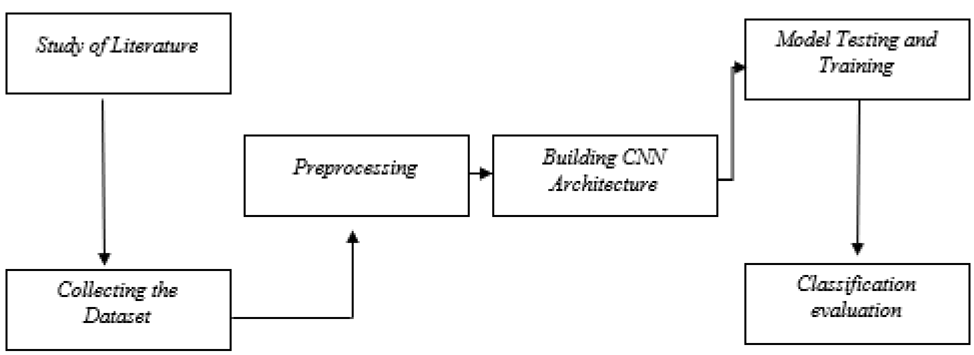


FIGURE 2. Methods to predict cracked concrete.

In preprocessing data, data preprocessing is a step to convert or encode a data into a form which the machine can parse it easily. So that the data features can be easily interpreted by the algorithm. The programming language used is Python with the tensorflow and keras to build neural networks, open cv from image processing and CNN architecture. The computer specifications used are the Tesla K80 GPU. Processor: AMD Ryzen 5 3400G, 16GB RAM, 512GB Nvme Storage. Figure 2 is a CNN modeling process, starting from creating the dataset, dividing the dataset into training and testing data, building the CNN architecture, training and evaluating the model[15]. The concrete crack dataset is a concrete crack image data that is used to transform the image earlier to make it easier for the program to read it. Then, the thing to do is to change all image sizes to be the same for all datasets. after that convert the dataset into a tensor so that the system can process the data, and normalize the data.

TABLE 1. Cracked Concrete Summary

Dataset	Training Image	Testing Image	Validation Image
Positive image	11200	6000	2800
Negative image	11200	6000	2800
Total Image	22400	12000	5600

CNN Architecture

The Convolutional Neural Network method is believed to be able to detect and recognize an object in a very complex digital image because CNN is very good at finding features in the image to the next layer to form nonlinear hypotheses that can increase the complexity of a model. CNN is a development of the backpropagation method that does not require large computations. Technically CNN is an algorithm that can be trained and consists of seve ral stages with the input and output of each stage consisting of several arrays called feature maps[16]. CNN uses three basic ideas, namely: local receptive fields, shared weights, and pooling[17]. Basic CNN architecture can be seen in the Figure 3.

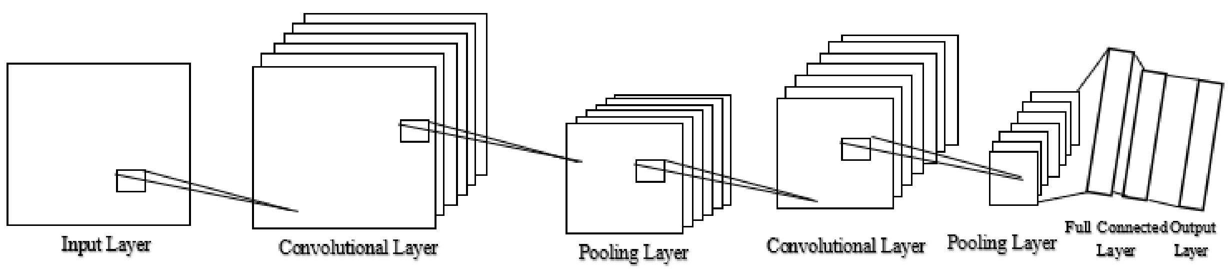


FIGURE 3. Basic Structure of CNN

The data modeling in this study uses the Convolutional Neural Network architecture, using a simple architecture. The simple Convolutional Neural Network architecture in this study uses 2 convolutional layers, global average pooling, and 1 fully connected layer with sigmoid activation. This CNN layer uses the Relu (Rectivied Linear Unit) activation function which functions to take the maximum value for each node calculation. At the data augmentation stage on the cracked concrete image, the next process to be carried out is the training process. This process is done to prevent overfitting. Then at this stage there is a stage to change the pixel size that will be used in this study. to 120 x 120. The Global Average Pooling layer is the same as the dropout layer, which is to prevent overfitting by reducing the number of parameters in the model [18]. A smaller number of parameters will speed up the learning process. Global Average Pooling converts 3D matrices to 1D or vectors. Dense layer is a neural network layer that has one input and an output whose number corresponds to the number of classes classified. Dense layer uses a sigmoid activation function which functions to transform values between values of -1 and 1 to values between 0 and 1. The optimization used in this research uses adam optimization. The hypermeters for model can be seen in the Table 2.

TABLE 2. The hypermeters for Model CNN

Layer (type)	Output Shape	Param #
input_1 (Input Layer)	[(None, 120, 120, 3)]	0
conv2d (Conv2D)	(None, 118, 118, 16)	448
max_pooling2d (MaxPooling2D)	(None, 59, 49, 16)	0
conv2d_1 (Conv2D)	(None, 57, 57, 32)	464
max_pooling2d_1 (MaxPooling2D)	(None, 28, 28, 32)	0
global_average_pooling2D	(None, 32)	0
dense (Dense)	(None, 1)	33
Total Params : 5,121		
Trainable params : 5,121		
Non-trainable params :0		
None		

Adam Optimizer

The optimization process is a solution to the CNN model problem which is called overfitting. Adam (Adaptive Moment Estimation) [19] is an optimization used to increase the accuracy of the model that has been made [20]. Adam optimization is an extension of the stochastic gradient descent which is gaining wider adoption in the development of deep learning [21]. Adam Optimization is very popular in the deep learning field because of the goodness and speed of the results obtained. In practice this optimization works well and is better than other stochastic optimization methods. This optimization is a combination of RMSProp and momentum with several important differences. Adam's optimization is tasked with reducing the speed in a more thorough search and then proceeding to store the exponential decay average of the previous gradient $\widehat{m_t}$. There're means of the first moment $(\widehat{m_t})$ and unconnected variance of the second-moment rupture gradient value $(\widehat{v_t})$[20]. These equations can be shown in equation (1) and (2).

$$\widehat{m_t} = \frac{m_t}{1-\beta^t 2} \tag{1}$$

$$\widehat{v}_t = \frac{v_t}{1-\beta^t 2} \tag{2}$$

RESULT AND DISCUSSION

In this research, we implement modeling using the Convolutional Neural Network architecture with 3x3 convolutional layers, high accuracy results are obtained, with a loss value of 0.5280 and an accuracy of 98.30. The image data entered is in the form of image data with RGB color concentration with a depth of value 3. The epoch carried out at this stage uses 10 epochs and uses adam optimization. It can be concluded that the accuracy obtained is very high with a simple Convolutional Neural Network architecture resulting in a loss value of 0.05280 and an accuracy of 98.30%. At the precision stage for positive and negative in the predicted value is the number of positive data that is classified correctly from the total number of positive data, with a final result of 0.98. Recall or Sensitivity is the number of positive data that is classified correctly from the number of positive data classified as true and positive data classified as false, with an average result of 0.98.

TABLE 3. Confusion Matrix

	Prediction	
	Negative	**Positive**
Negative	6003	66
Positive	138	5793

In the table 3, the 2x2 table is called the Confusion Matrix. The Confusion Matrix contains TP, FP, TN, FN.

TP (True Positive) : The predicted result is positive, and the actual data is positive.
FP (False Positive) : The predicted result is positive, and the actual data is negative.
TN (True Negative) : The result of the predicted data is negative, and the actual data is negative.
FN (False Negative) : The result of the predicted data is negative, and the actual data is positive.,

Precision for Postive and Negative Predicted Value is the number of positive data correctly classified from the total number of positive data overall. So because TP=5793, FP=66, it is calculated using the formula TP/(TP+FP) * 100%= 5793/(5793+66) *100%= 99%.

Recall or Sensitivity is the number of positive data that is classified correctly from the number of positive data that is classified as true and positive that is classified as false. So, because TP=5793, FN=138, it is calculated using the formula TP/(TP+FN) = 98%.

TABLE 4. Accuracy of Training CNN Model

	Precision	Recall	F1-score	Support
Negative	0.98	0.99	0.98	6096
Positive	0.99	0.98	0.98	5931
Accuracy			0.98	12000
Macro avg	0.98	0.98	0.98	12000
Weighted avg	0.98	0.98	0.98	12000

In the table 4, we tested the trained model to predict images that were not in the dataset. The images tested represent of the classes namely: positive and negative. F-1 Score is a balance of recall + precision divided by 2, so the test results are shows that CNN models have been trained and classify with an accuracy of 98.3%.

CONCLUSION

In this research we purpose a method to predict cracked concrete. The model is carried out for the classification of cracked concrete using the Convolutional Neural Network architecture. In CNN modeling, the architecture used to build CNN is the basic CNN architecture with 3x3 layer convolution, with 40,000 image data with two class data that have been trained. at this stage the test results that have been carried out in this study have shown that the CNN model can classify cracked concrete with an accuracy of 98.3% after getting the training process. in terms of increasing the accuracy of predictions on the results of the data issued, it can consider the CNN architecture used such as adding the number of layers, neurons, using better training algorithms, and network structures and can also develop training and validation data which has more varied data.

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REFERENCES

1. N. B. Parwanto and T. Oyama, “A statistical analysis and comparison of historical earthquake and tsunami disasters in Japan and Indonesia,” *Int. J. Disaster Risk Reduct.*, 2014, doi: 10.1016/j.ijdrr.2013.10.003.
2. L. Zhang, F. Yang, Y. Daniel Zhang, and Y. J. Zhu, “Road crack detection using deep convolutional neural network,” 2016, doi: 10.1109/ICIP.2016.7533052.
3. Z. Zhu, S. German, and I. Brilakis, “Visual retrieval of concrete crack properties for automated post-earthquake structural safety evaluation,” *Autom. Constr.*, 2011, doi: 10.1016/j.autcon.2011.03.004.
4. F. Özgenel and A. Gönenç Sorguç, “Performance comparison of pretrained convolutional neural networks on crack detection in buildings,” *ISARC 2018 - 35th Int. Symp. Autom. Robot. Constr. Int. AEC/FM Hackathon Futur. Build. Things*, no. Isarc, 2018, doi: 10.22260/isarc2018/0094.
5. A. Bianchini, P. Bandini, and D. W. Smith, “Interrater reliability of manual pavement distress evaluations,” *J. Transp. Eng.*, 2010, doi: 10.1061/(ASCE)0733-947X(2010)136:2(165).
6. R. S. Adhikari, O. Moselhi, and A. Bagchi, “Image-based retrieval of concrete crack properties for bridge inspection,” *Autom. Constr.*, 2014, doi: 10.1016/j.autcon.2013.06.011.

7. A. Jahangiri, H. A. Rakha, and T. A. Dingus, "Adopting Machine Learning Methods to Predict Red-light Running Violations," 2015, doi: 10.1109/ITSC.2015.112.
8. A. Jahangiri and H. A. Rakha, "Applying Machine Learning Techniques to Transportation Mode Recognition Using Mobile Phone Sensor Data," *IEEE Trans. Intell. Transp. Syst.*, 2015, doi: 10.1109/TITS.2015.2405759.
9. T. Zarra, M. G. Galang, F. Ballesteros, V. Belgiorno, and V. Naddeo, "Environmental odour management by artificial neural network – A review," *Environment International*. 2019, doi: 10.1016/j.envint.2019.105189.
10. W. Saputra, T. Tulus, M. Zarlis, R. W. Sembiring, and D. Hartama, "Analysis Resilient Algorithm on Artificial Neural Network Backpropagation," 2017, doi: 10.1088/1742-6596/930/1/012035.
11. A. Krizhevsky *et al.*, "ImageNet Classification with Deep Convolutional Neural Networks Alex," *Proc. 31st Int. Conf. Mach. Learn.*, 2012.
12. K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," 2016, doi: 10.1109/CVPR.2016.90.
13. C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," 2016, doi: 10.1109/CVPR.2016.308.
14. M. Sharma, W. Anotaipaiboon, and K. Chaiyasarn, "Concrete crack detection using the integration of convolutional neural network and support vector machine," *Sci. Technol. Asia*, 2018, doi: 10.14456/scitechasia.2018.11.
15. F. Rofii, G. Priyandoko, Istiadi, and M. Ifan Fanani, "Modeling of Convolutional Neural Networks for Detection and Classification of Three Vehicle Classes," *J. Phys. Conf. Ser.*, vol. 1908, no. 1, 2021, doi: 10.1088/1742-6596/1908/1/012018.
16. W. Ouyang *et al.*, "DeepID-Net: Deformable deep convolutional neural networks for object detection," 2015, doi: 10.1109/CVPR.2015.7298854.
17. G. LeCun, Y., Bengio, Y., Hinton, "Deep learning. nature 521 (7553): 436," *Nature*, vol. 521, pp. 436–444, 2015.
18. A. Ghosh, B. Bhattacharya, and S. B. R. Chowdhury, "AdGAP: Advanced global average pooling," 2018.
19. D. P. Kingma and J. L. Ba, "Adam: A method for stochastic optimization," 2015.
20. E. Sudarsono, A. Bustamam, and P. P. Tampubolon, "An optimized convolutional neural network using diffgrad for cataract image classification," 2020, doi: 10.1063/5.0030746.
21. V. V. Ramalingam and R. Ragavendran, "Prediction of liver disease using artificial neural network with adam optimizer," *J. Crit. Rev.*, 2020, doi: 10.31838/jcr.07.17.164.