Convolutional Neural Network for Pothole Detection in Different Road and Weather Conditions

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Abstract

Potholes are structural damage to the road which makes them the primary cause of accidents in many countries. In this study, a deep learning algorithm called Convolutional Neural Networks (CNNs) is proposed for pothole detection. In our model, we used three different datasets to justify the robustness of our model in detecting dry and wet potholes. Sigmoid and Softmax activation functions were separately used in the creation of the CNN algorithms. The CNN algorithm in the use of the Sigmoid function achieved 91%, 96%, and 83% accuracy scores over datasets 1,2, and 3 respectively. In contrast to this, the CNN algorithm in the use of the Softmax function has 81%, 96%, and 85% accuracy scores over datasets 1,2, and 3 respectively. This study revealed that the employed CNN algorithm in the use of the Sigmoid activation function can be considered more robust and effective in detecting the potholes images than the CNN algorithm in the use of the Softmax activation function.

Keywords: *Potholes Detection, CNN, Rebostness, Activation Function*

1. Introduction

Because of the large number of daily activities, most people are required to use their vehicles almost every day. Some countries have bad road conditions which need road maintenance. The accident rates are increasing continuously because of potholes on the roads. Not only car accidents, but also motorcycle accidents can have a higher chance of resulting in death than car accidents. The potholes on the roads should be detected and then repaired to reduce the deaths. However, this is not an easy task and is expensive. The use of motorcycles in Indonesia is pretty much and so the motorcycle accident rate is high compared to the other countries in the world [1-2]. In 2020, in the United States of America, motorcycle riders have been involved in crashes more than any other motor vehicle, 27% for motorcycles, 23% for passenger cars, 19% for light trucks, and 3% for trucks. [3]. Well-designed and paved roads can reduce road traffic accidents in the world.

In the literature, different studies about pothole detection were implemented. In [4], a new method to detect potholes based on a location-aware convolutional neural networks system is implemented and they have obtained precision and recall scores of 95.2% and 92.0% respectively. In [5], a CNN-based model has been implemented to detect potholes. The main idea here was to overcome the limitations of various expensive sensors. They have obtained accuracy, sensitivity, and F-measure of 99.02%, 99.03%, and 98.33% respectively. In [6], a pothole detection system was created using 4 models which are YOLO, V3, SSD, HOG with SVM, and Faster R-CNN. They have obtained accuracy scores for YOLO, SSD, HOG and Faster R-CNN of 82%, 80%, 27% and 74% respectively. In [7], a CNN algorithm was employed for the detection of road damage using the images obtained by phones. The proposed CNN algorithm achieved to provide convincing statistical scores in the detection of road damages.

Even if the above-mentioned studies achieved to provide convincing statistical scores based on their aims and objectives, there is an important limitation. The limitation is that they have not focused on the measurement of the robustness of the proposed approaches. Thus, in the present study, we aim to classify pothole detection in roads using different three publicly available datasets. Our model detects pothole images that are taken from a

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mounted camera inside the vehicle or images that are taken from a cell phone on the road. Also, it detects potholes in different seasons i.e. summer and winter, and different road conditions like paved and unpaved roads.

This paper is organized as follows. Section 2 gives information about the materials and methods including the data obtaining, data pre-processing, and architecture of the Convolutional Neural Network (CNN). Then, Section 3 evaluates the efficiency of the employed CNN algorithms for pothole detection. In the end, Section 4 presents the conclusion and future directions.

2. Materials and Methods

Figure 1 presents the proposed pothole detection approach in different road and weather conditions. This approach is treated under three headings: Dataset, Pre-processing, and architecture of the Convolutional Neural Network (CNN).

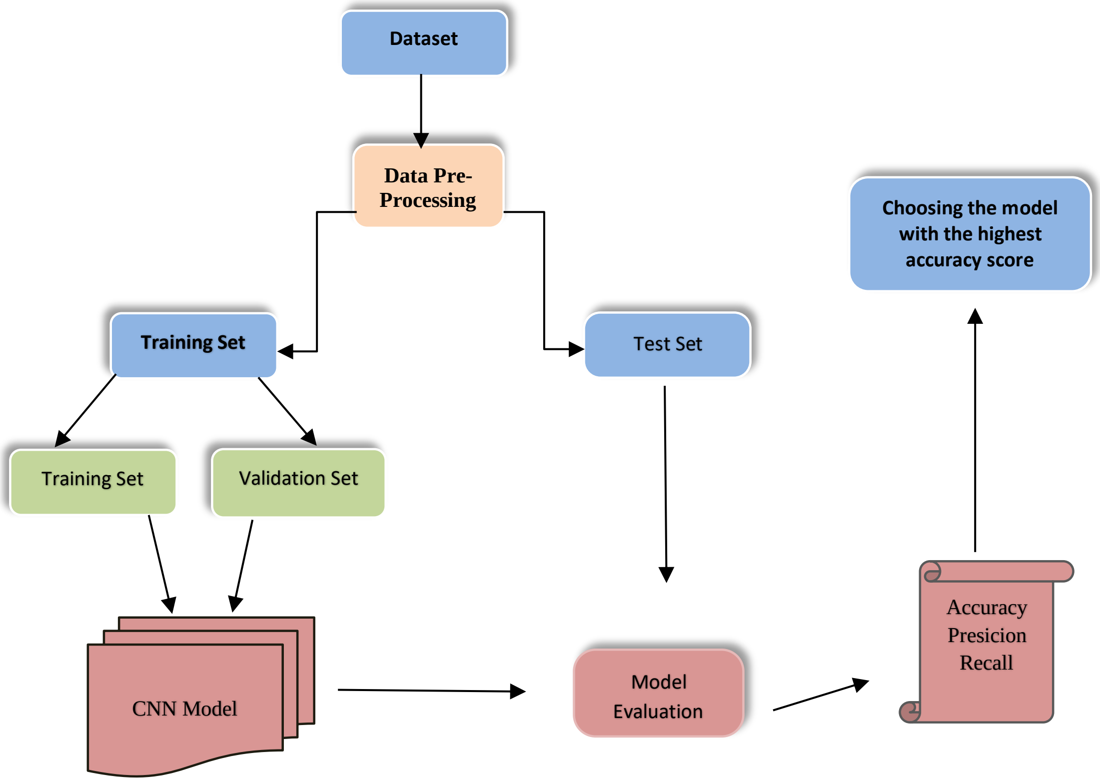

Figure 1. Proposed pothole detection approach in different road and weather conditions.

2.1. Dataset Description and Image Pre-processing

Three different datasets have been used in this study. The first dataset includes 500 samples obtained from [7-8]. The second dataset consists of 681 samples obtained from [9]. Finally, the third dataset has 650 samples obtained from [10]. Figure 2 presents an image from each dataset separately.

Figure 2. Example images used in this study.

2.2. Image Pre-Processing

The original pothole images have high resolution and using the original pothole image may take more computational time. Thus, the images are resized from 3680 x 2760 resolution to 64 x 64 resolution for faster processing and optimal segmentation. Also, the images are rescaled to 0-1 so the network tends to yield better results when the inputs are normalized. Moreover, the images are split into training (72%), validation (18%), and test (10%) images.

2.3. The architecture of the Convolutional Neural Network

The structure of the used CNN is shown in Figure 3, and this section provides information about the Convolutional Layer, Pooling Layer, and Fully Connected Layer (FC Layer) [11]. **Convolutional Layer** is used to reduce the dimensionality of the image. In our model we have 2 convolutional layers, each layer has 32 filters which consist of a 64x64 matrix, it will create 64x64 box in our images that evolve from the first box to the last, performing the convolutional operating on every 64x64 matrix. On the other hand, the **Pooling Layer** purposes to decrease the computational power by doing the dimensional reduction. It provides the maximum value within the covered image by the Kernel. In our model, we have 2 Pooling layers after each convolutional layer, what happens is it selects the maximum element from the region of the feature map covered by our 2x2 filter. Thus, the output after the max-pooling layer would be a feature map containing the most prominent features of the previous feature map. **Fully Connected Layer (FC Layer) flats the** output image into a form of a column vector after converting the image output to a specific form [11]. FC Layer of the first model consists of 3 hidden layers with 260 hidden units in each layer and 2 output nodes which has the Softmax Activation function. FC Layer of the second model consists of 3 hidden layers with 260 hidden units in each layer and 1 output node which has the Sigmoid Activation function. The output of our pooling layer will be the input of the FC Layer which is flattened and then fed into the fully connected layer. For each layer of the Artificial Neural Network, the following calculation takes place $g(Wx + b)$ where x is the input vector, W is the weight matrix, b is the bias vector and g is the activation function which is ReLU in all hidden layers in both models. This calculation is repeated for each layer. After passing through the fully connected layers, the final layer uses the Sigmoid Activation function in the first model and the Softmax Activation function in the second model. And so finally, we have the probabilities of the object in the image belonging to the different classes.

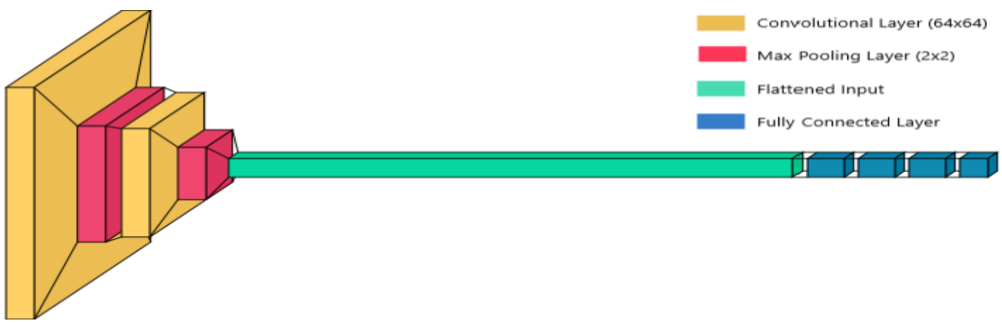

Figure 3. General Structure of the CNN.

3. Results and Discussion

This section provides the performance results of the convolutional neural network (CNN) model using sigmoid and softmax activation functions and subsequently discusses the training, validation, and testing accuracies. Table 1 presents the performance results of the convolutional neural network in detecting dry and wet potholes.

3.1. Evaluation Metrics

The following evaluation metrics were used in the evaluation of the created CNN [12]. The accuracy score is used as an evaluation metric in this study.

$$Accuracy \quad (TN + TP) / (TN + TP + FN + FP)$$

where TP is the True Positive, TN is the True Negative, FP is the False Positive, and FN is the False Negative.

3.2. Training, Validation, and Test Accuracies

As shown in Table 1, our model using the Sigmoid activation function in the output layer has 91%, 96% and 83% accuracy scores over datasets 1,2 and 3 respectively. Another model using the Softmax activation function in the output layer has 81%, 96% and 85% accuracy scores over datasets 1,2 and 3 respectively. Based on these results, it can be said that the Sigmoid activation function was more effective in detecting the potholes images than the Softmax activation function.

Table 1. Evaluation scores of the employed CNN based on three different datasets

Activation Function	Dataset	Training Accuracy (%)	Test Accuracy (%)	Validation Accuracy (%)
Sigmoid	Dataset 1	95	91	83
	Dataset 2	99	96	78
	Dataset 3	95	83	87
Softmax	Dataset 1	92	81	82
	Dataset 2	96	96	90
	Dataset 3	94	85	87

The sigmoid function achieved the highest training accuracy rate (99%) on dataset 2. The softmax activation function provided the highest training accuracy (96%) which is less than the accuracy given by the sigmoid activation function on dataset 2. On the other hand, the best validation accuracy is achieved by the softmax activation function and the least validation accuracy is given by the sigmoid function on dataset 2. These results highlighted the importance of choosing a proper activation function to solve cognitive tasks in convolutional neural network applications.

3.3. Robustness of the used CNN

The test accuracy rates of the CNN in the use of Sigmoid activation function on datasets 1,2 and 3 range from 83% to 96%. On the other hand, the accuracy rates of the CNN that have been created with Softmax activation function on datasets 1,2 and 3 range from 81% to 96%. The difference between the test accuracy rates of CNN (with Sigmoid activation function) is 13% while the difference between the test accuracy rates of CNN (with Softmax activation function) is 15%. It can be inferred from the rates, CNN (with Sigmoid activation function) algorithm can be considered more robust than the CNN (with Softmax activation function).

4. Conclusion and Further Direction

In this study, two convolutional neural networks (CNN) with Sigmoid and Softmax activation functions are created in detecting dry and wet potholes based on three different datasets. CNN algorithm in the use of Sigmoid activation function achieved to provide the best statistical scores for pothole detection in datasets 1, 2 and 3. Thus, Sigmod activation function can be considered as more effective than the Softmax activation function in detecting dry and wet potholes. Additionally, the CNN algorithm that was employed with Sigmoid activation function is more robust than the CNN in the use of Softmax function. The reason behind this is that the difference in test accuracy rate of CNN (with Sigmoid activation function) for three datasets is 2% less than the other. As a further study, a hybrid deep learning approach can be proposed to improve the accuracy score of the CNN (with Sigmoid activation function) that was creted in this study.

References

[1] Wibowo, A., (2010). Analisa Kecelakaan Lalu Lintas Pada Ruas Jalan Utama di Wilayah Kabupaten Sragen Tahun 2002-2006. *Universitas Muhammadiyah Surakarta*.

[2] Saputra, D., (2017). Studi Tingkat Kecelakaan Lalu Lintas Jalan di Indonesia Berdasarkan Data KNKT (Komite Nasional Keselamatan Transportasi) Dari Tahun 2007-2016. *Jakarta: KNKT*.

[3] Injury Facts, Motorcycles. Available at: https://injuryfacts.nsc.org/motor-vehicle/road-users/motorcycles/. Retrieved August 12, 2022.

[4] Chen, H., Yao, M. & Gu, Q. (2020). Pothole detection using location-aware convolutional neural networks. *Int. J. Mach. Learn. & Cyber*, 11, 899–911. https://doi.org/10.1007/s13042-020-01078-7

[5] Hanif, H. M., Lie, Z. S., Astuti, W., & Tan, S. (2020). Pothole detection system design with proximity sensor to provide motorcycle with warning system and increase road safety driving. *In IOP Conference Series: Earth and Environmental Science*, 426(1), 012039.

[6] Ping, P., Yang, X., & Gao, Z. (2020). A deep learning approach for street pothole detection. *In 2020 IEEE Sixth International Conference on Big Data Computing Service and Applications (BigDataService)*, pp. 198-204. IEEE.

[7] Maeda, H., Sekimoto, Y., Seto, T., Kashiyama, T., & Omata, H. (2018). Road damage detection using deep neural networks with images captured through a smartphone. *arXiv preprint arXiv:1801.09454.*

[8] Nienaber, S., Kroon, R. S., & Booysen, M. J. (2015). A comparison of low-cost monocular vision techniques for pothole distance estimation. *In 2015 IEEE Symposium Series on Computational Intelligence (pp. 419-426). IEEE.*

[9] Kumar, A. Labelled image dataset containing 300+ images of roads containing potholes. Available at: https://www.kaggle.com/datasets/atulyakumar98/pothole-detection-dataset. Retrieved August 08, 2022.

[10] Bhutad, S., & Patil, K. (2022). Dataset of road surface images with seasons for machine learning applications. *Data in brief, 42, 108023.*

[11] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521(7553), 436-444.*

[12] Yacouby, R., & Axman, D. (2020). Probabilistic extension of precision, recall, and F1 score for more thorough evaluation of classification models. *In Proceedings of the first workshop on evaluation and comparison of NLP systems* (pp. 79-91).