DETECTION OF BUILDING CRACKS FROM IMAGES IN CLOUD-FOG COMPUTING

Dušan Marković[1], Dejan Vujičić[2], Dijana Stojić[2], Uroš Pešović[2], Siniša Ranđić[2]

[1] *Faculty of Agronomy Čačak, University of Kragujevac, Serbia*
[2] *Faculty of Technical Sciences Čačak, University of Kragujevac, Serbia*

Abstract

Inspection of infrastructures, such as buildings, is significant to detect defects that can cause more damage. Finding defects, such as cracks on the building surface, timely represents information that helps to maintain stability, safety, and duration of the building. Certain parts of the building surface may be difficult to access manually. So, an automated system could be used with unmanned aerial vehicles (UAV) and computer vision techniques coupled with Convolutional Neural Networks (CNNs). Our work aims to present the process of training a neural network model for building crack detection on the Cloud with satisfactory accuracy. And then deploy that model at the Fog level for the new image classification. The subject of research is the distribution of processing tasks from a distance server or Cloud to the Fog node closer to the source to obtain the results of image processing without high value for delay, reduce data transmission to the Cloud platform, and thus reduce the network load and energy consumption on the Cloud.

Keywords: building crack detection, image classification, Convolutional Neural Networks, Cloud-Fog Computing.

INTRODUCTION

Inspection of many infrastructures such as buildings, bridges, or dams and their potential state is important to detect defects that can cause more damage. This information could also extend the duration of the objects. Inspection of potential infrastructure damage, such as building cracks, can be difficult for several reasons. The comprehensive crack classification depends on the reliability and objectivity of the assessment. Certain parts of the building surface may be difficult to access, and there are significant requirements for the time and cost of carrying out the process on external surfaces. This task could be automated using unmanned aerial vehicles (UAV), like drones, to image building surfaces from the air, which be used with computer vision systems. The limitations of standard computer vision techniques could be overcome by its combination with deep learning methods. Among the deep learning field, Convolutional Neural Networks (CNNs) stood out with the high potential in the detection of image features, and they are less sensitive to image noise [1]. Usually, the implementation of neural networks by creating and training models takes place in a Cloud with the support of a high-performance computing system. After training the model, it can be used for the classification of new images and crack detection. In those situations, it means sending all images from the sampling site to the Cloud, which can additionally burden the network, increase the energy consumption of the Cloud, and make it difficult to obtain detection results in real time. To avoid sending all the images to the Cloud for classification, the pre-train model can be transferred to the extension of Cloud computing near the data source, which is known as Fog computing.

This work aims to present the process of training a neural network model for building crack detection with satisfactory accuracy, and then use that model at the Fog level for classification of new images. The subject of research is the distribution of processing tasks from the Cloud to the Fog level closer to the source to obtain the results of image processing without high value for delay, reduce data transmission to the Cloud platform, and thus reduce the network load and energy consumption on the Cloud.

RELATED WORK

The use of deep learning techniques for image segmentation during the inspection of building facades is presented in the paper [2]. The authors stated the importance of the use of unmanned aerial vehicles (UAV) to efficiently inspect all surfaces of buildings to detect defects that may lead to further damage. They presented research aimed at the development of neural networks, which, together with computer vision, would represent a reliable tool for the implementation of the image inspection process.

Another system that deals with the detection of cracks on buildings' surfaces is presented in the paper [3]. The authors analyzed the advantages and disadvantages of neural network models used for crack detection in buildings.

The authors in paper [4] presented a study in which they examined deep learning methods for the classification of cracks on masonry surfaces. They achieved pixel-level crack segmentation in the implementation of deep learning models.

he importance and severity of detecting cracks at the right time are also shown in the paper [5] to ensure the safety of the building. Their focus was on computer vision technology in combination with artificial intelligence. For that purpose, they select the convolution neural network in the realization of the model used for the classification of crack images.

The authors in the paper [6] showed how pre-trained models with CNN can be used for new cases in the detection of building cracks without having to go into the details of the applied algorithms. They concluded that such models could be applied to other datasets with new building crack images and gave satisfactory results.

The use of CNNs in the classification of damage on historic masonry surfaces is presented in the paper [7]. Other CNNs could not identify multiple damages on the dataset images, so the authors proposed a sliding window CNN method. The mentioned method could recognize and locate four types of damage on a surface such as intact, cracked, efflorescence, and spall.

The significance of the use of CNN networks in the detection of images with cracks in buildings is shown in the papers [8], [9], [10], [11], [12].

Assessing the condition of the observed concrete elements based on visible cracks requires additional information, so it is necessary to recognize the disputed patterns on the surface. For this purpose, the authors of the paper [13] presented an automatic approach for the detection of certain crack patterns from images of concrete structures.

Also, in the paper [14], the authors presented an approach for crack detection in glass building facades and concrete.

In the mentioned examples, training neural network models and classification of new images took place on Cloud platforms. In this article, besides the model implementation on the Cloud platform, the goal was its use at the Fog computing level. A similar application of a pre-trained model with the help of CNN networks and its usage on Fog devices is presented in the paper [15] for early detection of forest fires.

A prognostic system based on Fog computing and CNN for optimization in machine processing was introduced in the article [16]. The system is organized so that the signals received during the machining are processed using a trained CNN model deployed at the Fog level to detect undesirable situations. CNN training and system re-optimization is done on the Cloud to use its computing power. In the mentioned article, the use of the CNN models at the Fog computing level results in a reduction in bandwidth requirements and a reduction in data transfer time.

MATERIALS AND METHODS

Our deep learning model implemented for image classification was conducted with the Keras framework. Keras has a high level of abstraction, which is relatively easy to use because it is written in Python programming language. Keras is built on top of the TensorFlow framework and could easily use all its capabilities and cover every aspect of the learning workflow. TensorFlow is an open-source platform for machine learning that has an entire ecosystem of tools and libraries with adequate community support. All these resources support application development based on machine learning by data scientists and Data engineers. [17].

Our proposed model was defined as a Convolutional Neural Network due to its achievements in the Computer vision area.

Besides Computer vision, CNNs have been used also with great success in Natural Language Processing, Speech Processing, Face recognition, etc. Of all the deep learning methods, it is one of the most representative and has attracted attention in industry and academia. CNN is a neural network that can extract features from convolution structures, and it is inspired by visual perception. The advantages of the CNNs are the local connection of neurons, weight sharing, and down-sampling dimensionality reduction that can reduce the amount of data and retain information usefulness [18].

CNN is used as the most attractive deep-learning architecture for the classification of images. The benefits of using CNN for Computer vision cases over traditional neural networks are presented in the following list.

- Weight sharing that reduces the number of parameters and makes it easier to improve generalization and avoid overfitting.
- Concurrent learning in layers causes the model output to be highly reliant on the extracted features.
- Implementation of large-scale networks could be conducted more easily with CNNs than with other neural networks.

The architecture of CNN consists of layers, which could be called multi-building blocks. The main components of CNN are the Convolutional Layer, Pooling Layer, Activation Function (non-linearity), and Fully Connected Layer [19].

We introduced the concept of image classifications in Cloud-Fog computing using a dataset named Concrete Crack Images for Classification from the Kaggle platform [20].

The dataset consists of 2000 images that are negative with no cracks and another set of 2000 positive images with surface cracks [6], [21].

Fig. 1. *Image with negative crack detection*

Fig. 2. *Image with positive crack detection*

An example of images from the used dataset was shown as negative in Fig. 1. and positive with a building crack in Fig. 2.

RESULTS AND DISCUSSION

CNN was implemented and trained on an Ubuntu server, with the assistance of Python and Jupyter Notebook, using the described Keras and Tensorflow support. During the training process, we used 70% of the random images for testing, while the remaining 30% was reserved for model testing. When compiling the model, the following parameters were used: optimizer='Adam', loss='mae', metrics=['acc'].

In configurations, it was defined that the number batch size is 56 and the 40 epoch.

After training, we tested the model on the new dataset and got an accuracy of 93%. The entire process of changing values of the accuracy score during every epoch is shown in Figure 3.

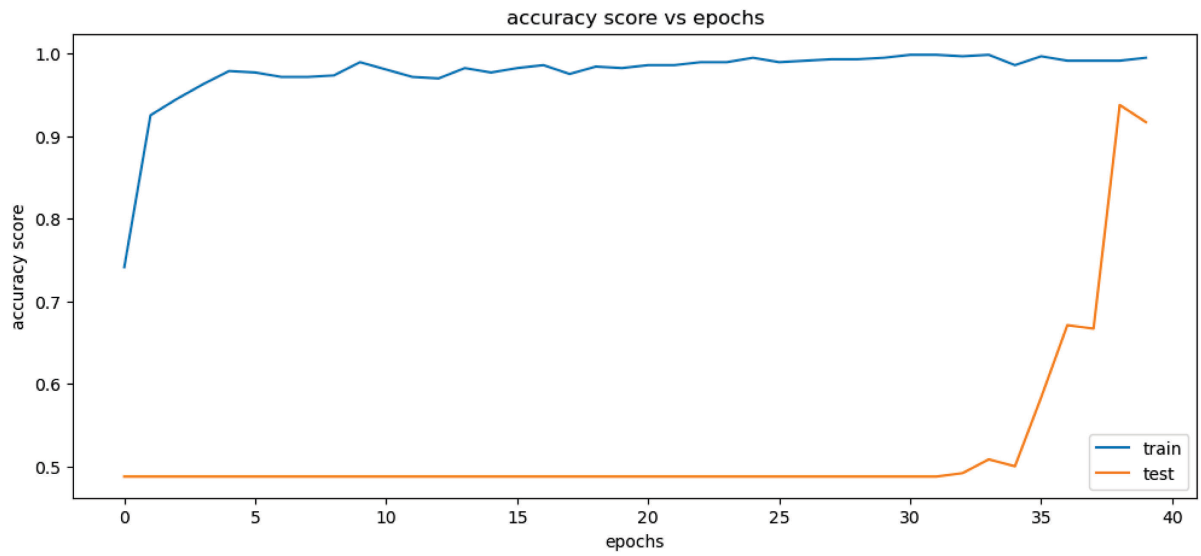

Fig. 3. *Accuracy score during epochs*

In Fig. 4. the Confusion matrix for our training example was shown and could be used to validate the model and calculate other metrics.

Predicted values	Actual values: Positive	Actual values: Negative
Positive	85	12
Negative	2	101

Fig. 4. *Confusion matrix*

One of those metrics is Accuracy, which can be calculated according to formula 1. From the Confusion matrix, we find the following values: TP=85, TN=102, FP=12, FN=2. The same as during system validation, we also get through the formula value of Accuracy, which is 93%.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

The trained model is intended to be placed on a Fog device to detect images close to the source without sending them to a remote server. Fog nodes can be formed with the help of devices such as Raspberry Pi or Pynq Z2 board, which can be included in the network directly at the location where the images are taken and perform their classification without the need to send them to the Cloud.

CONCLUSION

In this paper, the usage of CNN for image classification and detection of building cracks was presented using the concept of Cloud-Fog computing. CNN model implementation was on a server platform with an appropriate dataset. Then, we get a pre-train model that could be used to classify new images of the building surface. The main idea was to distribute processing tasks from a distance server or Cloud to the Fog node close to the source of images. Further research will be in the realization of the pre-train model in FPGA to achieve higher speed in image classification, which means obtaining conditions to process images in real time.

ACKNOWLEDGEMENT

The research presented in this article is part of Project Ref. No. 451-03-47/2023-01/200088 and Project Ref. No. 451-03-47/2023-01/200132 was funded by the Ministry of Science, Technological Development and Innovation, Republic of Serbia.

REFERENCE

[1] Munawar HS, Ullah F, Heravi A, Thaheem MJ, Maqsoom A. Inspecting Buildings Using Drones and Computer Vision: A Machine Learning Approach to Detect Cracks and Damages. Drones. 2022;6(1):5. doi:10.3390/drones6010005

[2] Chen K, Reichard G, Xu X, Akanmu A. Automated crack segmentation in close-range building façade inspection images using deep learning techniques. Journal of Building Engineering. 2021;43:102913. doi:10.1016/j.jobe.2021.102913

[3] Zheng M, Lei Z, Zhang K. Intelligent detection of building cracks based on deep learning. Image and Vision Computing. 2020;103:103987. doi:10.1016/j.imavis.2020.103987

[4] Dais D, Bal İE, Smyrou E, Sarhosis V. Automatic crack classification and segmentation on masonry surfaces using convolutional neural networks and transfer learning. Automation in Construction. 2021;125:103606. doi:10.1016/j.autcon.2021.103606

[5] Wu X, Liu X. Building crack identification and total quality management method based on deep learning. Pattern Recognition Letters. 2021;145:225–231. doi:10.1016/j.patrec.2021.01.034

[6] Özgenel ÇF, Sorguç AG. Performance Comparison of Pretrained Convolutional Neural Networks on Crack Detection in Buildings. In: ISARC Proceedings. IAARC; 2018. p. 693–700. https://www.iaarc.org/publications/2018_proceedings_of_the_35th_isarc/performance_comparison_of_pretrained_convolutional_neural_networks_on_crack_detection_in_buildings.html

[7] Wang N, Zhao Q, Li S, Zhao X, Zhao P. Damage Classification for Masonry Historic Structures Using Convolutional Neural Networks Based on Still Images. Computer-Aided Civil and Infrastructure Engineering. 2018;33(12):1073–1089. doi:10.1111/mice.12411

[8] Wijaya IGPS, Dwitama APJ, Widiartha IBK, Putra SA. Classification of Building Cracks Image Using the Convolutional Neural Network Method. In: 2020 International Conference on Advancement in Data Science, E-learning and Information Systems (ICADEIS). 2020. p. 1–6. https://ieeexplore.ieee.org/abstract/document/9276962. doi:10.1109/ICADEIS49811.2020.9276962

[9] Guo T, Dong J, Li H, Gao Y. Simple convolutional neural network on image classification. In: 2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA). 2017. p. 721–724. https://ieeexplore.ieee.org/abstract/document/8078730. doi:10.1109/ICBDA.2017.8078730

[10] Sultana F, Sufian A, Dutta P. Advancements in Image Classification using Convolutional Neural Network. In: 2018 Fourth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN). 2018. p. 122–129. https://ieeexplore.ieee.org/abstract/document/8718718. doi:10.1109/ICRCICN.2018.8718718

[11] Hallee MJ, Napolitano RK, Reinhart WF, Glisic B. Crack Detection in Images of Masonry Using CNNs. Sensors. 2021;21(14):4929. doi:10.3390/s21144929
[12] Sun Y, Xue B, Zhang M, Yen GG, Lv J. Automatically Designing CNN Architectures Using the Genetic Algorithm for Image Classification. IEEE Transactions on Cybernetics. 2020;50(9):3840–3854. doi:10.1109/TCYB.2020.2983860
[13] Liu Y, Yeoh JKW. Automated crack pattern recognition from images for condition assessment of concrete structures. Automation in Construction. 2021;128:103765. doi:10.1016/j.autcon.2021.103765
[14] Mohammad F, AlZoubi A, Du H, Jassim S. A generic approach for automatic crack recognition in buildings glass facade and concrete structures. In: Thirteenth International Conference on Digital Image Processing (ICDIP 2021). Vol. 11878. SPIE; 2021. p. 52–61. doi:10.1117/12.2601061
[15] Srinivas K, Dua M. Fog Computing and Deep CNN Based Efficient Approach to Early Forest Fire Detection with Unmanned Aerial Vehicles. In: Smys S, Bestak R, Rocha Á, editors. Inventive Computation Technologies. Cham: Springer International Publishing; 2020. p. 646–652. (Lecture Notes in Networks and Systems). doi:10.1007/978-3-030-33846-6_69
[16] Liang YC, Li WD, Lu X, Wang S. Fog computing and convolutional neural network enabled prognosis for machining process optimization. Journal of Manufacturing Systems. 2019;52:32–42. doi:10.1016/j.jmsy.2019.05.003
[17] Keras: Deep Learning for humans. [accessed 2023 Oct 21]. https://keras.io/
[18] Li Z, Liu F, Yang W, Peng S, Zhou J. A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects. IEEE Transactions on Neural Networks and Learning Systems. 2022;33(12):6999–7019. doi:10.1109/TNNLS.2021.3084827
[19] Alzubaidi L, Zhang J, Humaidi AJ, Al-Dujaili A, Duan Y, Al-Shamma O, Santamaría J, Fadhel MA, Al-Amidie M, Farhan L. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. Journal of Big Data. 2021;8(1):53. doi:10.1186/s40537-021-00444-8
[20] Concrete Crack Images for Classification. [accessed 2023 Oct 21]. https://www.kaggle.com/datasets/arnavr10880/concrete-crack-images-for-classification
[21] Zhang L, Yang F, Daniel Zhang Y, Zhu YJ. Road crack detection using deep convolutional neural network. In: 2016 IEEE International Conference on Image Processing (ICIP). 2016. p. 3708–3712. https://ieeexplore.ieee.org/document/7533052. doi:10.1109/ICIP.2016.7533052