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Review paper

OVERVIEW OF ARTIFICIAL NEURAL NETWORKS APPLICATION IN DAMAGE DETECTION OF MASONRY STRUCTURES

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Abstract

In order to ensure the durability of masonry structures, prevent their deterioration and serious damage, it is necessary to carry out regular inspections of the condition of building elements. Determining the condition of masonry structures is most often done manually, by visual inspection, which is a time-consuming process, the quality of which largely depends on subjective feeling. As there is an increasing need for automated data processing and work processes today, in recent years there has been an increasing application of artificial intelligence in the process of segmentation and damage detection in masonry structures using Artificial Neural Networks (ANNs). The aim of this paper is to carry out a detailed analysis of the application of artificial intelligence in the segmentation of masonry elements and the detection of damage to masonry structures through a review and analysis of papers published in the literature.

Key words: *Masonry Structures, Artificial Neural Networks, Damage Detection*

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1. INTRODUCTION

Masonry structures represent the largest part of building structures in the world, of which there are a large number of historical buildings that are part of the cultural heritage, and in addition, masonry structures are still widely used today for the construction of modern structures [1,2]. The materials used for the construction of masonry structures are among the oldest used for the construction of buildings, from stone masonry elements to those made of clay, as well as modern construction materials. Structural elements in masonry structures are formed from masonry elements (bricks, blocks, irregular stone, etc.) that are joined together with or without mortar [3]. Structural and non-structural elements formed by masonry are one of the main components in both modern and historical buildings around the world.

Cultural heritage is of great importance for the preservation of the nation's history and the transmission of the precious knowledge and skills of the ancestors. Due to the aging process, activities due to use, as well as unpredictable natural disasters, historical buildings deteriorate over time. The existence of a large number of old masonry structures shows that their lifespan can be significantly extended. In order to ensure the structural integrity of masonry buildings, regular inspection and maintenance are required [4].

As a result of the process of gradual deterioration, different forms of damage will be visible on the structures, which mainly leads to a decrease in load capacity, stiffness and integrity. Damage is always reflected on the surface of structures in the form of cracks, efflorescence, peeling. Cracks in masonry walls are a common problem that can have significant structural and aesthetic implications, so it is considered that cracks are the main concern for the durability and safety of masonry structures, so it is of great importance to identify and localize surface damage quickly and efficiently [5]. The key task for ensuring the safety and longevity of masonry structures is the timely detection of damage. The goal of damage detection is to identify and locate cracks, that is, the separation of masonry elements, which needs to be detected at the earliest stage in order to avoid unwanted situations, such as damage or collapse of the structure due to large cracks, and this is one of the key steps in analyzing the stability and load-bearing capacity of masonry structures.

In the process of inspection of masonry structures, detection and definition of damage pathology (cracks, breakage, etc.), traditional techniques are used mainly in the form of visual and manual inspection [2]. Manual inspection is the most common in practice due to its simplicity during the identification and assessment of surface damage of masonry structures. This approach is expensive and sometimes difficult to implement, because there are parts of objects with limited access and difficult to reach. To detect surface damage in real practice, a visual inspection performed by trained inspectors is used to detect various defects in historical structures in situ supplemented by professional equipment. Applying this method in the crack detection process has significant operational advantages, but requires an extremely high level of professional experience and is expensive, while operators must be able to fully understand the properties of the inspected cracks and determine whether repairs are needed. Manual and visual inspection can achieve an effective performance in most scenarios, however sometimes this approach is unreliable as serious damage may not be detected [5,6]. One of the methods for damage detection is based on sensor systems that are integrated and installed in historical structures, which also requires a professional workforce to operate them. In recent years, advances in laser scanning and photogrammetry have begun to change the construction industry as such techniques are able to rapidly and remotely capture objects and features in image and point format using drones [2,4]. However, in this approach, it is difficult to create appropriate datasets as the images become more complex, their complexity increases and it is difficult to distinguish the target and background region, i.e. the detection performance decreases, because the wall surface is complex.

Research in this area is increasingly focused on the development of new and innovative methods for fast, accurate and non-destructive damage detection. As the process of damage detection can be considered multidisciplinary, in recent years there has been an attempt to apply artificial intelligence in this area, i.e. in image processing for the quantification of deformations and damage detection on the wall. Image-based analysis can be considered a key step in stability analysis, condition assessment and damage detection of objects, i.e. in the detection and delineation of their structural components, which is a key and initial step in the process of documenting the state of a masonry structure. As a brick wall is a heterogeneous material that contains individual masonry elements (bricks, blocks, hewn and irregular stones and others) and bonding agents (mortar, clay, chalk, etc.) between the main elements, which connect them, it is often necessary to determine the original arrangement of brick and mortar parts of masonry components that are damaged, or obscured by various objects such as ornaments or vegetation [7,8]. In recent years, deep learning techniques have been applied to the analysis of masonry wall images, where large amounts of annotated data need to be provided to achieve high accuracy, which can be difficult. The aim of this work is to present the possibility of applying artificial intelligence in the segmentation of masonry walls and damage detection through the presentation and analysis of works available so far in the literature.

2. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) represent a special category of machine learning models inspired by the human brain. A specialized subtype of ANN is convolutional neural networks (CNN). CNN was created in response to the need for more efficient image analysis, because classical ANN networks were not adequate for processing data with a large number of dimensions (eg images with millions of pixels). CNN uses the basic principles of ANN, but adds specialized layers: Convolutional layers - extract features from images through filters, Pooling layers - reduce data dimensionality without losing key information, and Fully Connected layers (FCN) - perform classic ANN processing for decision-making at the end of the network. According to these possibilities, this type of network has also found application in many areas of construction, where an image can be used as an input data in the network. This era of application is being significantly refined and applied after the first applications of ANN in structural modeling [9], when Ghabousi et al. first showed possible applications in this area.

Over the last decade, ANNs have been applied in many areas of civil engineering, including soil behavior, flow, pile bearing capacity, support structure and slope stability, site characterization, tunnel design, and structure identification [10,11]. The application of ANN is especially pronounced in construction problems where, until now, it was not possible to define numerical dependencies.

During the creation, training and testing of a neural network, it can be taught to perform a specific task on a specific example, that is, a set of specific data that is used for training the network, just as humans process information and learn on a specific example. That is why the correct definition of input data, their segmentation, classification, normalization and preparation is a key process for the quality operation of the network itself.

Finding the best network model for a particular case is a difficult task that generally requires repeated testing and evaluation of results. The process of solving problems using ANN is reduced to learning or training and continues until the error between the response of the neural network and the desired output (called the goal) is minimized for the entire set of pairs: given input - known output. Such research has shown that CNNs are very suitable for solving problems that can be applied in construction. CNNs have made significant progress in the digital analysis of construction objects, and especially in the segmentation and detection of damage to masonry structures. The first significant CNN architecture, LeNet, was developed at AT&T Bell Laboratories during the period 1988-1998, laying the foundation for later developments. A large number of researchers improved this model, which resulted in the emergence of standard datasets for machine learning research and training. One of the representative ones is CIFAR-10 as well as ImageNet as a large visual database designed for use in visual object recognition software research. Since 2010, the annual Large Scale Visual Recognition Challenge (LSVRC) has been held, featuring AlekNet in 2012, which achieved an error rate of 15.3%, thanks to the development of parallel graphics processors, and ZFNet in 2013, which achieved an error of 13.5%. Its structure is similar to the AlexNet network, except that it uses the ReLU function. In 2014, at the same competition, Google presents the GoogLeNet network, which achieves an operating error of 6.7%, when in the same competition they share the first place with the VGGNet network, whose error is 7.4%, which is much simpler. All these results speak in favor of the quality and potential that these networks can have, and thus they are becoming more and more common in various applications [12].

CNN models have found a particularly significant application in wall segmentation and crack detection. U-Net is one of the first architectures specialized for segmentation, while the later DeepLabV3+ and FPN models improved the accuracy of wall construction analysis [9]. FPN (Feature-Pyramid-Network) is an FCN network for object detection and has shown good results in construction applications. LinkNet is a special type of FCN networks developed for pixel-by-pixel segmentation that can be used for real-time applications [2]. In order to improve performance, achieve high accuracy, robustness and adaptability in image classification, CNN models are becoming more and more complex.

It is shown that the complexity of the model and the obtained results are extremely dependent on the availability of training data. In paper [6], the models show good results in the detection of cracks on masonry facades, however, the performance of these models largely depends on the availability of training data. In addition, it is shown that not only the input data is crucial for certain types of problems, but that many problems also depend on the experience of the one who processes them. Based on the analysis of the review papers presented in the literature so far [10,11,13,14,15], it can be concluded that artificial neural networks have found their application in almost all areas of construction engineering and that due to the greater flexibility of work, the results obtained can be much better than if some of the traditional methods for solving construction problems were applied.

3. REVIEW OF PAPERS DEALING WITH DAMAGE DETECTION USING ARTIFICIAL NEURAL NETWORKS

In this part of the paper, different approaches to the application of artificial neural networks, i.e. deep learning in the detection, segmentation and analysis of damage to masonry structures are presented.

K. Chaiyasarn et al. [4] developed an automatic system for crack detection in masonry structures using a combination of convolutional neural networks and Support Vector Machines (SVM). Data was collected using a drone and a DSLR camera at historical sites. VGG16 CNN architecture was used for feature extraction, while SVM served as a classifier. The model was evaluated using accuracy, precision, sensitivity and F1-score metrics. The CNN-SVM combination achieved 86% accuracy and an F1-score of 78%, outperforming the classic CNN model (79.35% accuracy). The results show that the combination of CNN and SVM enables more accurate crack detection compared to the stand-alone CNN model.

In further research, K. Chaiyasarn et al. [16] deal with the application of CNN in crack detection, where they compared the performance of different classifiers: Softmax, Support Vector Machines and Random Forest (RF). The models were evaluated based on the accuracy, precision, sensitivity and F1-score metrics on the validation and test sets. The CNN+SVM model achieved the best performance with an accuracy of 86% on the validation set and 74% on the test set, with an accuracy of 89% and an F1-score of 87%. The CNN+RF model had an accuracy of 82% on the validation set, while the CNN+Softmax had the worst performance due to unbalanced classes. The results show that the combination of CNN for feature extraction and SVM for classification enables higher accuracy and robustness in crack detection compared to other classifiers.

N. Wang et al. (2018) [5] developed an automatic damage classification system on historic masonry structures using CNN. The system is trained to classify four types of damage: intact brick, crack, efflorescence and spalling. AlexNet and GoogLeNet models were used. GoogLeNet achieved 94.3% accuracy on a large dataset, while AlexNet achieved 92.1%. On a smaller dataset, GoogLeNet achieved 89.7% accuracy and AlexNet 87.4%. The conclusion of the paper is that GoogLeNet achieves better performance than AlexNet and enables higher accuracy and sensitivity in damage classification on historical masonry structures.

Luqman A. et al. [17] used Faster Region Convolutional Neural Networks (FRCNN) for damage detection and localization of masonry structures based on a set of historical wall images collected using a DJI Phantom 4 drone and a DSLR camera. The algorithm consists of a Region Proposal Network (RPN) for generating damage region proposals and Fast R-CNN for damage classification and localization. ZF-net architecture was implemented to improve efficiency. Model evaluation was performed using Mean Average Precision (mAP), with the model achieving 96.50% mAP. The paper shows that Faster R-CNN enables high accuracy and speed in automatic detection and localization of damage to masonry structures.

Yahya I. et al. [7] developed a technique for automatic brick segmentation on brick walls using a U-Net convolutional neural network for marker detection and the Watershed algorithm for precise brick segmentation. The experiment was conducted on a dataset of 162 images of walls from archaeological sites and modern buildings. The U-Net architecture uses ReLU activation and Max Pooling layers in the encoder, while the decoder uses up-convolution layers for image reconstruction. The Adam optimizer was used to train the network with a binary cross-entropy loss function. The performance of the model was defined based on the F1-score, which ranged from 76% to 97%, depending on the type of wall. The

Watershed algorithm showed better performance compared to Connected Component Analysis (CCA), especially on walls with complex brick-mortar structures.

D. Brackenbury et al. [18] developed an automated system for detecting defects (cracks, landslides, mortar loss, vegetation) on masonry arch bridges using the GoogleNet Inception v3 architecture, trained by transfer learning. Nine multi-story arched bridges were photographed, which generated around 24,500 images. The best results were achieved when mortar and brick were completely separated, with an accuracy of 94.7%, a response of 95.3% and an F1-score of 95.0%. Mortar and brick separation significantly increased classification accuracy and reduced performance variation between different masonry images. The strategy without mortar separation achieved the lowest accuracy, with an F1-score of 83.6%, due to confusion between cracks and mortar lines. The paper shows that the complete separation of mortar and bricks enables greater accuracy and reliability in the detection of defects on masonry arched bridges.

N. Wang et al. [19] developed an automated damage detection system on historic masonry buildings using Faster R-CNN with ResNet101 architecture. The model achieves high precision (AP 0.999 for flowering, 0.900 for collapse, mAP 0.950) and enables accurate detection, localization and classification of damage even in real conditions. They also implemented a mobile system for real-time inspection using IP cameras and smartphones.

A. Rózsás et al. [20] developed an automated method to quantify the similarity of cracks in masonry structures using deep neural networks. Using an 8-layer CNN model, they generated numerical crack similarities for objective damage assessment. Due to the lack of data, they created synthetic crack images using the Markov-walk algorithm. The model achieved an accuracy above 99% in crack classification, proving the high precision and reliability of the approach.

Yahya I. et al. [8] developed a fully automatic algorithm for the detection, segmentation and reconstruction of brick walls using the U-Net network and GAN models. Wall segmentation includes three classes: bricks, mortar and damaged regions, while GAN models enable virtual reconstruction of hidden parts of the wall. The Watershed algorithm precisely extracts the contours of the bricks, and the style transfer enables the transfer of color and texture. The model achieves an F1-score of up to 97.58%, proving the high precision of segmentation and reconstruction.

M. Sakamoto et al. [21] developed an improved method for the automatic extraction of stone blocks from the walls of historical buildings by combining multiscale image segmentation and a three-phase Stacked Conditional GAN (cGAN) network. Multiscale segmentation generates block polygons, while cGAN improves edge detection and fuzzy contour reconstruction. The method significantly increases segmentation accuracy, allowing better separation of stone blocks and reducing the need for manual parameter setting.

D. Dais et al. [1] focused on improving crack detection accuracy by testing different pre-trained CNN architectures. MobileNet proved to be the most accurate model, achieving 95.3% accuracy in patch classification and 79.6% F1-score for pixel-level segmentation. Kaiwen C. et al. they further investigated this problem by using drones for facade inspection. Their system, a combination of a CNN for patch-level classification and a U-Net model for pixel-level segmentation, achieved an F1-score of 96%, outperforming traditional crack detection methods.

In the paper Kaiwen C. et al. [22] developed an automated system for crack segmentation on building facades using UAV imagery and deep learning. Patch-level classification is performed by the CNN model, while U-Net performs crack segmentation at the pixel level. The CNN model achieves an accuracy and F1-score of 94%, while U-Net achieves 96%. The two-stage CNN+U-Net model outperforms Canny Edge Detector and stand-alone U-Net, providing higher detection accuracy. The study shows that the combination of patch-level classification and pixel-level segmentation enables accurate and robust detection of cracks on UAV images of facades.

In the continuation of the research, Yahya I. et al. [23] developed an end-to-end blind inpainting algorithm for the detection and reconstruction of damaged parts of brick walls. They used U-Net for segmentation and two GAN models for automatic damage detection and filling. The first GAN recovers the structure of the wall, while the second predicts the pixel color. The efficiency of the algorithm is confirmed by PSNR and SSIM metrics. The evaluation shows that the combination of U-Net segmentation and two GAN models enables high precision in the generation and realistic filling of the hidden parts of the walls.

The paper of D. Loverdos and V. Sarhosis [2] deals with the automation of brick segmentation and crack detection on brick walls using image processing and machine learning. Various deep neural network architectures, including U-Net, DeepLabV3+, LinkNet, and FPN, have been used for pixel-level segmentation. Watershed algorithm was applied for precise segmentation of bricks, while Inverted Distance Transform (IDT) and H-minima transform improved the accuracy of marker generation. U-Net achieved the best results, with an F1-score of 97.58% on bricks and 94.19% on pixels for fine cut stone and 79.93% for slate. The combination of CNN and Watershed algorithm enables precise and robust segmentation even in complex conditions.

The paper of L. Minh Dang et al. [24] focuses on automatic segmentation and length measurement of cracks in brick walls using deep learning. An extensive database of manually annotated cracks was created, and three neural network architectures were tested: U-Net, DeepLabV3+, and Feature Pyramid Network (FPN). The DeepLabV3+ model with ResNet-50 as the base model achieved the best result (IoU = 0.97) and was chosen for the final implementation. The Mask-RCNN model was used to detect bricks, allowing precise measurements of cracks in millimeters. The proposed method significantly improves the accuracy of segmentation and enables a quick assessment of damage severity, reducing the subjectivity of manual inspections.

The paper of S. Katsigiannis et al. [6] deals with the detection of cracks in brick walls using deep and transfer learning. The dataset consists of 700 images of facades with different types of cracks and complex backgrounds. Pre-trained CNN models, including MobileNetV2, InceptionResNetV2 and Xception, were tested with two training strategies: end-to-end and fine-tuning back layers. MobileNetV2 achieved 100% accuracy and F1-score with end-to-end training with data augmentation, while the fine-tuning strategy led to a decrease in accuracy (F1-score 92.99%). The results show that end-to-end training is a superior strategy for adapting models to masonry structures, while MobileNetV2, due to its high accuracy and small model size, enables the application of mobile devices and drones.

In the paper of Sheetal Sharma [25], an automatic system for damage detection and segmentation on historical masonry buildings was developed using Mask R-CNN model based on DenseNet architecture. The model uses Region Proposal Network (RPN) for damage identification and RoI Align for precise pixel-level localization. The dataset contains images of walls with efflorescence and spalling, manually annotated with bounding boxes and binary masks. The model achieves an accuracy of 99.9% and an F1-score of 98.5% for efflorescence, while for spalling the accuracy is 90% and an F1-score of 87.5%. Mask R-CNN on the DenseNet framework showed superior performance compared to Faster R-CNN and U-Net models, enabling high accuracy segmentation and damage classification of masonry objects.

Qinghua L. et al. [26] propose a new DeepCrackAT architecture for brick wall crack segmentation, aiming to improve accuracy in scenarios with different crack widths and complex backgrounds. The model uses a combination of Hybrid Dilated Convolution (HDC) to increase the receptive field and Tokenized Multi-Layer Perceptron (Tok-MLP) for optimized projection of high-dimensional features into a more compact space, thereby reducing the number of parameters and improving noise immunity. The model achieves an F1-score of 76.67% and an IoU of 64.44% on the Masonry dataset, while the results on the Rissbilder dataset are somewhat weaker. Experiments have shown that DeepCrackAT outperforms Unet, SegNet, DeepLabV3+ and UneXt models, especially in the segmentation of cracks.

D. Marín-García et al. [27] developed a deep learning model for efflorescence detection and classification on brick facades using YOLOv5. The model discriminates bricks that only require cleaning from those that need to be repaired, achieving an mAP of 0.894 after 100 training epochs. The classification accuracy was 85% for "clean" and 82% for "repair". The results show that YOLOv5 enables fast and accurate detection of efflorescence, even in real-time conditions.

Yahya I. et al. [28] developed an end-to-end deep learning-based system for the analysis, reconstruction, and stylization of brick walls. The U-Net network segments the wall into bricks, mortar and damaged regions, while two GAN models restore the structure and color of the obscured parts. Style transfer allows you to move textures and colors between walls. The model achieves an F1 segmentation score of 83.6% and a realistic wall reconstruction, proving the high precision and applicability of the method.

A. Iannuzzo et al. [29] deal with the identification of the causes of cracks in masonry structures using artificial neural networks. The research combined the piecewise-rigid displacement (PRD) method to quickly generate data on possible foundation settlement scenarios with neural network models that analyze crack patterns. Testing has shown that the model achieves an accuracy of 98.3% for vertical settlement and 97.1% for horizontal settlement, enabling automatic and precise analysis of the causes of cracks in masonry structures.

4. ANALYSIS OF THE PRESENTED PAPERS

As damages to masonry structures, especially those of historical importance, are frequent, and their knowledge is essential for the stability and durability of the building, it is sometimes necessary to determine the cause of their occurrence in the shortest possible period. The process of damage detection used to be laborious and time-consuming, so the use of modern means to detect them has been increasing in recent years. As part of this paper, papers were analyzed in which artificial intelligence was used, especially deep neural networks, in the area of damage detection and analysis of masonry structures. A total of twenty-one papers published in the period from 2018 to 2024 were analyzed, which mainly dealt with historical buildings at specific archaeological sites, brick bridges and facades of older buildings where cracks were detected and degradation of building materials was performed. The largest number of papers was published in 2023, which may indicate the increased application of deep learning in the analysis of masonry structures and the improvement of segmentation and damage detection methods. Most of the papers deal with the detection of cracks, classification and analysis of damage, segmentation and reconstruction of walls as well as detection and segmentation of wall elements when performing the following activities:

- Classification – categorization of damage (eg cracks, collapse, efflorescence).
- Segmentation – precise marking of damage areas at the pixel level.
- Detection – finding damage in the image using bounding boxes.
- Reconstruction - filling in damaged parts of the wall.

Certain areas in which the analyzed papers deal with are also noted.

Table 1. Areas of application in the analyzed works

Areas of application	Papers
Crack detection	[1],[4],[6],[16],[22],[24], [26]
Damage classification and analysis	[5], [19], [20], [25], [27], [29]
Segmentation and reconstruction of walls	[8], [21], [23], [28]
Brick/mortar detection and segmentation	[2], [7], [17], [18]

Analysis of the available papers in the literature shows that they have been used:

- Convolutional Neural Networks (CNN) for feature extraction.
- Transfer learning to improve model performance.
- Generative adversarial networks (GAN) for wall reconstruction and stylization.
- Region Proposal Network (RPN) and Mask R-CNN for damage detection.
- Watershed algorithm for precise brick segmentation.
- Piecewise Rigid Displacement (PRD) + ANN for crack cause analysis.
- DeepLabV3+, U-Net, YOLOv5 and other segmentation architectures.

The following neural networks were used:

- CNN architectures: VGG16, AlexNet, GoogLeNet, Inception v3, ResNet34, ResNet50, MobileNetV2, DenseNet, Xception.
- Specialized architectures: Faster R-CNN, Mask R-CNN, U-Net, DeepLabV3+, Feature Pyramid Network (FPN).
- GAN models: Conditional GAN (cGAN), Style transfer GAN.
- Multilayer Perceptron (MLP) in ANN models for crack analysis.

The most frequently used methods of validation and achieved values for the evaluation of applied models have been carried out:

- Accuracy: from 79% to 100% depending on the model.
- Precision, Recall, F1-score: values between 76% and 99.9%.
- Mean Average Precision (mAP) for damage detection and localization.
- Intersection over Union (IoU) up to 0.97 for precise segmentation.
- PSNR and SSIM for evaluating the quality of wall reconstruction.

As in the process of forming a network for the accuracy of the achieved results, a significant number of data in the analyzed papers was:

- Less than 1,000 images with 76-94% accuracy achieved
- 1,000 - 10,000 images with 85-97% accuracy achieved
- More than 10,000 images with 92-100% accuracy achieved

5. CONCLUSION

The largest number of papers focuses on historical buildings and archaeological sites, which shows the researchers' interest in preserving cultural heritage, while a smaller number of papers is focused on modern construction objects. Most of the papers deal with segmentation, because the precise detection of damage and boundaries of the masonry element is crucial for the analysis of the stability and durability of masonry structures. Larger datasets generally lead to better results, but some models successfully use transfer learning to compensate for the lack of data. Deep learning outperforms traditional methods in most cases, so it can be assumed that in the future classical image processing methods will be used as auxiliary techniques. The application of neural networks in damage detection can reduce the need for skilled labor, speed up inspection processes and enable more objective damage assessment. In this way, it can help civil engineers and archaeologists when studying the condition and stability of masonry structures during maintenance, documenting or assessing the required level of protection, especially for buildings of historical importance.

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REFERENCES

[1] Dimitris Dais, Ihsan Engin Bal, Eleni Smyrou, Vasilis Sarhosis: **Automatic crack classification and segmentation on masonry surfaces using convolutional neural networks and transfer learning**, *Automation in Construction*, Vol. 125 103606, 2021, ISSN 0926-5805 https://doi.org/10.1016/j.autcon.2021.103606

[2] Dimitrios Loverdos, Vasilis Sarhosis: **Automatic image-based brick segmentation and crack detection of masonry walls using machine learning**, *Automation in Construction*, Vol. 140 104389, 2022 ISSN 0926-5805 https://doi.org/10.1016/j.autcon.2022.104389

[3] Bojan K. Milošević: **AmQuake: Statička i dinamička analiza zidanih konstrukcija**, Fakultet za mašinstvo i građevinarstvo u Kraljevu, Univerzitet u Kragujevcu, 2022, ISBN 978-86-81412-18-3

[4] Krisada Chaiyasarn, Wasif Khanb, Luqman Ali, Mayank Sharma, Daniel Brackenbury, Matthew DeJong: **Crack Detection in Masonry Structures using Convolutional Neural Networks and Support Vector Machines**, 35th *International Symposium on Automation and Robotics in Construction*, Berlin, Germany, 118-125, 2018, DOI: https://doi.org/10.22260/ISARC2018/0016

[5] Niannian Wang, Qingan Zhao, Shengyuan Li, Xuefeng Zhao, Peng Zhao: **Damage Classification for Masonry Historic Structures Using Convolutional Neural Networks Based on Still Images**, *Computer-Aided Civil and Infrastructure Engineering*, 1–17, 2018, DOI: 10.1111/mice.12411

[6] Stamos Katsigiannis, Saleh Seyedzadeh, Andrew Agapiou, Naeem Ramzan: **Deep learning for crack detection on masonry façades using limited data and transfer learning**, *Journal of Building Engineering*, Vol. 76, 107105, 2023, ISSN 2352-7102, https://doi.org/10.1016/j.jobe.2023.107105

[7] Yahya Ibrahim, Balazs Nagy, Csaba Benedek: **CNN-based Watershed Marker Extraction for Brick Segmentation in Masonry Walls**, Proceedings Image Analysis and Recognition: *16th International Conference*, ICIAR 2019, Waterloo, Canada, Part I, 332 – 344, August 27–29, 2019, https://doi.org/10.1007/978-3-030-27202-9_30

[8] Yahya Ibrahim, Balázs Nagy, Csaba Benedek: **Deep Learning-Based Masonry Wall Image Analysis**, *Remote Sens.*, Vol. 12, 3918, 2020, https://doi.org/10.3390/rs12233918

[9] Luiza Dihoru, Colin Tazlor, Adam J. Crewe, nicholas A. Alexander: **A Neural Network Approach for Dynamics Identification of Reinforced Masonry Structures**, *14th World Conference on Earthquake Engineering*, Beijing, China, October 12-17, 2008.

[10] M. Lazarevska, M. Knezevic, M.Cvetkovska, A.Trombeva-Gavriloska: **Application of artificial neural networks in civil engineering**, *Tehnički vjesnik*, Vol. 21, No. 6, 1353-1359, 2014, ISSN 1848-6339

[11] Lagaros, N. D: **Artificial Neural Networks Applied in Civil Engineering**, *Appl. Sci.*, Vol. 13, 1131, 2023, https://doi.org/10.3390/app13021131

[12] Marko M. Dabović, Igor I. Tartalja: **Duboke konvolucijske neuronske mreže – koncepti i aktuelna istraživanja**, *Zbornik 61. Konferencije za elektroniku, telekomunikacije, računarstvo, automatiku i nuklearnu tehniku, ETRAN 2017*, Kladovo, VI1.1.1-6, 2017, ISBN 978-86-7466-692-0

[13] Pengzhen Li, Shengyong Chen, Yujun Zheng: **Artificial Intelligence in Civil Engineering**, *Mathematical Problems in Engineering,* Volume 2012, Article ID 145974, 22 pages, doi:10.1155/2012/145974

[14] Hojjat Adeli: **Neural Networks in Civil Engineering: 1989−2000**, *Computer-Aided Civil and Infrastructure Engineering*, Vol.16, 126–142, 2001, http://dx.doi.org/10.1111/0885-9507.00219

[15] Gupta T., Sharma R. K: **Structural analysis and design of buildings using neural network: A review**, *I.J.E.M.S.*, Vol.2, No.(4), 216-220, 2011, ISSN 2229 -600X

[16] Krisada Chaiyasarn, Mayank Sharma, Luqman Ali, Wasif Khan, Nakhon Poovarodom: **Crack detection in historical structures based on convolutional neural network**, *International Journal of GEOMATE*, *Geotec., Const. Mat. & Env.*, Vol.15, Issue 51, 240-251, 2018, ISSN: 2186-2982, DOI: https://doi.org/10.21660/2018.51.35376 2186-2990

[17] Luqman Ali, Wasif Khan, Krisada Chaiyasarn: **Damage detection and localization in masonry structure using faster region convolutional networks**, *International Journal of GEOMATE, Geotec., Const. Mat. & Env.,* Vol.17, Issue 59, 98-105, 2019, ISSN: 2186-2982, DOI: https://doi.org/10.21660/2019.59.8272

[18] D. Brackenbury, I. Brilakis, M. DeJong: **Automated defect detection for masonry arch bridges**, *International Conference on Smart Infrastructure and Construction*, (ICSIC) 2019, https://doi.org/10.1680/icsic.64669.003

[19] Niannian Wang, Xuefeng Zhao, Peng Zhao, Yang Zhang, Zheng Zou, Jinping Ou: **Automatic damage detection of historic masonry buildings based on mobile deep learning**, *Automation in Construction*, Vol.103, 53–66, 2019, https://doi.org/10.1016/j.autcon.2019.03.003

[20] Árpad Rozsas, Arthur Slobbe, Wyke Huizinga, Maarten Kruithof, Giorgia Giardina: **Development of a neural network embedding for quantifying crack pattern similarity in masonry structures**, *12th International Conference on Structural Analysis of Historical Constructions*, SAHC 2020

[21] M. Sakamoto, T. Shinohara, Y. Li, T. Satoh: **Wall stone extraction based on stacked conditional gan and multiscale image segmentation**, *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume XLIII-B2-2020, 2020 XXIV ISPRS Congress 2020

[22] Kaiwen Chen, Georg Reichard, Xin Xu, Abiola Akanmu: **Automated crack segmentation in close-range building façade inspection images using deep learning techniques**, *Journal of Building Engineering*, Vol. 43, 102913, 2021, https://doi.org/10.1016/j.jobe.2021.102913

[23] Yahya Ibrahim, Balazs Nagy, Csaba Benedek: **A GAN-based Blind Inpainting Method for Masonry Wall Images**, *25th International Conference on Pattern Recognition 2020* (ICPR), Milan, Italy, 3178-3185, 2021.

[24] L. Minh Dang, Hanxiang Wanga, Yanfen Li, Le Quan Nguyen, Tan N. Nguyen, Hyoung-Kyu Song, Hyeonjoon Moon: **Deep learning-based masonry crack segmentation and real-life crack length measurement**, *Construction and Building Materials*, Vol. 359, 129438, 2022, https://doi.org/10.1016/j.conbuildmat.2022.129438

[25] Sheetal Sharma: **Automatic Damage Detection of Historic Masonry Buildings Based on Densenet Deep Learning Model**, ESP *International Journal of Advancements in Science & Technology*, Vol. 1, Issue 3, 20–26, 2023, ISSN: 2583-9233, Doi: 10.56472/25839233/IJAST-V1I3P104

[26] Qinghua Lin, Wei Li, Xiangpan Zheng, Haoyi Fan, Zuoyong Li: **DeepCrackAT: An effective crack segmentation framework based on learning multi-scale crack features**, *Engineering Applications of Artificial Intelligence* Vol. 126 106876, 2023, https://doi.org/10.1016/j.engappai.2023.106876

[27] David Marín-García, David Bienvenido-Huertas, Manuel J. Carretero-Ayuso, Stefano Della Torre: **Deep learning model for automated detection of efflorescence and its possible treatment in images of brick facades**, *Automation in Construction* Vol. 145, 104658, 2023, https://doi.org/10.1016/j.autcon.2022.104658

[28] Yahya Ibrahim, Peter Szulovszky, Csaba Benedek: **Masonry Structure Analysis, Completion and Style Transfer Using a Deep Neural Network**, *Computer Vision, and Image Processing ICPR 2022 International Workshops and Challenges. ICPR 2022. Lecture Notes in Computer Science*, Vol 13645, 2023, Springer, Cham. https://doi.org/10.1007/978-3-031-37731-0_13

[29] A. Iannuzzo, V. Musone, E. Ruocco: **A neural network-based automated methodology to identify the crack causes in masonry structures**, *Comput Aided Civ Inf.*, Vol.39, 3769–3785, 2024, DOI: 10.1111/mice.13311