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Is it possible that AI can help us detect all damage in structural assets? A discussion on the scope of applicability of DL methods for diagnosis of the construction assets's technical condition

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ABSTRACT: The use of computer vision supported by artificial intelligence methods is growing in popularity for solving problems concerning the assessment of building and civil engineering structures. At the same time, SHM-class systems allow for the collection of large amounts of data. Despite the rapid development of machine learning and the increasing number of solutions supporting the process of technical condition diagnosis of objects, the amount of damage that can be detected in images using these algorithms is significantly limited. At the same time, due to the lack of publicly available datasets that can be used to train AI algorithms, the actual support of the civil engineer's work with these algorithms is limited to a few of the most common problems. This paper presents the current applicability of artificial intelligence methods for damage detection of buildings and engineering structures based on images. At the same time, the authors focus on showing the limitations for the development of artificial intelligence algorithms due to the lack of publicly available datasets. The paper identifies a research gap related to the lack of datasets for damage, pointing out the types of damage, types of damaged materials and solution classes not covered in research on the application of deep learning to the diagnosis of the technical condition of buildings and civil engineering structures.

KEY WORDS: SHMII-13; Extended Abstract; Deep learning; Dataset; Damage; Technical condition.

1 INTRODUCTION

The rapid development of artificial intelligence (AI) algorithms, including deep machine learning (DL), means that these methods are more and more often being used as tools to support the assessment of the technical condition of building and engineering structures. At the same time as SHM-class systems are adopted more widely, they facilitate the gathering of data on structural behavior, suitable for deep machine learning analysis. [1], [2]. The authors understand SHM-class systems as those that collect data about the structure's condition, analyze these data, and provide information when limit values are exceeded. This allows for early response to potential threats (e.g., informing about excessive strain in a structural element, which could lead to a reduction in load capacity) and supports the development of predictive maintenance strategies.

Researchers are implementing deep learning-based solutions for a wide range of data types. Satellite images [3], [4], Ground Penetrating Radar images [5], measurements from inclinometers and strain gauges [1], signals from devices passing over bridge structures [6], XCT images [7], damage images [8], video data [9] are being used.

The assessment of the technical condition of building and engineering structures can be carried out both on a global level (e.g., classification of damaged buildings after disasters [3], detection of ground deformations [4]) as well as with regard to building components (e.g., crack detection in brickwork masonry [8]), down to the level of detecting internal damage within materials (e.g., corrosion of reinforcement bars in concrete elements [7]).

This paper explores the current capabilities of applying deep learning and computer vision techniques to the damage detection in buildings and engineering structures using image data. For the purposes of this study, the term "image" is defined specifically as a photograph depicting damage, as opposed to general raster data derived through digital processing of alternative data sources - such as structural vibrations transformed into spectrograms with Digital Signal Processing. Moreover, it should be noted that satellite images [3], [4], Ground Penetrating Radar images [5], XCT images [7] are not discussed here. The article particularly highlights limitations in the development of artificial intelligence algorithms due to lack of publicly available datasets. A research gap is discussed regarding the absence of damage datasets, in terms of damage types and types of damaged materials.

Neural network architectures and their associated performance are not the subject of this discussion. However, it should be mentioned that a likely solution to the problem of limited datasets for construction-related data may be the adaptation of architectures dedicated to Embedded Vision Systems.

2 OVERVIEW OF SOLUTION. DEVELOPMENT AND AVAILABILITY OF DATASETS

The application of deep learning in the assessment of the technical condition of buildings and engineering structures based on image data involves addressing tasks such as damage classification, detection, and segmentation. Researchers are using deep learning for the classification of damage such as paint deterioration [10], vegetation [10], cracks [10], [11], [12], [13], corrosion [10], [11], [12], spalling [11], [12], efflorescence [11], exposed bars [11], [12]. Object detection is used, among others, for problems such as cracks [14], [15], [16], spalling [14], [15], [17], pop-out [14], exposed rebar [14],

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efflorescence [17]. Segmentation helps to solve problems such as cracks [16], [18], corrosion [19], mildew [19], ponding [19], exposed rebar [20], [21], delamination [20], [21], steel fatigue crack [22].

The development of deep learning algorithms is strongly dependent on the availability of data that can be used to train these models. Despite the wide range of damage types for which deep learning-based solutions have been developed, as described above, the number of open datasets (i.e., those available for download without the need to contact the author) remains significantly limited. As demonstrated by the research conducted by the authors of this publication [23], in the case of bridge structures, out of more than 120 identified damage types that may occur, yet open training datasets are available for only 10 of them. The lack of openly accessible datasets is a significant factor constraining the progress of deep learning algorithm development. In the lack of shared data, subsequent researchers are compelled to create new solutions from scratch, rather than refining or building upon existing methods.

Among the various research problems addressed in the field, crack detection - particularly in concrete and asphalt elements - emerges as the one for which the largest number of open datasets is available. Datasets have also been developed for components made of brick and structural steel. However, it is important to emphasize that, from an engineering point of view, the characteristics of cracks - especially their shape and size - differ significantly depending on the material. A considerable number of datasets are also available for issues related to the corrosion of concrete and reinforcing steel.

When categorized by material type, most identified datasets refer to damage in concrete and asphalt structures. In contrast, datasets concerning damage in timber and stone elements remain limited.

It is important to emphasize the existing imbalance between the range of damage types addressed in proposed solutions and the availability of corresponding datasets that have been made publicly accessible by the research community. A notable example is the detection of honeycomb defects, which, although investigated in scientific publications [24], [25]. In both cited cases, the datasets used in the experimental studies were not disclosed, and this specific type of defect is not represented in any existing public datasets. This situation highlights that, at present, the detection of honeycomb-related damage is only possible within individual research groups that maintain proprietary datasets, thereby limiting the broader applicability and scalability of deep learning methods for structural diagnostics.

To enable meaningful progress in this area, particularly regarding the development and refinement of algorithms targeting such defects, the creation and dissemination of open-access datasets is an essential prerequisite. Only then can the research community effectively train and improve deep learning-based diagnostic tools for widespread engineering applications.

For datasets, the following aspects should be noted [23]:

- Some of the open datasets are described in a not very detailed way and do not contain information relevant for the engineers (for example, the damage size).
- Some of the open datasets are shared in unusual locations (e.g., via the author's cloud storage, rather than on dedicated data sharing websites like Zenodo, GitHub, kaggle, Mendeley Data).
- For many damage types, available open datasets were not identified. As important, there are datasets in which different damage types are labeled as a single damage type class. Re-labeling them, using classes dedicated to specific damage types, could increase the applicability of DL methods for diagnosis of the construction asset's technical condition.
- It should also be taken into account that a large number of datasets for a particular damage type does not mean yet that the problem of damage detection has been solved. Often, the developed solutions allow only to detect damage of a certain size or occurring on a surface with a similar appearance.

An essential aspect of applying deep learning methods for the assessment of a construction asset's technical condition is the manner in which datasets are prepared. Most publicly available datasets contain damage labels that are purely geometric in nature. Based on these annotations, it is possible to localize pixels within an image that correspond to a specific damage type. However, such data is strictly visual and lacks critical contextual information necessary for a comprehensive engineering assessment - such as expert evaluation, georeferencing, the material type of the damaged element, or the date of damage detection.

Consequently, solutions developed using such datasets primarily address visual recognition tasks and enhance the visibility of defects in imagery, but they do not resolve engineering-level diagnostic challenges.

Data should comply with the FAIR principles [26] – that is, they should be Findable, Accessible, Interoperable, and Reusable. The datasets should be hosted in a permanent way on servers and be accessible to train deep learning models at any time, interoperable between different systems and replicable for different construction structures.

The datasets used for training should pass technical validation and have a high level of rawness. They should not be processed before training, in particular, it is not good practice to collect a small amount of data and then augment the data to present this as a dataset. Augmentation - if it is planned to be executed - should be implemented as part of the model training process. In particular, it should be considered that for engineering problem solving, inadequate planning of the data augmentation process can result in the loss of information relevant to structural engineers, such as the direction of damage or its size.

3 CONCLUSION

The conducted analysis has demonstrated that algorithms based on deep learning and computer vision are a frequent subject of research. Although the solutions presented by researchers address the detection of a wide range of defects in concrete, steel, brick, and asphalt components, the number of publicly available datasets for training deep neural networks is significantly smaller.

This situation considerably limits the potential for developing deep learning algorithms for the assessment of a construction asset's technical condition. Moreover, the time that researchers must dedicate to creating their own datasets -

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due to the lack of publicly available ones - could instead be allocated to improving the robustness or computational efficiency of deep learning algorithms.

However, in order to develop solutions that address engineering-level challenges (e.g., classification of the degree of damage), rather than solely visual tasks (e.g., identifying the damage area through pixel-wise prediction), it is necessary to establish guidelines for dataset creation. These datasets should include not only visual information but also metadata relevant from the perspective of structural and civil engineers.

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