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Autoencoder based damage detection in masonry structures

Tunahan Aslan[1], Kemal Hacıefendioğlu [*1], Ayşecan Bostan[1], Cemile Duman[2]

[1] *Karadeniz Technical University, Department of Civil Engineering, 61080 Trabzon, Türkiye*
[2] *Gazi University, Department of Civil Engineering, 06570 Ankara, Türkiye*

Abstract. This study aims to detect and evaluate damage in masonry structures using a contactless structural health monitoring method integrated with an Autoencoder deep learning model. Video recordings of a scaled minaret model constructed in a laboratory environment were taken at specific intervals using an industrial camera-based monitoring system. Subsequently, controlled damage was incrementally applied to the minaret model, and new video recordings were captured. Time-dependent displacement data from four different elevations of the scaled minaret model were extracted using a custom Python® script. A separate code based on an Autoencoder deep learning model was employed to calculate the damage index of the minaret model using the displacement data. Analyses conducted in the undamaged state revealed a stable damage index below 5%. However, analyses performed after the controlled damage steps showed that the damage index exceeded 5%. This study introduces a practical and rapid method for damage detection in masonry and similar engineering structures, facilitating faster diagnostic and decision-making processes in the field of structural health monitoring.

Keywords: Damage detection; Structural health monitoring; Masonry structures; Deep learning; Autoencoder

1. Introduction

Masonry structures represent a significant portion of the world's architectural heritage and are commonly found in both historical and modern constructions due to their durability, low cost, and ease of use. Despite these advantages, masonry buildings are highly vulnerable to various forms of damage, particularly under dynamic loads such as earthquakes. Given their widespread use and cultural importance, ensuring the structural integrity of masonry structures through effective damage detection and monitoring techniques is of utmost importance.

Structural health monitoring (SHM) is critical for ensuring the safety and longevity of civil infrastructure (Anjum et al., 2024; Avci et al., 2022). Machine learning (ML) techniques have emerged as powerful tools for detecting structural damage, with autoencoder-based methods gaining prominence due to their ability to handle unsupervised learning and dimensionality reduction. This response compares autoencoder-based methods with other ML techniques, highlighting their strengths, weaknesses, and applications in civil engineering (Gil Bravo et al., 2024; Mghazli et al., 2024).

Autoencoders, particularly variational autoencoders (VAEs), have shown promise in SHM by learning latent representations of structural data. These models are effective in unsupervised anomaly detection, requiring only normal (undamaged) data for training. For instance, VAEs combined with Hotelling's T2 statistical tool have demonstrated superior performance in identifying and quantifying structural changes in civil structures (Spínola Neto et al., 2024). Similarly, convolutional autoencoders have been successfully applied to detect damage locations in mechanical systems by analyzing changes in stiffness (Bono et al., 2023).

The integration of autoencoders with other techniques, such as mechanics-informed models, has further enhanced their capabilities. For example, a mechanics-informed autoencoder can detect and localize unforeseen damage with minimal training data, achieving up to 35% better performance than standard autoencoders (Li et al., 2024). Additionally, multi-objective VAEs have been used to fuse multi-sensor data for damage detection and localization, outperforming state-of-the-art methods (Anaissi et al., 2023).

Traditional ML techniques, such as K-nearest neighbors (KNN), Gaussian mixture models (GMMs), and one-class support vector machines (OCSVMs), have been widely used for structural damage detection. These methods rely on feature engineering and supervised or semi-supervised learning paradigms. While they are effective in specific scenarios, they often struggle with high-dimensional data and require labeled datasets, which can be challenging to obtain in real-world applications (Che & Tian, 2024; Wang & Cha, 2025).

In contrast, autoencoder-based methods excel in unsupervised settings and can automatically learn features from raw data, reducing the need for manual feature engineering. For example, a comparative study on a laboratory-

* Corresponding author, E-mail: kemalhaciefendioglu@ktu.edu.tr

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scale steel bridge demonstrated that autoencoders outperformed KNN and GMMs in detecting loosened bolts, highlighting their robustness in unsupervised damage detection (Wang & Cha, 2025).

Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have also been applied to SHM. These methods are particularly effective in processing time-series data and capturing temporal patterns. For instance, a deep residual network (DRN) optimized with Bayesian methods has shown superior performance in detecting, localizing, and quantifying structural damage compared to traditional ML methods (Alazzawi & Wang, 2022; Atia et al., 2024; Fernandez-Navamuel et al., 2024).

Moreover, hybrid models combining autoencoders with other deep learning architectures, such as long short-term memory (LSTM) networks, have been developed to enhance damage diagnosis. A multi-head self-attention LSTM autoencoder has demonstrated superior performance in detecting minor damage and localizing multiple damage locations on a full-scale bridge (Ghazimoghadam & Hosseinzadeh, 2024).

component of ML-based damage detection. Traditional methods often rely on handcrafted features, such as modal parameters and frequency-domain metrics, which can be time-consuming and require domain expertise. Autoencoders, on the other hand, can automatically learn damage-sensitive features from raw data, such as acceleration responses and vibration signals (Bono et al., 2023; Spínola Neto et al., 2024).

The effectiveness of autoencoders in feature extraction is further enhanced by their ability to handle multi-sensor data. For example, a multi-objective VAE has been used to fuse data from multiple sensors, capturing correlations and improving damage detection accuracy (Anaissi et al., 2023). Similarly, a deep convolutional variational autoencoder (DCVAE) has been shown to effectively extract features from multisensor data, outperforming traditional methods like principal component analysis (PCA) (Wan et al., 2025).

Autoencoder-based methods are computationally efficient and can be deployed in real-time SHM systems. For instance, a mechanics-informed autoencoder can learn from just 3 hours of data and autonomously detect and localize damage, reducing the need for human intervention (Li et al., 2024). Additionally, autoencoders can be trained on non-standardized time-series data, making them suitable for unsupervised damage localization without requiring extensive preprocessing (Römgens et al., 2023, 2024).

However, the performance of autoencoders can be influenced by the quality and quantity of training data. While they excel in unsupervised settings, their accuracy may degrade in the presence of noisy or incomplete data. Addressing these challenges requires careful data preprocessing and the integration of domain knowledge into the model architecture (Li et al., 2024; Wan et al., 2025).

This study presents a novel application of an Autoencoder-based deep learning approach integrated with a non-contact monitoring system to detect and evaluate damage in masonry structures. A scaled minaret model was constructed and subjected to a series of controlled damage scenarios in a laboratory setting. Displacement data were extracted from video recordings using a custom Python® script, and the damage index was calculated based on the Autoencoder's performance. The findings demonstrate that the proposed method can effectively distinguish between undamaged and damaged states, offering a practical and efficient alternative for structural diagnostics in masonry and similar engineering structures. Autoencoder-based methods have emerged as powerful tools in structural damage detection due to their advantages in unsupervised learning, automatic feature extraction, and ability to handle high-dimensional, multi-sensor data. Building upon these strengths, this study contributes to the advancement of SHM technologies by demonstrating a robust, data-driven approach that can be applied in real-world scenarios, while also highlighting the potential of hybrid models and domain-informed architectures for future research.

2. Materials and methods

Within the scope of this study, a scaled model of a historical masonry minaret was constructed at the Structural Health Monitoring Laboratory of Karadeniz Technical University. This model consists of four main sections: the podium, transition zone, body, and upper body, all designed to align with the architectural elements of minarets. These structural sections were meticulously designed to analyze the real behavior of the minaret through the scaled model. The model, with a total height of 3.85 meters, is supported from the inside by wooden staircase steps. Fig. 1 shows images of the miniature minaret model. After the completion of the model, a curing period of one month was expected. During this period, measurements were taken at regular intervals to observe the behavior of the structure. The aim is to obtain the horizontal and vertical displacements of the structure without subjecting it to any dynamic load through the measurements taken. Using these displacement values, damage detection can be performed through an Autoencoder-based method.



Fig. 1. Construction phase of the miniature minaret model

These measurements were carried out using a system built with high-speed industrial cameras. The most critical aspect of the video camera-based monitoring system is the hardware system created to record video footage. With this system, video recordings can be taken both in the laboratory environment and outdoors. The system consists of four industrial cameras, a camera lens for each of these cameras, a recording device to capture the images, a computer for connecting the CoaExpress recording device and CoreView software, and cables. The technical specifications of each component of the hardware system are provided in Table 1.

The Victorem™ CoaXPress series is a wide range of compact industrial video cameras featuring high-performance Sony CMOS image sensors and high-bandwidth CoaXPress video output. There are various models with different sensors available, allowing the selection of the appropriate Victorem camera for each application. These powerful cameras, with resolutions ranging from 0.4 MP to 26.2 MP and frame rates up to several hundred frames per second, are ideal for performance-oriented applications such as volumetric video capture, machine vision, and automatic optical inspection. When sensors generate hundreds or even thousands of megabytes of video data per second, systems using Victorem™ CoaXPress cameras need ways to access this data stream. The CoaXPress video interface is a perfect match for the bandwidth of these sensors and can support the full resolution and bit depth rate of each sensor without limitations. Other interfaces, such as GigE Vision or USB3 Vision, offer lower bandwidth than CoaXPress, requiring either fewer frames per second or lower bit depth. The CoaXPress protocol is standardized and widely adopted, allowing the use of low-cost, flexible coaxial cables over long distances of more than 100 meters. The CMOS sensors used in Victorem™ CoaXPress cameras offer state-of-the-art features, such as high resolution, low noise, excellent dynamic range, and color accuracy (URL-1, 2024). The cameras are equipped with adjustable exposure settings and image correction tables for gamma or contrast enhancement. They can be used either manually or automatically. Some lenses feature an in-camera correction algorithm to correct for vignetting effects and can be adjusted for flat-field homogeneity. For fast-moving objects, adjustable window settings allow the sensor's smaller areas to output at higher frame rates. The schematic of the created hardware system is provided in Fig. 2.

Table 1. Hardware components technical specifications

Components	Model	Technical Specifications
Video Camera-1	IO Industries CoaxPress VICTOREM 16B276MCX	Maximum Resolution: 1456×1088 Number of Frames: 276 FPS Pixel size: 3,45×3,45 µm²
Video Camera-2	IO Industries CoaxPress VICTOREM 32B216MCX	Maximum Resolution: 2064 x 1544 Number of Frames: 216 FPS Pixel size: 3,45×3,45 µm²
Video Recorder	IO Industries DVR Express Core 2 CoaXPress	Video Format: 8/10/12/14/16-bit Monochrome 24-bit RGB
Computer	HP Victus 16d1006nt	12th Gen Intel(R) Core (TM) i5-12500H 2.50 GHz

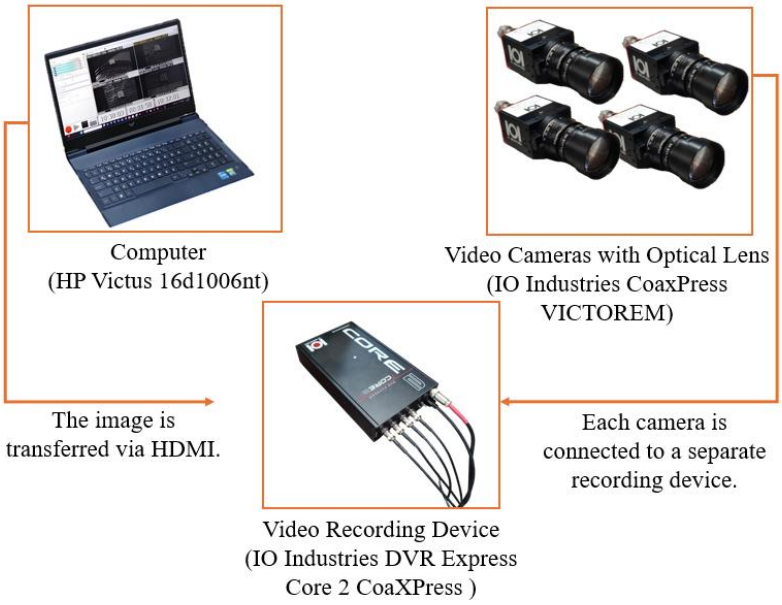


Fig. 2. Monitoring System Hardware Schematic

2.1. Obtaining displacements

A system utilizing template-matching-based displacement sensors has been developed for video camera-based monitoring of objects. Tested on a miniature minaret model in the laboratory environment using templates such as QR codes, the system operates on selected regions of interest (ROIs) on the minaret surface during field measurements. By determining the positions in the initial and final frames, object tracking is performed, and with the use of high-speed industrial cameras, better results are aimed to be achieved compared to conventional methods. The main objective of the study is to evaluate the performance of this system in capturing structural vibrations. Displacement values were obtained from pixel coordinates by applying a scaling factor (Hacıefendioğlu et al., 2024).

The optical flow method differentiates itself from other techniques in computer vision by focusing on object motion tracking. This method is more effective than traditional methods for detecting displacements in video images, as it tracks object movements through image sequences and calculates displacements. Although various methods have been developed to calculate optical flow, the Lucas-Kanade method, which is important for structural health monitoring in this study, has been employed (Lucas & Kanade, 1981). Developed by Bruce D. Lucas and Takeo Kanade, this method assumes that pixel intensity does not change significantly between consecutive frames and predicts pixel displacements by solving a linear system of equations for each point.

The Lucas-Kanade optical flow algorithm may exhibit performance degradation in the presence of large displacements and varying brightness conditions. To overcome these limitations, the Pyramidal Lucas-Kanade Optical Flow technique has been developed.

The Lucas-Kanade method calculates velocity by using the spatial and temporal derivatives of image intensity, and this process is expressed by Equation (1):

$$I(x,t) = I(x+\delta x, t+\delta t) \tag{1}$$

This equation explains the basic assumption of the optical flow method, known as the brightness conservation principle. The intensity of a pixel at position x and time t remains constant after a small time interval δt and a small displacement δx.

This assumption can be expressed in Equation (2) as follows:

$$\nabla I_t(x,t)u + I_t(x,t) = 0 \tag{2}$$

Here, $\nabla I(x,t)$ represents the spatial derivatives across the image, and $I_t(x,t)$ represents the temporal derivatives. u denotes the two-dimensional optical flow vector.

To determine the displacement vector, the least squares approach is applied, and this approach is expressed in Equation (3):

$$E(u) = \sum \left[\nabla I(x,t)u + I_t(x,t)\right]^2 \tag{3}$$

The minaret model has been placed on the shaking table and fixed to the table using anchors. Subsequently, the monitoring system has been positioned perpendicular to the templates. Fig. 3 shows the positioning of the minaret on the shaking table and the monitoring system.

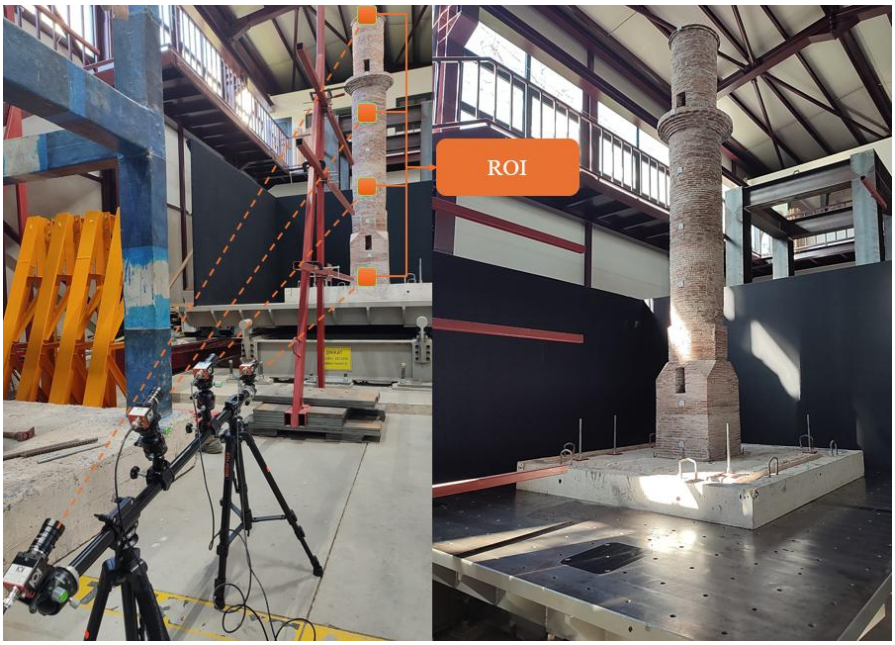


Fig. 3. Monitoring system positioning and shaking table

The miniature minaret model, along with the reinforced concrete block on which it was built, has been fixed to the shaking table with a total of six 50 cm long anchors. As shown in Fig. 3, the front camera is focused on the template located at the bottom of the minaret model, while the rear camera is focused on the template at the top. Four cameras have been mounted on a steel pipe with a 30 cm interval, and the system has been completed with two tripods. This arrangement has completely restricted the movement of the cameras, preventing deviations in the results. A three-stage test was performed on the unidirectional shaking table. The dynamic load was gradually increased, applying a sinusoidal wave to the minaret with the following parameters: 1 Hz frequency, 10 mm amplitude, and 5 cycles; 1 Hz frequency, 20 mm amplitude, and 5 cycles; and 1 Hz frequency, 30 mm amplitude, and 5 cycles. During the final loading, a fracture was observed on the body 30 cm above the transition zone, which was recorded via video. After the tests, an inspection revealed a crack in this region.
The horizontal displacement graphs obtained are shown in Fig. 4. Each graph represents the displacements at the level of the templates tracked by the cameras. These displacements, which are too small to be visible to the naked eye, show a decrease in values when moving from the top to the bottom. These graphs were obtained as a result of analyses performed before and after the shaking table tests. In this way, the data can be compared in the autoencoder-based damage detection system to determine the percentage of damage.

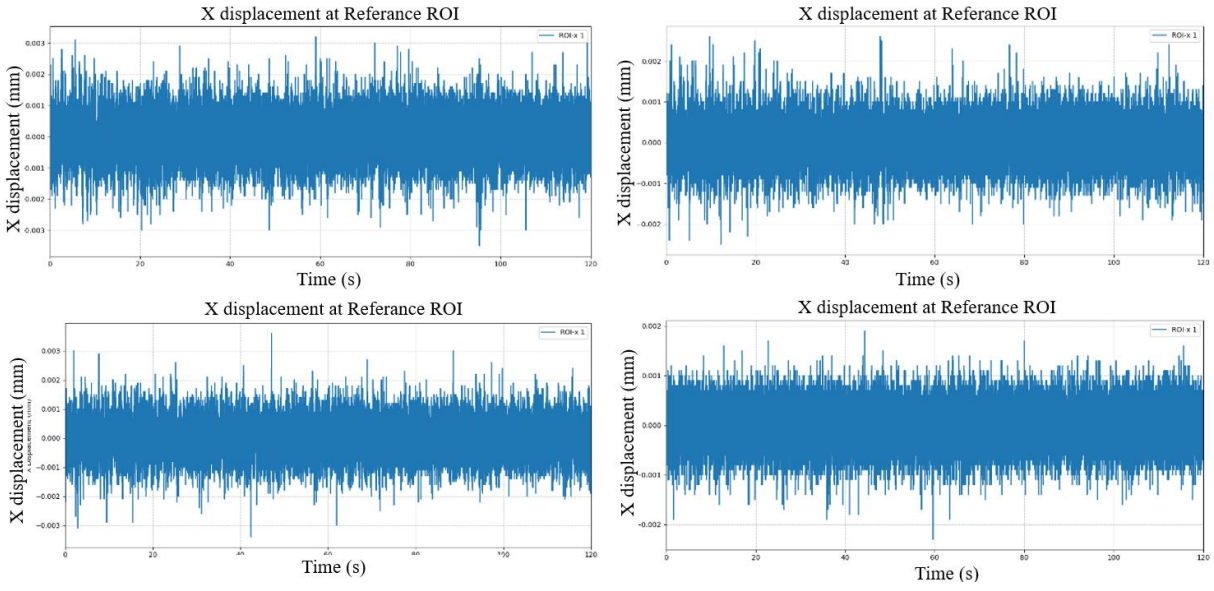


Fig. 4. Horizontal displacements of the miniature minaret model

This study presents a machine learning-based analysis method for structural damage detection using sensor data. The process of separately processing and comparing healthy and damaged data for each sensor enabled the determination of the damage percentage for each sensor. The model predicts reconstructions of the healthy and damaged data, and the reconstruction errors are calculated. The damage percentage is then determined by comparing the errors of the damaged data with a threshold derived from the healthy data. The results are visualized using bar charts, where the sensors with a damage percentage exceeding the threshold are marked. This approach allows for an effective detection of damaged sensors, and the average damage percentage across all sensors is calculated, providing an overall assessment of the structural health. The graphs presented in Fig. 5 were calculated separately for the 30 healthy days. Measurements taken during healthy days revealed that the damage index remained below 5%. After the damage was introduced, the same analyses were performed, and it was observed that the damage percentage exceeded 5%. The damage index graph obtained for both healthy and damaged states is shown in Fig. 6.

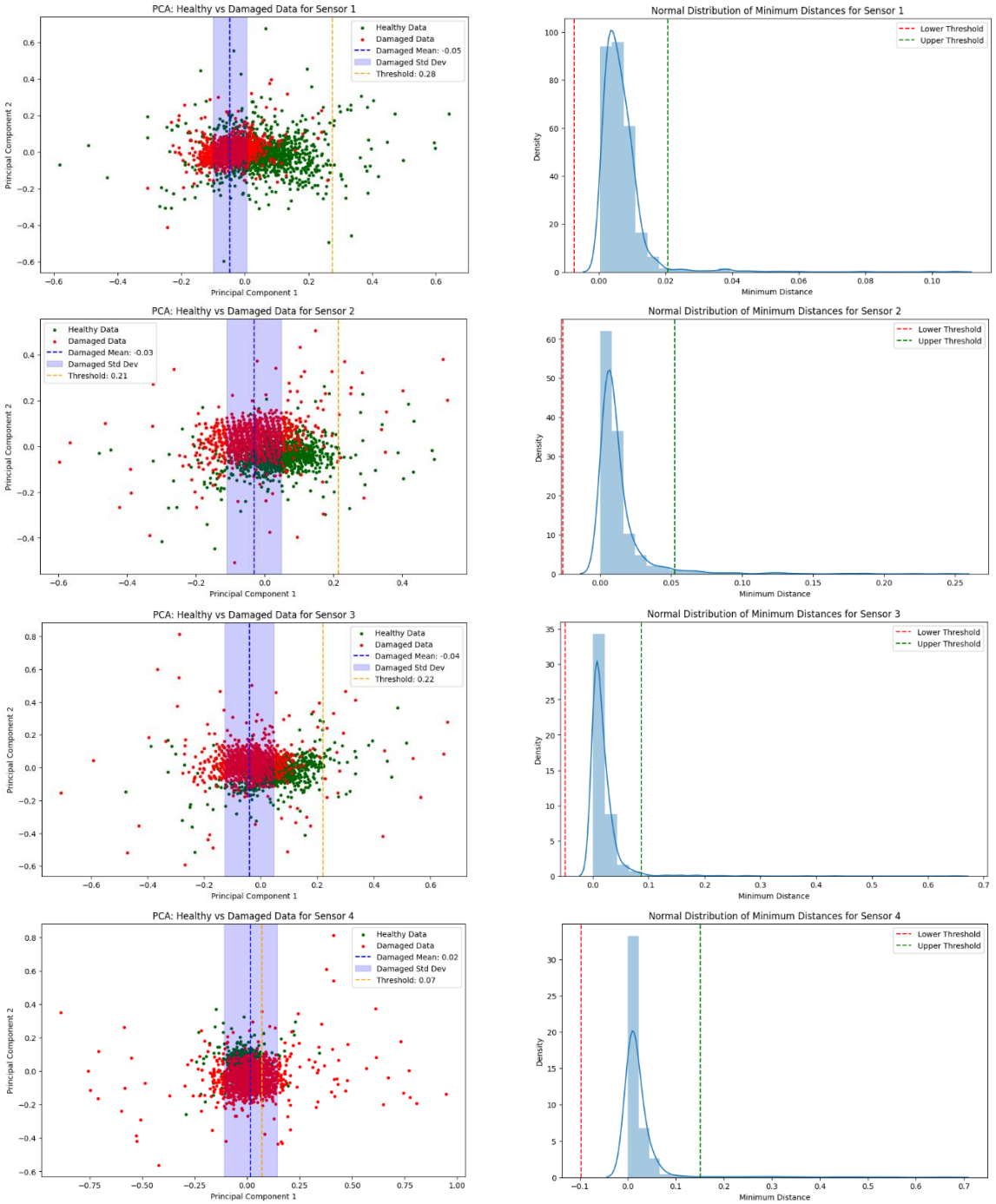


Fig. 5. Calculation of damage index values using the autoencoder model

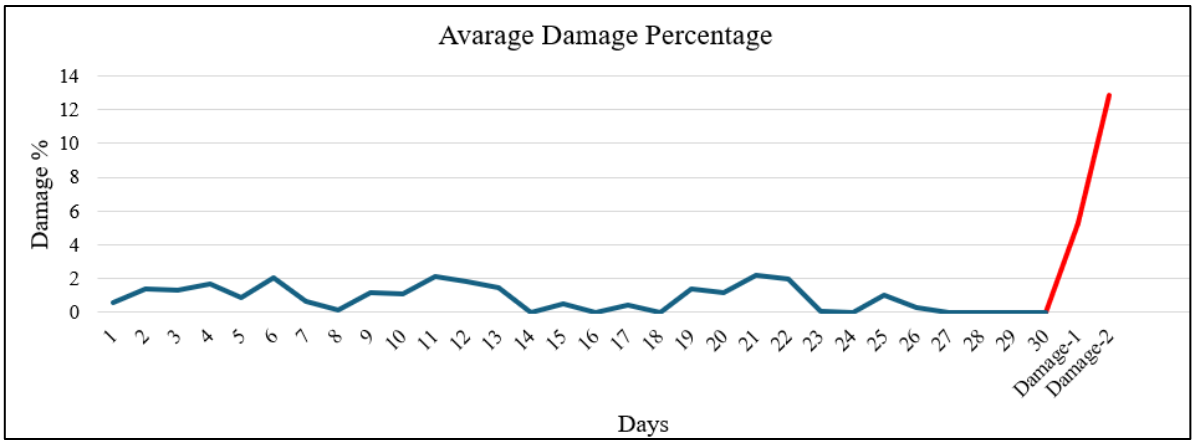


Fig. 6. Average damage percantage

The methodology includes the calculation of reconstruction errors for each sensor and the use of a Z-score-based adaptive threshold for damage detection. This innovative approach enhances the sensitivity of the damage detection process by employing statistical measures to account for variability in the reconstruction errors. A threshold is set based on the standard deviation of healthy reconstruction errors, and the damage percentage is computed by evaluating the reconstructed data of the damaged set against this threshold. The results are presented visually using aesthetically enhanced bar graphs, which also highlight the sensors likely to be damaged. This method, with its detailed and robust analysis, offers a reliable approach for assessing structural health using sensor data and machine learning techniques.

3. Conclusions

This study presents a novel and effective approach to structural health monitoring (SHM) for masonry structures using a non-contact method integrated with an Autoencoder-based deep learning model. The proposed methodology, applied to a scaled minaret model in a controlled laboratory setting, demonstrates the potential of combining advanced machine learning techniques with optical flow-based displacement measurement for the detection and evaluation of damage in masonry structures.

- The results highlight that the Autoencoder-based approach can successfully differentiate between undamaged and damaged states of the structure by calculating a damage index derived from displacement data. The key advantage of this approach lies in its ability to work in an unsupervised manner, relying solely on healthy state data for training, thus eliminating the need for labeled data. This is particularly significant as it reduces the complexity and time-consuming nature of traditional damage detection methods, which often require extensive data labeling and feature engineering
- The laboratory-scale experiments, which involved incremental damage applied to the minaret model, provide compelling evidence that the proposed method can detect even subtle damage changes. In the healthy state, the damage index remained below 5%, but after controlled damage was introduced, the index consistently exceeded 5%, clearly indicating the presence of structural degradation. This threshold-based detection method, enhanced with Z-score adaptive thresholds, allows for a more sensitive and precise assessment of the structural condition, making it a reliable tool for real-time SHM applications.
- One of the critical aspects of this study is the integration of video camera-based monitoring systems and optical flow methods to obtain precise displacement data, which is crucial for accurate damage assessment. The use of industrial-grade cameras and advanced image processing algorithms ensures that the displacement measurements are both accurate and reliable, even under dynamic loading conditions. Moreover, the ability to track displacements at multiple elevations and across different sections of the minaret model further strengthens the robustness of the proposed methodology.
- The application of Autoencoder models, particularly in damage detection tasks, provides several benefits over traditional machine learning methods. By automatically extracting features from raw data and reducing the dimensionality of the input data, Autoencoders are able to identify patterns and anomalies that might not be apparent using conventional methods. Additionally, the ability of these models to handle multi-sensor data and high-dimensional inputs allows for comprehensive damage detection across large-scale structures, such as full-sized masonry buildings or bridges.
- While the current study focused on a scaled model of a masonry minaret, the methodology is highly transferable to other masonry or similar engineering structures, such as historic buildings and infrastructure. The ability to monitor these structures with minimal human intervention, using automated damage detection systems, offers significant advantages in terms of efficiency and cost-effectiveness. Furthermore, this study

contributes to the broader field of SHM by demonstrating how machine learning techniques, particularly Autoencoders, can be seamlessly integrated with modern sensor systems for real-time structural diagnostics.

- Looking forward, future research can explore the enhancement of the current model by incorporating hybrid techniques, such as the combination of Autoencoders with other deep learning architectures, like convolutional neural networks (CNNs) or recurrent neural networks (RNNs). Additionally, expanding the dataset to include a wider variety of damage scenarios, as well as implementing the method on full-scale structures, could further validate and refine the model's performance in real-world applications.

In conclusion, this study not only presents a robust and efficient method for damage detection in masonry structures but also sets the stage for further advancements in SHM through the integration of machine learning techniques. The promising results of this approach suggest that Autoencoder-based models can play a crucial role in the future of structural health monitoring, enabling faster, more accurate, and less resource-intensive damage detection in civil engineering applications.

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