Development of an expert system for the deformation monitoring of historical sites using Artificial Intelligence (AI)

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Abstract

Historic buildings are invaluable national heritage assets that require diligent conservation. To ensure their preservation, regular surveying and physical deformation measurements are essential. These measures provide continuous or periodic data supporting conservation efforts. Additionally, non-invasive photogrammetric techniques offer valuable insights. Industry data, such as geological, mining, meteorological information, and satellite imagery, provide substantial context for understanding the Earth's surface and its impact on historic structures. Structural monitoring is typically conducted using total stations. A key challenge lies in effectively integrating and validating data from these diverse sources. Combining these data allows for developing artificial intelligence (AI)-based approaches, specifically applying machine learning (ML) models. These models can then be verified against monitoring results to identify and address potential overfitting issues. This research presents an expert system developed to automate the monitoring of historic buildings. The system leverages a methodology that incorporates various measurement techniques and ML models. A case study focusing on one representative object of the Coal Basin Museum in Będzin - The Mieroszewski Palace, Silesian region, Poland, demonstrates the application of this approach. The object encompasses unique challenges, necessitating the use of specific measurement technologies. This research, conducted between 2022 and 2024, highlights the successful integration and application of modern measurement methods in developing fully automated structural monitoring systems.

Keywords: historical objects, deformation monitoring, data integration, automation, model building

1 Introduction

Studying the technical condition of historical buildings is one of the key aspects of Cultural Heritage. For many years, works have been carried out to combine the achievements of technical sciences with historical and conservation knowledge. In assessing the technical condition of structures, monitoring systems using the advantages of integrating multi-source measurement data play an essential role (Markiewicz et al., 2019; Thirugnanam et al., 2022). Research on monitoring systems for engineering objects is an important branch of science and technology in civil engineering, surveying, and related disciplines. The results of conceptual work, as well as the examples of specific implementations, have been described in numerous publications. The directions of monitoring system development are worth mentioning, especially in modern sensors and data communication technologies (Wielandt, 2023). Moreover, most of the research published (Lasaponara & Masini, 2011; Bassier et al., 2018; Chetverikov et al., 2024) focus on remote methods of capturing spatial data without considering metrological (geotechnical) sensors. It allows for the detection of external changes in the examined historical structures. It is, however, crucial to explore the whole object, making the studies more integral. Such an integrated approach demands the introduction of many additional technologies and – what is very important – the integration of them within a coherent, database-related examination system. At this stage, it is essential to consider diverse – and direct methods of examining the objects. Nowadays, wireless systems are becoming important, as are those based on the so-called “Internet of Things” (IoT) (Thirugnanam et al., 2022). In the context of general accessibility to the aforementioned modern solutions, it is also worth noting the low-cost technologies (Ćmielewski et al., 2020; Lăpădat et al., 2021; Wielandt et al., 2023). Their continued development offers the possibility of widespread application for various objects - also with at least partial cost reduction. Integration of measurements can be carried out in many ways - from establishing analytical functions using specific data to advanced numerical methods and those based on artificial intelligence (AI) and its subfield, namely machine learning (ML). Nowadays, these solutions are the backbone of ongoing scientific research due to the ability to process large data sets quickly and reliably and formulate adequate conclusions (Aslanyan, 2023).

Hence, the paper describes the investigation of applying ML to diagnose the condition of historic structures and develop a reliable monitoring system capable of integrating diverse measurement data. This research focused on analyzing the buildings managed by the Coal Basin Museum in Będzin, Silesian Voivodship, Poland (www.muzeumzaglebia.pl). These structures were chosen due to their location in a high-risk area. Regarding that, numerous factors influencing stability can be observed, including:

- post-mining activity: these highly urbanized and industrialized areas have undergone significant transformations over time,
- climate change: dynamic shifts in temperature and water relations may cause unpredictable phenomena,
- combined effects: these factors accelerate geotechnical and rheological processes, leading to unforeseen consequences when combined with the aging of historic buildings.

For the purposes of this article, the focus is on the main building of the Coal Basin Museum - the Mieroszewski Palace, dating from the 18th century (Figure 1).

The two palace bastions - the annexes visible on the left and right - were added more than 150 years after the main body of the building was erected (www.muzeumzaglebia.pl). As the left bastion is located on a slope (fig. 2), the architectural element is subjected to increased displacement, resulting in the appearance of cracks and dilatations inside and outside the building (fig. 3). Condition monitoring of the building has been carried out by the authors since 2022 (Świerczyńska et al., 2024), and the two-and-a-half-year observations allow preliminary conclusions to be drawn about the behavior of the measured historic structure.

Figure 1 Frontal view of the Mieroszewski Palace, Będzin, Poland

Figure 2 View of the location of the left bastion of the Mieroszewski Palace on the escarpment

Figure 3 View of damage to the facade and interior of the palace

To perform this task, the authors use the existing ML-based solutions, adjusting them to the specific conditions and environment. Moreover, the studies are unique in terms of applying them to the existing structures, which have not been monitored so far except for spontaneous measurements done many years ago. The currently established cooperation between the Warsaw University of Technology and the Coal Basin Museum has opened up the possibility of using the achievements of science in the study of the technical condition of accessible, historic buildings – both their interiors and exteriors.

The article summarizes the studies conducted as part of scientific projects founded by the Scientific Council of the Discipline of Civil Engineering, Geodesy, and Transport, Warsaw University of Technology titled “Application of modern 3D Modeling Tools to determine the Technical Condition of historical buildings” (Dr. Ewa Świerczyńska) and ”Evaluation and modeling of geometric changes in the structures of historical buildings located in the areas of risk” (Dr. Krzysztof Karsznia).

2 Materials and methods

2.1 Integrated structural monitoring

Site monitoring was designed to consider the multi-scale and multi-source nature of the data to be acquired. Geodetic methods were used to observe geometric changes in the palace structure:

- precise leveling of benchmarks (performed quarterly or after a significant reason) with an accuracy of ±0.3 mm/km,
- total-station measurements with the use of an electronic total station (two campaigns so far), with an accuracy of ±1.0 mm,
- laser scanning of the palace interiors and façade (two campaigns so far) with an accuracy of ±2-3 mm,
- photogrammetric survey with UAV (two campaigns so far) with an accuracy of approximately ±5 mm,

as well as geotechnical:

- crack measurements using crack gauges (nine campaigns so far) with an accuracy of approximately ±0.1 mm and
- continuous structural monitoring of the left wing of the Mieroszewski Palace using the Axis precision hydrostatic inclinometer (https://ultraxis.eu, Ornoch et al., 2021) with an accuracy of approximately ±5 µm/1m.

The data being acquired, therefore, has different characteristics, precision, accuracy, and frequency of sensor readings. Consequently, building a coherent system based on them is a real challenge. It should be added that except for these values, the temperature and humidity of the palace interiors have also been measured. Undoubtedly, it is possible to conduct a comprehensive analysis by assessing the individual results separately and concluding the expert knowledge. Nevertheless, the task of the monitoring system is to warn users of possible undesirable events on an ongoing basis, which would be impossible in this approach.

A fundamental problem is, therefore, the consistency of the data and the frequency with which it is collected. The answer to such a problem may be linked to using various learning models.

2.2 Expert system design

Based on the work carried out, an information audit plan was developed, which is the core of the expert system being built. This system is supported by ML solutions. Its flowchart is shown in Figure 4.

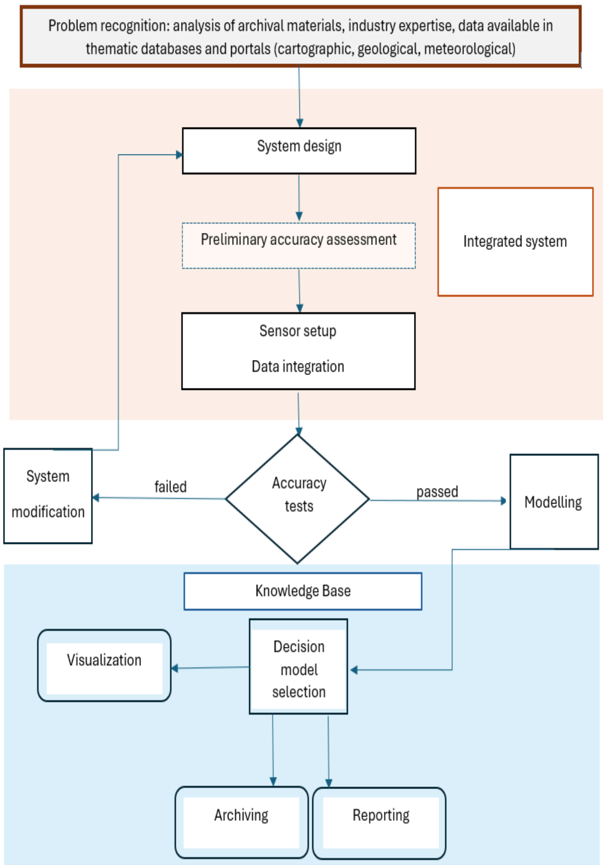


Figure 4 Conceptual scheme of the designed expert system (information audit)

To carry out the relevant input, the pertinent data was prepared and grouped according to the structure shown in Table 1.

Table 1. Summary of sensors providing input data

Sensor	Degrees of freedom	Description
crack meters	2	Linear values 2D
hydrostatic inclinometer	3	Angular values, temperature, vessel heights
leveling	1	precise leveling of benchmarks
total station	3	measuring control points
TLS	3	point clouds (3D, reflectivity, RGB)
UAV photogrammetry	3	point clouds, RGB
meteo data	1	temperature, moisture (indoor, outdoor)

The variety of data acquired necessitates its integration and modeling. To this point, ML algorithms were used.

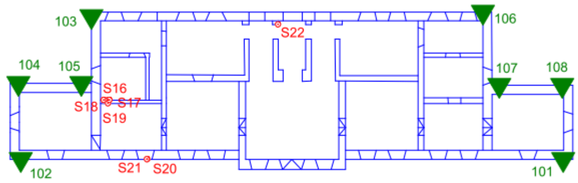
3 ML-driven modelling

The research was divided into two stages - aimed at detecting displacements inside the building (prediction of displacements based on cracks in the museum rooms) and outside (identification of cracks in the palace façade). The diversity of the measurement data determines the need for proper integration and inference. To achieve this goal, various machine learning (ML) models were explored.

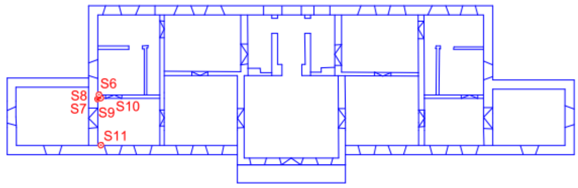
3.1 Indoor data

The modeling process used data from crack gauges stabilized on three floors of the palace in the location of the most extensive observed cracks, the results of leveling of benchmarks located outside the building on the ground floor, as well as the results of continuous measurements with a hydrostatic inclinometer situated in the left bastion in the attic (Fig. 5).

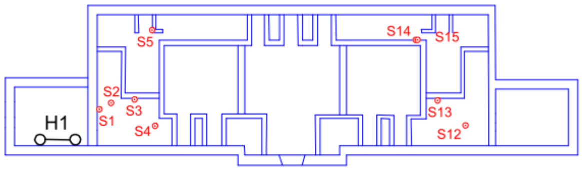
In addition, temperature and humidity readings taken at these locations were used in the computing process. A view of the measuring sensors is shown in Fig. 6 and 7.



a) ground floor (crack meters marked red and leveling benchmarks marked green)



b) 1st floor (crack meters marked red)



c) attic (crack meters marked red and tiltmeter H1 marked black)

Fig. 5 Location plan of measuring sensors (a – ground floor, b – the first floor, and c – the attic)

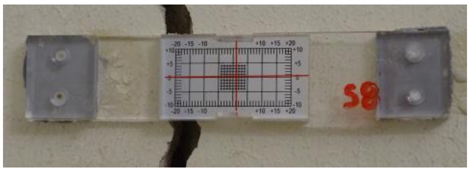


Fig. 6 View of a crack meter installed inside the Mieroszewski Palace

Fig. 7 View of the hydrostatic tiltmeter installed in the attics

Inexpensive crack meters have been installed where accessible, providing precise geometric data. The reading precision for the simplest type of crack gauge is 0.1 mm. A hydrostatic inclinometer is a high-precision sensor that tracks changes in the building segment movements toward the building façade.

The geotechnical sensor data, while valuable, is inherently localized, providing information only about the specific section of the structure where the sensor is installed. To accurately determine the displacement parameters of individual segments affected by cracks, a unique methodology is required. The first solution may be to create a mathematical model of the structure, considering the separate segments produced by the appearance of cracks. Such a task can only be performed after thoroughly analyzing the building structure and the material losses. Another key element contains the positions and spatial orientation of all crack gauges. An alternative solution can be proposed as collecting all the information is difficult or impossible. It uses an AI-based model that can find a relationship between a set of local sensor readings and the behavior of an object. The measurement results are control data that can be used to train the model. The data was processed using three ML variants: two based on neural networks and one based on a decision tree (DT). The first variant uses an artificial neural network (ANN), specifically a feed-forward neural network trained by a backpropagation algorithm. The second variant relies on deep learning (DL) and consists of a multi-layer feed-forward artificial neural network trained with stochastic gradient descent using backpropagation (RapidMiner, 2025). The procedure workflow is shown in Figure 8.

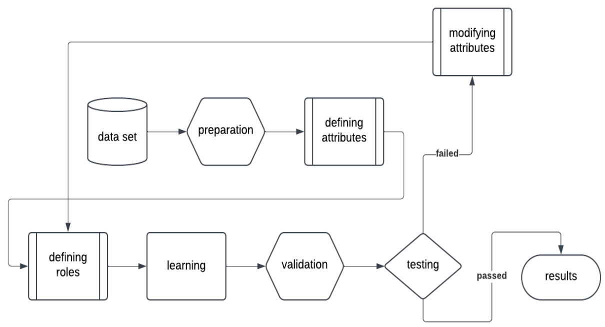


Fig. 8 Workflow chart of the ML modeling process

All processes used 33 features for which attributes were defined: 22 crack gauges, two hydrostatic inclinometer vessels, seven control benchmarks (due to destruction, benchmark 104 was eliminated from processing), and two developed fracture scans located on the ground and first floor). The data set comprised the difference between two survey periods - the reference epoch (the moment of installation of the hydrostatic inclinometer in May 2023) and the most recent survey epoch of December 2024. The attributes of the above-mentioned features were the differential values of the 2D displacement vector, the increase in the attic tilt angle, the change in the height of the leveling benchmark characteristic for a specific location of the crack meters (a particular wing of the palace), the difference in temperature and humidity inside the building (different for individual stories), as well as the average width of the cracks identified from the scan. As stated, the calculations were done for three variants: 1) using ANN, 2) DL, and 3) DT. A diagram of the modeling process is shown in Fig. 9.

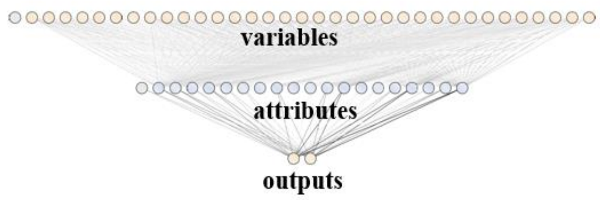


Fig. 9 Diagram of the modeling process using neural networks

As a result of the tests, the system identified the attribute relating to the crack gauge readings as the key variable in determining the deformation that occurred.

The resulting displacement qualification was ~ 0.3 mm for the 2D vector. The resulting accuracy rate was 100%, which, according to the authors, indicates the relatively small set of data analyzed. This set should, therefore, be successively supplemented, and, as far as possible, the number of variables should be expanded by adding more measurement points, especially at newly appearing cracks in the rooms of the object.

In the next step, the change in the angle of inclination of the structure of the left palace bastion should be considered.

The given limit for the difference in the angle of inclination results in 45.213 arc seconds, which, according to the manufacturer, corresponds to a displacement of 252 micrometers per one meter (1''= 4.85 μm/m) (https://ultraxis.eu). This means that the eligibility limit as displacement is 0.25 mm for each running meter of the structure tested. This calculation, however, demonstrates the high variability of the monitored processes and the excessive resolution of the device's operation. Absolutely, this implies the need for further measurements and the expansion of the test network at the site.

3.2 Outdoor data

In order to identify the cracks on the façade of the Mieroszewski Palace, photogrammetric images acquired from a UAV were used. To accurately reference the obtained cloud, photo points were located on the façade of the palace, according to the scheme shown in Fig. 10.

Fig. 10 View of the palace façade with attached photo points (red dots)

The UAV flight was carried out using DJI Mavic 3 Enterprise with the parameters described in (https://enterprise.dji.com/mavic-3-enterprise).

Of all the ML algorithms available in Matlab software, those involving supervised machine learning (one in which the model is provided with data and an appropriate output response) were selected. The modeling was carried out for specific samples - a fragment of a point cloud. The input data consisted of various features extracted from point cloud data. The research aimed to identify the most informative features for accurately classifying points as either belonging to gap points or non-gap points. The responses in the classification method given by the classifier thus belonged to a finite set (the opposite of the regression method, where we predict a continuous reaction). The output data was the answer: 0 (false - no, this is not a gap point) or 1 (true - yes, this is a gap point). A schematic of the procedure is shown in Fig. 11.

In the case of data preprocessing, it is important to reasonably identify and eliminate gross errors, as the quality of the model and prediction directly depends on this step.

The most crucial approach in machine learning is the proper design of the samples on which the models learn and the appropriate selection of features for analysis. In the present study, including normal vector parameters in addition to color (RGB) proved more accurate. In turn, increasing the samples by one was associated with significantly improving classification performance.

The two variants of the test fields analyzed are shown in Fig. 12, while the classification results are presented in Fig. 13.

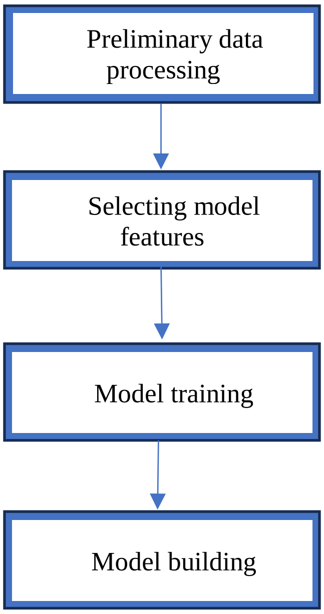
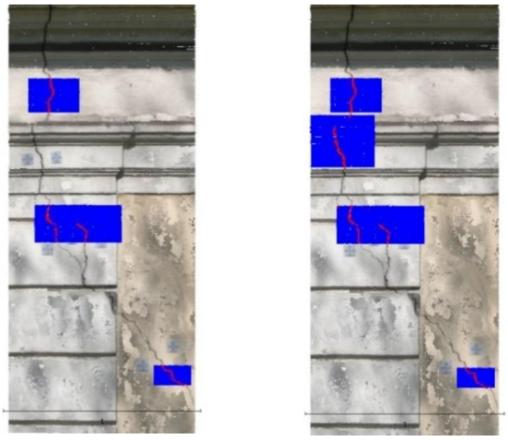


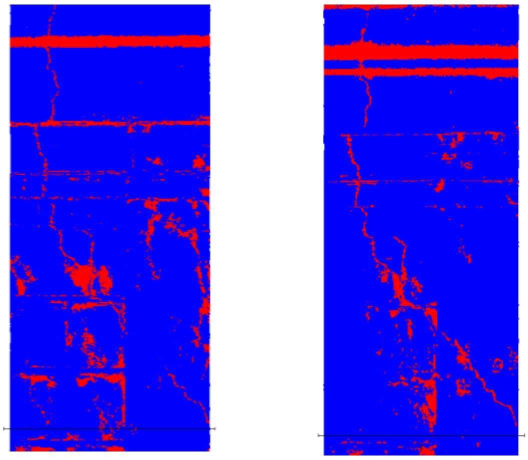
Fig. 11 The data modeling process in the façade crack detection



a) b)

Fig. 12 Point cloud with marked test fields in the two variants analyzed: a) three test fields, b) four test fields

Figure 13 a) shows the effect of classifying the points of the cloud fragment with the narrow neural network model, which was trained based on three test areas and RGB feature (97,5% validation). Figure 13 b) shows the effect of classifying the points of the cloud fragment with the narrow neural network model, which was trained based on four test areas, RGB feature, and normal vector. Model response is 1 – crack (red color), 0 - no crack (blue color). Figure 12 a shows the location of the test areas for the results from Figure 13 a, and Figure 12 b shows the location of the test areas for the results from Figure 13 b. Increasing the number of inputs to the model by a further sampling area improved the effect of the classification process of the whole gap area.



a) b)

Fig. 13 View of an improved crack recognition result

Of the algorithms available in Matlab software, the best results were obtained by training classifiers based on neural networks. Example results for all the algorithms analyzed are given in Table 2. The average accuracy was calculated based only on the test fields in order to keep its relevance and avoid noise.

Table 2. Average accuracy of individual data classifiers (Classification Learner application)

Classifier	Accuracy (Validation) [%]			
	RGB	RGB+ Normal	RGB+ Normal Angle	RGB+ Normal+ Angle
Decision Trees	95,8	97,0	96,9	97,1
Discriminant Analysis	95,9	96,8	96,4	96,9
Logistic Regression	96,1	96,4	96,6	96,8
Efficiently Trained Linear	95,8	96,2	96,3	96,3
Naive Bayes Classifiers	89,5	91,8	92,1	92,0
Support Vector Machines	77,5	97,5	97,3	97,5
Nearest Neighbor Classifiers	96,3	98,1	97,9	97,9
Ensemble Classifiers	93,2	96,7	96,6	96,9
Neural Network Classifiers	97,5	98,3	98,3	98,2
Kernel Approximation	95,8	96,4	96,9	97,5

Increasing the number of features significantly improves the validation factor of each classifier analyzed. In a classifier based solely on RGB coordinates, coarse errors were introduced by the shadow cast on the elevation by a nearby tree. As a result, detecting even minor damage and newly formed scratches is possible. The proposed method of classifying images and, as a result, recognizing the effects of damage to the façade surface contained in them is an important element in automating the process of building a knowledge base about the object.

4 Conclusions

Developing a monitoring system for engineering structures, especially historic buildings, demands a comprehensive, multi-modal, and integrated approach to both measurement and analysis. A critical aspect indicative of the solution's scientific rigor is the thoughtful definition of safety thresholds that trigger appropriate notifications. In the context of monuments, measurement, and condition monitoring systems must prioritize non-invasive technologies – e.g. TLS and close-range photogrammetry. The processing of such data sets and their integration is not easy and leaves a large margin for interpretation uncertainty. AI and ML solutions appear as reasonable solutions, allowing multithreaded and consistent data processing and reliable definitions of alarm thresholds.

Acknowledgments

The authors especially wish to thank Dr. Jacek and Dr. Małgorzata Sztubecki from the Bydgoszcz University of Technology, Poland for their significant contribution to the measurements and computations. Additional thanks go to Prof. Izabela Karsznia, University of Warsaw, Poland, a specialist in applied AI in cartography, for consultations and substantive support in terms of AI.

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