# An Integrated IoT–AI Framework for Bridge Infrastructure: Z24 Bridge Case Study


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***Abstract*—This paper presents an integrated IoT–AI framework for bridge structural health monitoring using the Z24 bridge case study. The workflow combines vibration data processing, feature extraction, ML, XAI, and BIM-based visualization. The model classifies the bridge condition as healthy, partially damaged, or damaged, while XAI supports interpretation of the main features influencing predictions. The results show that the proposed approach enables reliable, interpretable, and visually accessible damage assessment for bridge infrastructure.**



***Index Terms*—Structural Health Monitoring, BIM, IoT, AI, explainability**


## I. Introduction

The monitoring and management of existing infrastructure represent today one of the main challenges for transportation systems and the construction sector. In particular, the gradual aging of the infrastructure, combined with the increase in traffic loads and the growing exposure to extreme environmental phenomena, makes it necessary to develop advanced tools for the continuous assessment of the health status of structures. In this context, Structural Health Monitoring (SHM) techniques are taking on a central role in supporting predictive maintenance strategies and data-driven decisions. At the same time, the evolution of digital technologies has introduced new paradigms for infrastructure management, including the integration of Building Information Modeling (BIM), Internet of Things (IoT) data acquisition systems, and Digital Twin (DT) models. These tools allow for the creation of dynamic digital representations of structures, capable of integrating geometric information, data from sensors, and results from advanced analyses. Within this context, the use of artificial intelligence (AI) and Machine Learning (ML) techniques opens new perspectives for the automated interpretation of monitoring data and for the early detection of degradation phenomena [1]. To this end, this work explores an approach based on global dynamic monitoring, through the analysis of vibrational signals acquired via sensors installed on the structure. In this case, ML models are used to classify the structural state based on modal characteristics and variations in dynamic response, allowing for the identification of any anomalies in the overall behaviour of the infrastructure.

The main contribution of the research, therefore, lies in the definition of an integrated approach to infrastructure monitoring, expanding the work of [3], [4] to the Z24 bridge, providing concrete evidence of the applicability of the proposed framework and demonstrating that the combination of advanced feature extraction, Random Forest (RF) classification and Explainable AI (XAI) techniques (e.g., [2]) can be used to efficiently discriminate between a number of structural health conditions, while also increasing the interpretability of damage-related predictions and allowing their integration within a BIM-based Digital Twin environment.

## II. Background: Z24 Bridge

The Z24 bridge was a road viaduct located in the Canton of Bern, Switzerland. The bridge used to connect the municipalities of Koppigen and Utzenstorf, spanning the A1 Bern-Zurich expressway. It was designed and built between 1961 and 1963. It was a classic box girder bridge, with two post-tensioned concrete cells, a main span of 30m, and two side spans of 14m each. The bridge was demolished at the end of 1998 because a new railroad adjacent to the highway required a new bridge with a wider side span. Between 1997 and 1998, the bridge was the subject of an extensive experimental campaign as part of the European SIMCES project involving the installation of environmental and dynamic monitoring systems, including networks of accelerometers and temperature sensors, before a scheduled demolition. This experiment combined synchronized environmental data with high-frequency dynamic measurements and realistically incremented damage tests: such a combination is rare and made the Z24 one of the most important experimental benchmarks in the field of SHM and operational modal identification [5].

## III. METHODOLOGY

The methodological process begins with a data processing stage, made necessary by the nature of the already available vibrational data (Fig. 1). The experimental acquisitions are indeed subjected to pre-processing operations aimed at making them suitable for the subsequent phases of analysis. This phase includes the normalization of signals and the reduction of noise presented in the input data, but also involves operations of feature extraction and feature synthesis, aimed at deriving more compact and significant informative representations of the dynamic behaviour of the structure. Once the processing phase is completed, the workflow continues with the implementation of the classification model. At this stage, the previously processed data is organized into a structured dataset and used for training the ML model. In this case study, the analysis is entrusted to the application of the Random Forest algorithm, selected for its ability to handle multiclass classification problems and its robustness against data variability. Subsequently, the produced results undergo an interpretation and evaluation step via quantitative metrics that enable the estimation of the model's performance in terms of accuracy and reliability in recognizing different damage scenarios. Alongside performance metrics, XAI techniques (via the Python libraries *eli5* and *alibi*) are also utilised, allowing for the analysis and understanding of the decisions made by the model, making the classification process more transparent and interpretable from an engineering perspective. The workflow concludes with the results visualization, where the information obtained from the data-driven analysis is translated into tools that support the understanding and management of the structural condition. In particular, a Digital Twin of the bridge is created in a BIM environment, within which the health status of the structure is represented intuitively by means of graphical feedback. At the same time, a dedicated user interface is developed, designed to allow even non-expert users to quickly access information on the type and level of damage occurring, facilitating effective use of the monitoring results.

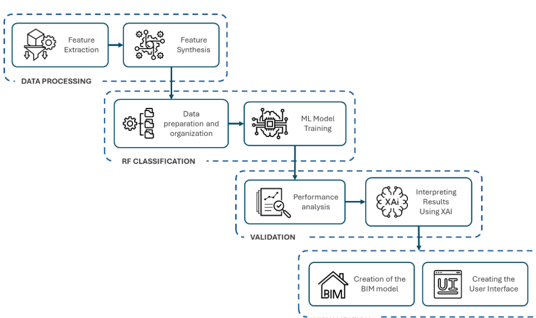


Fig. 1. Proposed IoT-AI workflow.

## IV. RESULTS AND DISCUSSION

The proposed workflow achieved reliable damage classification on the Z24 bridge dataset after grouping the original damage scenarios into three macroscenarios: healthy, partially damaged, and damaged (Table I). The Random Forest model showed high overall accuracy, with consistently strong precision and recall across the three classes. The healthy state was identified most accurately, while the damaged class was also recognized with good reliability, confirming the model's ability to detect critical structural conditions with limited underestimation. Most errors occurred in the partially damaged class, reflecting the expected overlap between intermediate and more severe damage states. A second hierarchical classification stage further distinguished individual scenarios within each macrocategory, showing strong performance for healthy and partially damaged configurations and slightly lower, but still robust, performance for the most complex damaged scenarios. XAI analyses showed that the most influential features were mainly related to frequency content, energy distribution, and signal regularity, confirming that the classifier captured physically meaningful changes in the bridge's dynamic response. The predicted health states were also successfully linked to the BIM model and prototype interface, enabling intuitive visualization of healthy, partially damaged, and damaged conditions through colour coding, confidence indicators, and key explanatory features.

| Classification Task | Accuracy | Precision (avg) | Recall (avg) |
|---|---|---|---|
| *Macroscenarios* | 94% | 92% | 94% |
| *Healthy Scenarios* | 97% | 96% | 97% |
| *Partially Damaged Scenarios* | 98% | 95% | 98% |
| *Damaged Scenarios* | 91% | 90% | 93% |

TABLE I
RANDOM FOREST CLASSIFICATION RESULTS.

## V. CONCLUSION

Overall, the results demonstrate the potential of the proposed framework as an integrated decision-support system for bridge monitoring. Although the user interface and BIM integration remain prototypes, the case study shows that combining SHM data, machine learning, explainability, and digital visualization can provide a robust and interpretable basis for infrastructure assessment and management.

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