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Integrating Ambient Vibration Monitoring and Machine Learning for Condition Assessment of Heritage Masonry Bridges: A Venetian Case Study

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Abstract. Preserving the structural integrity of heritage masonry arch bridges presents unique challenges, particularly within historically dense environments like Venice where non-invasive methods are paramount. Ambient vibration monitoring (AVM) offers a well-established starting point by capturing the dynamic behavior of these structures under their normal operating conditions. This research involves a large-scale AVM campaign across Venice, using velocimeters, to extract key dynamic parameters like dominant frequencies, mode shapes and damping ratios, alongside essential geometric features. Simultaneously, careful visual inspections provide the critical qualitative context regarding each bridge's state of conservation. By integrating these distinct quantitative and qualitative data streams, a unique baseline archive was developed to move beyond characterization towards meaningful interpretation.

This paper explores how this integrated dataset can be leveraged to address the significant challenge of automated condition assessment. A supervised machine learning framework was employed to bridge the gap between measured data and assessed structural condition. The curated archive, which links the dynamic and geometric measurements (inputs) to discrete condition categories derived from the visual inspections (outputs), provides the training ground for established classification algorithms, specifically Support Vector Machines (SVM) and Random Forest (RF). Standard pre-processing techniques, including feature scaling, are incorporated to ensure the classifiers can effectively learn from the data without scale-induced biases. Initial explorations with this framework have already yielded valuable insights. For instance, feature importance analysis of the Random Forest model, strongly suggests that the dynamic parameters captured via AVM—particularly damping ratio and dominant frequency—offer considerably more diagnostic information about condition than the simpler geometric descriptors alone. This finding reinforces the value embedded in vibration monitoring. Moreover, the study confirms the feasibility of training these models to distinguish between different condition states using only the combined instrumental and geometric data. Importantly, from an engineering perspective, we recognize that raw classification accuracy is insufficient; ensuring high sensitivity (Recall) in identifying potentially compromised structures is critical for responsible heritage management and risk mitigation.

This AVM-ML methodology provides a scalable foundation for developing more objective, data-supported tools to assist in condition assessment and guide proactive maintenance for vital cultural infrastructure. Further research will necessarily involve expanding the dataset and undertaking validation of the models.

Keywords: Structural Health Monitoring (SHM), Ambient Vibration Monitoring (AVM), Machine Learning, Condition Assessment, Masonry Arch Bridges

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https://doi.org/10.58286/34006

Introduction

The historical urban fabric of Venice is defined by its complex network of over 400 bridges. These historic structures are invaluable but vulnerable to age and environmental factors, and traditional monitoring can be invasive and risk damaging these heritage infrastructures [1, 2]. Therefore, as these bridges age, the need for objective, non-destructive health assessment becomes critical.
Traditional Structural Health Monitoring (SHM) often relies on visual inspections, which are inherently qualitative and subject to observer bias [3]. Conversely, invasive testing is strictly limited by heritage conservation protocols. Ambient Vibration Monitoring (AVM) has emerged as a robust alternative, providing global dynamic parameters that reflect the health of the structure without physical intervention [4, 5, 6]. However, the interpretation gap between raw dynamic data and structural decay remain a significant challenge in engineering practice.
This paper proposes an integrated framework that bridges this gap using Machine Learning (ML) [7, 8]. By training classifiers on an initial archive of Venetian bridges' characteristics [9, 10], it aims to automate condition assessment and allow damage prediction and maintenance planning. This study focuses on the diagnostic power of dynamic signatures and discusses the engineering implications of automated health classification.

1. Experimental Campaign and Data Acquisition

The study focuses on a representative sample of 25 bridges (part of a broader ongoing archive of 80+ bridges) in Venice [9, 10]. While having similarities in material and shape, these bridges (Fig. 1) cover various span lengths, widths, and structural conditions, ranging from recently restored structures to those showing advanced signs of decay.



Fig. 1. Examples of monitored masonry arch bridges in Venice

Dynamic testing was performed using synchronized Tromino® digital velocimeters. These 3D sensors are ideal for the Venetian context due to their high resolution and portability (1.1 kg) [11]. To minimize anthropic noise due mainly by pedestrians, measurements were conducted between 0:00 AM and 6:00 AM [12]. The standardized protocol involved 3 different timings, 4, 8 and 16-minute recordings at a sampling frequency of 128 Hz. Sensors were placed in two complementary setups, a longitudinal configuration: one at the mid-span and two at the first and third quarter-spans, and a transversal configuration: on the bridge's midspan, one in the center and two on the sides (Fig. 2). These two setups help to distinguish between the flexural and torsional mode shapes [13, 14].



Fig. 2. Instrumentation and sensor placement protocols on a typical Venetian masonry arch bridge

2. Data Processing and Signal Analysis

The extraction of modal parameters from raw ambient noise necessitates a rigorous processing pipeline to isolate structural resonances from environmental disturbances. Initially, the time-histories recorded by the tromographs are partitioned into discrete time windows [19]. To suppress high-frequency anthropic noise and mitigate low-frequency drift, a band-pass filter is applied to the raw signals. This pre-processing stage ensures that the data is sufficiently cleaned and stabilized before undergoing spectral transformation.
The transition from the time domain $h(t)$ to the frequency domain $H(f)$ is achieved via the Fast Fourier Transform (FFT) [15]. For a continuous signal, this transformation is mathematically expressed as:

$$H(f) = \int_{-\infty}^{+\infty} h(t) e^{-i2\pi f t} dt$$

Following the spectral transformation, natural frequencies (f_n) are identified using the Peak Picking (PP) method, correlating spectral maxima with the fundamental structural response modes of the masonry arches (Fig. 3) [10, 16, 17]. Then, from the frequency amplitude spectrums, the damping ratio ζ, which serves as a sensitive indicator of material degradation and structural compactness in masonry, is estimated using the Half-Power Bandwidth method [18-21]:

$$\zeta = \frac{f_b - f_a}{2 f_n}$$

where f_a and f_b are frequencies at which the amplitude drops to 1/√2of the peak value.

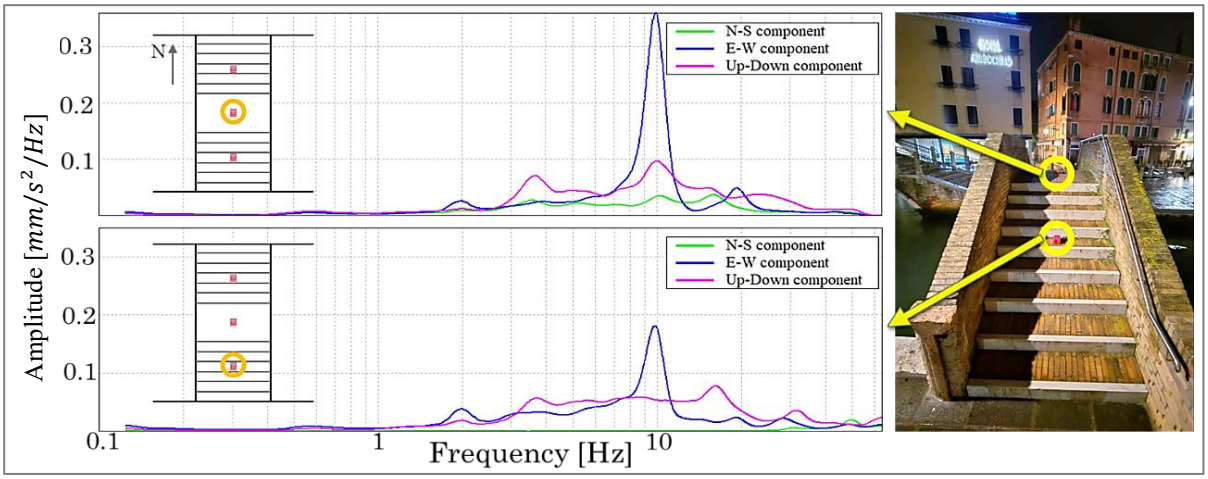


Fig. 3. Typical amplitude spectra of Ponte Cosetti by AVM, identifying dominant frequency peaks

3. Machine Learning Framework

Machine learning models are broadly categorized into three main groups based on how they learn from data: Supervised Learning, Unsupervised Learning, and Reinforcement Learning [22, 23]. Having a data archive of 25 bridges with labels [9], the focus would be on the supervised learning models.

3.1 *Feature Engineering and Labelling*

To construct the classification models, a primary feature set was developed consisting of 5 quantitative descriptors (X) for each bridge:

- Geometric Features: Overall span length (L), bridge width (W), and arch height (H).

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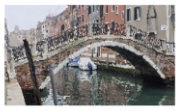
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- Dynamic Features: Dominant frequency (f_n) and damping ratio (ζ).

These parameters represent the core signature identified during the preliminary stage of the Venice monitoring campaign [9]. By focusing on these fundamental descriptors, the models attempt to find correlations between the physical dimensions and the structural response as a function of the conservation state.

The target variable (Y) consists of three discrete condition categories: "Poor", "Fair", and "Good". These labels were assigned based on visual inspections that scored damages like cracks, mortar loss, vegetation growth, weathering, erosion, and settlement. Table 1 showcases five representative entries from the archive that is going to be used for training and testing of ML models for conservation predictions.

Table 1. Representative sample from the Venetian Bridge Archive

No.	Photo of the Bridge	Bridge Name	Level of Conservation	Dimensions (m)			Peak Frequencies (Hz)	Dominant Mode	Damping Ratio (%)
				Length	Width	Height			
1		Ponte Cosetti	Poor	7.75	2.22	2.10	0.62		-
							2		-
							3.6		10.9
							10.2	Flexural	14.2
							16		-
2		Ponte Santa Maria Maggiore	Poor	10.23	3.59	2.85	2.72		-
							9.6	Torsional	-
3		Ponte de le Terese	Fair	9.30	4.12	2.05	2.05		10.7
							6.64	Flexural	18.9
							16.5		-
4		Ponte S. Nicolò	Fair	8.06	4.33	2.10	0.61		-
							1.65	Flexural	19.8
							6.7		-
5		Ponte De La Piova	Fair	8.06	3.78	2.35	1.4		22.3
							5.15		-
							7.4		-
							11.4	Torsional	-

3.2 *Data Preparation*

The models cannot read text labels ("Poor") or understand mixed units (Hz, %, m); therefore, all data must be translated into a purely numerical format. To do so, the level of conservation of Poor, Fair and Good were translated into numbers of 0, 1 and 2, respectively. Furthermore, to ensure the model judges each feature fairly, based only on its predictive power, and to remove any bias towards the features with higher ranges, the data must be calibrated to a common scale (mean=0, std=1) [24].

3.3 *Classification Algorithms*

Initially, the dataset of 25 bridges was split into a training set (17 bridges) and a test set (8 bridges, to be predicted by the model), and then to address the multi-class problem, two robust supervised algorithms were evaluated: Support Vector Machine (SVM) [25-27]and Random Forest (RF) [28-30]

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3.3.1 *Support Vector Machine (SVM):*

SVM is a powerful classifier that finds an optimal hyperplane (decision boundary) which best separates the classes (e.g., "Poor" vs. "Good") in a high-dimensional feature space [25, 26]. To handle the 3 classes of output, it uses a one-vs-rest strategy (Fig. 4), by building three separate hyperplanes, that each one separates one output class (e.g. Poor) from the other two classes (e.g. Fair and Good). The algorithm works to maximize the margin between the hyperplane and the closest data points of each class (the "support vectors"). Finally, a new bridge is then assigned to the class of the hyperplane that classifies it with the highest confidence.

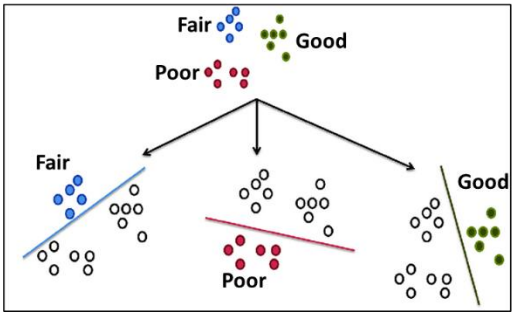


Fig. 4. An Example of SVM with 3 Classes and with two features (2D)

To find the hyperplane of $\omega^T x + b = 0$, the model solves the optimization problem:

$$\min_{\omega,b} \frac{1}{2} ||\omega||^2$$

subject to the constraint that all points are classified correctly:

$$y_i(\omega^T x_i + b) \geq 1$$

For the current non-linear data, SVM uses a Kernel Function $K(x_i, x_j)$ to project the data into a higher-dimensional space where it can be separated [27]. To do so, the RBF Kernel is used to project the data into a higher-dimensional space, allowing the hyperplanes to find a non-linear separation.

$$K(x_i, x_j) = \exp(-\gamma ||x_i - x_j||^2)$$

where, x_i is the input vector for a single bridge (i.e., its 5 features: [Length, Damping, Freq...]), y_i is the class label for that bridge (e.g., "Poor" or "Not Poor"), ω is the weight vector, which defines the angle or orientation of the hyperplane, b is the bias term, which defines the offset or position of the hyperplane, and γ is a "hyperparameter" that controls the flexibility of the RBF kernel's boundary. SVM works well for finding complex, non-linear boundaries between conservation levels using many input features available.

3.3.2 *Random Forest (RF):*

Random Forest is an ensemble model that builds hundreds of individual Decision Trees during training and merges their outputs for a single, highly accurate prediction [28, 29]. Each of the T trees is trained on a different random subset of the bridge data by sampling with replacement. At each split in a tree, only a random subset of features (e.g., "Length" and "Damping") is considered, and this method helps decorrelating the trees. Finally, each tree asks a series of simple questions (e.g., "Is Damping < 10.5?") and then "votes" on the bridge's condition. The model takes a "majority vote" from all T trees to determine the final class.
Each tree split (question) is chosen to minimize impurity, G, (i.e., maximize homogeneity) in the resulting nodes [30, 31]. A "pure" node with only "Poor" bridges would have G = 0).

$$G = 1 - \sum p_i^2$$

where p_i is the proportion of samples belonging to class i at that node. The predicted class $\hat{y}$ is the one most voted for by all T trees (h_t):

$$\hat{y} = arg\,\max_k \sum_{t=1}^{T} 1(h_t(x) = k)$$

where $h_t(x)$ is the prediction of a single tree, k is a specific class (e.g., Poor, Fair, or Good), $arg\,\max_k$ is a function that finds the class k which maximizes the sum (i.e., gets the most votes) and 1(...) is an indicator function that equals 1 if the tree's vote $h_t(x)$ is for class k and 0 otherwise.

4. Results and Engineering Discussion

4.1. Feature Importance (by Random Forest)

One of the significant findings is the statistical confirmation of the diagnostic value of dynamic parameters. Random Forest analysis (Fig. 5) revealed that damping ratio and dominant frequency are the most influential predictors of structural health, significantly outperforming purely geometric descriptors [28, 31, 32]. This reinforces the hypothesis that instrumental monitoring captures internal structural changes (e.g., stiffness degradation) that are invisible to geometric archives.

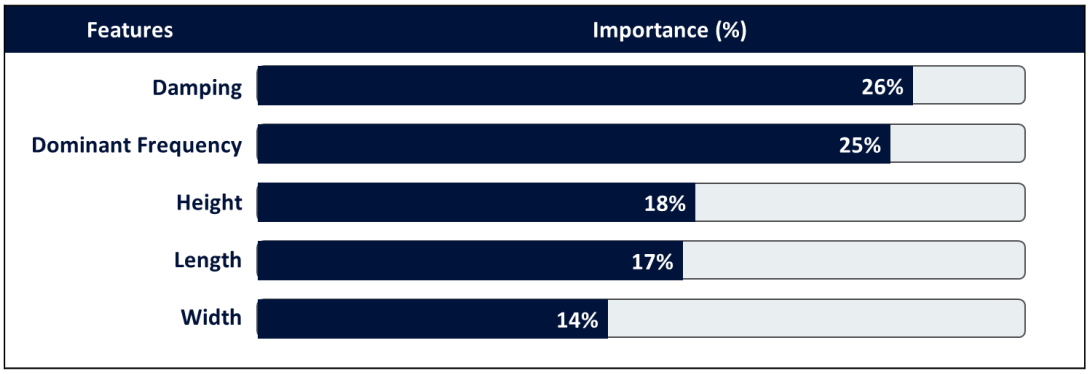


Fig. 5. Feature Importance for Predicting Bridge's Level of Conservation

4.2. Sensitivity and Engineering Error Analysis

On the unseen test set, the implemented machine learning models yielded preliminary classification accuracies of 62% for the SVM model and 50% for the RF model. While the global accuracy metric suggests a superior performance by the SVM classifier for this specific baseline dataset, standard statistical measures do not fully capture the structural safety implications inherent in Structural Health Monitoring [32, 33]. Table 2 provides a detailed, comparative breakdown of the predictions made by both models across eight representative test bridges against the visual inspection results.

Table 2. Detailed predictions on the 8-bridge test set by the two ML models

Bridge Name	Visual Inspection (Human Judge)	RF Prediction	SVM Prediction
Ponte del Forno	Poor	Fair	Fair
Ponte Sartorio	Good	Poor	Poor
Ponte dei Pugni	Fair	Fair	Fair
Ponte Rosso	Fair	Fair	Fair
Ponte de San Basegio	Poor	Poor	Poor
Ponte Briati	Poor	Fair	Poor
Ponte San Barnaba	Fair	Poor	Poor
Ponte De La Piova	Fair	Fair	Fair

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In practical heritage management, it is critical to differentiate between misclassification types based on their risk level. We define "Safe Errors" as the over-estimation of damage (e.g., classifying 'Fair' as 'Poor'), and "Critical Errors" as the potential under-estimation of deterioration (e.g., classifying 'Poor' as 'Fair' or 'Good') [33]. The latter poses a significant risk to risk mitigation and infrastructure safety.

A detailed examination of Table 2 indicates that while accuracy remains a useful benchmark, the models' primary value lies in their ability to correctly isolate high-risk structures. For instance, both models successfully identified Ponte de San Basegio as 'Poor', demonstrating the framework's capability to detect severely deteriorated conditions critical for immediate intervention. However, the superior sensitivity of the SVM model is evident in cases like Ponte Briati (Visual: Poor), where SVM correctly classified the condition while RF incurred a Critical Error by predicting 'Fair'.

Conversely, both models exhibited Safe Errors for Ponte Sartorio and Ponte San Barnaba, over-estimating their damage levels. From an engineering perspective, such conservative biases may suggest that certain healthy or slightly degraded bridges exhibit dynamic signatures that mimic advanced deterioration, potentially due to hidden geometric complexities. While these errors reduce overall accuracy, they are acceptable within a responsible risk mitigation strategy, as they trigger precautionary, detailed inspections rather than missing critical structural flaws.

4. Conclusion

This study demonstrates that the integration of Ambient Vibration Monitoring and Machine Learning provides a scalable and objective framework for the condition assessment of Venice's heritage masonry bridges [9]. The use of vibration signatures extracted via nighttime Operational Modal Analysis allows for a robust, non-invasive screening of historical structures, prioritizing those in need of maintenance without compromising their material integrity. By leveraging supervised models, it is possible to transform raw dynamic data into actionable insights for heritage management.

Looking forward, the research trajectory focuses on several critical developments to enhance the reliability of the diagnostic system:

- The expansion of the current dataset to over 80 bridges remain a primary goal to expand the Venetian bridge archive [9], which will significantly improve the models' generalization capabilities and provide a more statistically significant representation of diverse structural pathologies.
- Refinement of advanced signal processing techniques, including automated windowing optimization and adaptive filtering, is planned to further isolate structural features from persistent environmental noise and improve the quality of the input data.
- Evaluation of a broader spectrum of algorithmic architectures, such as Logistic Regression, K-Nearest Neighbors (KNN), and Gradient Boosting Machines (GBM), will be conducted to identify the most effective tool for achieving maximum diagnostic accuracy in masonry-type infrastructures.
- In-depth investigation into the root causes of misclassification will be prioritized, specifically focusing on outlier cases where models fail to provide consistent predictions.
- Development of a zero-tolerance diagnostic approach aiming to eliminate critical classification errors by refining the model logic, can help ultimately in providing a proactive, data-driven management tool for the long-term preservation of cultural heritage.

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