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Development of a Digital Twin of a Laboratory Structure for Machine Vision-Based Structural Health Monitoring Approach

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Abstract:

This study presents a cost-effective Structural Health Monitoring (SHM) approach that integrates machine vision, digital twin technology, and machine learning. Machine vision serves as a sensor to capture the response of a three-story laboratory structure under base excitation, using the optical flow method and the Lucas-Kanade algorithm to track displacements. These measurements are validated against radar and accelerometer sensors, demonstrating the effectiveness of radar sensors for vibration-based displacement monitoring in SHM. A digital twin is then developed by integrating vibration data with a physics-based model to simulate structural behavior, enabling the detection of damage type, location, and severity under various conditions. Different machine learning classifiers are trained on data from both simulated and physical models, with the Manhattan distance-based classifier achieving the highest accuracy of 92%. The results indicate that this digital twin system offers a reliable tool for real-time SHM and predictive maintenance, facilitating early damage detection and enhancing structural resilience.

Keywords: Structural health monitoring, Computer vision, Machine learning, Digital twin, Optical flow algorithm, Lucas-Kanade algorithm, Physics-based model, Manhattan distance

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1- Introduction

Structural Health Monitoring (SHM) ensures the safety and durability of structures by continuously assessing their condition and identifying damage over time. This real-time data informs maintenance and repair decisions, ultimately extending the structure's lifespan and enhancing safety (Mohseni Moghaddam et al., 2024). In recent years, the integration of digital twin technology and computer vision into SHM systems has received increasing interest. A digital twin acts as a virtual counterpart of a physical system or structure, created by utilizing sensor data, data analytics, and modern technologies. The digital twin concept, introduced by Michael Grieves (2014), comprises three key elements: the physical twin, the virtual twin, and a data connection that facilitates the exchange of information between the two (Grieves, 2014). Establishing a digital twin of a structure enables the simulation of its performance under various conditions, allowing for more precise and effective monitoring (Jones, 2020). Advancements in Artificial Intelligence (AI) and Machine Learning (ML) have further enhanced the capabilities of digital twins, enabling them to process large datasets and predict future structural behavior with greater accuracy (Chakraborty and Adhikari, 2021, Hamidian et al., 2022).

Research into digital twins has expanded across numerous fields, particularly in improving modeling and monitoring. Wagg et al. (2020) investigated the use of digital twins to address vibration issues in mechanical systems, demonstrating how data augmentation can enhance models to compensate for discrepancies. Gardner et al. (2020) applied digital twins to SHM, combining data-driven models with machine learning to optimize predictions of structural behavior and detect damage. Johansen et al (2019) explored digital twin applications in marine power systems to monitor drivetrains, while Loverdos and Sarhosis (2023) utilized computer vision and convolutional neural networks (CNNs) to create geometric digital twins for documenting and assessing masonry structures. Wang et al. (2023) proposed a method integrating digital twin technology and hierarchical deep learning to identify damage in cable dome structures. Their approach accurately captured damage features, validated through analysis of cable forces, demonstrating the effectiveness of digital twins for structural representation. Ali et al. (2021) developed an autonomous UAV system integrated with a modified Faster R-CNN to detect structural damage in GPS-denied environments, effectively identifying small and blurry defects with high precision. Kim and Cha (2024) introduced the Attention-based Modified Nerfacto (ABM-Nerfacto) model to enhance 3D reconstruction quality, facilitating accurate damage mapping within digital twins. These advancements demonstrate the growing role of digital twins in structural health monitoring by combining real-time data acquisition with sophisticated AI-driven analysis.

Computer vision employs algorithms and machine learning to process visual data, making it valuable for Structural Health Monitoring (SHM) by analyzing images or videos to detect changes or anomalies

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indicating damage. It serves as a sensor, capturing even small structural movements, and uses image sequences along with techniques such as pattern matching and edge detection to measure structural displacements. Various methods for vision-based SHM have been developed, including Digital Image Correlation (DIC), template matching, and optical flow. DIC uses grayscale images to measure surface displacements in three dimensions and has benefited from advances in high-resolution cameras and computing power, enabling precise deformation monitoring even during large-scale movements (Siebert and Crompton, 2010). Template matching compares patterns in an image to a reference template, identifying areas with close matches through similarity scores (Mondal and Jahanshahi, 2022). Optical flow calculates a vector field representing the movement between successive image frames, tracking displacements to visualize structural responses (Dong et al., 2019). Recent advancements in motion magnification techniques, phase-based optical flow methods, and unscented Kalman filters have enhanced displacement measurement and damage detection without requiring physical markers on the structure (Cha et al., 2017a). Video cameras, using these techniques, provide a cost-effective way to remotely measure structural displacements and vibrations, with the methodology verified against laser vibrometer and accelerometer measurements for modal identification (Chen et al., 2015). Additionally, deep learning has improved vision-based SHM by enabling automated and accurate structural damage detection. Convolutional neural networks (CNNs) are used to identify defects like concrete cracks without relying on predefined features, improving robustness under varying environmental conditions (Cha et al. 2017b). Region-based models, such as Faster R-CNN, enable simultaneous detection of multiple damage types with near real-time performance. These advancements reduce reliance on manual inspections and enhance the accuracy and efficiency of structural monitoring (Cha et al., 2018).

This study investigates the effectiveness of a computer vision algorithm for tracking structural movements at different levels of a test structure. An experimental setup was established with targets placed on various stories, and the Optical Flow algorithm was employed to monitor their motion over time. The results from the computer vision approach were validated by comparing them with data from radar sensors and accelerometers attached to the structure. The findings also demonstrate that radar sensors can be effectively utilized for vibration-based displacement measurement in SHM and other related fields. Additionally, a digital twin of the structure was developed using a machine learning algorithm, which was trained on both damaged and undamaged conditions. The input data derived from the computer vision algorithm served as features for the model, enabling it to predict the structural state accurately. By training the model with labeled data, the system facilitates early detection of damage or degradation. The integration of the digital twin with machine learning provides a more accurate and efficient monitoring approach, offering timely warnings to inform maintenance decisions and ensure the safety of the structure. In the following sections,

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the structure’s specifics, the implementation of computer vision techniques, and the process of generating the digital twin are explained. A flowchart of the research process is shown in Figure 1.

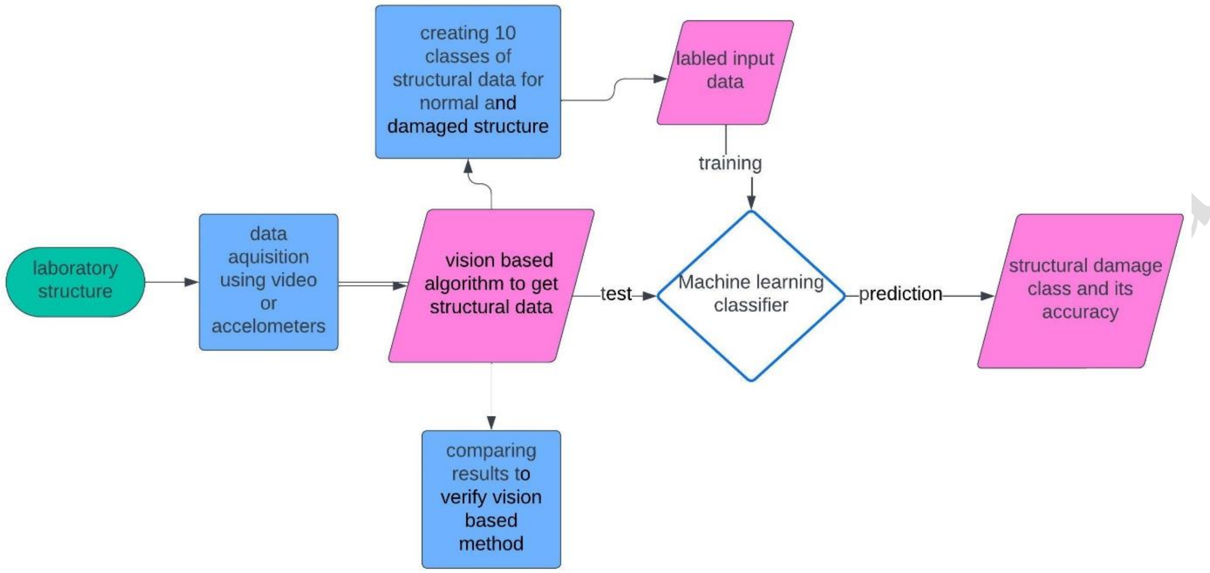

Fig. 1. Flowchart of the steps in this research

2- Laboratory Structure Specifications

In this study, a three-story aluminum structure was used as a case study for developing a digital twin. The structure, illustrated in Figure 2, was subjected to external forces applied through a movable plate connected to a shaker. The key specifications of the structure are detailed in Table 1.

To track the structure's movement on different floors, circular and rectangular Aruco markers were installed. A stationary mobile camera, positioned at a fixed distance and angle, recorded the structure's vibrations with a resolution of 1080p at 60 frames per second. The displacement of the structure was calculated by analyzing the movement of the embedded markers in successive video frames, providing the input data for assessing the structure's status within the digital twin model.

Table 1. Geometrical and physical properties of the three-story structure

Material	**Young's Modulus**	**Column height**	**Column thickness**	**Column width**	**Width of plate at each level**	**Width of plate at each level**	**Damping Ratio**
Aluminum	E	L	H	B	L	D	ζ

	69 Gpa	150 mm	3 mm	30mm	25 cm	20 cm	5%

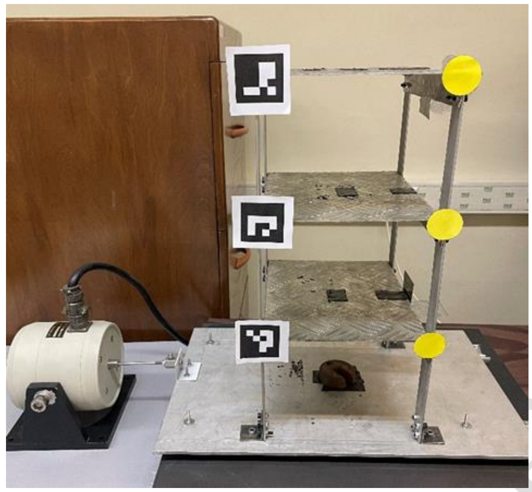

Fig. 2. View of the laboratory structure connected to the shaker

3- Machine Vision for Response Measurement

In this study, the structure was stimulated using white noise force, and its vibrations were recorded across various modes with a fixed camera mounted on a stand. Several methods were employed to estimate the displacements of the targets installed on each floor of the structure.

In addition to video-based measurements, accelerometer sensors were installed on the structure's floors to validate the displacement data obtained from video processing. A radar sensor was also positioned on a stationary stand to further validate and compare the results. The methods for image processing, target detection, and motion tracking are outlined in the following section.

3-1- Optical Flow for Motion Tracking

During this process, the optical flow method was employed to calculate floor displacements of the test structure. The Lucas-Kanade method (Liu et al., 2015) was chosen due to its effectiveness in assuming constant flow within local pixel neighborhoods. Rather than scanning subsequent images for exact pixel matches, the algorithm estimates motion by analyzing local intensity changes between frames, making it ideal for SHM applications.

The implementation begins by detecting specific features in each frame for tracking. Here, ArUco markers were placed on the structure, serving as trackable reference points for motion calculation. ArUco markers, known for their distinctive square patterns and robust detection capabilities, consist of a black border enclosing a binary matrix that encodes a unique ID. This design enables easy identification, even in varied

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lighting, making it suitable for real-time motion tracking in structural applications. Figure 3 shows examples of the ArUco markers used.

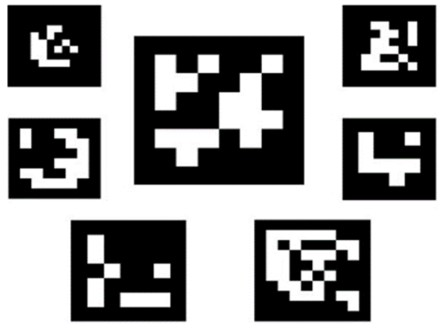

Fig. 3. Example of ArUco marker images

To detect these markers, the OPENCV library in Python was employed. The detection process identifies each marker's position (the four corners) and ID. The detection consists of two key stages:

1. **Marker Candidate Detection**: The image is analyzed to find square shapes that could be potential markers. Additional filters are applied to remove irrelevant shapes (e.g., contours that are too small, too large, or too close to each other).

2. **Markers Identification**: After candidate shapes are detected, their internal encoding is analyzed. A perspective transformation is applied to standardize the shape, and Otsu's method is used to apply a threshold that separates black and white bits. The image is divided into cells based on the marker's size, and the number of black and white pixels in each cell is counted to determine the marker's binary bits. Finally, the bits are checked against a dictionary to identify the marker. Figure 4 shows the Recognition of Aruco markers within video frames.

Once the markers are detected, the identified feature points (p0) are fed into the Lucas-Kanade algorithm, implemented with the `cv2.calcOpticalFlowPyrLK()` function. This algorithm tracks the motion of feature points across frames by calculating the optical flow for a set of scattered points. The following parameters were used in the algorithm:

- winSize = (15, 15): The window size used to compute the optical flow.

- maxLevel = 2: The number of pyramid levels for multi-scale tracking.

- criteria = (cv.TERM_CRITERIA_EPS | cv.TERM_CRITERIA_COUNT, 10, 0.03): The termination criteria, based on either the desired accuracy (0.03) or a maximum iteration count (10).

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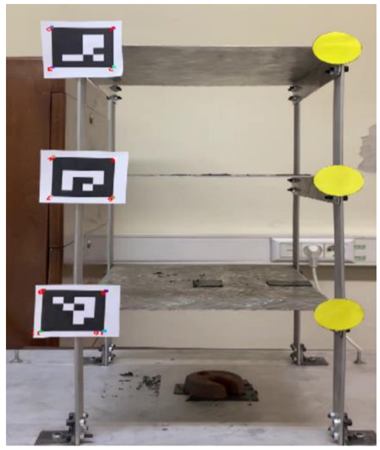

Fig. 4. Recognition of Aruco markers in video footage

The processed video, recorded as the structure responded to white noise excitation, yielded frame-by-frame displacement data for each floor (Figure 5). This motion data, derived from optical flow, was subsequently validated using Fast Fourier Transform (FFT) analysis to compare the detected displacement frequencies with the structure's natural frequency. The resulting FFT plot (Figures 6 and 7) further confirmed the high accuracy of the optical flow method, aligning closely with data from accelerometers placed on the structure.

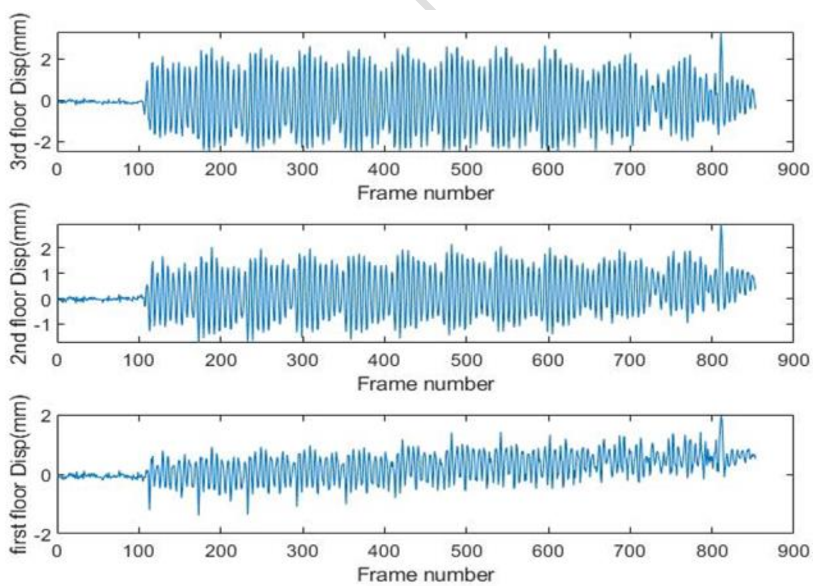

Fig. 5. Displacement graph obtained from each frame using the optical flow method

The experimental setup involved three MPU-9250 accelerometers positioned on each floor to measure the vibrational response. Synchronization between the accelerometers was achieved using the Serial Peripheral Interface (SPI) protocol. The Arduino Due microcontroller handled data acquisition, with a sampling

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frequency of 400 Hz and a time interval of 75 microseconds between data captures from the sensors. This setup ensured synchronization and accurate data collection.

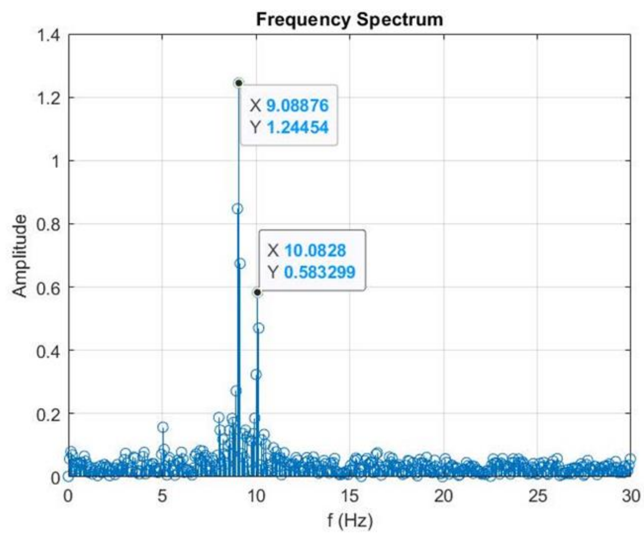

Fig. 6. FFT plot of the displacement signal on the third floor, generated using the optical flow method

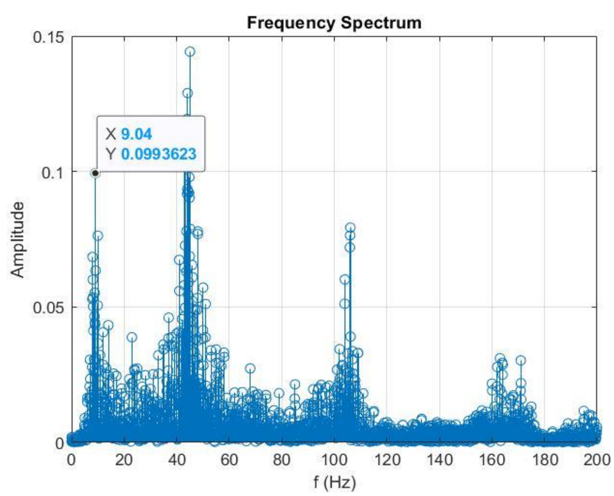

Fig. 7. FFT plot of the acceleration signal on the third floor, obtained from the accelerometer

The results showed a high degree of accuracy between the video-based optical flow method and the accelerometer data. The first natural frequency peak observed from the video processing occurred at 9.08 Hz, while the accelerometer data indicated a peak at 9.04 Hz, resulting in a 99.5% conformity between the two methods. Furthermore, by modeling the structure as a mass-spring system (Figure 8), the first natural frequency was calculated as 9.01 Hz, which closely matches both the accelerometer and machine vision results. However, due to the video's frame rate of 60 frames per second, the optical flow method was limited to detecting frequencies below 30 Hz. As a result, only the first natural frequency could be captured using this approach.

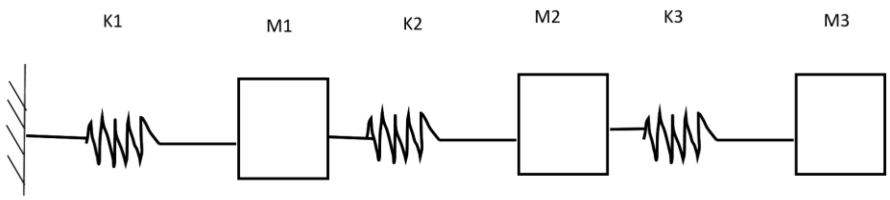

Fig. 8. spring-mass model of the structure

3-2- Radar Sensor for Displacement Measurement

In this stage, the displacement of the structure is calculated by a multi-input multi-output ground-based[2] radar sensor (Figure 9). The radar sensor operates by continuously emitting electromagnetic waves toward the structure and detecting the reflected signals to determine displacement. The reflected waves are processed to calculate the relative motion of the structure's floors, using the Doppler shift to estimate both velocity and displacement. The radar sensor's high sensitivity to movement allows it to track even small displacements, making it suitable for structural health monitoring (SHM) (Hosseiny et al. 2023, Hosseiny et al. 2024).

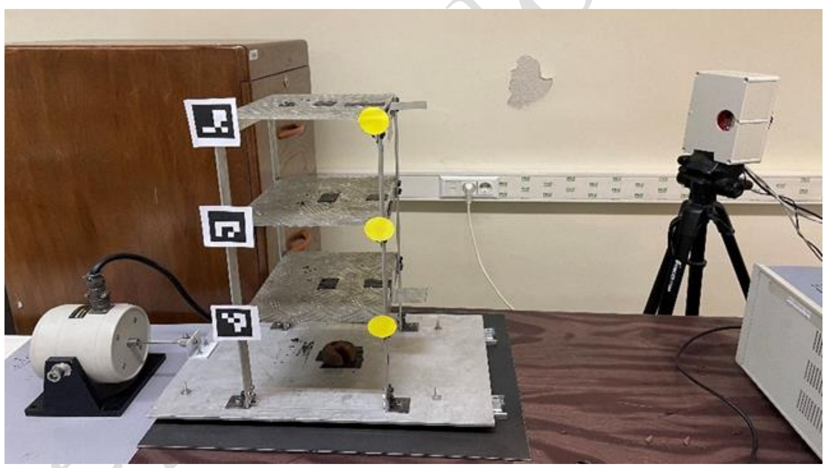

Fig. 9. Use of a radar sensor for measuring the displacement of the structure

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[2] MIMO GBSAR

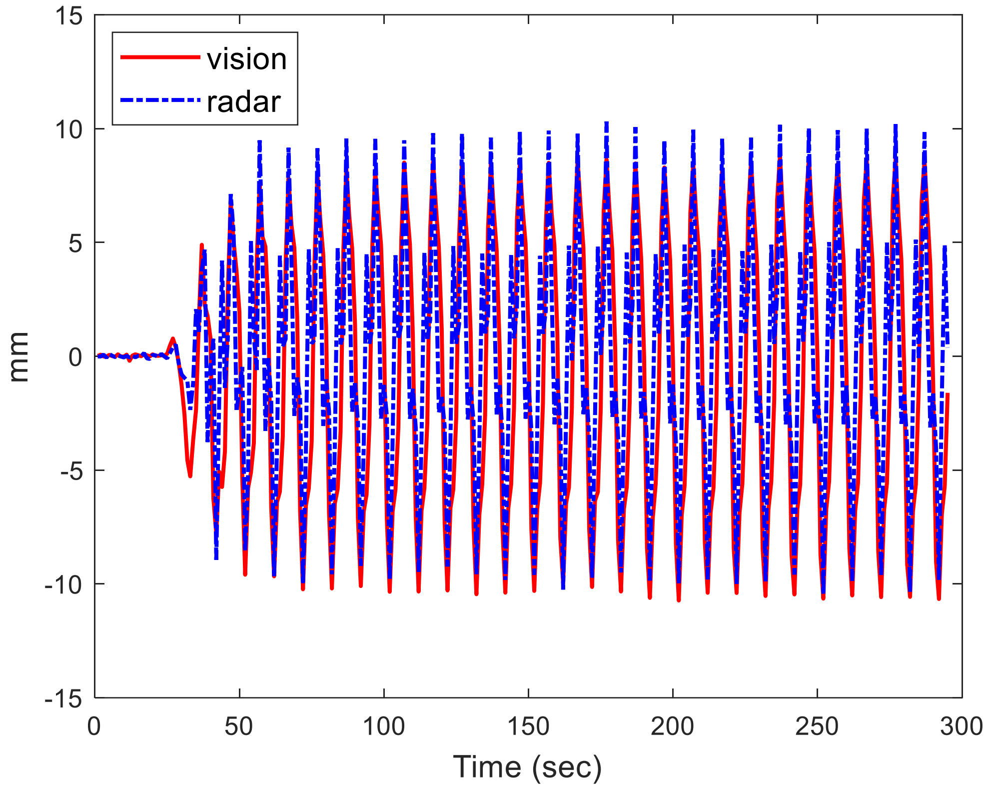

Fig. 10. Displacement graph comparison of machine vision sensor (red) and radar sensor (blue)

The radar sensor's performance was validated by comparing its results with those from the machine vision method and accelerometers. Despite the slight time lag observed between radar-based and vision-based results, the overall displacement trend measured by the radar sensor closely aligns with those obtained from other methods. Assessing radar-based data in the frequency domain shows that the first mode of the structure is accurately captured using this technique to measure displacement. The results demonstrated the radar sensor's effectiveness in displacement measurement. However, the inherent time delay observed in radar measurements (as shown in Figure 10) is a key characteristic of this technology. The delay occurs because radar sensors process the reflected wave signals to calculate displacement, and this processing introduces a latency that is not present in the vision-based system. This time lag should be considered when synchronizing data between radar and other real-time monitoring systems. Despite the delay, radar sensors offer several advantages in SHM. They are capable of measuring displacement over long distances, are not affected by lighting conditions, and can operate in various environmental conditions (e.g., fog, rain). In this study, the radar sensor provided reliable measurements of the structure's displacement, making it a valuable complement to the machine vision-based system.

4- Machine Learning Classifier for Digital Twin

To enable real-time damage detection within the digital twin, physics-based models were used to simulate diverse damage scenarios, providing data to train a machine learning classifier. This classifier forms the core of the digital twin, allowing it to detect, locate, and assess the severity of structural damage. By combining physics-based modeling with machine learning, the digital twin achieves greater interpretability and accuracy in SHM.

Damage detection in structures poses an inverse problem: sensor data (inputs) must be interpreted to infer the type, location, and severity of damage (outputs). This task is particularly complex in real-time SHM (Ritto and Rochinha, 2021, Ghafouri et al., 2024). To address these challenges, a supervised machine learning classifier was trained on synthetic data generated from the physics-based model, which represents the structure's dynamic behavior under multiple conditions. The classifier then maps real sensor inputs to potential damage scenarios, informed by offline model predictions.

A successful digital twin for damage detection must fulfill three main objectives: detecting damage presence, identifying location, and determining severity. These objectives were achieved by calibrating the digital twin's classifier with both synthetic and real-world data. Initially, a computational model of the structure was developed as a three-degree-of-freedom mass-spring system, where each floor represented a concentrated mass connected by springs symbolizing the columns' stiffness. This model provided a substantial amount of training data at a manageable computational cost while capturing the essential dynamic responses of the physical structure (Figure 8).

Using this model, various damage scenarios were simulated by adjusting mass and stiffness parameters. The natural frequencies of the undamaged system were calculated as 9.016 Hz, 25.26 Hz, and 36.5 Hz. These simulated datasets, combined with real sensor data, enabled training of the machine learning classifier to recognize distinct damage conditions accurately.

In summary, the machine learning classifier allows the digital twin to perform real-time SHM, efficiently predicting structural conditions by linking sensor data with the pre-modeled damage states. The following section details the specific machine learning techniques used and their respective performance.

5- Training Dataset Creation

In this study, a supervised learning approach was used to train the machine learning classifier. The dataset, referred to as X_{data}(features), was constructed from numerous samples of system displacements, while the corresponding damage scenarios, y_{label} (labels), served as the input-output pairs for the training process. The dataset structure consists of n random samples for each of the m damage scenarios. The damage scenarios in this study included adding 97.1 grams to each level and removing two or four bolts from each column

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connection, resulting in a total of ten structural conditions, including the healthy state (Figure 11). A detailed summary of these damage scenarios is presented in Table 2.

There is no strict formula for determining the minimum amount of input data required to train the machine learning model. Instead, the dataset size is typically adjusted based on trial and error and data availability. In practice, model development often starts with the available data and gradually increases until the desired accuracy is achieved. The quantity of data needed for training depends on several factors, including the nature of the data, the machine learning model's objective, and the theoretical framework guiding the process. In this study, satisfactory results were achieved using 1000 training samples. These training data were generated by applying white noise input to the computational model, while varying mass and stiffness parameters to simulate different structural behaviors. For each damage scenario, 100 data points were used to train the machine learning classifier.

In addition to the training data, 15% of the dataset was reserved as test data. These test data were collected from the physical structure by applying white noise input to the base of the structure using a shaker and recording its movements on video. The recorded videos were processed using the optical flow method to extract the displacement data for each floor of the structure. The corresponding structural state, based on the applied damage scenario, was used as the correct label and fed into the machine learning algorithm for validation.

Table 2. Different damage scenarios considered in this study

damage scenario Number	Damage Scenario Description
1	97.1 gram mass added to level 1
2	97.1 gram mass added to level 2
3	97.1 gram mass added to level 3
4	2 bolts were removed in level 1
5	2 bolts were removed in level 2
6	2 bolts were removed in level 3
7	4 bolts were removed in level 1
8	4 bolts were removed in level 2
9	4 bolts were removed in level 3

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(a) (b) (c)

Fig. 11. (a) Laboratory-scale structure with added mass on the floors. (b) Column connection with two bolts in place. (c) Column connection with all four bolts removed.

6- Building the Digital Twin

This section describes the development of a digital twin for the laboratory structure to monitor and analyze its behavior. As mentioned earlier, a computational model was used to simulate system responses under different damage scenarios. The dataset generated from these simulations was used to train the digital twin, which functions as a machine learning classifier. The classifier is designed to identify the type, severity, and location of damage within the structure (Figure 12).

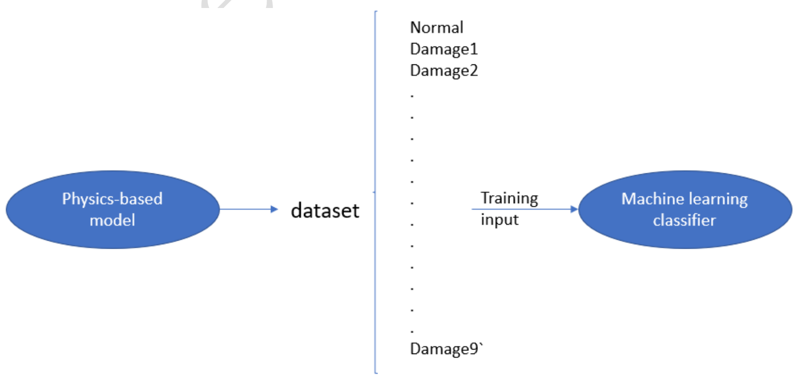

Fig. 12. Physics-based computational model used to generate the dataset for training the machine learning classifier.

The digital twin demonstrated high accuracy in detecting structural damage, including its severity and location. The input data, in the form of time series, was processed using statistical features such as mean, variance, skewness, and kurtosis to enhance classification efficiency. Several classifiers were tested and validated on this dataset, with their performance measured by the percentage of correctly classified inputs.

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These classifiers use various mathematical approaches to discover relationships in the data. Some rely on time series distances, while others utilize statistical features. The varying accuracy of the models stems from the differences in the features they consider. The best classifier was the one that identified the most relevant feature set for distinguishing damage classes.

To select the most suitable machine learning method for classifying time series inputs, several well-known algorithms were evaluated:

- Manhattan Distance Feature-Based Dissimilarity Space Classifier (92.67% Accuracy): This classifier achieved the highest accuracy by calculating absolute distances between feature sets, effectively representing the time-series data for SHM. Its strength in feature-based dissimilarity space made it particularly suitable for detecting subtle variations in structural conditions (López-Iñesta et al., 2015)
- Feedforward Neural Network by Levenberg-Marquardt Rule (90.00% Accuracy): This neural network demonstrated high accuracy, aided by the Levenberg-Marquardt optimization, which combined gradient descent with Gauss-Newton methods for efficient parameter tuning. This classifier effectively captured complex data relationships, though it required more computational resources (Gavin, 2019).
- Quadratic Classifier (89.33% Accuracy): Using quadratic decision boundaries, this classifier handled multi-class problems by allowing each class to have its own covariance matrix, which improved accuracy in detecting variations across structural damage classes (Tharwat, 2016).
- Logistic Linear Classifier (74.67% Accuracy): Though generally effective for binary classification, the logistic linear classifier showed limitations in capturing the nuanced responses of this multi-class SHM dataset (Solainayagi, 2024).
- Normal Densities-Based Linear (Multi-Class) Classifier (64.67% Accuracy): This classifier applied linear decision boundaries based on shared covariance, but it struggled to capture complex structural responses as effectively as the quadratic variant (Trentin, 2023).
- Normal Densities-Based Quadratic Classifier (87.33% Accuracy): By assuming class-specific covariance matrices, this classifier provided quadratic decision boundaries, similar to the quadratic classifier, enhancing accuracy across multi-class scenarios (Salar, 2022).
- k-Nearest Neighbor (k-NN) Classifier (36.00% Accuracy): k-NN achieved the lowest accuracy, as its reliance on nearest-neighbor voting was insufficient for distinguishing structural damage patterns (Cunningham and Delany, 2021)

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- Decision Tree Classifier (23.33% Accuracy): The decision tree struggled to capture complex relationships within the feature space, resulting in significant misclassifications (Salkhordeh et al., 2021).
- Naive Bayes Classifier (41.33% Accuracy): Based on probabilistic assumptions, the Naive Bayes classifier struggled with feature dependencies in the dataset, resulting in lower accuracy (Wickramasinghe and Kalutarage., 2021).
- Random Neural Network Classifier (52.67% Accuracy): This neural network variant performed lower than expected, indicating that the random initialization of network weights was insufficient for accurately modeling the complex SHM dataset (Gallicchio and Scardapane, 2020).
- Support Vector Classifier (54.67% Accuracy): The SVM achieved moderate accuracy by maximizing the margin between classes, which was beneficial for distinguishing clear class separations but limited for subtle damage detection (Gui et al., 2017).

As shown in Table 3, the Manhattan Distance-based Classifier achieved the highest classification accuracy. This method effectively represented the complex time series data by calculating absolute distances between objects. The feedforward neural network with the Lunberg-Marquardt algorithm also performed well, optimizing parameters through a combination of gradient descent and Gauss-Newton methods. This approach outperformed traditional neural network classifiers that rely solely on gradient descent.

Table 3. Trained classifiers and their corresponding accuracy

Classifier	Accuracy
Manhattan distance feature-based dissimilarity space	92.67
Feed forward neural network by Levenberg-Marquardt	90.00
Quadratic classifier	89.33
Logistic linear classifier	74.67
Normal densities based linear (multi-class) classifier	64.67
Normal densities-based quadratic (multi-class) classifier	87.33
k-nearest neighbor classifier	36.00
Decision tree classifier	23.33
Naive Bayes classifier	41.33
Random neural network classifier	52.67
Support vector classifier	54.67

Table 4 presents the classification accuracy of the Manhattan Distance-based Classifier for different damage scenarios. The accuracy values represent the percentage of correctly classified inputs for each scenario. As shown, the classifier achieves perfect accuracy for several conditions, including the normal state and specific stiffness reductions on certain floors. However, accuracy varies for scenarios involving added mass and reduced stiffness across different floors.

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Confusion matrices in Figure 13 highlight the classifier's precision, particularly in identifying the undamaged state with minimal misclassifications. The Manhattan distance classifier effectively identifies the undamaged state and severe damage conditions (e.g., stiffness reductions of 90%) with minimal misclassification, suggesting robustness in detecting both healthy and significantly altered structural states. For minor structural changes, such as small added masses or slight stiffness reductions, the classifier occasionally misclassifies these conditions as either less severe or normal. This indicates that while the classifier performs well for larger deviations, it may benefit from further training data to improve sensitivity to subtle damage. The SVM classifier exhibited superior results when the stiffness change was 10% but faced challenges when additional mass was added to the first floor, often misclassifying it as the normal condition. Overall, the digital twin demonstrated high accuracy in identifying damage type, location, and severity. Future improvements aim to expand the training dataset to capture a broader range of subtle damage scenarios, enhancing the model's sensitivity and detection capabilities, particularly for minor structural changes.

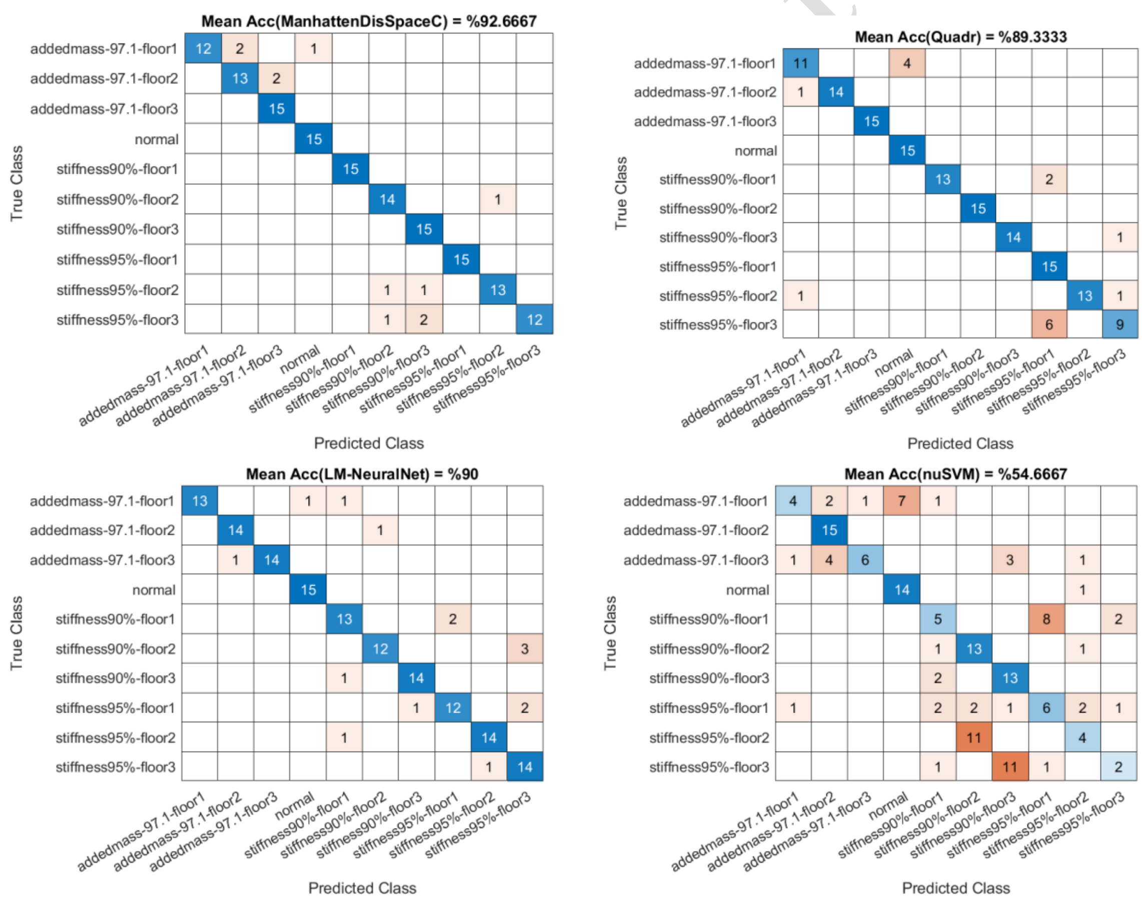

Fig. 13. Confusion matrix for the most accurate classifiers

Table 4. Classification results of the Manhattan Distance-based Classifier for different damage scenarios.

Class	Accuracy
addedmass-97.1-floor1	80.00
addedmass-97.1-floor2	86.67
addedmass-97.1-floor3	100
Normal	100
stiffness90%-floor1	100
stiffness90%-floor2	93.33
stiffness90%-floor3	100
stiffness95%-floor1	100
stiffness95%-floor2	86.67
stiffness95%-floor3	80.00

7- Conclusion

This study successfully developed a digital twin of a laboratory structure by integrating machine vision, physics-based simulations, and machine learning to enable real-time structural health monitoring (SHM). The digital twin accurately identified damage type, location, and severity across various scenarios, with the Manhattan distance-based classifier achieving the highest accuracy, particularly in detecting significant structural changes. This classifier proved to be a powerful tool for SHM applications, offering high accuracy in real-world testing.

The digital twin demonstrated strong alignment with experimental data, and the responses measured through machine vision were validated using radar and accelerometer measurements. While the classifier performed well for major damage, it showed limitations in detecting subtle changes, such as minor mass variations or slight stiffness reductions. Expanding the training dataset to include a wider range of subtle damage scenarios could improve sensitivity to early-stage damage, enhancing detection capabilities for gradual deterioration.

Future research could explore advanced feature extraction techniques and hybrid models to further enhance classifier accuracy. Scaling the digital twin for full-scale structures and diverse environmental conditions would enable broader SHM applications, providing a robust solution for predictive maintenance and real-time monitoring of civil infrastructure.

Overall, this digital twin approach holds significant promise for advancing SHM systems through improved accuracy, efficiency, and responsiveness, ultimately contributing to safer and more durable structural engineering practices.

Acknowledgement

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Declaration of generative AI in scientific writing

During the preparation of this work, the authors used ChatGPT3.5 to check grammatical errors and improve the clarity of the English language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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