Health monitoring of historic buildings using machine learning in real-time internet of things (IoT)

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ABSTRACT

In this paper, structural health monitoring (SHM) is used to detect the damage level for the historic building. The damaged level is defined based on the support vector machine (SVM) algorithm to extract the damage feature. Physical checks allow us to detect any damage or structural degeneration. Supervised training machine learning (ML) is used as a tool to examine accelerometer data to ascertain the condition of structures following an occurrence. The three training models, the SVM, the random forest linear classification, and the k-nearest neighbor (KNN) model are tested and compared to classify data. The data obtained from structural health monitoring, teams of responders, and investigators can be used to manage the most vulnerable structures. The accuracy of the SVM algorithm was found up to 94% accurate and precise, at a high level. The internet of things (IoT) architecture is also introduced with SVM learning algorithms for early warning. The proposed system makes use of an SHM system to identify seismic events or accelerations. The IoT system SHM uses real data from the structure, allowing for online damage identification and ongoing monitoring. A dashboard is used to represent the monitoring data and the damage level.

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1. INTRODUCTION

Earth structures are vulnerable to threats like earthquakes, hurricanes, strong winds, and floods. Every year, hundreds die when unreinforced earth buildings collapse during earthquakes. Designers must consider risk, topography, and seismic stresses to utilize appropriate structural forms and reinforcement. Reinforced concrete structures can be damaged in many ways, including wall or roof failure/tilting and cracks [1]. Stronger earthquakes cause more building displacement, potentially damaging beams, columns, walls, and braces. Damage patterns were observed in structures near the M6.8 Luding earthquake epicenter in China's Sichuan Province [2], including collapsed walls, tilted columns, and cracked beams/slabs. Structural health monitoring (SHM) systems have received more attention in the last decade. They evaluate and track all structure types. Damage is defined as structural changes in properties (material, geometry) that alter dynamic responses and impair functionality. Data features extracted from structural responses characterize the damage condition. These are called damage-sensitive features [3].

We value historic buildings because they preserve history, showcase ingenuity, and satisfy our desire for enduring memory [4]–[6]. Their presence enables us to track social changes and gain a deeper understanding of factors shaping current cities, communities, and traditions. Consequently, SHM systems using damage-sensitive features have great potential to monitor earth structures vulnerable to natural hazards. This is especially important for preserving invaluable historic buildings and monuments that embody our cultural heritage.

Several SHM system types exist. Vibration-based sensors monitor changes in model parameters to detect damage. The primary observed parameters are natural frequencies and mode shapes [7], [8]. An SHM system continuously records a structure's acceleration using a wireless network of accelerometers [9] connected via radio frequency identification (RFID) tags. Damage states were calculated from the recordings based on changes in natural frequencies. The technique was improved by adding a strain gauge to the sensor chip for more sensitive detection of structural deterioration [10]. A network of accelerometers and piezoelectric transducers monitored mode shape changes for fault localization [11]. Displacement-based SHM systems have also been developed. Frequency-modulated continuous-wave (FMCW) radar monitored inter-story drift ratio (IDR) by measuring signal echo time [12]. A camera-based SHM system also measured displacement [13]. However, current displacement-based systems require wired or wireless sensor networks, which are expensive to deploy widely [14]. Most structures thus rely solely on post-event visual inspections.

Machine learning (ML) algorithms have proven useful for SHM [15], [16]. The ML is a set of algorithms that can automatically find uncovering hidden patterns in a large body of data [17], [18]. González and Zapico [19] discusses the identification of the damage at the structural frame of the steel moment. The approach was based on modal variables and artificial neural networks. The network's input was the mode frequency, while stiffness as its output. By comparing the stiffness at each story to the stiffness that was first assessed at the beginning, or without damage, it was possible to calculate the damage index after an earthquake. The k-nearest neighbor (KNN) and support vector machine (SVM) methods were suggested for fault classification in rotating machinery [20]. Therefore, while various SHM system types exist, the wide deployment of sensor networks remains challenging. ML approaches show promise but require large data volumes. Improving accuracy and reducing costs will enable SHM systems to better monitor more structures. internet of things (IoT) sensor technology and the real-time data it provides are indeed transformative for monitoring and preserving structures of all kinds, and the approach you described leverages many of the key aspects of IoT-enabled condition monitoring (CM).

The key steps to developing the proposed IoT-based SHM system include: designing the sensor network; gathering data from unknown structures; extracting relevant damage features from the data; diagnosing issues based on those damage features; and Using ML models to predict damage levels. Thus, the proposed IoT-based SHM system combined sensors, ML models like SVM, and dashboards to monitor historic structures and artifacts in real-time, with the potential to help preserve invaluable cultural heritage. The sensor device is suitable for protecting historic buildings and museum objects. Real-time, rapid data makes it ideal for preserving structures and visualizing the environment [21], [22]. Three supervised learning models were trained and tested; the KNN model [23], the random forest classifier [24], and SVM [25]. In this work, we found that SVM, which can handle both linear and non-linear problems, performed well in this real-world problem. A dashboard presented the recorded data and damage level. The damage level resulted from comparing readings from the MPU-6050 sensor module with the built SVM ML model.

The main contributions of this work are:

- An IoT-based SHM system with a damage level sensor and Raspberry Pi 4 single-board computer to collect a large amount of training data.
- Training and testing of three different supervised ML algorithms are presented.
- Damage level detection based on sensor module measurements and the SVM model.
- A dashboard presenting recorded data from monitoring sensors and the damage level.

Our proposal will be presented in several sections as follows: The section 2 explains the architecture of the proposed IoT-based SHM system. The section 3 discusses the implementation of the SHM system based on three main parts: sensors components to collect a large amount of testing data, the effectiveness of various ML algorithms in accurately and precisely determining damage levels through training and testing, and a dashboard that presents the sensor data and damage level in a human-readable format, and section 4 present the conclusions of the paper.

2. THE ARCHITECTURE OF THE PROPOSED IOT-BASED SHM SYSTEM

The proposed IoT-based SHM system consists of three main parts: i) Sensor components-including the MPU-6050 sensor [26], [27] and Raspberry Pi 4 single-board computer [28], [29]. Oxygen and nitrogen oxide sensors gather environmental data, ii) Supervised ML algorithms-are used to detect damage levels based on sensor data, and iii) A dashboard-presents the recorded data from the sensors and the damage level determined by comparing MPU-6050 readings with the SVM model output. The IoT-based SHM system structure is shown in Figure 1. The proposed system follows these steps by utilizing sensors to collect data from the unknown structure. The machine is trained to forecast the type of structural state using the data sets of the displacement [30]. This process makes it possible to identify and categorize the structural condition. After that, testing is carried out by inserting measured data from the structure into the ML algorithms. Various experiments have been carried out to measure the impact of the different types of ML algorithms in identifying the damages with high accuracy and precision values. Extracting displacement data as damage features, diagnosing damage states, and testing KNN, random forest, and SVM algorithms to predict damage levels. The Raspberry Pi, Wi-Fi module, and dashboard enable an IoT structural health monitoring system. The IoT dashboard for the SHM system displays human-readable data collected by the monitoring sensors and damage levels.

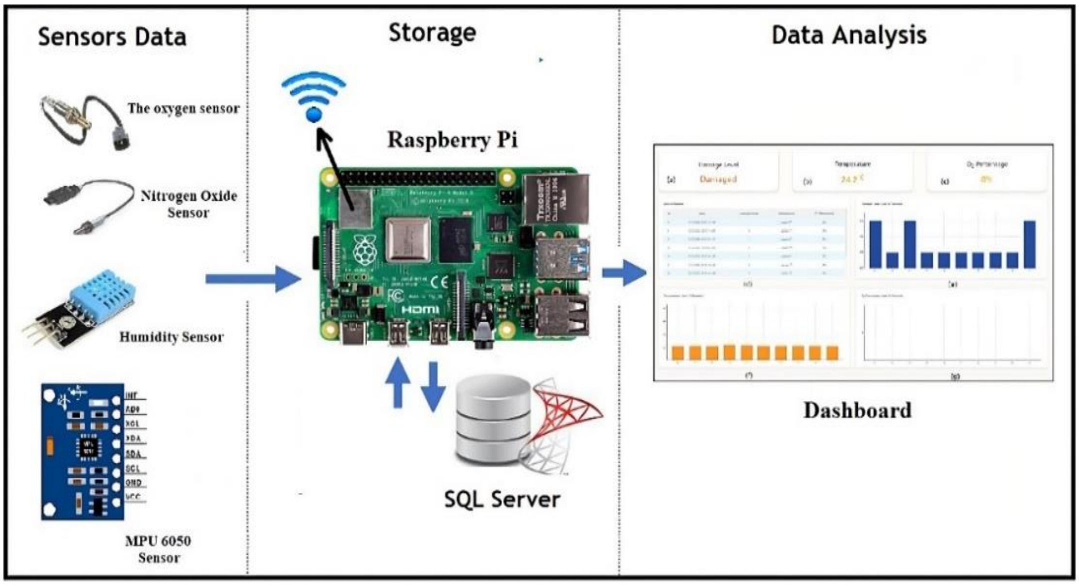


Figure 1. The component of real-time monitoring IOT for the SHM system

3. IMPLEMENTED AN IOT-DRIVEN SHM PLATFORM FOR BUILDING MANAGEMENT AND MAINTENANCE

In this section, we present our proposed system, including sensor elements, ML algorithms, and the dashboard. The main steps in designing an SHM system are to design the sensor network, gather data, extract features, diagnose the problem, and predict the outcome. This three-pronged approach effectively monitors the structure’s health as:

3.1. Sensors parts

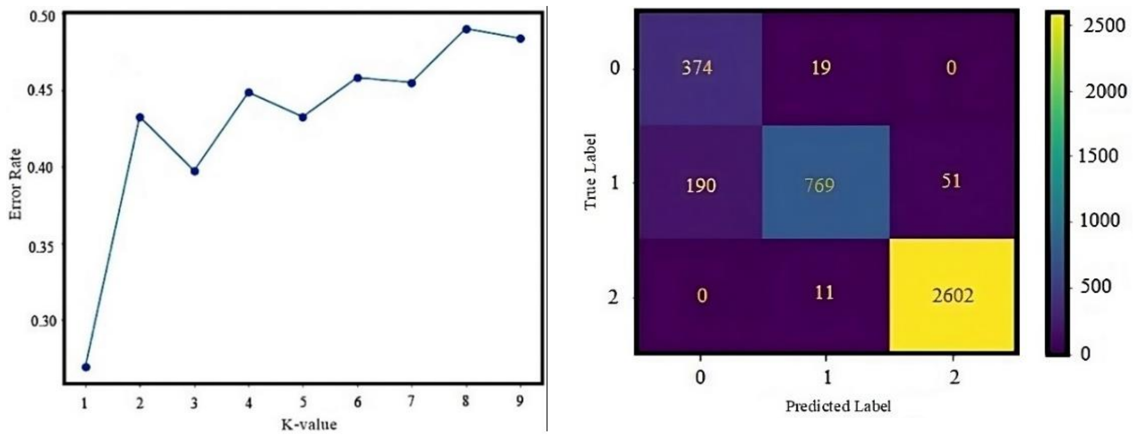
Sensors in IoT monitoring systems must have suitable sensing capabilities to accurately collect data [31]. Changes in environment or weather like oxygen content, temperature, humidity, and air quality can damage historic structures and artifacts. An oxygen sensor would be installed where fire combustion may occur since oxygen levels are often lower [32]. A nitrogen oxide sensor can be used since nitrogen oxide is important for preserving structures and collections [33]. A humidity sensor monitors humidity and transforms it into an electrical output [34]. Relative humidity (RH) and absolute humidity (AH) sensors exist. The MPU-6050 sensor module detects damage by sensing movements or door failures [35]. It uses a gyroscope and a 3-axis accelerometer. The Raspberry Pi functions like a desktop computer [28], [29]. It uses a 1.5 GHz ARM processor. The sensors collected data from 11,000 displacement records, each value measured based on 5,000 samples. Hence, a range of suitable sensors is required for an effective IoT-based SHM system. Oxygen, nitrogen oxide, and humidity sensors monitor the environment while accelerometers and gyroscopes detect structural movements and damage. The data collected can then be analyzed to detect damage levels and monitor structural health.

3.2. Machine learning algorithms

The main steps in designing an SHM system are to design the sensor network, gather data, extract features, diagnose the problem, and predict the outcome. Data fusion techniques, statistical modeling, and pattern recognition algorithms form the first four steps. To compute and predict damage using our proposed system; we used a large training dataset of displacement based on SHM [30]. We used data from the MPU-605 sensor in our system as test data for each machine-learning algorithm. Three supervised learning models were tested and compared; i) KNN model [23], ii) random forest classifier [24], and iii) SVM model [25]. Testing and comparing the performance of different ML algorithms help identify the most suitable models for structural health monitoring applications.

3.3. KNN: k-nearest neighbor

KNN stands for the number of closest neighbors to an unknown data point used to predict its class. It's a distance-based algorithm that identifies the closest neighbors to determine the class [36]. To select close points, KNN measures distances between points. The resulting tested values of the KNN algorithm are represented in Figure 2. The grid search technique was used to find the best K with minimum error. Figure 2(a) shows various K values were tested and K=1 had the lowest error rate. As shown in Figure 2(b) the confusion matrix allows the understanding of misclassified classes of damaged level. By examining diagonal values and the matrix, the model's accuracy can be determined. However, with K=1 and 96% prediction accuracy in Figure 2(b), errors still occurred. The confusion matrix's precision had a margin of error across damage levels. This showed the model was overfitting the data by finding the closest region instead of making accurate predictions. Since the dataset has over 11,000 displacement records, K=1 cause overfitting. More neighbors were included to leverage a larger region and make robust decisions. So, the random forest classifier, known for more precise and accurate outputs, was used instead. In essence, while KNN achieved high accuracy, it suffered from overfitting and imprecise predictions due to the large, noisy dataset. Random forest proved to be a more robust model for structural health monitoring using the proposed sensor data.

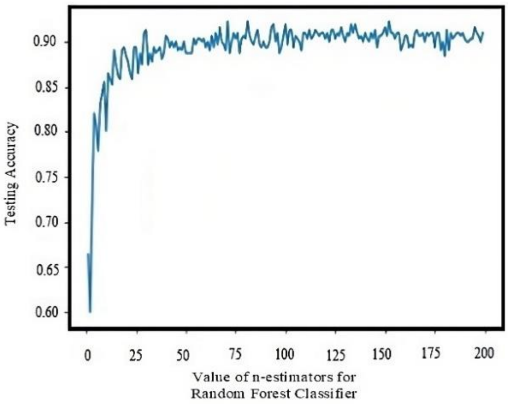


(a) (b)

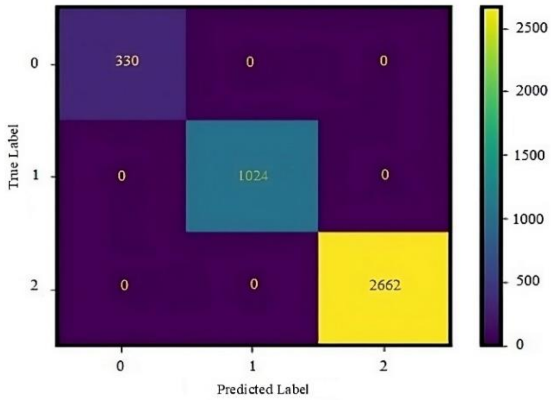
Figure 2. KNN-supervised algorithm (a) error rate graph and (b) the confusion matrix

3.4. Random forest classifier

The tested values of the random forest classifier represented the results in Figure 3. The random forest classifier achieves optimal test accuracy when the hyperparameter n reaches a value of 20 or higher, as shown in Figure 3(a). The random forest works by randomly selecting n records from the full dataset, and then building unique decision trees from each sample [37], [38]. Each decision tree produces an output, and the outputs are averaged to make the final prediction. We used sklearn's confusion matrix function, as illustrated in Figure 3(b), to evaluate performance. However, random forests have some drawbacks. As the number of trees increases, they become slower and less efficient for real-time predictions. Training is fast but prediction latency increases with the number of trees. Overfitting during training can also lead to issues. The high number of estimators (n_estimators) required for accurate damage level prediction increases power consumption and shortens the lifespan of components.



(a)



(b)

Figure 3. The results of random forest classifier algorithm (a) the value of n-estimators and (b) the confusion matrix

3.5. SVM linear classifier

SVM works by selecting support vectors that best define the decision boundary [39]. The algorithm looks for records that have much in common with the dataset, like those with high damage levels and elliptic shapes. As shown in Figure 4, the x-axis represents damage levels (0 in blue, 1 in brown, and 2 in red) while the dots represent records. Linear lines separate the regions to accurately identify the predicted value. The C value hyper parameter was optimized using grid search cross-validation and hyper parameter tuning. The precision and recall in the confusion matrix that has been illustrated in Figure 5 are acceptable, achieving 94% accuracy and 6% tolerance. This avoids overfitting by the model's ability to generalize to new data.

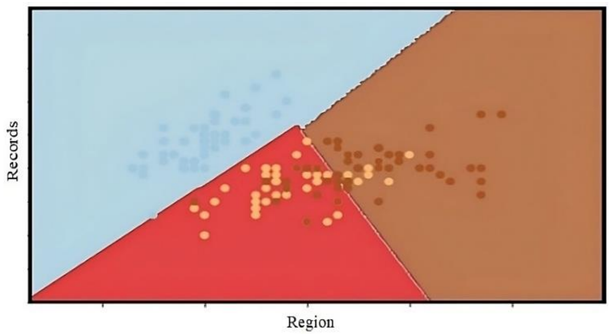


Figure 4. Linear kernel representation

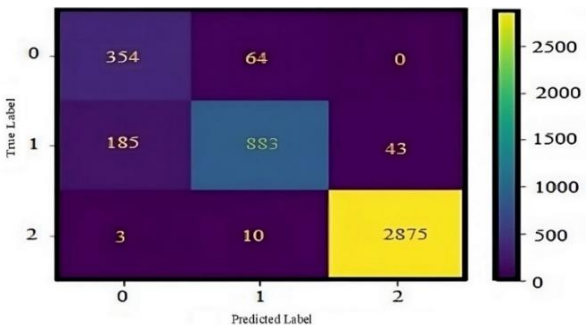


Figure 5. The confusion matrix of SVM algorithm

The classification report visualizer shown in Figure 6 shows support, F1 score, precision, and recall. All heat maps are on a 0 to 1 scale for easy comparison across models. In this work, we found that SVM, which can handle both linear and non-linear problems, performed well in this real-world problem. However, some degree of overfitting still occurred. So, SVM achieved high accuracy but still exhibited some overfitting, limiting its effectiveness for this application. Hyper parameter tuning helped optimize model performance.

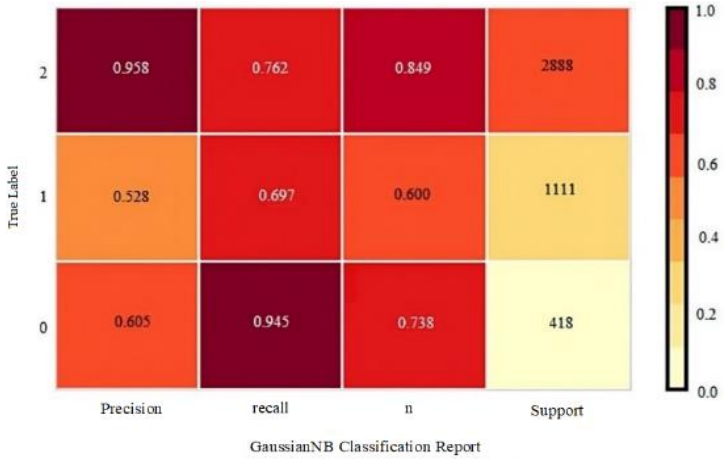


Figure 6. Gaussian classification report

3.6. Dashboard

The IoT dashboard for the SHM system presents sensor data in a human-interpretable way. It determines damage levels by comparing MPU-6050 accelerometer readings against an SVM model trained on our Raspberry Pi device. Raw numeric readings appear in line charts formatted clearly for people using the dashboard in a web browser. High-level management can view summary metrics across all buildings in one place. The dashboard gives an overall "snapshot" of performance as shown in Figure 7. This holistic view allows real-time monitoring of the entire structure's various aspects. Individual sensors like the MPU-6050 and O_2 sensor present damage levels, temperatures, and percentages respectively in dashboard panels as shown in Figures 7(a)-7(c). The most recent 10 data points also appear with all attributes readily available in panel as shown in Figure 7(d). Period-specific histograms in panels as shown in Figures 7(e)-7(g) help analyze the building's condition over time. We retrieve this sensor information from a structured query language (SQL) database. The IoT dashboard provides an intuitive interface for continuously tracking key structural health metrics from the monitoring systems in a visual, easy-to-understand format. Table 1 represents the 10 data records from the measurement sensors.

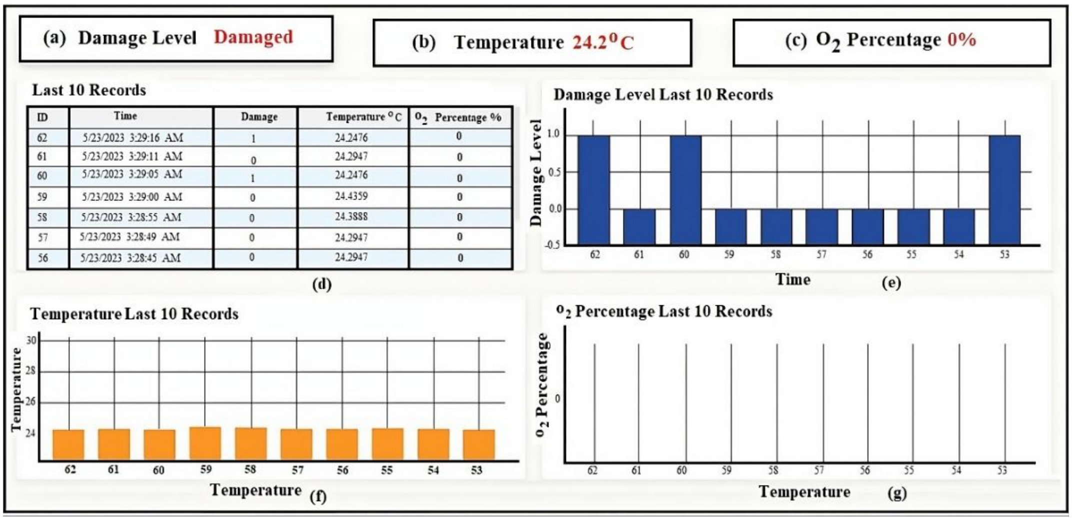


Figure 7. The dashboard; (a) record damage level, (b) record temperature, (c) record oxygen level, (d) record of 10 recent points, (e) histogram of damage level, (f) histogram of temperature, and (g) histogram of O_2 level

Table 1. The record of 10 recent points in the dashboard

ID	Time	Damage	Temperature (^OC)	O_2 Percentage (%)
62	5/23/2023 3:29:16 AM	1	24.2476	0
61	5/23/2023 3:29:11 AM	0	24.2947	0
60	5/23/2023 3:29:05 AM	1	24.2476	0
59	5/23/2023 3:29:00 AM	0	24.4359	0
58	5/23/2023 3:28:55 AM	0	24.3888	0
57	5/23/2023 3:28:49 AM	0	24.2947	0
56	5/23/2023 3:28:45 AM	0	24.2947	0

4. CONCLUSION

This paper addresses the damage level health monitoring of historic structures and museum artifacts, which is urgently needed due to numerous potential threats. The proposed real-time SHM system uses the IoT to monitor damage levels and environmental data. ML algorithms aim to detect any changes in these features relative to a baseline. Dashboards display the sensor data. The proposed IoT-based SHM system utilizes sensors to collect; environmental data like oxygen, temperature, and damage data from an MPU-6050 sensor module to detect structural movements or door failures, supervised learning models were investigated. Several supervised ML algorithms are employed as; KNN, random forest, and SVM. The SVM was found to perform well for real-world problems, addressing both linear and nonlinear issues. The SVM algorithm achieved up to 94% accuracy and precision, at a high level. In summary, the proposed IoT-based SHM system combines sensors, ML algorithms like SVM, and dashboards to effectively monitor the damage levels and environments of historic structures and museum artifacts in real-time. This has the potential to help preserve invaluable cultural heritage.

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