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Review

Development of Intelligent Technologies in SHM on the Innovative Diagnosis in Civil Engineering—A Comprehensive Review

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Abstract: This comprehensive review focuses on the integration of intelligent technologies, such as the Internet of Things (IoT), Artificial intelligence (AI), and Nondestructive Testing (NDT), in the Structural Health Monitoring (SHM) field of civil engineering. The article discusses intelligent technologies in SHM for residential, commercial, industrial, historical, and special buildings, such as nuclear power plants (NPPs). With the incorporation of intelligent technologies, there have been remarkable advancements in SHM, a crucial aspect of infrastructure safety, reliability, and durability. The combination of SHM and intelligent technologies provides a cost-effective and efficient building monitoring approach, significantly contributing to energy and resource conservation. This article explores using electronic instruments, such as sensors, microcontrollers, and embedded systems, to measure displacement, force, strain, and temperature, which are crucial for detecting structural damage. Implementing intelligent technologies in SHM reduces the reliance on manual and hazardous inspection practices, simplifying and reducing the cost of building monitoring. The article highlights the social, economic, and environmental benefits of adopting intelligent technologies in SHM by presenting key findings from existing research. This review aims to increase the reader's understanding of the significance of these technologies in enhancing the efficiency of SHM in civil engineering by illuminating their advancements and applications.

Keywords: structural health monitoring (SHM); civil engineering; intelligent technologies; building monitoring; energy savings; sustainability

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1. Introduction

There is an evident requirement for consistent and appropriate data in construction and life-threatening infrastructure operations [1]. Until recently, data collection for SHM was primarily a manual process requiring specialists to go on the field and acquire critical measurements [2]. Unfortunately, manual collection has the disadvantages of being inefficient, slow, and unreliable. However, the rise of the 'Internet of Things' has massively benefited the civil and structural engineering industries [3]. Due to significant cost reductions in sensors and connectivity, including the emergence of platform-as-a-service business models, it is now possible to collect large amounts of data remotely and aggregate them, and then perform necessary analysis to extract meaningful data from the IoT [4]. The IoT is a concept that entails the publication of data generated by operational points of interest [5]. Its primary objective is to enhance situational awareness by displaying critical field data. SHM-IoT conserves natural resources by reducing consumption due to a longer service life; this reduces waste generation. Less waste has a positive environmental impact. SHM-IoT can help with resource allocation, flexible scheduling and effective maintenance. This emerging technology influences "sustainable development" and "energy savings". SHM-IoT systems are socially desirable, economically viable, environmentally friendly, and essential for building sustainability. SHM integrated with the IoT is a revolutionary idea which holds a great promise for improvement of safety and integrity of structures. A growing body of literature has recently examined the possible advantages and applications of SHM-IoT. The idea was introduced and the benefits of fusing SHM and IoT were highlighted by Abdelgawad and Yelamarthi [6]. Basko et al. [7] presented a review for health monitoring and maintenance actions. Early anomaly detection was made possible by Moallemi et al. [8], who successfully implemented a bridge monitoring system. In a thorough review of various industries, Buckley et al. [9] emphasized the increased efficacy and accuracy of SHM systems brought about by IoT integration. The importance of standardized protocols and cutting-edge data analytics was emphasized by Doghri et al. [10] in their discussion of challenges and future directions. These studies demonstrate the transformative potential of SHM-IoT and its applicability in various fields and highlight a demand for additional study and technological development in this quickly developing field.

In comparison, SHM is the procedure of monitoring and evaluating the structure condition to obtain information about its current state [11]. It is accomplished by tracking variables such as strain, vibration, stress, and other physical responses, phenomena, and circumstances [12,13]. It aims to facilitate nondestructive examinations to determine the damage location and extent, calculate the asset's remaining life, and predict potential mishaps [14,15].

Figure 1 illustrates the applications of IoT in a wide range of industries.

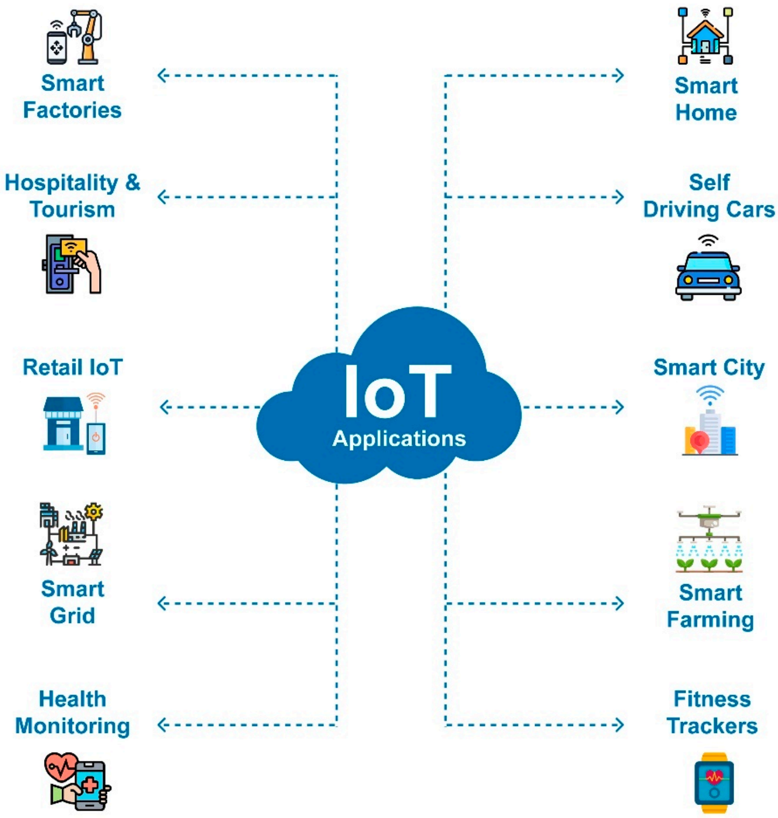

Figure 1. IoT applications in a variety of industries.

Harshitha et al. [16] demonstrated a method of locating faults in structures by utilizing an advanced-yet-inexpensive IoT platform comprising sensors, analog-digital converters (ADC), digital-analog converters (DAC), Raspberry Pi platform, piezoelectric transducers (PZT), and a Wi-Fi module. The collected data were compared to data from construction using a numerical method. The test subject for validating this method was an aluminum beam exposed to sinusoidal waves via a PZT transducer. The data were gathered using sensors, converted to digital ones using an ADC and compared to a flawless structure. The outcome aided in developing an early warning system for imminently damaged structures.

Okina et al. [17] proposed a predictive model employing Conceptual Graphs (CG) to evaluate the mechanism of bridge deterioration. To evaluate the evolution of structural conditions, the model combines formalized assumptions, degradation factors, and expert knowledge. The method facilitates comprehension of the deterioration sequence and improves decision making based on actual condition and inspection history.

Figure 2 depicts a comprehensive framework of SHM, including a variety of essential elements, such as smart structures, sensors and actuators, smart materials, signal processing, artificial intelligence (AI), and computation. The figure illustrates the interaction between these components, highlighting their collective contribution to the successful implementation of SHM. It depicts visually how smart structures are outfitted with sensors and actuators to collect structural behavior data, which are then processed using signal processing techniques. The integration of AI algorithms and computation further enhances the SHM system's advanced analysis and decision-making capabilities. This figure serves as a visual representation of the multidisciplinary nature of SHM, highlighting the importance of utilizing intelligent technologies and computational tools to improve structural monitoring and maintenance strategies.

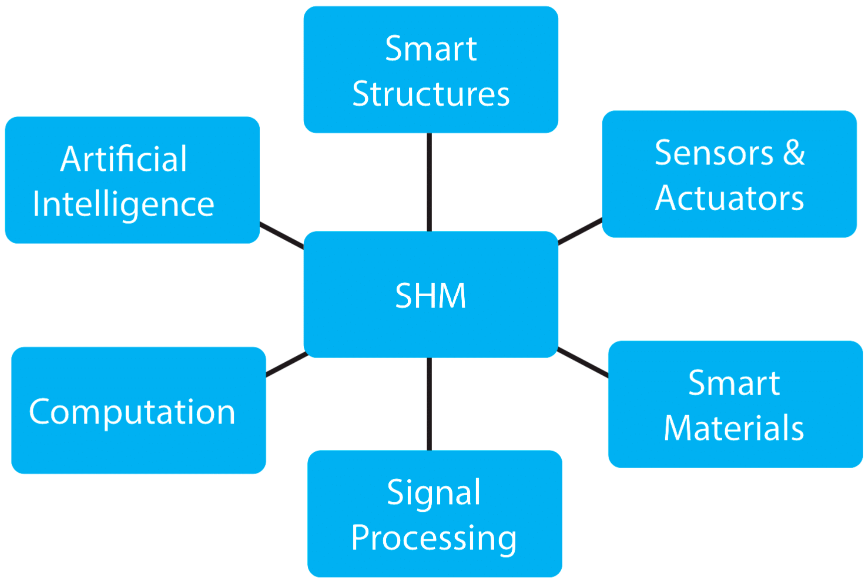

Figure 2. Comprehensive framework of Structural Health Monitoring (SHM) integration.

Alsamhi et al. [18] provided a bird's eye view of newer methods proposed to achieve green IoT through the Unmanned Aerial Vehicles (UAVs) framework, attaining a reliable and sustainable bright globe. The proposed UAV framework is a powerhouse of emerging technologies that can improve daily lives by significantly upscaling various sectors, such as agriculture, power, health care, and environmental conservation. Additionally, creating a real-time feedback application can take 5G to the next level singularly, with minimal collaboration from IoT devices. Indeed, the gathered data can help in the development of a dependable and environmentally friendly industry. Finally, a rational argument is made for its uniqueness compared to similar studies. Taffese et al. [19] made an argument describing methods for calculating and assessing the longevity of reinforced concrete (RC) structures using the IoT. The proposed new method outperforms the old and outdated traditional methods and requires actual laboratory testing for being less labor-intensive, more accurate, and more cost-effective. Additionally, the IoT can be beneficial for potentially forecasting damage in construction, enabling the continuous and timely collection of data for an extended period and giving owners a better chance to make structural repairs and extend their life. The IoT demonstrates exceptional efficiency and accuracy in repairing RC structures.

1.1. Structural Health Monitoring

Development in structural engineering has become critical in recent years and SHM has been implemented to increase its reliability and effectiveness. SHM is a process that collects data from structures and uses it to detect and forecast damage based on current and future conditions. Structure prediction enables the early detection of damage to any structure. For instance, the life of a bridge with loads based on daily traffic can be predicted based on the commutation of vehicles and loads on the bridge. Similarly, the load a building can withstand over time can be used to determine the building's lifespan using predictive analysis. Sensors installed at various connection points (joints) can monitor the structures. It can be accomplished using strain gauges, inclinometers, accelerometers, and other sensors. The SHM system will maintain a regular historical record of the structures. As a result, SHM is extremely useful for detecting structural changes resulting from unpredictable events, such as earthquakes or blast loading.

Scuro et al. [20] examined the role of IoT in masonry SHM, providing an overview and highlighting several new and innovative models. IoT in SHM of masonry constructions has been significantly impacted by high-speed data processing and an open deck for innovation. The tests conducted with IoT enhanced its value and accuracy and ensured future improvements, most notably by identifying earlier cracks and their significance. By analyzing the new method data for damage caused by natural factors over time, the configured SHM method made with the help of IoT has proven to be more accessible and more beneficial for checking ancient constructions and their longevity. The proposed system is most efficient when combining mechanical and cyber-related components. Abruzzese et al. [21] discussed using the IoT to monitor the health of newly constructed structures and civil engineering structures with an expected life of less than a hundred years. This proposed method opens up a new horizon because the technology can be used highly precisely, will retain daily data for an extended time, and is less expensive than conservative models that rely on periodic third-party lab testing to determine the structure's health over time. The installation entails placing sensors and structures in strategic locations and connecting them to nearby IoT devices. The collected data can be critical for the long-term maintenance of the constructed structure, and due to its low cost, it can be applied to all new constructions for improved results.

1.2. Internet of Things (IoT)

The IoT is a network of linked devices which use integrated technology to communicate and interact with the natural world [22]. The phrase "IoT" refers to all these connected objects and the technology which share data with the outside world. They are often used for the automation of mundane activities and monitoring.

Jia et al. [23] demonstrated a novel method for enhancing inventive constructions through the IoT. The proposed method enables modern structures to provide high-quality services, efficient usability, improved operating characteristics, and compliance with sustainable goals. IoT is discussed in detail in necessary topics, including industrial and academic applications. The article discusses the various outcomes obtained through IoT in modern building constructions and the advantages of IoT over conventional methods. The final phase discusses the difficulties inherent in applying these methods, thereby paving the way for additional research until they become viable for use in modern homes and industrial buildings. Koot et al. [24] demonstrated an organized review of tracking and inspecting appliances in the supply chain via IoT and Big Data Analytics (BDA). The discussion focuses on obtaining academic writings demonstrating methods for utilizing the instantaneous values of manually operated things in businesses to get solutions. The capabilities of IoT analytics were examined through a paper review that resulted in 79 broad-ranging articles. A trend toward combining traditional Information and Communication Technologies (ICT) with new IoT was observed to achieve comparable or better system dynamics prediction. The resulting performance was superior in quality, usability, and dependability. On the other hand, logistic operations demonstrated increased flexibility. Finally, some recommendations for future improvements were made, including unconventional thinking.

Kassab and Darabkh [25] discussed an in-depth examination of IoT protocols, usability, current advancements, recommendations, architectures, and the future. Recent advances in the IoT environment have enabled the integration of disparate fields into a system capable of analyzing, processing, and sensing all data from its surroundings in real time and storing the data for an extended period. The IoTs provide cutting-edge, state-of-the-art technologies that improve embedded actuators, radio frequency verification tags, readers, and sensor nodes for the future internet's improved performance. The various phases and their evolution over time and future possibilities are discussed. Current challenges and the definition of middleware were illustrated, and finally, all IoT applications were critically analyzed.

2. Intelligent Technologies in SHM for Diverse Structures

This comprehensive investigation delves into the application of intelligent technologies in SHM across various structures such as bridges and buildings, including special buildings. Highlighting their transformative impact on enhancing accuracy and efficiency ensures effective structural integrity monitoring.

2.1. Bridges

Numerous studies have been reported on the health monitoring of bridges to monitor the damages and lifetime based on the load applied and other natural calamities. Different types of sensors and predictive analysis techniques have been used to monitor the bridge's lifetime. Maeck and DeRoeck [26] monitored damage detection on the Z24 Pre-stressed concrete bridge in Switzerland. Park et al. [27] monitored four-story steel frame structures with FEA to test the rigidity of a bridge's beam column connection. Wang et al. [28] observed the single-span plate Girder Bridge to detect the damage. Wang et al. [29] monitored Kishwaukee Bridge in Illinois, USA, for damage assessment. Peil and Mehdianpour [30] monitored Highway Bridge for life cycle prediction. Enright and Frangopol [31] adopted the Bayesian approach, while Elhattap et al. [32] worked on kinetic energy to detect the damage in bridges in the USA by using SHM.

Figure 3 illustrates SHM applications in bridge structures, along with sensor placement.

Jang et al. [33] used a wireless smart sensor network for monitoring the cable-stayed bridge (Jindo Bridge, Republic of Korea). Fraser et al. [34] worked on reinforced concrete Highway Bridge at different locations to identify the vibration due to acceleration and traffic. Mehrani et al. [35] monitored the bridge structure in Florida, the USA using a fiber optic sensor to identify the bridge behavior at heavy loads. Pines and Eminaktan [36] applied SHM of the long-span bridge in the USA to detect damages. Liu et al. [37] worked on damage diagnosis, vibration detection, and dimensionality reduction of the bridge in the USA to monitor the bridge's health. The SHM process is illustrated in Figure 4.

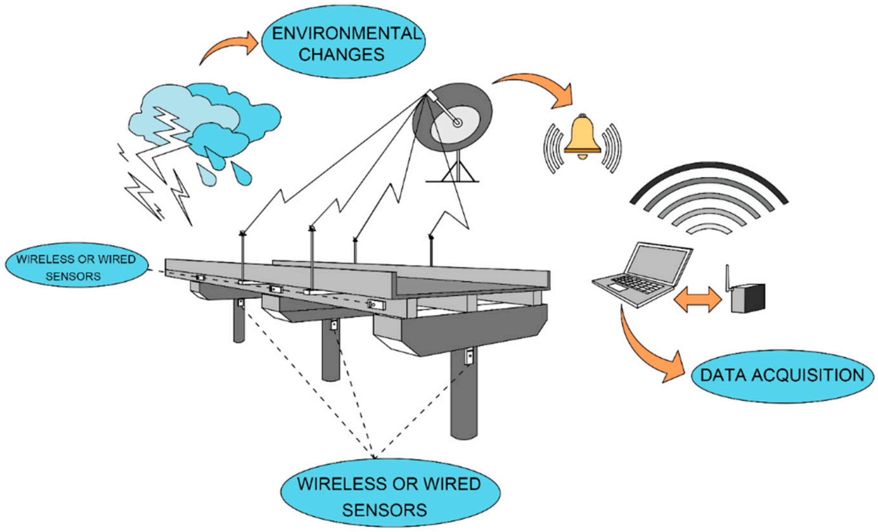

Figure 3. SHM uses in bridge structures, as well as sensor placement.

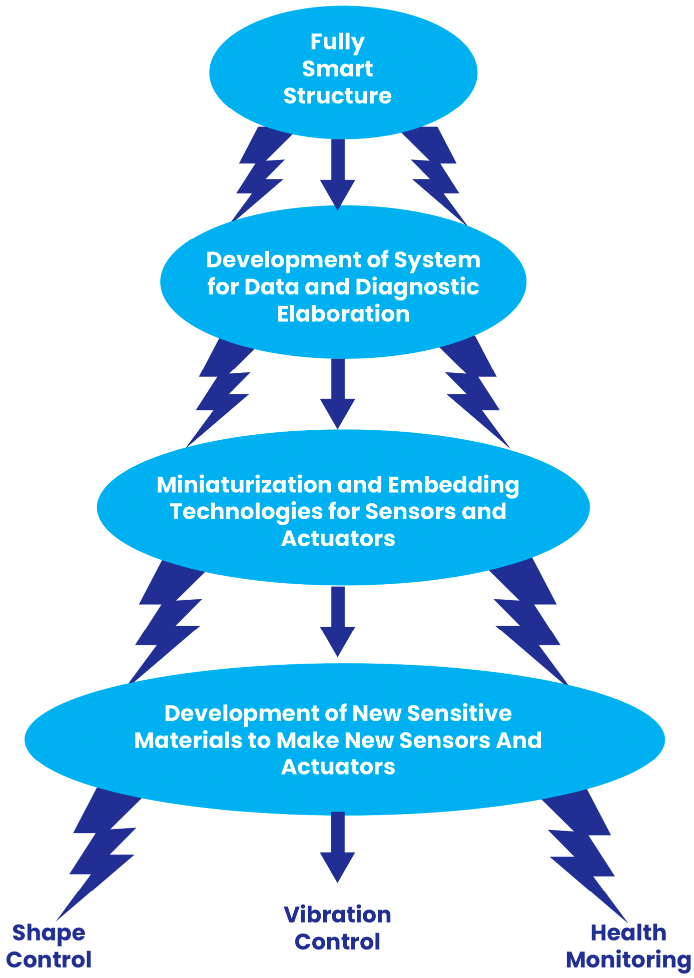

Figure 4. SHM process flow.

In cyclically stressed bridges, in addition to strength and stability assessments, it is also necessary to evaluate the residual fatigue resistance, which is often related to corrosion damage in bridges made of standard steel or high-strength steel (HSS). Scientific works focused on fatigue resistance were published for structures with significant corrosion damage, including work focused on the fatigue resistance of HSS [38]. These studies are based on the results of experimental testing on samples. When evaluating the effect of specific corrosion disorders, it is usually not possible to produce samples for destructive tests. However, with the development of modern technologies, new alternative methods are being offered, which will make it possible to evaluate the fatigue resistance of corrosion-damaged details without the need for destructive testing. In particular, it is possible to use detailed numerical modeling, probabilistic analysis, surface nondestructive measurements, methods used to analyze images taken of corrosion-damaged surfaces, and, more recently, robotic technologies for monitoring. Zhang et al. [39] proposed a novel method for assessing a safety condition of bridges based on long-term monitoring data from the weigh-in-motion (WIM) and SHM systems. As evaluation indicators for early warning and condition assessment, the method uses vehicle load and strain mapping models. The method is stable and effectively integrates the WIM and SHM systems for bridge health assessment, as demonstrated with continuous monitoring data on a concrete box girder bridge. Yi et al. [40] recommended a Bayesian robust tensor learning model for reconstructing monitoring data tensors by extracting spatiotemporal features. Noise is modeled using a combination of Laplace and generalized inverse Gaussian distributions, ensuring robustness and eliminating interference from outliers, baseline shifts, and noise. The model is evaluated using actual monitoring data from a concrete box girder bridge, demonstrating good data-cleansing performance when dealing with many data anomalies and maintaining good performance as the rate of data anomalies increases. Zhao et al. [41] investigated abnormal vibration in the cables of a railway-highway-combined cable-stayed bridge during operation. They extracted nonstationary sections of abnormal vibration using Gaussian mixture modeling and introduced a new method for identification of modal parameters. The damping ratio of the cables with abnormal vibration was less than 0.05%, and the wind speed–vibration frequency correlation model was fitted to predict the frequency of abnormal vibrations before they are fully completed.

2.2. Buildings

Buildings exist in a wide range of sizes, forms, and functions. They have evolved through time due to several factors, such as construction materials availability, weather conditions, property prices, ground conditions, particular applications, and aesthetic concerns. There are several types of structures listed below, which will be discussed in this article:

- Residential buildings;
- Commercial buildings;
- Industrial buildings;
- Special buildings.

2.2.1. Residential Buildings

A residential building refers to any structure primarily used for human habitation. This term includes both single-family and multifamily buildings. Specific ancillary uses are permitted in residential buildings; usually, these will be retail or office spaces, but must be used primarily for residential purposes. Meng et al. [42] studied the impact of traffic pollution on roadside residential buildings' health and safety. They developed a spatial distribution model using Machine Learning to estimate $PM_{2.5}$ concentration and assess the decrease in life expectancy (DLE) of residents. The results showed a decrease in $PM_{2.5}$ concentration within 0 to 120 m distance and a maximum DLE of 5.11 years. The SDC model can help develop precaution guidelines and future planning for urban health and safety buildings. Alarcón et al. [43] validated a low-cost seismic instrumentation system (LCSIS) for SHM of South America's first experimental six-story light-frame timber building, Peñuelas Tower. Operational modal analyses determined the building's mode shapes and frequencies. Shake table and earthquake response tests validated the LCSIS. The BME280 sensor continuously monitors temperature and relative humidity. Timber structures are more sensitive to temperature and relative humidity changes, according to the study. The

48-h state-space model accurately estimated natural frequencies, demonstrating its ability to separate ambient-induced variations from damage or unknown sources. Koci et al. [44] pointed out the European Union's emphasis on reducing building energy consumption. Phase change materials (PCMs) can be incorporated into conventional materials, but there are still some concerns. This paper examines the impact of PCM-modified plasters on the energy performance of building envelopes, taking into account climatic loads and material compositions. Depending on the material composition and geographic location, latent heat storage systems can save between 3.7 and 6.5 kWh per square meter annually. Nevertheless, PCM-based systems should be evaluated with caution due to their economic and environmental viability. The obtained geographical and anatomical perspectives provide an excellent foundation for estimating preferable PCM exercises in buildings' wrappers. Since the current state of the art focuses primarily on specific load-bearing frameworks, the conceptual perspective demonstrated in this research can introduce a new permeance into using latent heat methods in dwelling structures.

Kemplon et al. [45] suggested that a cohort of 233 abode characteristics with newly remediated mold problems be examined to determine which factors contribute to mold enlargement during the remediation process. The research indicates that remediation without addressing the mold problem's root cause can effectively prevent mold growth from re-occurring in the short term, with 40% of the subset of characteristics involved in re-growth within 12 months. Several characteristics were associated with widespread mold enlargement, most notably high wall ground temperatures compared to the room air humidification temperature. Shokouhi et al. [46] aimed to comprehend the perception of fire-related injury safety in Iranian residential buildings. They utilized content analysis and semi-structured interviews, with 25 interviewees selected through purposive sampling. The study focuses on six categories: building safety, fire safety regulations, safety-conscious individuals, efficient relief organizations, urban safety, and economic and financial capacity. The findings indicated that multidisciplinary functions and a holistic approach are necessary for ensuring residential building fire safety. It is recommended that additional research be conducted to improve fire safety in these buildings.

2.2.2. Commercial Buildings

Commercial buildings refer to structures that can generate revenue through rental or capital gains. This structure comprises mainly distinct segments in the retail real estate market. However, any building whose main function is to generate profit can be considered a commercial building. As a result, even residential buildings, intended for rent, called PRS (Private Rented Sector), may be considered as a commercial facility. Park and Oh [47] managed an SHM program with real-time strategies for giant structural buildings to assess the massive buildings' safety and state. In Korea, the colossal LWT (Lotte World Tower) was chosen for observation to visually identify the damping ratio and mode shape of modal behaviors. The System Identification (SI) technique was used in conjunction with well-percolated modal responses to shorten the duration of the experiment. In 2015, environmental vibration experiments were conducted on the Lotte World Tower. The results establish a clarified artificial setting representation to develop a commercial setting representation to simulate the commencement of construction for the world's tallest buildings using monitored data.

The data acquisition unit of a system is explained in Figure 5. Data from the structure in which health monitoring is carried out are fed to the sensor. Based on the type of application, the sensor will be chosen. Then, the signal will be conditioned with the amplification and filtering process. The next step in DAQ is data conversion, where the analog data will be converted into digital form for computational processing. Then, the processed data will be stored or transmitted to the corresponding base station.

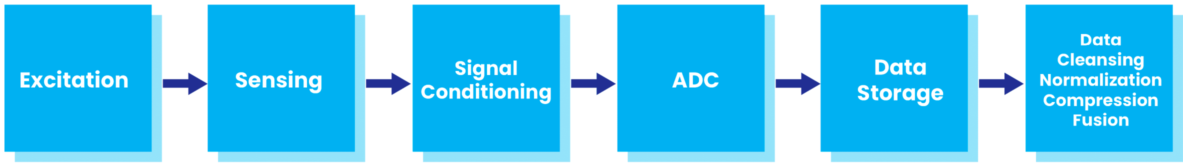

Figure 5. Data acquisition unit.

Statistical fraud and structural distortion monitoring for the tallest buildings during construction distortion were investigated by Gao et al. [48]. Utilizing a 48-story, 335-m-high structure, the vertical distortion through 128 shaking cable tension gauges was calculated. To calculate the maximum nonlinear effect of vertical distortion on construction, the result was applied to various Relative Humidity (RH), structural closure, and concrete characteristics. When considering the impact of different weather conditions on the creep and diminishment of concrete in the vertical distortion of the tallest buildings, RH values were seen as crucial and enormous.

Zhang et al. [49] described the foundational tool dubbed 'all-printed strain sensors' for inspecting and assessing the health of aircraft structures. On an absolute substratum, all-printed strain sensors are preferred due to their long-term dependability, strain detector response, and cross-wise strain sensitivity, which are advantageous when measuring printed, inkjet strain detectors on polyethylene-terephthalate (PET). When one-way fatigue and tensile loading are performed, an assessment is made using the gauge factor of meandering strain detectors, the quality of market-ready inks, the effect of temperature, and a detector trust factor. The assessment assisted in determining the optimal parameter for screen printed and inkjet formations under load—along with other minute factors, such as ink. Additionally, cost-effectiveness, area of strain parameters, and fracture details were discussed, concluding with prospects and capacities. Clayton et al. [50] demonstrated a sophisticated method for determining the true meaning of sustainable and energy-efficient, market-ready housing by adding three additional specifications beyond building certification, such as Capex (nature-based capital expenses), occupant interactions, and monitoring in the making. The interdependence properties were analyzed along with the electricity consumption. A decade-long study was conducted to pilot the observations in the United States and Canada, with the assistance of the investment's global institutional manager. The findings contributed to a greater understanding of this subject and established the impact and dependability of various natural interventions on the current usage of marketed houses. Additionally, a Capex and electricity consumption were established, concluding that numerous natural interventions are required to reduce consumption. Asadi et al. [51] developed a novel, more effective, and more precise SHM tool based on the combination of SHM and parts-focused resilience estimation. The provided method calculates, mitigates, and manages construction's quacking risk by utilizing instantaneous values. The data collected from homegrown sensors are used to identify crack improvements from the provided safety evaluation protocol and create tool-based functionality graphs to determine a structure's quaking resilience. The factors are evaluated using an autoregressive exogenous (ARX) prototype. All types of damage are also considered, considering two distinct types of buildings located in earthquake-prone zones. The conclusions stated that the floor is prone to earthquakes. The findings showed that structural floor acceleration should be extensively studied to estimate structural damage accurately.

2.2.3. Industrial Buildings

An industrial building is a structure constructed on land designated for industrial purposes. The permitted uses will be specified in the city or township's building code or zoning regulation. Typical applications include factories, assembly plants, foundries, railroad maintenance facilities, warehouses, garment distribution centers, breweries, dog food plants, etc. Tuloup et al. [52] discussed in situ piezoelectric sensor advances in polymer-matrix composite (PMC) manufacturing and SHM. These sensors harvest energy, control vibrations, and record environmental conditions. Real-time health monitoring data can help designers build stronger aero planes, spacecraft, buildings, and bridges. Composite materials' future is smart manufacturing and structures. Lin et al. [53] introduced a sensor optimization preparatory based on a talented algorithm that emerged in the neoteric years. This article discusses several well-known professional optimization algorithms and presents a clever hybrid algorithm that combines GA (genetic algorithm) and PSO (particle swarm optimization). The intelligent hybrid algorithm is used to renovate the sensor's preparation. The optimal sensor layout allows for the estimation and operation of civil engineering using an appropriate variety of finite sensors, a mixed optimization problem. The practical result demonstrates that the optimal sensor layout lacks sentience and usability.

Das and Saha [54] focused on applying six SHM algorithms on a quarter-scaled American society of civil engineers (ASCE) standard framework using rigidity-based objective work. The correction has been proposed by incorporating chaotic maps into the BSA's fodder dealings and the firefly algorithm's (FA) erratic motion to improve execution. Additionally, the algorithms were evaluated for multiple losses of low sharpness in the presence of moderate sound desecrations. It is noted that chaotic FA and bird swarm algorithms have a high degree of precision in explaining losses, with 95 percent of loss outcomes falling within the permissible limit. Köppe and Bartholmai [55] emphasized the dangers of construction component failures, such as bridge collapses, which can cause extensive damage to structures. Increasing traffic volume and ageing bridges also contribute to decreased load-bearing capacity. In collaboration with ScatterWeb Company, the Federal Institute for Materials Research and Testing developed a self-configuring measuring system to prevent accidents. For long-term monitoring of buildings and engineering facilities, the system employs self-sustaining, wireless sensor modules, particularly in transport and traffic structures and large industrial facilities with difficult wiring installation.

A summary of the discussion of residential, commercial, and industrial buildings is presented in Table 1, which illustrates works incorporating SHM-IoT into residential, commercial, and industrial structures.

Table 1. Studies referring to SHM-IoT in residential, commercial, and industrial structures.

Sl. №	Authors' Name and References	Different Types of Buildings	Sensors Used	Parameters Measured
1	Kempton et al. [45]	Residential	Sensors capable to predict indoor environmental conditions	The indoor environment's requirements, such as humidity and temperature, were monitored.
2	Zhang et al. [49]	Commercial	Strain sensors	Fatigue and tensile testing were monitored throughout time.
3	Asadi et al. [51]	Commercial	Wireless sensors network	Structure's seismic behavior
4	Park and Oh [47]	Commercial	accelerometer, strain sensors, inclinometer, anemometer, etc.	Building dynamic behavior with ambient vibration and modal responses
5	Lin et al. [53]	Industrial	A variety of sensors can be used in IoT applications; the most common are accelerometers.	The sensor layout is optimized using a hybrid intelligence method.

2.2.4. Special Buildings

Nuclear power plants are protected by structural health monitoring, which evaluates containment integrity, identifies flaws, and ensures safe operations within their fortified walls. Continuously monitoring structural conditions can identify and promptly mitigate potential risks, upholding the highest safety standards. Chu et al. [56] proposed a reliable routine standard operation procedure (SOP) for structural health monitoring and diagnosis of nuclear power plants (NPPs). They recommended using three methods, i.e., Recursive Least Squares (RLS), Observer Kalman Filter Identification/Eigensystem Realization

Algorithm (OKID/ERA), and Frequency Response Function (FRF), for signal screening and identification procedures. The SOP can be verified by comparing results from different methods. A preliminary containment (CTMT) healthy record can be established as a quantitative reference for restart procedures. Yin et al. [57] suggested an intelligent fault diagnosis method using a multisensor and deep residual neural network for improved diagnostic performance in nuclear power plants. The method uses multisensor data and deep learning models to identify fault types in rotating machinery. The method's efficacy is evaluated using motor and bearing datasets, and its anti-noise capability is examined. Using a metallic adhesive and a copper/carbon (Cu/C)-coated fiber, Chong et al. [58] developed an FBG acoustic sensor for Integrated structural health monitoring (ISHM) technology of high-temperature NPP structures. The Cu/C-coated fiber proved its excellent radiation and temperature resistance and compatibility with standard fibers, adapters, connectors, and instruments. During temperature cycles ranging from 25 °C to 345 °C, the metallic adhesive provided superior bonding dependability. The Cu/C-coated FBG sensor could detect acoustic-ultrasonic waves generated by the breaking of pencil lead and laser beam excitation.

In order to improve the sensitivity of fiber-optic-laser-induced breakdown spectroscopy for trace element detection in nuclear power plants, Qiu et al. [59] developed a dual-pulse spectral enhancement system. The system optimizes key parameters, including inter-pulse delay, gate delay, pulse energy ratio, and lens-to-sample distance, to decrease iron self-absorption and increase sensitivity. This system decreases the matrix iron's self-absorption coefficient and increases the number of detectable trace element lines without increasing the ablation mass. The system determines the chromium and manganese concentrations in low alloy steel samples using internal standardization, partial least squares regression, and random forest regression. The leave-one-out cross-validation method assesses the precision of chromium quantification. Yong-kuo et al. [60] investigated NPP's distributed condition monitoring and fault diagnosis system to improve fault diagnosis precision and speed. They proposed a method for intelligent diagnosis based on fuzzy neural networks (FNN) for local diagnosis and multisource information fusion technology for global diagnosis. The method accurately diagnoses the various fault levels and types of multiple faults, ensuring rapid and precise diagnosis.

2.3. Dams

Dams are generally made of concrete or natural materials such as soil and rock; large-scale engineering projects such as the Hoover Dam and the Three Gorges take years to finish. Kang et al. [61] developed algorithms that integrate Support vector machines (SVM), Salp swarm algorithms (SWA), and the Jaya optimizer for precisely simulating the temperature impact in dam health monitoring modeling. The introduced SVMS algorithms with extended air temperature roots are validated using invigilating data from a solid gravity dam. The findings show that hybrid designs may effectively mine the impact of air temperature on dam operations. The proposed method is now being tested on a solid gravity dam and further tests on concrete arch dams will be required shortly. Kang et al. [62] showed a dam health-monitoring model using long-term air temperature for thermal impact pretension. The machine learning technique RBFN is used to forecast the temperature effect of the vast air temperature chain. The hydrostatic season length prototype mimics the weather impact through harmonic sinusoidal performance and assesses general dam health. The results demonstrate that the rough RBFN prototype achieves superior results when the extended air temperature is used rather than the harmonic sinusoidal performance prototype.

Milillo et al. [63] used Cosmo-Skymed (CSK) and TerraSAR-X (TSX) data to operate seasonal-induced distortion at the Pertusillo dam through the use of multitemporal SAR (Synthetic aperture radar) data. They used hydrostatic seasonal temporal (HST) and hydrostatic temperature temporal (HTT) prototypes to explain the dam wall's nonlinear distortion, combining surface metering with SAR duration series explication. The various standards produce slightly different results when illustrating the aging term at the dam wall. The results demonstrate how small revisit SAR satellites combined with widely used models for decorating GPS and pendulum information can aid SHM and provide critical data to ground consumers directly annexing in field metering [64]. Ruiz-Armenteros et al. [65] demonstrated the technology of 383 SLC SAR images in both scansorial and decrescent track up to March 2019. Variations in the dam's framework substructure, such as impeding slopes, can be effectively recorded using InSAR processing, more precisely, multitemporal InSAR duration chain explication. Remo Dams is a Spain-based research project dedicated to providing distortion monitoring of various embankment dams via time series InSAR processing. The results indicate that the dam's primary dislocation is vertical, costing about 1 cm/annum in the central part of the dam corporis.

3. Advancements in Artificial Intelligence for SHM

This section reveals the advances of Artificial Intelligence (AI) in SHM and highlights the transformative power of AI techniques to enable accurate and proactive structural anomaly detection. Predictive analysis of the SHM will help predict the lifetime of the structures such as bridges, beams, columns, slabs, and shear walls. Many construction companies have started working on the predictive analysis of the structures to maintain the structures constructed by them. Lehner et al. [66] proposed a newly developed methodology for evaluation of the residual life of existing steel structures in terms of fatigue damage. SHM usually employs statical models for the predictive analysis to detect the damage in the structures using supervised and unsupervised learning. Unsupervised learning takes data from the damage and gives the presently identified damage. Supervised learning can be adopted when the data are received from both the damaged and undamaged structures.

3.1. Supervised Learning Methods for SHM

Different methods were adopted in the supervised learning for SHM, such as:

- Response Surface Analysis;
- Fishers Discriminant;
- Neural Networks (NN);
- Genetic Algorithms (GA);
- Support Vector Machines (SVM);
- Direct Optimized Probabilistic Computation (DOProC).

Luo and Hanagud [67] have worked on dynamic behavior prediction using NN to identify the error rate at two consecutive points. Jeng and Lee [68] used NN to predict glass fiber-reinforced plastic composite laminated beam defect size and location using a numerical model. Nakamura et al. [69] used NN for damage detection prediction of a 23-m building for beam-column connection damage. Masri et al. [70] used a nonlinear system identification technique using NN to predict the nonlinear behavior of the structures based on the vibration measurements. Barai and Pandey [71] used two different types of NN for damage detection and vibration detection. Chang et al. [72] used NN to predict the structural parameters with the FEA analysis. Haywood et al. [73] indicated the impact location and amplitude of the composite plate using NN.

Gordan et al. [74] used ANN with data mining algorithm to predict the structural health condition. Smarsly et al. [75] used the machine learning approach to predict the damages from vibration in different structures. Ghiasi et al. [76] used ANN to detect structural damage by classifying the dynamic and static test data.

Mares et al. [77] used GA to minimize the cost function to predict the dynamic analysis of a four-storied building. Liu et al. [78] used GA to place optical sensor for strain prediction in 12-bay truss model. Chou et al. [79] also used GA for strain measurement to predict and detect the displacement in any structural member. Koh and Dyke [80] used GA for damage detection and prediction in long cable-stayed bridges. Zheng et al. [81] used GA with a hybrid learning technique to detect and predict the linear least model frequencies in glass laminate beams. Yi et al. [82] used GA to detect and predict the damage and strain displacement in any structure. He et al. [83] used GA to predict defects and damages in suspension bridge structures. Huang et al. [84] used GA for predicting the data from the harsh environment to detect the damages in structures. Kuang et al. [85] used GA for predicting the damages in fiber composite beams.

Worden and Lane [86] used SVM to predict the damage classification in the truss structure. Park et al. [87] used SVM with the piezoelectric sensor to classify the damages in railway road tracks. Ho Thu and Mita [88] used SVM for damage prediction and detection in shear structures. Xiang Li [89] used the SVM technique to predict the cracks and corrosion in aluminum beams.

Janas et al. [90] as well as Krejsa et al. [91] used DOProC to probabilistic prediction of fatigue damage in steel structural element subject to fatigue load, particular attention being paid to cracks from the edge and those from surface. When determining the required degree of reliability, it is possible to specify the time of the structural inspections which will focus on the fatigue damage.

3.2. Unsupervised Learning Methods for SHM

Different methods were adopted in the unsupervised learning for SHM, such as:

- Control Chart Analysis (CCA);
- Outlier Detection (OD);
- Neural Networks;
- Self-Organizing Map;
- Adaptive Resonance Theory;
- Hypothesis Testing;
- Other probability analysis techniques.

Lu et al. [92] used CCA for bridge management by indicating the damage mathematically by showing the strain variations. Sohn et al. [93] used CCA for predictive analysis of vibration-based damages in different structures. Deng Yang et al. [94] used CCA for predictive analysis of the damages in the suspension bridge by detecting the frequency and displacement.

Worden et al. [95,96] used OD to predict the damage in the aluminum plates with the dimension 750 mm × 300 mm × 3 mm as well as to predict the damages in composite plates. Nichols et al. [97] used OD to predict the vibration-based SHM to detect the damages. Park and Inman [98] used OD to predict the damages in structures based on impedance input from the sensors.

The most common used unsupervised NN algorithms are self-organizing maps and adaptive resonance theory. These algorithms are used in the SHM. Avci and Abdeljaber [99] used a self-organizing map to predict global structural damage detection. Buethe et al. [100] used the self-organizing map to predict the damage and dynamic behavior of the structure. Avazdavani and Borazjani [101] have worked on adaptive resonance theory to design the structural members.

Todd and Nichols [102] used hypothesis testing to predict damage in different structures. Few more techniques have been used for the predictive analysis of SHM. Huang et al. [103] used the Bayesian approach to analyze the modal parameter for predicting the damage in structures. Ching and Beck [104] used the Bayesian technique to detect the damage due to hammer impact and ambient vibration in structures. Kuok and Yuen [105] as well as Lucero and Reda Taha [106] used the Bayesian approach to predict the deterioration of structures from acceleration by loading the input data to FEA. Chandrashekhar and Ganguli [107] used the fuzzy logic system to detect the size of the damage in structures. Farrar et al. [108] used a pattern recognition system for detecting damage in different structures. Michaels [109] used coherent function to detect damage and localization of damage in structures. Schulza et al. [110], Mishra et al. [111], and Maraveas et al. [112] used coherent function to detect the damages in beam and panel structures.

4. Integrating Nondestructive Testing Sensors in SHM

Yong Zheng et al. [113] discussed the development of fiber optic displacement sensors for geotechnical health monitoring (GHM), focusing on fiber Bragg grating sensors and bend loss-based sensors. The paper analyzes their characteristics, state-of-the-art research, and compares the advantages and disadvantages of these sensing technologies. The study aims to evaluate the safety of geotechnical structures, such as slopes, dams, tunnels, and excavation engineering. Gómez et al. [114] addressed a newly advanced observing technology in Barcelona, and it is an advancement to the TMB L9 metro tunnel for SHM with DOFSs (Distributed Optical Fiber Sensors), which was impacted due to a neighboring building. This study adopted complex algorithms to recognize and replace irregularity in fiber concrete bonding strategies. Finally, the DOFSs were established to compare nearby construction situations better.

The ability of piezoelectric materials to act as simultaneous sensors through electrical-mechanical transformations has gained popularity in recent years. Particularly, piezoceramic sensors have been incorporated into civil engineering systems' structural health monitoring (SHM), with measurements of electrical impedance and elastic waves in mind. Bhalla et al. [115] investigated a low-strain fatigue behavior of piezoceramic sensors in a real-sized reinforced concrete (RC) structure. As dual-mode sensors for universal vibration technology and regional electromagnetic interference (EMI) technology, concrete vibration sensors (CVS) were utilized. Incorporating CVS into the framework enabled a calculation of a remaining flexural rigidity. Hasni et al. [116] proposed using self-powered piezo-floating (PFG) sensors with adjustable injection rates as a novel method for anatomical health monitoring. Utilizing the concept of sensor grouping, the researchers extracted various features from the accumulated voltage data of each memory gate to improve the precision of loss detection. A method was developed to optimize the classifier's parameters, thereby improving the accuracy of loss progression detection. The performance of the introduced system in detecting loss progression in steel sheets was satisfactory.

MEMS technology predicts an increase in vibration in a structure and comprises fabric designs that deliver superior performance and reliability. Tondolo et al. [117] established a new paradigm for instrumented reinforced steel bars with embedded MEMS strain sensing capabilities, providing a cost-effective civil framework and infrastructure solution. Multiple trials were conducted to demonstrate the method's efficacy, and the research demonstrated using a low-cost embedded process to construct concrete structures. Notably, a compressive test revealed a significant practical application potential. Similarly, Guidorzi et al. [118] emphasized using more adaptable quantity models in SHM-oriented recognition systems, specifically extending autoregressive (AR) models to account for additional measurement noise. The strength spectral densities of these models and the data used for their recognition were compared comprehensively. In addition to presenting the outcomes of the considered systems, the study compared the performance of MEMS-based solutions to that of conventional approaches employing piezoelectric seismic accelerometers.

Kim et al. [119] estimated using cost-effective Real-Time Kinematics-Global Positioning System (RTK-GPS) sensors in the construction field. These sensors work based on collecting signals from the satellite and transferring them. To avoid the obstacles during the displacement computation, an advanced RKT-GPS detector was embraced for the excellent result in the satellite signal received. The displacement, acceleration, and velocity calculations were tested through several fields and lab tests at South Korea Yeongjong Grand Bridge, where the precision computed specimens' rate was about 100 Hz for 2 mm displacement. Gatti [120] analyzed the anatomical validity of a prestressed concrete bridge, built in the 1960s. The study involved evaluating the execution and performance of the bridge under jointly directed static and dynamic loads. A sophisticated finite element model of the bridge was created as a result of the dynamic load test. The use of dynamic load trials in conjunction with static load trials for anatomical testing of new bridges and ongoing monitoring of operational bridges was demonstrated by comparing the results.

Adamcová et al. [121] investigated landfill displacements, which are important for reclamation and geotechnical safety enhancement. They involve the vertical displacement of waste bodies due to compression, decomposition, and creep. The study aimed to examine landfill settlement estimation methods and propose a simulation model using a Global Navigation Satellite Systems (GNSS) measurement. Using Gauss–Newton iteration and Runge–Kutta methods, the new model estimates landfill surface displacements. The results demonstrated a transformation of the landfill body over time, with waste displacement curves congruent with total displacement. Even for steep slopes, the landfill did not experience significant displacements or slope failures [122]. To ensure geotechnical safety in municipal solid waste (MSW) landfills, Pasternak et al. [123] compared various measurement techniques, including linear and angular measurements, satellite measurements, terrestrial laser scanning (TLS), and unmanned aerial vehicle (UAV) scanning and photogrammetry. Consideration is given to cost and time resolution when proposing solutions for long-term monitoring of landfill geometry changes.

Table 2 shows various types of sensors frequently used for SHM and their applications.

Table 2. Major sensors used for SHM and its application.

Sl. Nº	Primary Sensors Used in SHM	Measured Parameters	Types of Structures
1	Fiber Optic sensor	• Strain • Temperature • Displacement • Pressure	Long pipeline work in the oil and gas sector Bridges
2	Piezoelectric sensors	• Dynamic behavior • Structural stiffness • Displacement • Strain	Structural elements Spot welded joints Bridges
3	MEMS accelerometers	• Vibration sensing • Stress • Natural frequency • Damping ratios • Mode shapes	Heritage buildings Residential buildings Bridges
4	Global positioning satellites	• Acceleration • Fluctuation • Dynamic displacement	Bridges Dams Tower structures
5	Linear variable differential transformer	• Deflection • Crack monitoring • Movement in joints • Fluctuation	Bridge Dams Buildings

5. SHM Applications in Historical Buildings

SHM has numerous applications in historical structures, aiding in preservation and conservation of these cultural objects of beauty. By employing SHM technologies such as sensors and data analytics, it is possible to continuously monitor the structural integrity of historical buildings, thereby ensuring their long-term stability and preserving their distinctive architectural heritage. Califano et al. [124] were concerned with studying and regulating indoor microclimate in historic buildings, particularly those made of organic materials such as wood. They showed that temperature and relative humidity fluctuations can impact the mechanical properties of wooden objects and structures. They examined the Norwegian stave churches of Ringebu and Heddal, which contain wooden medieval statues and paintings. They emphasized the need for regularly and systematically updated specifications tailored to each case study and energy- and cost-saving strategies. They also examined the indoor microclimate of the historic Scots pine-constructed Ringebu Church [125]. Using European Standard EN15757, an indoor environment's relative humidity (RH) is analyzed. They propose a Median of Data Strategy (MoDS) for identifying RH drops, an empirical model for calculating hygro-mechanical stress, and a machine learning technique for predicting the catastrophic effects of climatic fluctuations on historical wooden materials. These methods can aid in assessing the risk of decay in wooden samples and pave the way for future conservation and preservation research in fracture mechanics, fatigue behavior, and smart time-series prediction [126].

6. Future Scope and Recommendations

As most structures worldwide are about 40 to 100 years old, SHM is an essential and more convenient technique than direct inspection, especially for structures. As a result, sustaining structures is regarded as a fundamental requirement worldwide. SHM seems to be the most appropriate and consistent technique for detecting various defects under static and dynamic loading. Some of the future study scope and trends have been covered below.

1. A multilevel system which can integrate global and local level diagnostics in SHM—a better strategy to differentiate changes in structural response due to damage and environmental circumstances; diagnostics at the worldwide level will provide rapid condition screening and diagnostics at the local level will give the location and severity of the damage.
2. To predict the health of any structure, SHM requires a more excellent grasp of equipment, signal processing, and mathematical approaches.
3. Low-cost dense sensor arrays and new techniques are developing to power the sensing system with energy harvested from the structure's working environment.
4. Data-driven time series and predictive modeling tools can forecast future system loading based on current conditions.
5. SHM is expected to forecast bridges, dams, buildings, and stadiums. A large number of building firms are pursuing the SHM approach.
6. SHM may be used as a portable testing and continuous monitoring system; the portable monitoring system can monitor the current condition, whereas constant monitoring will be used to collect real-time data of a structure to identify early detection of any damage.
7. Improved wireless communication systems and advanced sensor technologies for sensing changes in structures to improve SHM efficiency at a cheap cost.
8. High-performance DAQ system for collecting and analyzing sensor data to improve monitoring and forecasting. Positives and negatives should be presented appropriately so that the same technical language is used globally and misunderstandings are prevented.
9. To predict the baseline and determine the dynamic response, the finite element model should be updated according to the model's parameters. Identifying model analysis parameters is crucial for monitoring the dynamic activities of the bridge structure.

7. Conclusions

This article provides an overview of SHM-IoT and its prospects. Depending on the working principle for different civil structures, a discussion on the complete examination of the sensors employed in SHM-IoT has been offered. The study goes into great detail about DAQ and its various variants in SHM-IoT. The application of SHM-IoT to various civil structures and the different works have been investigated thoroughly. The following points have been stated based on extensive discussions.

1. Key sensors such as FOS, MEMS, PZT, acceleration, displacement, strain, and temperature sensors are investigated in application and techniques. Fiber optic and piezoelectric sensors have been widely employed in bridge SHM for the past two decades for both global and local monitoring. The many possibilities for anticipating damages have been examined in depth in this review study.
2. Bridge maintenance and rehabilitation strategies have been thoroughly explored in light of current developments. As for bridges, only a long-term monitoring method is

applied; the sensors and other SHM components must be stable in all environmental changes.
3. Static analysis allows for the enhancement of the SHM system of SHM-IoT for static and dynamic loading conditions, as well as the prediction of damages due to strain, displacement, and acceleration. In contrast, dynamic analysis allows for time history analysis, natural frequency, ambient vibration techniques, and seismic coefficient prediction.
4. Effective implementation of SHM techniques permits a comprehensive investigation of a dam's actual behavior, allowing for the prompt identification of damages caused by natural hazards, such as cracks, deformations, heat effects, and other potential damages. This knowledge is indispensable for maximizing the structural capacity of dams and ensuring their long-term performance and safety.
5. This study has provided insights into the construction industry's progress due to numerous breakthroughs in SHM-IoT. The paper's discussion concludes the SHM and its capacity to identify any damage at an early stage. Different sensors for predicting civil structures, such as bridges, concrete, and steel structures, are discussed.

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