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Optimization of Structural Health Monitoring Using Artificial Neural Networks and Comparison with Traditional Methods: A Comprehensive Review

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Abstract

Structural health monitoring (SHM) has a critical role in ensuring civil infrastructure safety, reliability, and durability through real-time, condition-based monitoring. Traditional SHM systems employ hundreds of sensors such as accelerometers, strain gauges, and displacement transducers for monitoring vast amounts of data for structural inspection, but do not effectively manage complicated nonlinear data. This research paper, "Optimization of Structural Health Monitoring Using Artificial Neural Network and Comparison with Traditional Methods," investigates the feasibility of the optimization of SHM performance by employing artificial neural networks (ANN) for improved interpretation of data, accuracy of prediction, and decision-making in maintenance. The research process constituted extensive literature review, bridge modeling as a simulation platform, and experimentation with ANN models like feedforward, convolutional, and recurrent networks. ANN enables efficient analysis of sensor outputs, pattern recognition of damage, and prediction of damage growth with increased accuracy in structural diagnosis. Comparative investigation with conventional SHM methods verifies that ANN-based systems exhibit better computational efficiency, accuracy, and real-time performance. But needs such as data quality demands, interpretability of the model, and computationally intensive analysis remain. The results highlight that the integration of ANN makes SHM an intelligent, dynamic, and futuristic system, and thus a leap and bound improvement in the digitalization of urban infrastructure. Smarter decision-making and predictive maintenance by ANN-based SHM enhance safety considerably, cost savings are realized, and smart city sustainability is enhanced.

Keywords: Structural health monitoring, artificial neural networks, damage detection

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INTRODUCTION

Structural health monitoring (SHM) is an important part of condition-based maintenance solutions that are cost-effective and viable. The condition of the structure is monitored during service through the operation of an automated monitoring system [1]. Decision-making, particularly damage evaluation, which involves analysis and data processing, and a network of sensors, is an inevitable part of an SHM scheme. The potential of SHM technology to provide significant life and financial safety benefits is considerable. However, the practical implementation of SHM technological innovations to engineering structures is still in its infancy, and its interdisciplinary character requires the creation of many disciplines [2]. Therefore, to take advantage of this new technology, infrastructure managers need to utilize additional resources. The SHM system framework and approach, and the history of SHM technology, are examined. There is controversy regarding the future benefits and key challenges of implementing SHM in large civil engineering structures. Finally, the challenges of SHM methods for civil engineering applications and additional research required are discussed [3].

Using period-sampled reaction measurements, organized SHM provides for long-term monitoring and analysis of systems, which in turn enables the monitoring of changes in the geometrical properties and materials of engineering structures, such as buildings and bridges [4]. The implementation of a damage identification plan that is generally related to a negative alteration of the material properties, geometry, support conditions, or loading that affects the current or future strength or longevity of the structure is known as SHM [5].

Development of SHM Methods

The degradation of the structure can be qualitatively detected by tracking its dynamic response over a long period. Damage detection techniques that engineers are interested in date back to the days when tapping out code was the normal way of discovering bugs. However, the field did not catch on in research until the 1980s, when there was an incredible emphasis on the structural integrity of offshore constructions and, consequently, aerospace structure quality [6]. There has been a tight interconnection between the evolution of quantifiable SHM methods and recent technological developments, and cost decreases in digital computer hardware and sensor equipment. In addition to these developments, SHM has attracted considerable attention in technical literature.

Since the early 1980s, structural engineers have researched the detection of vibration-based damage in bridges, buildings, and other structures [7]. Dynamic flexibility matrix indices and mode shape the curve, which are both quantities derived from the modal properties, have been the most significant features utilized for identifying damage in civil engineering ventures.

LITERATURE REVIEW

SHM is becoming increasingly common as a method for maintaining the safety, performance, and durability of structures because they are aging (buildings, bridges, etc.). With sensor networks and monitoring systems, engineers can track the health of the structure to enable real-time evaluation of structure health so that maintenance can be performed more quickly and potentially disastrous failures can be avoided [8]. New SHM technologies continue to improve the diagnosis and prediction of structural issues; however, they have also provided engineers with new information on material performance and ultimate failure. This new developing field, with new developing technologies, including artificial neural networks (ANN), will certainly remain part of the optimization of SHM [9].

Variations in operating and environmental conditions significantly impede the ability to monitor the health of civil structures [10]. The process of vibration-based damage assessment is also faced with numerous practical difficulties owing to the large scale and high number of components of civil structures resulting from their physical size. One major challenge for SHM technology is the need for real-time structure and condition evaluation following severe discrete occurrences. Regulatory demands are the main drivers of current research into the production of SHM systems for megastructures in Asian nations, such as China. SHM is a developing and well-known research discipline among civil engineers and is rapidly moving towards the mainstream [11]. Over the past few years, there has been unprecedented progress in signal collection and transmission, sensor monitoring, data processing and analysis, and mathematical modeling and simulation. Currently, technical advances can be used to gather and analyze available and timely past and present data about civil structures [12]. SHM techniques utilize data from real-time monitoring to define structural conditions with greater accuracy using new technologies [13].

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According to Jerome (2006), wireless sensor networks overviewed for SHM are fast becoming the sensor networks of choice for most developers and managers, primarily because they are less costly compared to the cost to install and utilize, particularly in systems that would be difficult to install due to the wiring, longer distances, and more extensive monitoring schemes [14]. The efficiency of wireless monitoring systems offers cost-effectiveness and enables facile and rapid monitoring schemes for very large structures, such as buildings and bridges, without the tedious cabling and installation. Jerome (2006) stated, "wireless sensors ought not to be viewed as the sole method of monitoring, rather as an alternate sensor type to supplement, supplement, and support the capability to monitor the condition of a particular structure for indications of degradation." Jerome (2006) argued that new designs for monitoring systems should address complementary problems for wireless sensors, such as distance and sensor reliability in the field, and other significant unknowns (winter storms and other unforgiving environmental exposures).

Scuro (2021) further discusses the integration of Internet of Things (IoT) technologies into SHM systems in terms of monitoring [15]. SHM systems based on IoT allow constant monitoring of structures while maintaining low energy consumption levels, thereby enabling sustained monitoring for a longer duration and avoiding frequent maintenance. Scuro's research is aimed at the potential of acoustic emission technology, a critical method employed to observe building materials, which comprise a significant part of SHM. Acoustic emission identifies the progressive stages of damage precipitating different stress wave emissions from materials subjected to load, thereby enabling preventive maintenance for structural failure. Liu (2012) addressed the overall status of SHM in many fields of engineering, including civil, mechanical, aerospace, and DOD applications [16]. He cited advances being made when creating self-sensing materials that can be integrated into structures for the self-detection of structural health. Specifically, advances in smart materials and nanomaterials offer promise for SHM, including the self-healing of compromised materials, far beyond extending the life of structures. Liu's subsequent work indicates that any emerging SHM system will also have to consolidate and draw upon new materials and sophisticated diagnoses to establish future maintenance plans.

Mesquita (2016) offered an overview of SHM platforms, namely, those developed between 1993 and 2015, and states the necessity of efficient, adaptive systems [17]. His paper highlighted the growing requirement for dynamic monitoring system methods and the upgrade of sensor technology to enhance SHM system performance, accuracy, and reliability. Mesquita (2016) recognized another aspect of SHM, which is the consideration of maintenance and monitoring for heritage structures. These sophisticated SHM platforms can potentially observe the safety of culturally significant structures without compromising the integrity of the structure in its design or alteration.

Song (2017) explained the long-term challenges with infrastructure, namely, aged civil structures that were constructed utilizing early construction materials [18]. He cited the fact that many of the buildings and bridges constructed during the 19th and 20th centuries continue to be used today, only to be plagued with deterioration. Song emphasizes the need for SHM to contain the risks of aging infrastructure and references that the National Academy of Engineering has listed the rehabilitation of infrastructure as one of the grand challenges that will soon appear in the decades ahead. He is convinced that advancements in monitoring technologies (specifically SHM) will be crucial in addressing these challenges while extending the useful life of civil structures.

Brownjohn's evidence indicates that although SHM technologies are becoming better and better, issues in formulating procedures for interpreting data still exist. To simply offer transparent and comprehensible information from multiple potential combinations of intricate sets of data is an added challenge [19].

Farrar (2007) conceptualized damage prognosis (DP), an integral component of SHM, to foretell the future performance of a structure based on its existing conditions [20]. By assessing a structure in terms of its responses to loading along with its past history, one can foretell a structure's remaining useful life. Although Farrar admits that development plan (DP) is still in its infancy, he is optimistic about the potential to enhance the ability to forecast when a structure will fail using SHM systems.

Gatti (2019) contrasts static and dynamic load testing for bridges constructed in the late 1960s and outlines how dynamic load testing can complement and potentially supplant static load tests [21]. Gatti's illustration supports the advantages of dynamic load testing, as it is capable of providing more information regarding the behavior of a bridge when subjected to actual life loads, a compelling means of supplementing SHM systems.

Douglas Adams (2011) discussed the application of modal analysis to identify structural damage in wind turbines. He illustrated that slight changes in blade stiffness can be detected using modal deflection measurements, which are crucial for the identification of damage prior to failure [22]. The study indicated the capability of SHM systems to monitor complicated mechanical structures, such as wind turbines, alongside conventional civil infrastructure.

Shukla (2019) emphasized the advantage of SHM in terms of expenditure. The improved lifespan of buildings and the fact that SHM can detect risk earlier, which allows remediation to take place prior to damaging inspection, all offer compliance to ensure during safety testing on behalf of the public [23]. Alokita cautions that mistakes due to random events or environmental influences will have a stochastic impact on the data and information to consider when monitoring with SHM systems.

In summary, the application of artificial neural networks to optimize SHM is a promising possibility. ANNs can enhance data analysis efficiency, thereby enabling faster and more efficient detection of damage in structures [24]. The use of sophisticated sensors and information systems may change structural monitoring to a more proactive and cost-effective approach for infrastructure maintenance. Nevertheless, according to the literature, the successful implementation of ANNs in SHM can handle multiple problems associated with data processing, sensor reliability, and predictive accuracy. Interdisciplinary studies and future technological innovations are required to utilize and advance the contribution of SHM towards increasing infrastructure safety and lifespan [25].

SHM is now an essential part of sustainable infrastructure management, as it allows for real-time monitoring of civil structure conditions and performance. Latest developments in ANNs have enhanced the ability of SHM systems to identify damage patterns, forecast deterioration, and make optimal maintenance decisions compared to conventional monitoring practices [26–29].

In previous research, Nagarajan and Charhate (2016) demonstrated the viability of modal analysis for quantifying the structural response of multi-story buildings, opening the door for vibration-based SHM methods. Subsequent research has progressed in the direction of exploiting IoT technologies for the smart curing of concrete, hence establishing a data-driven foundation for the real-time monitoring of structural behavior. Similarly, Nagarajan, Narwade, and Patil (2019) proposed an IoT-based real-time water leakage monitoring system, which is a sensor-based data acquisition system commonly used in structural diagnosis [30–34].

The emergence of digital technology for structural analysis and management was further underscored by studies on 4D and 5D GIS modeling, which brought with it the fusion of spatiotemporal data with project monitoring systems. These papers reflect a growing use of software-based methods to improve visualization and prediction modeling capability, which is an essential prerequisite for ANN-based optimization in SHM [35–39].

In chloride penetration tests of concrete with novel formwork liners in monitoring material behavior and deterioration in Nagarajan, Narwade, and Sharma (2021) and carbon-neutral fly-ash aggregates in Nagarajan, Narwade, and Shetty (2023) provided empirical datasets to train machine learning models for the prediction of material degradation. Nagarajan, Narwade, and Andhyal (2021) also addressed cost optimization in ground improvement for large scale development, with a methodological framework to supplement optimization methods in ANN-based SHM modeling. SHM has been widely studied using various advanced technologies and optimization techniques. A comparative analysis of previous research work is presented in Table 1.

In addition, risk management and resilience studies and intelligent disaster management system research supported the contribution of intelligent systems to enhanced structural reliability and public safety. These studies suggest a natural progression in the combination of artificial intelligence, data analysis, and optimization in civil engineering applications.

Bolstered by this proven foundation, the current research attempts to maximize the performance of SHM through ANNs and compares the results with traditional monitoring methods. Drawing on the implications of previous research on IoT integration, software modeling, and material performance analysis, the current research develops an intelligent, adaptive, and cost-effective methodology for infrastructure health monitoring.

RESEARCH METHODOLOGY

The research procedure for optimizing SHM systems through the application of ANNs begins with a thorough review, assessment, and integration of current literature prior to data processing. The review and assessment of SHM systems should commence with a method for operationalizing ANN in real or experimental structural monitoring.

More specifically, the evaluation and review will examine how ANN leverages numerous structural monitoring systems that employ different methods, such as multiple sensor principles, for example, accelerometers, wired and wireless strain gauges, and wired and wireless sensor networks. The review will demonstrate how ANN can process the large quantity of data that background sensors generate in SHM systems.

The methodology involves examining different ANN architectures used in SHM (e.g., feedforward, convolutional, and recurrent networks) and their accuracy of detection and predictive performance for structural damage, given training data that may be from simulated models or real tests on structures. Most studies will also include ANN performance considerations, such as accuracy, computational efficiency, and the ability to apply ANNs to various types of structural systems (i.e., buildings, bridges, and dams). There may also be aspects of data preprocessing, especially regarding whether activities such as feature extraction, normalization, and noise filtering lead to ANNs having a better-based SHM performance.

The methodology will review case studies in which ANNs have been successfully incorporated into SHM systems to enhance damage detection, classification, and prognosis. These case studies will help to determine best practices, pitfalls, and the applicability of ANNs in real-world scenarios. The final step of the methodology will involve comparing ANN-based SHM systems with traditional monitoring methods to assess improvements in predictive integrity, real-time monitoring, and cost. Overall, this methodology aims to provide a detailed overview of the use of ANNs to enhance SHM systems and highlight the potential of ANNs to enhance the safety, longevity, and maintenance of infrastructure.

System Model

In this study, we considered a bridge as the simulation environment. A bridge is represented as a two-dimensional space where an unmanned aerial vehicle (UAV) operates for crack detection during ongoing traffic. An illustration of the system model is presented in Figures 1–4. The UAV surveys a bridge deck and sends crack images along with their locations to the base station.

Table 1. Comparative analysis of literature on structural health monitoring (SHM) and optimization using advanced technologies.

Author	Year	Key focus	Technologies/methods discussed	Key findings/conclusions
Jerome P	2006	Overview of wireless sensor networks in SHM	Wireless sensor networks, data analysis, structural deterioration	Wireless sensors are cost-effective but should complement traditional wired systems for improved data analysis. New system designs are necessary to address wireless sensor limitations.
Carmelo Scuro	2019	SHM systems based on IoT to assess safety of structures	IoT, Acoustic emission, low energy consumption	IoT-based SHM enables continuous monitoring with low energy. Acoustic emission technology offers significant benefits in detecting structural failures early, contributing to cost-effective maintenance.
Yingtao Liu	2012	SHM in civil, mechanical, aerospace, and DoD applications	Prognostics, diagnostics, nanomaterials, smart materials	Integration of self-sensing materials into structures offers advanced diagnostic capabilities. Self-healing materials can influence future SHM and maintenance strategies.
Esequiel Mesquita	2016	SHM platforms, particularly between 1993–2015	Dynamic monitoring, adaptive systems, SHM platform optimization	Advancements in SHM platforms have led to cost reduction and more adaptive systems. Dynamic monitoring techniques and optimized sensor technology are crucial for improving SHM accuracy and application.
Gangbing Song	2017	Long-term durability of civil structures and the importance of SHM	SHM, Infrastructure deterioration, predictive maintenance	SHM technologies are key in addressing infrastructure deterioration. Song stresses the importance of innovative monitoring for preserving aging infrastructure and extending its lifespan.
JMW Brownjohn	2020	SHM applications across various types of architecture	SHM diagnostic tools, data processing, communication channels	Case studies show the evolving application of SHM across various architectures. Emphasizes the need for advanced diagnostic tools, data processing, and communication systems for accurate health assessment.
Charles R. Farrar	2006	Damage prognosis (DP) in SHM for predicting future structural performance	Damage prognosis, simulations, historical data	DP can predict the future performance of structures, estimate remaining usable life, and guide proactive maintenance. It is an emerging but promising tool for SHM.
Marco Gatti	2019	Comparison of static and dynamic load testing for bridges	Dynamic load testing, finite element models, accelerometers	Dynamic load testing provides valuable insights into the performance of bridges and may replace static load testing in some cases for more accurate evaluations.
Douglas Adams	2011	Modal analysis for detecting damage in wind turbines	Modal analysis, blade stiffness, operational data analysis	Small damage in wind turbines can be detected through modal deflection measurements, which provide insights into structural health even under varying conditions like changing wind speeds.
Shukla Alokita	2019	Advantages and challenges of SHM in structural safety and maintenance	SHM, early risk detection, data measurement challenges	SHM reduces costs, extends lifespan, and enhances safety. However, environmental factors and building faults must be accounted for when interpreting monitoring data.

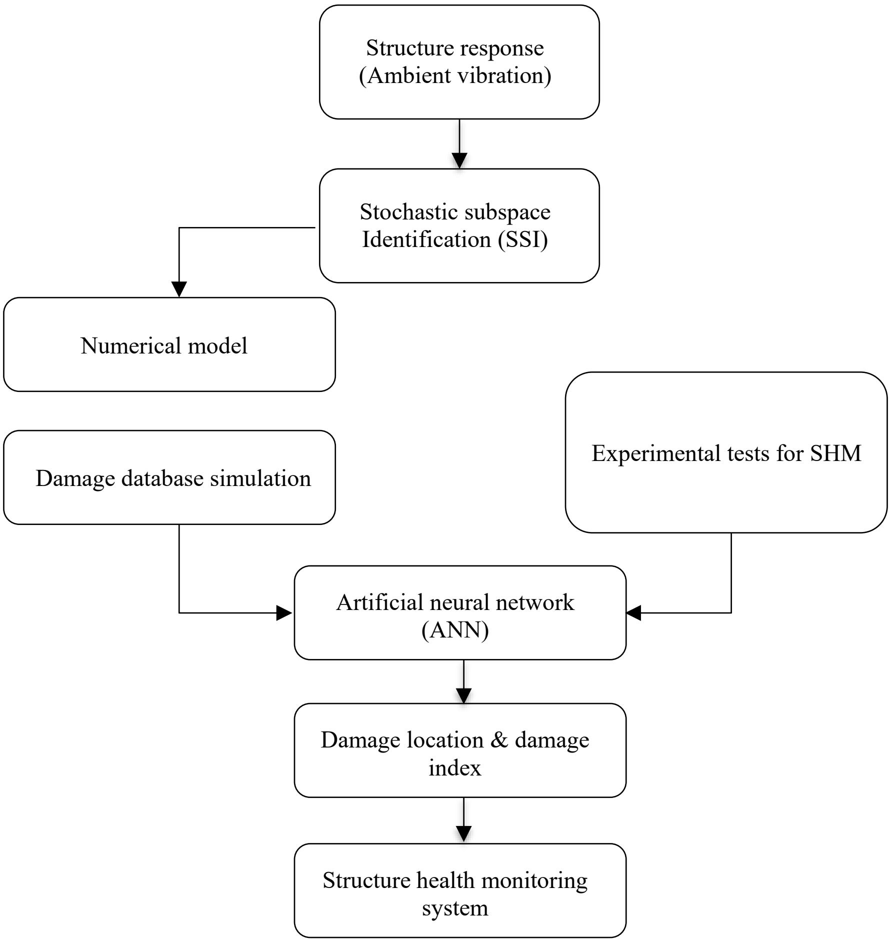

Figure 1. Flow chart of the proposed SHM system.

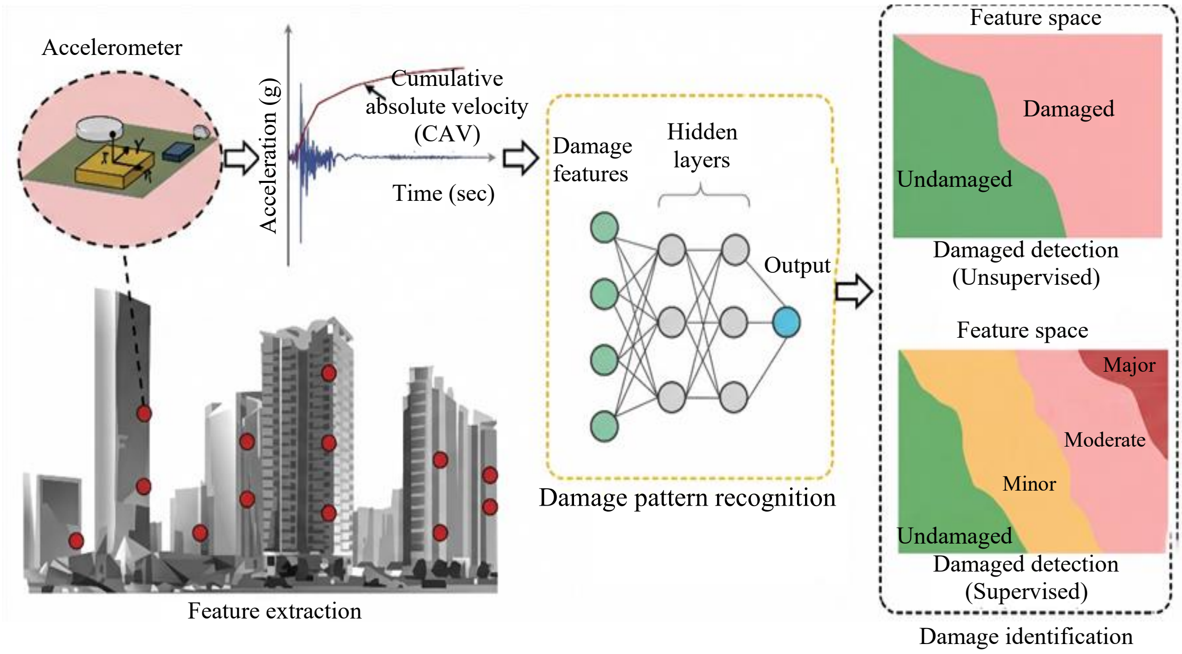

Figure 2. Proposed framework using acceleration data from an instrumented structure to assess its damage conditions following an earthquake event.
Source: Adopted with permission from *Muin S, Mosalam KM. Structural health monitoring using machine learning and cumulative absolute velocity features. Applied Sciences. 2021;11(12):5727. doi:10.3390/app11125727.*

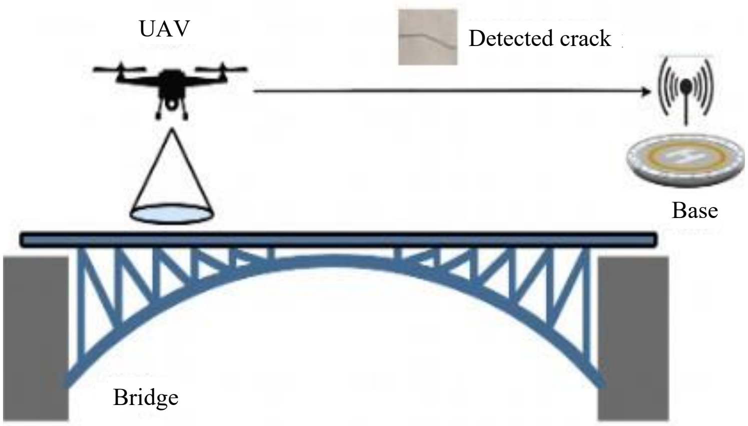

Figure 3. The system model illustrates bridge survey and crack detection using UAV.

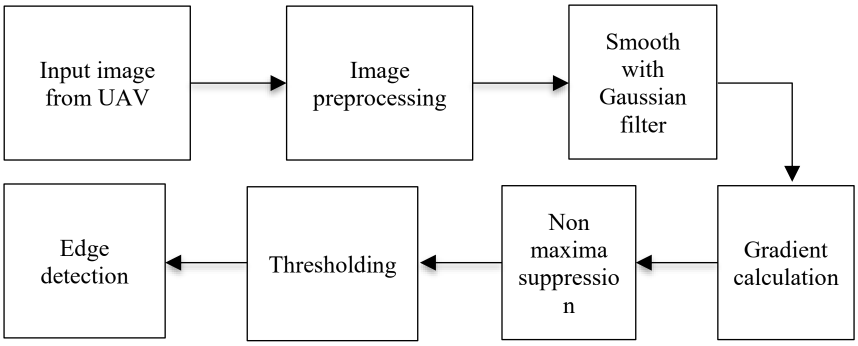

Figure 4. System model illustrating bridge surveys and crack detection using UAV.

CONCLUSION

Optimization of SHM by ANN has revolutionized structural and civil engineering. SHM systems ensure constant monitoring of structural health and safety through real-time measurements of structural conditions, which can detect damage and schedule maintenance. SHM systems conventionally use multiple sensors, such as accelerometers, strain gauges, and displacers, with related technologies that provide enormous amounts of data to determine the condition of structures that need to be analyzed. In recent times, ANNs have also been found to be an optimized opportunity for analyzing and interpreting complex data.

When applied to sensor data, an ANN can make predictions regarding the future performance of structures, assess their remaining useful life, and identify potential failure points prior to their occurrence, thereby helping to prevent catastrophic failures. The system model for bridge inspection using an UAV is shown in Figure 3, while the detailed workflow for crack detection is illustrated in Figure 4.

When an ANN is applied to sensor data, it can predict the future performance of structures, assess the remaining useful life, and identify failure points prior to their occurrence; thereby preventing catastrophes.

The integration of ANN and SHM systems overcomes some limitations of conventional system monitoring. The most important advantage of ANN is its capability to rapidly assess and respond to nonlinear data relations that are unmeasurable with traditional methods in complex structures subjected to dynamic loadings and interacting with environmental impacts. Apart from being capable of evaluating sophisticated relationships, ANN-based models are also capable of learning from past and historical data to enhance the accountability of future reports, sorry, to enhance prediction and inform decision-making. Furthermore, ANN systems are self-learning; therefore, it is simpler to use them in real-time monitoring and decision-making scenarios because they can learn, adapt, and react to evolving conditions in structural behavior.

The use of ANN-based optimization for SHM has numerous benefits; however, it has some drawbacks and challenges. Similar to any ANN, training the model requires a tremendous amount of high-quality input data, and the predictions, classifications, or recommendations are no better than the input data in terms of quantity and quality. Additionally, ANN models may be extremely complicated and difficult to understand and require trained professionals to use them properly as part of the larger SHM process. However, recognizing that machine learning techniques have improved significantly over the past few years and that computational power and sensor technologies are also advancing, the optimism regarding embracing ANN ideas within SHM is pragmatic and more likely to result in fruitful activity.

The optimization of SHM based on ANN is a potential solution to transform the way we check and maintain infrastructure. With improved data analysis and forecasting capabilities, as well as decision-making processes, ANN makes SHM systems faster and more dependable, which has implications for managing safer and more sustainable infrastructure.

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