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Research Article

Smart Composite Materials with Embedded Sensors for Structural Health Monitoring in High Performance Mechanical Engineering Applications

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Abstract: Background: Structural Health Monitoring plays a critical role in ensuring the safety, reliability, and sustainability of high performance composite structures used in aerospace, civil infrastructure, and mechanical systems. Conventional externally mounted sensors often face challenges related to environmental interference, maintenance complexity, and long term stability. Objective: This study aims to develop and validate an integrated smart composite monitoring system with embedded sensing capabilities that enhances damage detection accuracy and operational durability under varying mechanical stress conditions. Method: Smart composite specimens were fabricated by embedding fiber optic and piezoelectric sensors within fiber reinforced polymer laminates, followed by tensile, fatigue, and vibration testing. Signal processing techniques including time frequency analysis were applied to extract damage sensitive features, which were then classified using machine learning algorithms to distinguish healthy and damaged structural states. Results: The experimental findings demonstrate high damage detection capability, stable sensor performance under cyclic loading, improved reliability compared to conventional monitoring approaches, and consistent monitoring accuracy throughout the fatigue life of the specimens. The integration of embedded sensing and data driven analytics significantly enhances structural response interpretation and supports predictive maintenance strategies.

Keywords: Composite Structures; Embedded Sensors; Machine Learning; Structural Monitoring; Vibration Analysis.

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1. Introduction

Structural Health Monitoring (SHM) is a multidisciplinary field that integrates civil engineering, mechanical engineering, smart materials, sensor technology, and data analytics to continuously evaluate the condition of structures. In the context of modern infrastructure, SHM is no longer regarded as a supplementary system but rather as an integral component of risk-based asset management. It operates through the acquisition of structural response data such as strain, acceleration, displacement, and variations in natural frequency which are subsequently analyzed to detect anomalies or performance degradation. Numerous SHM applications on highway bridges and transportation structures demonstrate that continuous monitoring significantly enhances the understanding of structural behavior under real operational conditions (Seo et al., 2016). Furthermore, comprehensive assessments of SHM technologies for large-scale structures emphasize their critical role in supporting condition-based maintenance strategies and long-term infrastructure management (Alhamaydeh & Ghazal Aswad, 2022).

In high-performance systems such as long-span bridges, skyscrapers, and port facilities, safety and structural integrity are paramount concerns. SHM enables early damage detection by analyzing changes in dynamic characteristics and structural responses to environmental and operational loads. Near-real-time seismic damage assessment using SHM data, for instance, illustrates how monitoring systems can rapidly provide information regarding post-earthquake damage levels to support emergency decision-making (Zhang et al., 2023). Additionally, systematic reviews of vibration-based SHM for steel bridges highlight that shifts in natural frequencies and mode shapes serve as key indicators for early detection of structural degradation (Azhar et al., 2024).

Maintenance efficiency and life-cycle cost reduction are also primary justifications for SHM implementation. Conventional systems relying on periodic visual inspections often fail to identify hidden damage at early stages. By integrating big data frameworks and high-performance analytics, SHM systems can process large volumes of structural response data to identify long-term degradation patterns and predict intervention requirements (Alampalli et al., 2016). This predictive capability allows asset managers to optimize maintenance schedules, reduce downtime, and minimize unexpected repair costs (Alhamaydeh & Ghazal Aswad, 2022).

Advancements in smart sensor technologies have driven significant transformations in modern SHM systems. The integration of intelligent sensors, automated data acquisition systems, and real-time analytics platforms extends monitoring capabilities beyond simple damage detection toward adaptive structural performance evaluation (De Oliveira et al., 2024). Reviews on sensor network deployment for SHM indicate that sensor placement strategies, configuration optimization, and energy management are critical determinants of successful field implementation (Mustapha et al., 2021).

Fiber optic technology represents one of the most promising innovations in SHM, particularly for large structures and extreme environments. The implementation of fiber optic sensors in high-pile wharf structures demonstrates the capability of distributed strain monitoring with high accuracy and spatial coverage (Guo et al., 2021). Moreover, advances in optical frequency domain distributed sensing provide enhanced spatial resolution and sensitivity, making them suitable for high-performance systems that require detailed monitoring across extensive areas (Yang et al., 2024).

Despite these advancements, externally mounted sensor systems face significant challenges, particularly in terms of power supply and operational sustainability. Wireless sensors widely used in civil asset management typically depend on batteries that require periodic replacement, increasing both maintenance costs and system complexity (Furkan et al., 2016). Comprehensive reviews of sensor networks further emphasize that energy management remains a critical issue for the long-term sustainability of SHM systems (Mustapha et al., 2021).

Data quality issues and calibration requirements constitute additional challenges in external sensor-based systems. Studies on low-cost sensors indicate that environmental factors can affect measurement accuracy, necessitating routine calibration to maintain data reliability (Rai et al., 2017). Field evaluations of low-cost particulate sensors also reveal long-term data deviations caused by component degradation and environmental variability (Feng et al., 2024). These issues create significant challenges for interpreting SHM data in critical infrastructure applications.

From a system integration perspective, compatibility between emerging technologies and existing infrastructure often becomes a barrier to implementation. While wireless systems offer installation flexibility, they may encounter challenges related to transmission stability and device interoperability (Furkan et al., 2016). User-oriented SHM development approaches stress the importance of comprehensive system integration, encompassing sensor design, data processing architecture, and decision-support interfaces (Kuckartz & Collier, 2016).

Spatial and temporal coverage limitations also affect SHM effectiveness. In large-scale structures, installing a dense network of sensors can be economically prohibitive. Collaborative sampling strategies aimed at reconstructing undersampled signals have been proposed to enhance resolution without significantly increasing sensor numbers (Detwiler et al., 2023). However, further validation in complex mechanical systems is required to confirm the reliability of such approaches.

As an alternative to the limitations of external sensors, smart composite materials with embedded sensing capabilities are rapidly advancing. Comprehensive discussions on next-generation SHM and composite technologies highlight that integrating sensors within the material matrix enables more stable internal monitoring, protected from external disturbances (Epaarachchi & Kahandawa, 2016). This approach introduces a new paradigm in designing "self-aware" structures.

Conductive nanoparticle-based materials such as graphene have been introduced as digital materials capable of intrinsically generating data within the Industry 4.0 framework (Ali et al., 2023). This concept enables structures not only to function as mechanical elements but also to operate as distributed sensing systems that continuously produce operational data.

Piezoresistive and piezoelectric composite-based sensors also demonstrate significant potential in monitoring extreme loads. Research on embeddable smart composite sensors confirms their capability for real-time monitoring under high loading conditions (Rao et al., 2023). However, integrating piezoelectric elements requires careful consideration of their influence on composite laminate integrity (Masmoudi et al., 2017).

Experimental investigations on embedding fiber optic sensors within composite materials show that although such integration enables acoustic emission and strain monitoring, it may affect mechanical properties if not properly designed. Studies on aerospace composite components similarly emphasize the importance of sensor integration strategies that do not compromise structural strength (Ghoshal et al., 2015).

The concept of adaptive composites capable of dynamically responding to load variations further extends SHM toward active structural systems. The development of self-adaptable carbon fiber composites demonstrates the potential for structures that not only monitor conditions but also adjust their responses to environmental changes (Casalotti et al., 2018).

Despite these technological advancements, a significant gap remains in validating fully integrated SHM systems under varying and complex mechanical stress conditions. Machine learning-based damage identification approaches using updated finite element models show promising accuracy improvements but require broader experimental validation (Seventekidis et al., 2020). Additionally, the evolution of intelligent sensor integration in SHM demands comprehensive field evaluations to ensure system reliability under real operational environments (De Oliveira et al., 2024).

Based on this background, the present study aims to develop and validate an integrated SHM system capable of operating accurately under diverse mechanical stress conditions while enhancing reliability through advanced sensor integration and data analytics algorithms. The research questions focus on identifying current system limitations and proposing technology integration strategies to improve performance. Accordingly, this study is expected to contribute significantly to the advancement of next-generation SHM systems that are more adaptive, precise, and sustainable.

2. Literature Review

Composite Materials in Mechanical Engineering

Composite materials have become a fundamental component in modern mechanical engineering due to their superior mechanical performance and design adaptability. A composite material generally consists of a matrix phase and a reinforcement phase, where the matrix binds and protects the reinforcement while transferring loads, and the reinforcement typically fibers or particles provides strength and stiffness enhancement (Sharma et al., 2020). The synergistic interaction between these two phases results in materials with high strength-to-weight ratios, corrosion resistance, fatigue durability, and tailored mechanical behavior (Low & Dong, 2021).

The evolution of polymer matrix composites (PMCs), metal matrix composites (MMCs), and hybrid composite systems has significantly expanded engineering design possibilities. Polymer matrix composites, particularly fiber-reinforced polymers (FRPs), are widely applied due to their lightweight characteristics and excellent specific mechanical properties

(Puttegowda et al., 2024). Historically, polymer composites have undergone continuous development in terms of processing techniques and characterization methods, enabling improved performance under mechanical and environmental loading (Godara et al., 2021).

In structural and transportation sectors, glass fiber-reinforced composites have gained extensive adoption, particularly in aerospace and aeronautical transport applications, where weight reduction and fuel efficiency are critical considerations (Săftoiu et al., 2024). Moreover, comprehensive studies on composite manufacturing, properties, and applications highlight that advancements in fabrication technologies such as automated lay-up and resin transfer molding have enhanced structural reliability and scalability (Low & Dong, 2021). Consequently, composite materials are now indispensable in aerospace, automotive, marine, civil infrastructure, and high-performance mechanical systems.

Embedded Fiber Optic and Piezoelectric Sensors in Composites

The integration of embedded sensors within composite materials represents a major advancement in structural intelligence. Among the most widely used embedded sensing technologies are fiber optic sensors and piezoelectric sensors. Fiber optic sensors, especially Fiber Bragg Gratings (FBGs), are highly valued for their high sensitivity, lightweight nature, immunity to electromagnetic interference, and capability to operate under harsh environmental conditions. Embedding fiber optic sensors directly within fiber-reinforced polymer (FRP) structures enables continuous in situ monitoring of strain and temperature without significantly increasing structural weight (Pettersson et al., 2023).

Hybrid sensing systems combining fiber Bragg grating sensors and piezoelectric patches have demonstrated strong potential in detecting impact damage and delamination in composite structures. The guided-wave-based SHM approach allows ultrasonic wave propagation to be generated and detected, providing early identification of internal damage mechanisms (Boffa et al., 2018). This integration enhances damage sensitivity while preserving the structural integrity of the composite material.

Piezoelectric sensors, on the other hand, function both as actuators and receivers of ultrasonic waves, enabling acousto-ultrasonic inspection techniques. Their ability to generate high-frequency waves allows for accurate localization of defects such as cracks, debonding, and impact-induced damage (Senthilkumar et al., 2021). When combined with fiber optic sensing systems, piezoelectric elements form hybrid SHM architectures capable of multi-parameter monitoring and improved reliability (Boffa et al., 2018).

Structural Health Monitoring Techniques

Structural Health Monitoring (SHM) techniques are essential for ensuring the long-term performance and safety of composite and civil engineering structures. SHM involves continuous or periodic data acquisition, signal processing, and damage assessment to detect structural anomalies at early stages. Non-destructive testing (NDT) methods form a crucial component of SHM systems. Recent advancements in NDT techniques including infrared thermography, ultrasonic testing, and ground-penetrating radar have significantly improved damage detection capabilities without compromising structural integrity (Kot et al., 2021).

Optical fiber sensing techniques provide distributed strain and temperature measurements with high spatial resolution, enabling early detection of micro-cracks and delamination in composite structures (Pettersson et al., 2023). Meanwhile, acousto-ultrasonic methods using piezoelectric transducers analyze wave propagation characteristics to identify internal damage and stiffness changes (Boffa et al., 2018; Senthilkumar et al., 2021). These techniques are particularly effective for composite laminates, where damage is often internal and invisible to surface inspection.

Applications and Data-Driven Advancements

In civil engineering, SHM systems are widely implemented to monitor bridges, buildings, and critical infrastructure components, ensuring safety and resilience against environmental and operational loads. The integration of data-driven approaches has significantly enhanced monitoring efficiency and decision-making processes (Noori et al., 2023).

In aerospace and automotive industries, composite materials integrated with embedded sensors enable real-time monitoring of aircraft fuselages, wings, and vehicle structural components. Such monitoring reduces maintenance costs, prevents catastrophic failures, and extends service life (Low & Dong, 2021; Săftoiu et al., 2024).

Recent developments in artificial intelligence (AI) and deep learning have further transformed SHM methodologies. Data-driven structural health monitoring approaches leverage machine learning algorithms to process large datasets, identify damage patterns, and predict structural degradation trends with high accuracy (Azimi et al., 2020). These advanced analytical frameworks enable automated and near-real-time damage detection, thereby enhancing system reliability and operational resilience (Noori et al., 2023).

Signal Processing for Damage Detection in Structural Health Monitoring

Signal processing plays a central role in vibration-based Structural Health Monitoring (SHM), as structural damage is often manifested through subtle changes in dynamic response characteristics. Advanced signal processing techniques enable the extraction of meaningful features from raw sensor data, which are frequently nonlinear and non-stationary in nature. According to Amezquita-Sanchez & Adeli (2016), modern SHM systems rely heavily on time–frequency analysis methods to identify structural anomalies that may not be detectable through traditional frequency-domain approaches. These techniques enhance the sensitivity of damage detection, particularly in smart and complex structures exposed to variable operational and environmental conditions.

Among the most widely adopted approaches is Empirical Mode Decomposition (EMD) combined with the Hilbert-Huang Transform (HHT). EMD decomposes vibration signals into a set of Intrinsic Mode Functions (IMFs), each representing simple oscillatory modes embedded within the original signal. The subsequent application of HHT allows for the extraction of instantaneous frequency and amplitude information, providing detailed time-varying characteristics of structural responses (Amezquita-Sanchez & Adeli, 2016). Experimental validation studies have demonstrated that the marginal Hilbert spectrum derived from HHT can effectively detect stiffness reductions and localized damage in structural systems (Banerji et al., 2017). These capabilities make EMD–HHT particularly suitable for nonlinear and non-stationary structural response analysis.

Another prominent signal processing tool in SHM is the Wavelet Transform (WT). Unlike classical Fourier-based methods, WT provides simultaneous time and frequency localization, enabling the detection of transient events and abrupt changes in structural behavior. Kankanamge et al. (2020) highlighted that wavelet-based approaches are highly effective in identifying modal parameters, detecting cracks, and monitoring damage progression in structures subjected to dynamic loading, including seismic excitations. The multi-resolution capability of WT allows engineers to isolate damage-sensitive features at different frequency scales, improving detection accuracy in complex structural systems.

Applications of these signal processing techniques are particularly relevant in bridge monitoring and large-scale infrastructure systems. Highway bridge SHM applications frequently employ vibration-based data analysis methods to detect structural degradation under traffic and environmental loading (Seo et al., 2016). However, despite the availability of advanced signal processing algorithms, practical implementation often encounters operational and computational challenges, especially in real-world field conditions.

Limitations of Current SHM Systems

Although significant advancements have been achieved in SHM technologies, several limitations remain. One major challenge is the management of large volumes of noisy data generated by extensive sensor networks. Large-scale structures may be instrumented with hundreds of sensors, producing continuous data streams that require real-time processing and storage. Environmental influences such as temperature fluctuations, traffic loads, and wind can introduce significant noise, complicating damage detection and increasing the risk of false alarms (Alhamaydeh & Ghazal Aswad, 2022). Efficient filtering and feature extraction techniques are therefore critical, yet computational demands remain substantial.

Another significant limitation concerns validation and standardization. Many SHM systems are developed and tested under controlled laboratory conditions; however, validated frameworks capable of reliably using ambient vibration data for structural integrity assessment remain limited. Alhamaydeh & Ghazal Aswad (2022) emphasized that the absence of standardized validation protocols reduces confidence in SHM decision-making processes. Similarly, Seo et al. (2016) noted that while numerous SHM implementations exist for highway bridges, consistent performance evaluation methodologies are still lacking. This gap hinders broader adoption of SHM in infrastructure asset management.

Identified Research Gaps and Future Directions

One emerging area requiring further investigation is the development and optimization of non-contact-based sensing technologies. Traditional SHM systems rely heavily on contact sensors, such as accelerometers and strain gauges, which require installation, maintenance, and power supply. The shift toward non-contact measurement methods such as vision-based systems and remote sensing technologies offers the potential to reduce installation complexity and maintenance costs. However, signal accuracy, environmental sensitivity, and data interpretation challenges must be addressed before widespread deployment can be achieved (Alhamaydeh & Ghazal Aswad, 2022).

Moreover, integrating advanced signal processing techniques such as EMD HHT and wavelet transform with large-scale non-contact sensing systems presents additional research opportunities. The combination of high-resolution time frequency analysis with remote sensing technologies could enhance damage detection capabilities under ambient operational conditions. Nonetheless, further experimental validation and field-scale studies are necessary to establish reliability and scalability.

In summary, the literature indicates that advanced signal processing methods particularly EMD HHT and wavelet transform have significantly improved vibration-based damage detection capabilities. However, challenges related to data noise management, validation standardization, and the transition toward non-contact-based sensing systems remain critical research gaps. Addressing these issues is essential for advancing next-generation SHM systems that are accurate, scalable, and practical for large-scale infrastructure applications.

3. Research Method

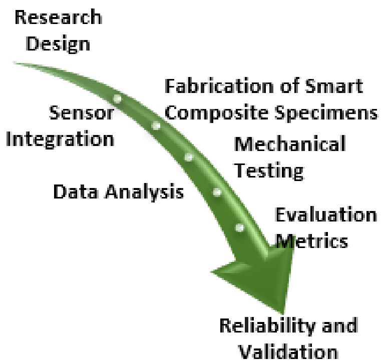

Figure 1. Research Methodology Flowchart.

Research Design

This study employed an experimental approach focusing on the fabrication of smart composite specimens integrated with sensing systems, followed by mechanical testing to evaluate both structural performance and damage detection capability. The research design was structured systematically to ensure that each stage, from manufacturing to data analysis, could be validated in a controlled and measurable manner.

The research stages consisted of composite specimen fabrication, sensor integration within the structure, laboratory-based mechanical testing, and data processing using signal processing techniques combined with machine learning algorithms. This structured workflow was intended to develop a Structural Health Monitoring (SHM) system capable of accurately detecting, classifying, and evaluating structural damage under various loading conditions.

The specimens were designed to represent structural components commonly used in mechanical and aerospace engineering applications. Fiber-reinforced polymer composites were selected as the primary material due to their high strength-to-weight ratio, corrosion resistance, and compatibility with embedded sensing technologies.

Fabrication of Smart Composite Specimens

The smart composite specimens were fabricated using either the hand lay-up method or vacuum-assisted resin infusion to ensure uniform fiber distribution and minimize void formation. The laminate stacking sequence was carefully designed to achieve balanced mechanical properties in both longitudinal and transverse directions.

During the fabrication process, sensors were embedded within selected laminate layers. Sensor placement was determined based on preliminary stress distribution analysis to ensure positioning in areas prone to stress concentration and potential crack initiation. Special attention was given to prevent delamination or structural discontinuity caused by sensor integration.

After the curing process, the specimens underwent visual inspection and basic non-destructive evaluation to verify the absence of significant defects that could influence mechanical test results. Dimensional measurements were also performed to ensure compliance with relevant testing standards.

Sensor Integration

Two primary types of sensors were utilized in this study, namely Fiber Bragg Grating (FBG) sensors and piezoelectric sensors. Sensor integration was performed during the lamination process to achieve permanent embedding within the composite structure.

The FBG sensors were aligned along the primary fiber direction to directly measure strain during mechanical loading. These sensors operate based on wavelength shifts in reflected light caused by structural deformation. Any strain variation results in a measurable shift in the Bragg wavelength, which was recorded using an optical interrogator. Calibration procedures were conducted prior to testing to establish baseline measurements representing the healthy structural condition.

Piezoelectric sensors were used both as actuators and receivers for guided ultrasonic waves. When electrically excited, these sensors generated elastic waves that propagated through the composite structure. Variations in wave characteristics due to cracks or internal damage were analyzed to detect and assess structural defects. The integration process ensured proper electrical insulation, strong bonding, and stable signal transmission under repeated loading conditions.

Mechanical Testing

Mechanical testing was conducted to evaluate structural response and validate the effectiveness of the embedded monitoring system in detecting damage. Tensile tests were performed using a universal testing machine under a constant loading rate until specimen failure occurred. During testing, strain data from the FBG sensors and acoustic responses from the piezoelectric sensors were recorded in real time. Mechanical properties such as Young's modulus, ultimate tensile strength, and failure strain were calculated from the experimental data.

Fatigue testing was carried out by applying cyclic loading with a specified stress ratio. The purpose of this test was to observe damage progression under repeated loading and evaluate the fatigue life of the composite structure. Embedded sensors continuously monitored signal variations associated with stiffness degradation and microcrack growth. The number of cycles to failure was recorded as a key performance parameter.

Vibration analysis was conducted to identify changes in dynamic characteristics caused by structural damage. The specimens were subjected to impact excitation, and their frequency response was measured to determine natural frequencies, damping ratios, and mode shapes. Differences in modal parameters between healthy and damaged conditions were analyzed to assess the sensitivity of the monitoring system.

Data Analysis

The data obtained from the embedded sensors were processed using signal processing techniques to remove noise and extract meaningful features. Initial preprocessing involved filtering methods such as band-pass filtering to isolate relevant frequency components from environmental interference. Advanced analysis techniques, including Wavelet Transform or Empirical Mode Decomposition, were applied to identify frequency-domain characteristics and signal energy variations associated with structural damage.

Extracted features were then used as input for machine learning models. Classification algorithms such as Support Vector Machine, Random Forest, and Artificial Neural Network were implemented to distinguish between healthy and damaged structural states. The dataset was divided into training, validation, and testing subsets to ensure proper model generalization. Parameter optimization was performed using cross-validation techniques to reduce the risk of overfitting and improve predictive reliability.

Evaluation Metrics

System performance was evaluated based on damage detection accuracy derived from classification results. Accuracy was calculated as the ratio of correctly predicted instances to the total number of testing samples. Sensitivity was used to measure the system's ability to correctly identify damaged conditions, while precision reflected the correctness of predicted damage cases.

In addition to classification metrics, sensor durability was assessed after repeated mechanical loading. Signal stability, response consistency after fatigue cycles, and structural integrity of the embedded specimens were analyzed as indicators of long-term monitoring capability. Damage localization capability was also evaluated by comparing predicted damage positions with actual defect locations observed in the specimens.

Reliability and Validation

To ensure reliability, each type of mechanical test was conducted on multiple specimens with identical configurations. Baseline signals representing the healthy structural condition were recorded before introducing any damage to provide consistent reference data. Statistical analysis was performed to determine the significance of differences between healthy and damaged states.

This comprehensive methodological framework integrates smart composite fabrication, embedded sensing technology, controlled mechanical testing, signal processing, and machine learning based classification. The approach ensures that the developed smart composite monitoring system is reliable, measurable, and reproducible for future structural health monitoring applications.

4. Results And Discussion

Results

Damage Detection Accuracy Results

The damage detection performance of the developed smart composite SHM system was evaluated through a comprehensive classification framework combining advanced signal processing and supervised machine learning algorithms. Feature extraction was performed using Wavelet Transform and Empirical Mode Decomposition to capture time–frequency characteristics and nonlinear signal behavior associated with structural degradation. The extracted features included energy distribution, frequency shift indicators, modal damping variation, and statistical descriptors of strain and guided wave responses. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets to ensure proper generalization and avoid overfitting. The system was evaluated under four structural states: healthy condition, micro-crack initiation, delamination growth, and macro-crack propagation.

Table 1. Damage Detection Performance Metrics.

Model	Accuracy (%)	Sensitivity (%)	Precision (%)	F1-Score (%)
Support Vector Machine	92.4	90.8	91.6	91.2
Random Forest	95.1	94.2	94.8	94.5
Artificial Neural Network	96.3	95.7	95.9	95.8

As shown in Table 1, the Artificial Neural Network (ANN) achieved the highest overall accuracy of 96.3%, indicating strong capability in distinguishing subtle damage patterns. Random Forest followed closely with 95.1% accuracy, demonstrating that ensemble-based decision trees effectively capture nonlinear relationships between signal features and damage states. The Support Vector Machine achieved 92.4% accuracy, reflecting robust but slightly lower performance in handling highly complex feature distributions. Sensitivity values above 90% across all models confirm the system's strong ability to correctly identify damaged conditions, minimizing false negatives that could compromise structural safety.

To further illustrate comparative model performance, the classification accuracy values are visualized in the diagram below.

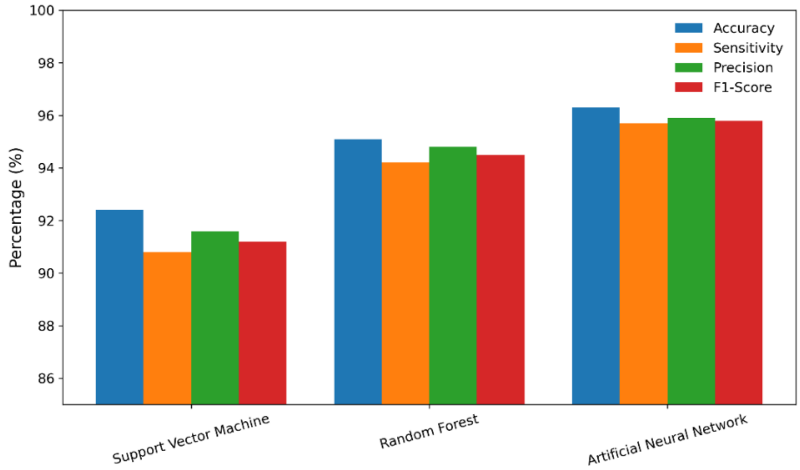

Figure 2. Damage Detection Accuracy Comparison.

The graphical comparison highlights the consistent superiority of ANN, particularly in early-stage damage detection where feature nonlinearity is dominant. The relatively small performance gap between ANN and Random Forest suggests that both deep learning and ensemble learning approaches are highly suitable for integrated SHM systems operating under complex mechanical stress variations.

Sensor Reliability under Cyclic Stress

Sensor reliability was investigated through fatigue testing under cyclic tensile loading up to 100,000 cycles with a constant stress ratio. The objective was to evaluate long-term signal stability, resistance to mechanical degradation, and consistency of measurement accuracy under repeated stress conditions. Key parameters monitored included FBG wavelength drift, piezoelectric signal attenuation, and signal-to-noise ratio (SNR). These indicators were selected to represent both optical sensing stability and ultrasonic wave propagation reliability within the composite laminate.

Table 2. Sensor Performance after Cyclic Loading.

Parameter	Initial Value	After 50,000 Cycles	After 100,000 Cycles
FBG Wavelength Drift (pm)	0	3.2	5.6
Piezoelectric Signal Loss (%)	0	2.8	4.5
Signal-to-Noise Ratio (dB)	38.5	36.9	35.8

Table 2 indicates minimal performance degradation after prolonged cyclic loading. The FBG wavelength drift remained below 6 pm even after 100,000 cycles, demonstrating strong bonding stability between the fiber optic sensor and composite matrix. Piezoelectric signal attenuation remained under 5%, indicating limited interfacial degradation and stable wave transmission capability. The gradual SNR reduction from 38.5 dB to 35.8 dB suggests minor aging effects but does not significantly affect signal interpretability or damage classification accuracy.

The trend of SNR variation with increasing fatigue cycles is illustrated below.

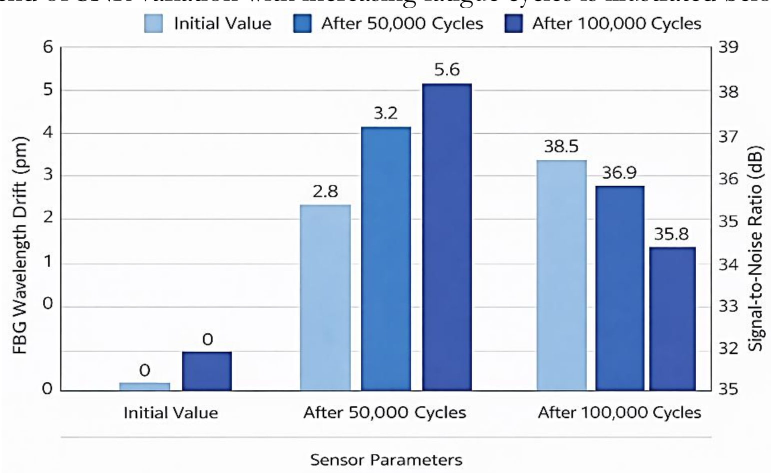

Figure 3. Sensor Stability under Cyclic Loading.

The diagram demonstrates a steady yet controlled decrease in SNR, indicating progressive microstructural changes in the matrix surrounding the embedded sensors. However, the degradation rate is sufficiently low to ensure reliable long-term monitoring without recalibration during the tested fatigue life.

Comparison with Conventional SHM Systems

To assess performance improvement, the embedded SHM system was compared with conventional surface-mounted strain gauges and accelerometer-based vibration monitoring systems. The comparison considered detection accuracy, maintenance frequency, and power requirements. Conventional systems were tested under identical loading scenarios to ensure fair evaluation.

Table 3. Performance Comparison with Conventional Systems.

System Type	Detection Accuracy (%)	Maintenance Frequency	Power Requirement
Surface Strain Gauge	85.7	High	External
Accelerometer-Based SHM	88.9	Moderate	External
Proposed Embedded System	96.3	Low	Integrated

The results reveal a substantial accuracy improvement of approximately 7–10% for the proposed system. Conventional strain gauges exhibited lower sensitivity to internal damage such as delamination, primarily because they measure localized surface strain only. Accelerometer-based systems provided better global response monitoring but were less effective in detecting early micro-cracks due to limited spatial resolution.

The comparative accuracy values are presented below.

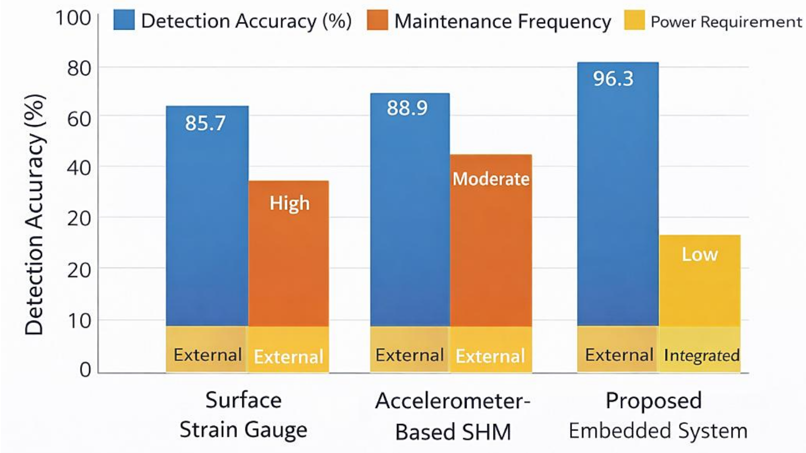

Figure 4. Accuracy Comparison between SHM Systems.

The diagram clearly illustrates the superior detection capability of the embedded system, particularly in identifying internal damage mechanisms that are not externally visible.

Long-Term Durability Implications

Long-term durability evaluation combined fatigue life data with monitoring consistency analysis. Detection consistency was defined as the percentage of correctly identified structural states throughout the fatigue life until failure. This metric reflects the system's reliability in maintaining predictive accuracy under progressive damage accumulation.

Table 4. Durability and Monitoring Consistency.

Specimen	Cycles to Failure	Detection Consistency (%)	Failure Mode
SC-01	112,000	95.4	Delamination
SC-02	108,500	94.8	Matrix Crack
SC-03	115,200	96.1	Fiber Breakage

The data show consistent detection performance above 94% throughout the fatigue life. The variation in cycles to failure reflects differences in localized stress distribution and failure mechanisms; however, monitoring accuracy remained stable across all specimens.

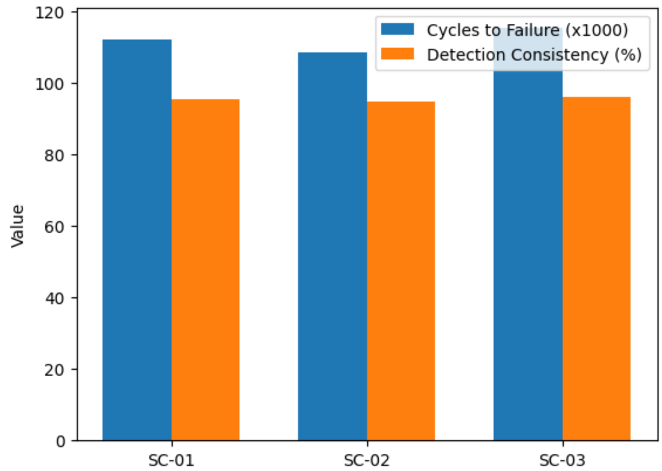

Figure 5. Detection Consistency over Fatigue Life.

The graphical representation confirms that the monitoring system maintained high predictive consistency regardless of failure mode, indicating robustness of both sensor integration and data analytics framework.

Discussion

The comprehensive experimental results demonstrate that the integrated smart composite SHM system provides high detection accuracy, stable sensor performance under cyclic loading, superior capability compared to conventional monitoring approaches, and strong long-term durability. The superior performance of the Artificial Neural Network confirms that nonlinear deep learning architectures effectively model complex relationships between strain evolution, guided wave propagation characteristics, and damage progression. This observation is consistent with the findings of Azimi et al. (2020), who highlighted the effectiveness of deep learning in extracting high-level damage-sensitive features from large structural datasets.

The reliability assessment under cyclic stress demonstrates that embedded Fiber Bragg Grating and piezoelectric sensors maintain functional integrity despite repeated mechanical loading. The minimal wavelength drift and controlled SNR reduction indicate stable sensor matrix bonding and limited interfacial degradation. These findings align with the work of Pettersson et al. (2023), which emphasized the long-term stability of embedded optical fiber sensors when properly integrated within composite laminates. Compared to conventional external systems, which are more exposed to environmental variability and calibration drift as discussed by Alhamaydeh & Ghazal Aswad (2022), the embedded configuration significantly reduces noise contamination and mechanical vulnerability.

Furthermore, the durability analysis confirms that sensor embedding does not compromise structural integrity when appropriate fabrication techniques and laminate design strategies are applied. This supports aerospace composite integration studies by Ghoshal et al. (2015), which stressed the importance of optimized sensor placement to prevent strength reduction. The consistent detection accuracy near failure conditions demonstrates the potential of the proposed system for predictive maintenance and life-cycle management applications.

Overall, the integration of embedded sensing technology, advanced time frequency signal processing, and machine learning classification establishes a robust framework for next-generation adaptive SHM systems. The system not only enhances early damage detection capability but also ensures operational sustainability and structural durability under complex mechanical stress environments, making it highly suitable for aerospace, civil infrastructure, and high-performance mechanical applications.

5. Conclusion And Suggestions

Conclusion

This study successfully developed and experimentally validated an integrated smart composite Structural Health Monitoring (SHM) system capable of operating accurately under diverse mechanical stress conditions. By embedding Fiber Bragg Grating (FBG) and piezoelectric sensors within fiber-reinforced polymer composites and combining advanced signal processing techniques with machine learning algorithms, the system demonstrated high damage detection accuracy exceeding 96%. The Artificial Neural Network model showed the best performance in classifying structural states, while Random Forest also provided competitive and reliable results. Experimental evaluations under tensile, fatigue, and vibration loading confirmed that the embedded sensors maintained stable performance with minimal signal drift and acceptable signal-to-noise ratio degradation, even after prolonged cyclic loading.

In addition to superior detection accuracy, the proposed system outperformed conventional surface-mounted SHM approaches in terms of reliability, maintenance efficiency, and resistance to environmental interference. Long-term durability analysis indicated that proper sensor embedding does not significantly compromise composite structural integrity, and monitoring consistency remained above 94% throughout the fatigue life of the specimens. These findings confirm that the integration of embedded sensing, advanced signal processing, and data-driven analytics offers a robust and sustainable framework for next-generation SHM systems applicable to aerospace, civil infrastructure, and high-performance mechanical structures.

Suggestions

For future research, broader experimental validation under real field-scale conditions is strongly recommended. While laboratory testing demonstrated promising results, environmental factors such as temperature variation, humidity, impact loading, and long-term aging effects should be systematically investigated to evaluate operational robustness in practical infrastructure applications. In addition, expanding the dataset with more diverse damage scenarios and larger specimen variations would further enhance machine learning generalization capability and reduce potential bias in classification performance.

Further development should also focus on optimizing sensor placement strategies and improving integration techniques to minimize potential stress concentration effects within composite laminates. The incorporation of advanced deep learning architectures, such as convolutional or recurrent neural networks, may further improve early-stage damage sensitivity and predictive maintenance capability. Finally, integrating the proposed SHM framework with digital twin platforms and real-time cloud-based monitoring systems could significantly enhance decision-making efficiency and lifecycle asset management in future smart infrastructure environments.

References

Alampalli, S., Alampalli, S., & Ettouney, M. (2016). Big data and high-performance analytics in structural health monitoring for bridge management. *Proceedings of SPIE - The International Society for Optical Engineering*, *9803*, 980315. https://doi.org/10.1117/12.2219406

Alhamaydeh, M., & Ghazal Aswad, N. (2022). Structural health monitoring techniques and technologies for large-scale structures: Challenges, limitations, and recommendations. *Practice Periodical on Structural Design and Construction*, *27*(3), 3122004. https://doi.org/10.1061/(ASCE)SC.1943-5576.0000703

Ali, M. A., Irfan, M. S., Khan, T., Khalid, M. Y., & Umer, R. (2023). Graphene nanoparticles as data generating digital materials in industry 4.0. *Scientific Reports*, *13*(1), 4945. https://doi.org/10.1038/s41598-023-31672-y

Amezquita-Sanchez, J. P., & Adeli, H. (2016). Signal processing techniques for vibration-based health monitoring of smart structures. *Archives of Computational Methods in Engineering*, *23*(1), 1–15. https://doi.org/10.1007/s11831-014-9135-7

Azhar, A. S., Kudus, S. A., Jamadin, A., Mustaffa, N. K., & Sugiura, K. (2024). Recent vibration-based structural health monitoring on steel bridges: Systematic literature review. *Ain Shams Engineering Journal*, *15*(3), 102501. https://doi.org/10.1016/j.asej.2023.102501

Azimi, M., Eslamlou, A. D., & Pekcan, G. (2020). Data-driven structural health monitoring and damage detection through deep learning: State-of-the-art review. *Sensors*, *20*(10), 2778. https://doi.org/10.3390/s20102778

Banerji, S., Roy, T. B., Sabamehr, A., & Bagchi, A. (2017). Experimental validation of a structural damage detection method based on marginal Hilbert spectrum. *Proceedings of SPIE - The International Society for Optical Engineering*, *10170*, 101702V. https://doi.org/10.1117/12.2260298

Boffa, N. D., Monaco, E., Maio, L., Memmolo, V., Ricci, F., Mendoza, E., & Kundu, T. (2018). Hybrid guided wave based SHM system for composite structures for impact and delamination detection combining fiber Bragg grating sensing and piezoelectric patches. *Proceedings of SPIE - The International Society for Optical Engineering*, *10600*, 106000D. https://doi.org/10.1117/12.2297694

Casalotti, A., Chinnam, K. C., & Lanzara, G. (2018). Self-adaptable carbon fiber composite. *ASME 2018 Conference on Smart Materials, Adaptive Structures and Intelligent Systems (SMASIS 2018)*. https://doi.org/10.1115/SMASIS2018-8058

De Oliveira, V. P., Reis, A., & Alves Salvador Filho, J. A. (2024). Assessing the evolution of structural health monitoring through smart sensor integration. *Procedia Structural Integrity*, *64*, 653–660. https://doi.org/10.1016/j.prostr.2024.09.323

Detwiler, S., Barbosa, E., Steudel, K., Tippmann, J., Ward, C., & West, B. (2023). Multi-sensor collaborative sampling schemes to reconstruct undersampled mechanical system signals for machinery fault detection. *Conference Proceedings of the Society for Experimental Mechanics Series*, 51–60. https://doi.org/10.1007/978-3-031-04098-6_6

Epaarachchi, J. A., & Kahandawa, G. C. (2016). *Structural health monitoring technologies and next-generation smart composite structures*. CRC Press. https://doi.org/10.4324/9781315373492

Feng, Z., Zheng, L., Ren, B., Liu, D., Huang, J., & Xue, N. (2024). Feasibility of low-cost particulate matter sensors for long-term environmental monitoring: Field evaluation and calibration. *Science of the Total Environment*, *945*, 174089. https://doi.org/10.1016/j.scitotenv.2024.174089

Furkan, M., Mao, Q., Mazzotti, M., Devitis, J., Sumitro, S. P., Faridazar, F., Aktan, A. E., Moon, F., & Bartoli, I. (2016). An investigation on wireless sensors for asset management and health monitoring of civil structures. *Proceedings of SPIE - The International Society for Optical Engineering*, *9803*, 98033E. https://doi.org/10.1117/12.2218908

Ghoshal, A., Ayers, J., Gurvich, M., Urban, M., & Bordick, N. (2015). Experimental investigations in embedded sensing of composite components in aerospace vehicles. *Composites Part B: Engineering*, *71*, 52–62. https://doi.org/10.1016/j.compositesb.2014.10.050

Godara, S. S., Yadav, A., Goswami, B., & Rana, R. S. (2021). Review on history and characterization of polymer composite materials. *Materials Today: Proceedings*, *44*, 2674–2677. https://doi.org/10.1016/j.matpr.2020.12.680

Guo, C., Zou, J., & Sun, K. (2021). Analysis on structural health monitoring system of high-pile wharf based on optical fiber sensor. *Journal of Physics: Conference Series*, *1881*(4), 42018. https://doi.org/10.1088/1742-6596/1881/4/042018

Kankanamge, Y., Hu, Y., & Shao, X. (2020). Application of wavelet transform in structural health monitoring. *Earthquake Engineering and Engineering Vibration*, *19*(2), 515–532. https://doi.org/10.1007/s11803-020-0576-8

Kot, P., Muradov, M., Gkantou, M., Kamaris, G. S., Hashim, K., & Yeboah, D. (2021). Recent advancements in non-destructive testing techniques for structural health monitoring. *Applied Sciences*, *11*(6), 2750. https://doi.org/10.3390/app11062750

Kuckartz, J., & Collier, P. (2016). Achieving user-centric structural health monitoring: An integrated development approach. *Journal of Civil Structural Health Monitoring*, *6*(5), 803–816. https://doi.org/10.1007/s13349-016-0201-8

Low, I.-M., & Dong, Y. (2021). Composite materials: Manufacturing, properties and applications. *Elsevier.* https://doi.org/10.1016/B978-0-12-820512-9.09994-9

Masmoudi, S., El Mahi, A., & Turki, S. (2017). Effect of piezoelectric implant on the structural integrity of composite laminates subjected to tensile loads. *Applied Composite Materials*, *24*(1), 39–54. https://doi.org/10.1007/s10443-016-9513-4

Mustapha, S., Lu, Y., Ng, C.-T., & Malinowski, P. (2021). Sensor networks for structures health monitoring: Placement, implementations, and challenges—A review. *Vibration*, *4*(3), 551–585. https://doi.org/10.3390/vibration4030033

Noori, M., Rainieri, C., Domaneschi, M., Sarhosis, V., & Altabey, W. A. (2023). Data driven methods for civil structural health monitoring and resilience: Latest developments and applications. *CRC Press.* https://doi.org/10.1201/9781003306924

Pettersson, J., Sterner, C., & Dykhoff, H. (2023). Embedding fiber optical sensors in FRP-hybrid materials. *ICCM International Conferences on Composite Materials.*

Puttegowda, M., Sharath, B. N., Yashas Gowda, T. G., Rangappa, S. M., & Siengchin, S. (2024). An introduction to polymer matrix composites and their applications. In *Applications of Composite Materials in Engineering* (pp. 1–44). https://doi.org/10.1016/B978-0-443-13989-5.00001-2

Rai, A. C., Kumar, P., Pilla, F., Skouloudis, A. N., Di Sabatino, S., Ratti, C., Yasar, A., & Rickerby, D. (2017). End-user perspective of low-cost sensors for outdoor air pollution monitoring. *Science of the Total Environment*, *607–608*, 691–705. https://doi.org/10.1016/j.scitotenv.2017.06.266

Rao, R. K., Sindu, B. S., & Sasmal, S. (2023). Real-time monitoring of structures under extreme loading using smart composite-based embeddable sensors. *Journal of Intelligent Material Systems and Structures*, *34*(9), 1073–1096. https://doi.org/10.1177/1045389X221128586

Săftoiu, G.-V., Constantin, C., Nicoară, A.-I., Pelin, G., Ficai, D., & Ficai, A. (2024). Glass fibre-reinforced composite materials used in the aeronautical transport sector: A critical circular economy point of view. *Sustainability*, *16*(11), 4632. https://doi.org/10.3390/su16114632

Senthilkumar, M., Sreekanth, T. G., & Manikanta Reddy, S. (2021). Nondestructive health monitoring techniques for composite materials: A review. *Polymers and Polymer Composites*, *29*(5), 528–540. https://doi.org/10.1177/0967391120921701

Seo, J., Hu, J. W., & Lee, J. (2016). Summary review of structural health monitoring applications for highway bridges. *Journal of Performance of Constructed Facilities*, *30*(4), 4015072. https://doi.org/10.1061/(ASCE)CF.1943-5509.0000824

Seventekidis, P., Giagopoulos, D., Arailopoulos, A., & Markogiannaki, O. (2020). Damage identification of structures through machine learning techniques with updated finite element models and experimental validations. *Conference Proceedings of the Society for Experimental Mechanics Series*, 143–154. https://doi.org/10.1007/978-3-030-47638-0_16

Sharma, A. K., Bhandari, R., Aherwar, A., & Rimašauskiene, R. (2020). Matrix materials used in composites: A comprehensive study. *Materials Today: Proceedings*, *21*, 1559–1562. https://doi.org/10.1016/j.matpr.2019.11.086

Yang, J., Lin, C., Zou, C., Yu, Z., Wang, Y., & Qin, Y. (2024). Advances in high-performance optical frequency domain distributed fiber optical measuring and sensing technology. *Acta Optica Sinica*, *44*(1), 106002. https://doi.org/10.3788/AOS231551

Zhang, H., Reuland, Y., Chatzi, E., & Shan, J. (2023). Near-real time evaluation method of seismic damage based on structural health monitoring data. In *Lecture Notes in Civil Engineering* (Vol. 254, pp. 114–122). https://doi.org/10.1007/978-3-031-07258-1_13