International Journal of Scientific Research and Modern Technology (IJSRMT) *ijsrmt.com*
Volume 3, Issue 8, 2024
DOI: https://doi.org/10.38124/ijsrmt.v3i8.420

Machine Learning-Driven Predictive Modeling for FRP Strengthened Structural Elements: A Review of AI-Based Damage Detection, Fatigue Prediction, and Structural Health Monitoring

James Avevor[1]; Michael Adeniyi[2]; Lawrewnce Anebi Enyejo[3]; Selasi Agbale Aikins[4]

[1]Department of Mechanical Engineering, Rowan University, Glassboro New Jersey, USA
[2]Department of Mechanical Engineering, Georgia Southern University, Statesboro Georgia, USA.
[3]Department of Telecommunications, Enforcement Ancillary and Maintenance, National Broadcasting Commission Headquarters, Aso-Villa, Abuja, Nigeria
[4]Department of Mechanical Engineering, Temple University, Philadelphia, USA

Publication Date: 2024/08/28

Abstract

The integration of Machine Learning (ML)-driven predictive modeling has revolutionized the assessment and optimization of Fiber-Reinforced Polymer (FRP) strengthened structural elements, offering advanced methodologies for damage detection, fatigue prediction, and structural health monitoring (SHM). This review provides a comprehensive analysis of AI-based predictive modeling techniques, including deep learning (DL), convolutional neural networks (CNNs), recurrent neural networks (RNNs), support vector machines (SVMs), and ensemble learning methods, for evaluating the mechanical performance and longevity of FRP-reinforced structures. The study explores how ML algorithms process sensor-acquired data from acoustic emission (AE), digital image correlation (DIC), fiber Bragg gratings (FBGs), and structural vibration measurements to predict crack initiation, fatigue failure, and progressive degradation in composite-strengthened bridges, high-rise buildings, and aerospace structures.

Additionally, this review investigates thermomechanical and aeroelastic effects on FRP-strengthened elements under dynamic loading conditions, highlighting the ability of ML-based hybrid models to enhance accuracy in multi-variable stress-strain behavior prediction. The incorporation of physics-informed neural networks (PINNs) and hybrid AI-physics models further refines damage localization and severity estimation, addressing uncertainties in material anisotropy, bond degradation, and environmental aging effects. Moreover, advances in transfer learning and federated learning (FL) enable real-time SHM in large-scale infrastructure by leveraging cloud-based and edge computing frameworks for decentralized anomaly detection and predictive maintenance. This paper also discusses the integration of digital twin (DT) technology with ML-based SHM, enabling the real-time simulation, performance prediction, and life-cycle analysis of FRP-strengthened structures. Challenges such as model interpretability, data scarcity, and computational efficiency are examined, along with the potential of explainable AI (XAI), uncertainty quantification (UQ), and reinforcement learning (RL) in optimizing decision-making processes for infrastructure sustainability. The review concludes by identifying future research directions in hybrid AI methodologies, adaptive learning frameworks, and quantum-enhanced predictive modeling, aiming to enhance the resilience and durability of FRP-strengthened structural systems in aerospace and civil engineering applications.

Keywords: *Machine Learning (ML) in Structural Engineering; Fiber-Reinforced Polymer (FRP) Strengthening; Structural Health Monitoring (SHM); AI-Based Damage Detection; Fatigue Prediction in Composite Structures; Predictive Modeling for Infrastructure Resilience.*

Avevor, J., Adeniyi, M., & Enyejo, L. A. (2024). Machine Learning-Driven Predictive Modeling for FRP Strengthened Structural Elements: A Review of AI-Based Damage Detection, Fatigue Prediction, and Structural Health Monitoring. *International Journal of Scientific Research and Modern Technology*, *3*(8), 1–20. https://doi.org/10.38124/ijsrmt.v3i8.420

I. INTRODUCTION

A. Background on Fiber-Reinforced Polymer (FRP) Strengthening in Structural Engineering

Fiber-Reinforced Polymer (FRP) composites have emerged as a pivotal material in structural engineering, primarily due to their superior mechanical properties and resistance to environmental degradation. Comprising high-strength fibers embedded within a polymer matrix, FRPs offer an advantageous combination of light weight and high tensile strength, making them ideal for reinforcing and retrofitting existing structures (Bakis et al., 2002). The application of FRP in structural strengthening gained momentum in the late 20th century, addressing the limitations of traditional materials like steel, which are susceptible to corrosion and increased dead load (Balsamo et al., 2012). FRP materials, being non-corrosive and lightweight, provide a durable alternative for enhancing the load-bearing capacity of structures without significant alterations to their weight. In the context of marine environments, the use of seawater and sea sand in concrete, combined with FRP reinforcement, has been explored to mitigate the scarcity of freshwater and river sand (Ahmed et al., 2020). Studies indicate that while FRP bars exhibit commendable durability in such aggressive conditions, factors like water molecules, hydroxide ions, chloride ions, elevated temperatures, and stress can influence their long-term performance. Understanding these interactions is crucial for the effective application of FRP in coastal infrastructure.

Moreover, the integration of FRP composites in concrete structures has been extensively studied, revealing that FRP reinforcement can significantly enhance the structural performance and extend the service life of deteriorated components (Almusallam et al., 2012). The non-metallic nature of FRP eliminates issues related to electrochemical corrosion, a common concern with steel reinforcements, thereby ensuring longevity and reduced maintenance costs.

In summary, the evolution of FRP strengthening techniques in structural engineering reflects a strategic shift towards materials that offer resilience, durability, and efficiency. Ongoing research continues to refine these applications, ensuring that FRP composites meet the rigorous demands of modern infrastructure projects.

B. Importance of Predictive Modeling and AI-Based Approaches

In the realm of structural engineering, predictive modeling and AI have become indispensable tools for enhancing the safety and longevity of infrastructure. The integration of AI into structural health monitoring (SHM) systems enables the efficient analysis of vast datasets, facilitating the early detection of anomalies and the prediction of structural responses under various conditions. For instance, Presno Vélez et al. (2024) developed a methodology employing machine learning to predict the effects of retrofitting on civil structures, achieving an impressive accuracy of 99.77% in their final model. This high level of precision underscores the potential of AI-driven models in forecasting structural behavior and informing maintenance strategies.

Moreover, AI-based approaches offer probabilistic assessments that account for uncertainties inherent in structural performance. Amer and Kopsaftopoulos (2021) introduced a framework utilizing Gaussian Process Regression Models for active sensing in SHM, providing probabilistic predictions across multiple damage and loading scenarios. Such probabilistic models are crucial for informed decision-making, as they offer a quantified measure of confidence in the predictions, thereby enhancing the reliability of maintenance and intervention plans.

The adaptability of AI algorithms to process complex, nonlinear relationships within structural data further amplifies their importance. Chatzi and Smyth (2012) demonstrated the application of a particle filter scheme with mutation for the estimation of time-invariant parameters in SHM, highlighting the capability of AI to manage dynamic and uncertain environments effectively. This adaptability ensures that AI-based models remain robust under varying operational conditions, making them invaluable for real-time monitoring and predictive maintenance of structures.

In summary, the integration of predictive modeling and AI-based approaches in structural engineering not only enhances the accuracy of health monitoring systems but also provides a comprehensive framework for proactive maintenance, ultimately contributing to the resilience and safety of infrastructure.

C. Objectives of the Review

This review aims to provide a comprehensive analysis of ML-driven predictive modeling for FRP strengthened structural elements, focusing on AI-based damage detection, fatigue prediction, and structural health monitoring (SHM). It seeks to explore the integration of advanced AI methodologies, including deep learning, convolutional neural networks (CNNs), and hybrid physics-informed ML models, to enhance the reliability of FRP-strengthened structures under dynamic loading conditions.

A key objective is to assess the effectiveness of AI algorithms in processing multi-sensor data from fiber Bragg gratings (FBGs), acoustic emissions (AE), and digital image correlation (DIC) techniques for real-time anomaly detection. The study also aims to evaluate predictive modeling techniques, such as Gaussian process regression and reinforcement learning, in forecasting crack propagation, delamination, and long-term structural degradation in FRP-enhanced infrastructure.

Additionally, this review investigates the integration of federated learning with digital twin technology to improve real-time SHM in large-scale FRP applications. By identifying current limitations and emerging trends, this study provides a roadmap for optimizing AI-driven predictive modeling in aerospace, civil, and marine engineering applications.

D. Organization of the Paper

This paper is systematically structured to explore the integration of Machine Learning (ML) and Artificial Intelligence (AI) in Structural Health Monitoring (SHM), focusing on FRP-strengthened infrastructure. Section 1 provides an introduction, detailing the background, importance of predictive modeling, and research objectives. Section 2 discusses the fundamentals of FRP composites, emphasizing their material properties, applications in aerospace and civil engineering, failure mechanisms, and limitations of traditional SHM systems. Section 3 delves into AI-driven defect identification, covering supervised learning techniques, deep learning methods like CNNs and RNNs, and hybrid AI-physics-based models. Section 4 addresses fatigue modeling, crack propagation prediction, and the impact of thermomechanical and aeroelastic factors on FRP structures. Section 5 introduces Digital Twin technology, federated learning for real-time monitoring, and uncertainty quantification (UQ) with Explainable AI (XAI) to enhance SHM decision-making. Section 6 explores challenges in AI-based SHM, including data limitations, computational efficiency, and quantum computing applications. Finally, Section 7 summarizes key findings, contributions of AI to FRP strengthening, and policy recommendations for AI-driven structural analysis and predictive maintenance.

II. FUNDAMENTALS OF FRP STRENGTHENED STRUCTURAL ELEMENTS

A. Material Properties and Mechanical Behavior of FRP Composites

FRP composites are increasingly recognized for their exceptional mechanical properties, making them ideal for strengthening structural elements. These composites consist of high-performance fibers such as carbon, glass, and aramid embedded in a polymer matrix, enhancing their durability and load-bearing capacity. The mechanical behavior of FRP is largely influenced by fiber type, orientation, volume fraction, and the bonding interface between the fiber and matrix (Idoko et al., 2024). Carbon fibers, for example, offer superior tensile strength and stiffness, while glass fibers provide impact resistance, making them suitable for diverse engineering applications.

The polymer matrix plays a crucial role in transferring loads between fibers and protecting them from environmental degradation. Epoxy-based FRP composites exhibit superior thermal stability and chemical resistance, making them widely used in aerospace and civil infrastructure projects (Ijiga et al., 2024). However, external environmental factors such as temperature fluctuations, moisture absorption, and UV exposure can degrade FRP materials over time, leading to reduced mechanical performance. Studies indicate that prolonged exposure to high humidity can lead to interfacial debonding, weakening the overall structural integrity of FRP-reinforced elements (Ibokette et al., 2024). The mechanical response of FRP composites under dynamic loading conditions also depends on the interfacial adhesion between the fiber and matrix. Weak bonding can result in delamination, fiber pull-out, and premature failure under cyclic loading. Recent advances in AI-driven structural health monitoring have enhanced the predictive assessment of FRP degradation, enabling real-time failure detection and predictive maintenance strategies. These innovations contribute to improving the resilience and long-term reliability of FRP-strengthened structures in high-performance applications.

B. Application in Aerospace and Civil Engineering

The use of FRP composites in aerospace and civil engineering has expanded significantly due to their high strength-to-weight ratio, corrosion resistance, and durability. In aerospace engineering, the need for lightweight materials that enhance fuel efficiency without compromising mechanical integrity has made FRP composites a critical component in modern aircraft. The integration of FRP-reinforced fuselage panels, wing spars, and turbine blades reduces structural weight while maintaining superior tensile strength, allowing for increased payload capacity and energy efficiency (Idoko et al., 2024) as represented in figure 1. The aviation industry has increasingly relied on AI-driven predictive modeling to optimize FRP structural behavior, ensuring long-term reliability under extreme aerodynamic forces. In civil engineering, FRP composites are widely used for reinforcing bridges, buildings, and marine infrastructure. Their non-corrosive nature makes them ideal for structures exposed to harsh environmental conditions such as coastal and offshore installations (Ibokette et al., 2024). Structural health monitoring (SHM) systems employing AI-based detection models have been developed to assess real-time stress distribution in FRP-reinforced components, allowing for early fault detection and predictive maintenance. These systems integrate IoT sensors to improve performance evaluation in critical infrastructure. The versatility of FRP composites also extends to environmental and sustainability applications. In marine engineering, FRP is used in fisheries infrastructure, offshore platforms, and vessel construction, where it offers resistance to saltwater-induced deterioration (Idoko et al., 2024). The use of AI-enhanced numerical simulations has further optimized the design and deployment of FRP structures, reducing long-term operational risks. The integration of ML algorithms into structural analysis tools enhances the design and adaptability of FRP materials, making them integral to the future of aerospace and civil engineering applications.

C. Failure Mechanisms and Damage Progression in FRP-Strengthened Structures

Failure mechanisms in FRP-strengthened structures occur due to a combination of material degradation, mechanical fatigue, and environmental factors. The progressive damage in FRP systems often initiates with matrix cracking, followed by fiber-matrix debonding, delamination, and fiber rupture. The structural integrity of FRP-strengthened beams and columns is highly dependent on bond strength at the interface between the composite and the substrate, as weak adhesion leads to premature peeling and failure under cyclic loads (Enyejo et al., 2024). The use of predictive probabilistic models has significantly improved the assessment of flexural crack propagation in FRP-strengthened reinforced concrete beams, enabling engineers to anticipate and mitigate potential failure points (Ferreira et al., 2020).

Long-term durability of FRP-strengthened structures is compromised by sustained mechanical stress and environmental exposure. Studies indicate that moisture ingress, ultraviolet (UV) radiation, and temperature variations accelerate matrix degradation, weakening the fiber-polymer interface and leading to structural instability (Zhou et al., 2023). This degradation is particularly critical in marine and humid environments, where chloride ion penetration further exacerbates the weakening of FRP reinforcements. In response, ML-based damage assessment systems have been developed to enhance real-time detection of FRP deterioration, integrating sensor data and AI-driven predictive analytics to extend service life (Enyejo et al., 2024). In high-stress applications, fatigue-induced damage progression is a primary concern, as cyclic loading leads to gradual stiffness reduction and energy dissipation within FRP composites. Advanced AI-driven monitoring techniques are being deployed to optimize maintenance schedules by predicting crack initiation and propagation patterns, reducing the risk of sudden catastrophic failure in bridges, high-rise structures, and aerospace components.

Figure 1 provides a detailed breakdown of Carbon Fiber Reinforced Plastic (CFRP) and Thermoplastic applications in aerospace engineering, specifically on the Airbus A380. CFRP is extensively used in critical structural components such as wings, fuselage, landing gear doors, engine cowlings, tail plane, and wing ribs, owing to its high strength-to-weight ratio, corrosion resistance, and fatigue performance. In aerospace engineering, CFRP enhances fuel efficiency by reducing the aircraft's overall weight, allowing for greater payload capacity, improved aerodynamics, and extended operational life. The vertical and horizontal tail planes, rear pressure bulkhead, and flap track panels made from CFRP contribute to improved structural rigidity and impact resistance under high-stress flight conditions. Civil engineering applications similarly leverage CFRP for retrofitting bridges, reinforcing high-rise structures, and improving seismic resilience, where its lightweight properties reduce dead loads while maintaining superior tensile strength. The center wing box and unpressurized fuselage components illustrate CFRP’s adaptability in complex load-bearing structures, which translates into safer, more durable infrastructure designs in both aviation and large-scale civil projects. These advancements highlight CFRP’s pivotal role in enhancing aerospace efficiency and modernizing civil infrastructure for sustainability, resilience, and performance optimization.

Fig 1 Picture of Advanced CFRP Applications in Aerospace Engineering. (Mrázová, M. 2013)

D. Challenges in Traditional Structural Health Monitoring (SHM)

Traditional Structural Health Monitoring (SHM) systems face multiple challenges that limit their effectiveness in real-time assessment and failure prediction of structural elements. One of the primary issues is the high complexity of data acquisition and processing. SHM systems generate vast amounts of sensor data from strain gauges, fiber Bragg gratings (FBGs), accelerometers, and acoustic emission (AE) sensors, requiring advanced computational frameworks for meaningful interpretation (Enyejo et al., 2024) as represented in table 1. However, many traditional SHM systems rely on manual threshold-based detection, making them less responsive to dynamic environmental variations and sudden loading conditions. Another major challenge is the integration of SHM systems with digital infrastructure. Traditional systems often suffer from limited connectivity, data synchronization issues, and high latency in sensor response, which can delay critical decision-making (Enyejo et al., 2024). This is particularly problematic in aerospace applications, where real-time stress analysis of

FRP-reinforced components is essential to prevent catastrophic failures. For example, in the battery-powered aircraft industry, SHM plays a crucial role in monitoring composite wing structures subjected to aerodynamic forces, but traditional techniques struggle to deliver real-time insights due to computational inefficiencies and inadequate edge computing capabilities. Additionally, uncertainty in damage assessment models remains a persistent issue. Traditional SHM systems often assume linear behavior in FRP-strengthened structures, yet real-world structural responses are often nonlinear and influenced by variable boundary conditions, temperature fluctuations, and load redistribution (Enyejo et al., 2024). This can lead to false-positive damage detections or, worse, an inability to identify micro-cracks before they propagate into critical failures. To address these challenges, advancements in AI-driven anomaly detection, digital twin technology, and cloud-based SHM architectures are being developed to replace outdated models. Implementing predictive AI-based algorithms alongside sensor fusion techniques can significantly enhance damage detection accuracy, automate maintenance scheduling, and reduce false alarms, making SHM systems more reliable and efficient.

Table 1 Summary of Challenges in Traditional Structural Health Monitoring (SHM)

Challenge	Description	Impact on SHM Systems	Possible Solutions
High Data Volume and Processing Limitations	SHM generates massive sensor data, requiring efficient storage, transmission, and real-time analysis.	Slows decision-making, increases computational load, and leads to delayed failure detection.	Use of Edge Computing and Federated Learning (FL) to process data locally and in real-time, reducing latency and bandwidth dependency.
Sensor Reliability and Environmental Variability	Variations in temperature, humidity, and loading conditions affect sensor readings, leading to false alarms or missed defects.	Inconsistent damage assessment, reduced accuracy of AI models, and difficulty in long-term monitoring.	Implementation of self-calibrating sensors, AI-driven anomaly detection, and data normalization techniques.
Model Generalization Across Structures	Traditional SHM models often fail to adapt to different structural types, materials, and operational conditions.	Limited scalability, reduced predictive accuracy, and high training data dependency.	Application of Physics-Informed Neural Networks (PINNs) and transfer learning for better adaptability across diverse infrastructure.
High Installation and Maintenance Costs	Deployment of SHM systems requires specialized sensors, communication networks, and regular maintenance.	Limits adoption in developing regions, increases operational expenses, and restricts large-scale implementations.	Development of low-cost AI-powered SHM solutions, integration of wireless sensor networks, and adoption of predictive maintenance strategies.

III. MACHINE LEARNING FOR DAMAGE DETECTION IN FRP STRENGTHENED STRUCTURES

A. Supervised Learning Techniques for Defect Identification (SVM, Decision Trees, Random Forest)

Supervised learning techniques, including Support Vector Machines (SVM), Decision Trees, and Random Forests, have been widely adopted for defect identification in FRP-strengthened structures due to their ability to detect and classify structural anomalies with high accuracy. These machine learning models analyze labeled datasets to recognize failure patterns, enabling proactive maintenance strategies and reducing the risk of sudden structural failures (Ferreira et al., 2020). Support Vector Machines (SVMs) classify structural defects by constructing hyperplanes in high-dimensional space to separate normal and defective structural states. In FRP-reinforced concrete beams, SVM models have been used to differentiate between tension-induced cracks, shear failures, and delamination based on input parameters such as load history, displacement profiles, and acoustic emission signals (Zhou et al., 2023). This predictive capability allows engineers to quantify failure probabilities and preemptively address areas prone to stress accumulation. Decision Trees operate by iteratively splitting datasets based on feature importance, allowing the classification of failure types such as matrix cracking, fiber rupture, and bond failure in FRP composites. One of the advantages of Decision Trees in structural health monitoring (SHM) is their transparency in decision-making, as engineers can trace the exact conditions leading to structural degradation. Decision Tree models have been successfully deployed in real-time SHM systems to identify early-stage fatigue damage in bridge girders and high-rise FRP-reinforced structures, improving predictive maintenance scheduling (Enyejo et al., 2024). Random Forests, an ensemble method combining multiple Decision Trees, enhances defect classification accuracy by reducing overfitting and improving robustness against environmental noise in sensor data. Random Forests have been instrumental in predicting crack propagation and interfacial delamination in FRP-strengthened concrete beams, where structural responses are influenced by loading cycles, temperature fluctuations, and humidity variations (Enyejo et al., 2024). These models process large sensor datasets from fiber Bragg gratings (FBGs) and digital image correlation (DIC) systems, providing probabilistic assessments of structural integrity and enabling automated defect prioritization in critical infrastructure (Enyejo et al., 2024). The integration of SVM, Decision Trees, and Random Forests into real-time SHM frameworks improves anomaly detection, enhances predictive accuracy, and optimizes structural maintenance strategies, ensuring the longevity and safety of FRP-strengthened infrastructure in aerospace, civil, and marine applications.

B. Deep Learning and Convolutional Neural Networks (CNNs) for Crack Detection

The application of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly advanced the field of structural health monitoring by enhancing the accuracy and efficiency of crack detection in infrastructure. CNNs are adept at automatically learning hierarchical feature representations from raw image data, making them highly effective for identifying complex patterns associated with structural cracks. In a seminal study, Cha et al. (2017) developed a vision-based method utilizing a deep CNN architecture to detect concrete cracks without manual feature extraction as represented in figure 2. The proposed model was trained on a dataset of 40,000 images with a resolution of 256×256 pixels, achieving an impressive accuracy of approximately 98%. This approach demonstrated the potential of CNNs to autonomously learn and identify crack features under varying conditions, thereby reducing the reliance on traditional image processing techniques. Building upon this foundation, Zhu et al. (2021) introduced a hierarchical CNN with feature preservation and an autotuned thresholding mechanism for crack detection. This architecture addresses the challenge of information loss during down-sampling by incorporating branch networks that concatenate outputs from previous convolutional blocks. The model was evaluated on images captured by unmanned aerial vehicles inspecting monorail bridges, showcasing superior performance in identifying surface cracks compared to existing methods. Further advancements were made by Kumar and Ghosh (2020), who proposed a dual-channel deep CNN tailored for detecting concrete cracks. Their model was trained on a diverse dataset of 3,200 labeled images, encompassing variations in contrast, lighting, orientation, and crack severity. The dual-channel design effectively captured both fine and coarse features of cracks, resulting in a robust detection accuracy of approximately 92.25% in realistic scenarios. Collectively, these studies highlight the efficacy of deep learning and CNNs in automating crack detection processes. The ability of CNNs to learn complex feature hierarchies directly from image data positions them as indispensable tools in the proactive maintenance and safety assurance of critical infrastructure.

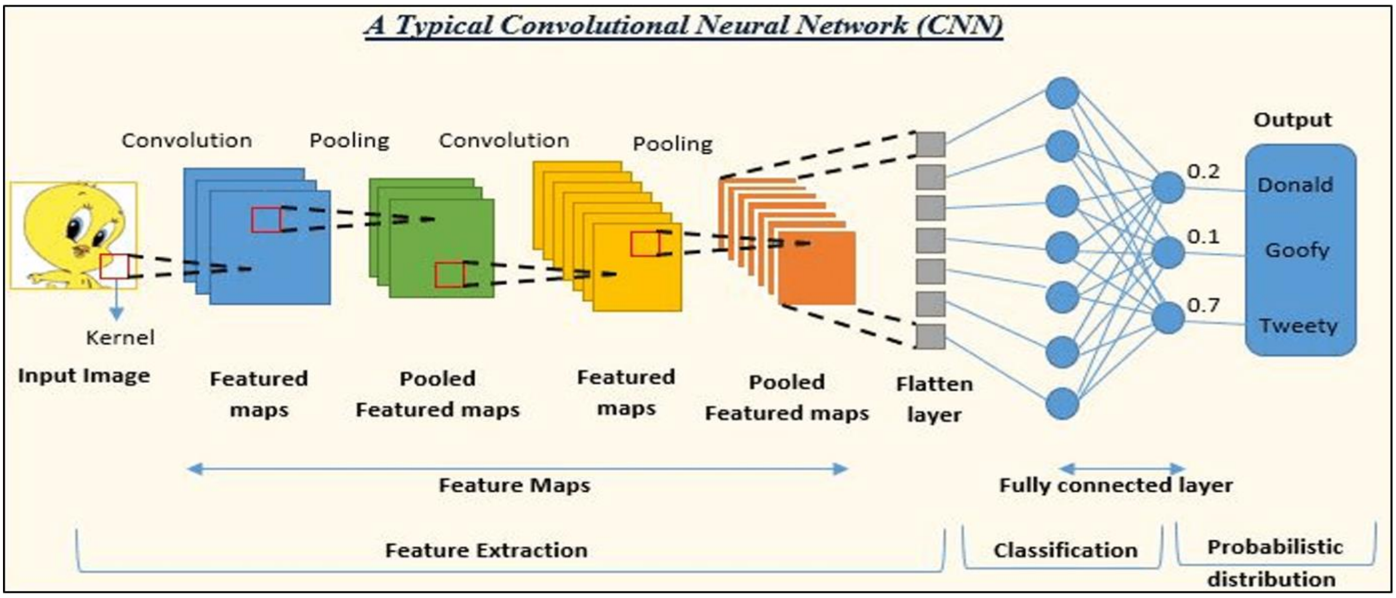

Fig 2 Picture of CNN Architecture for Automated Image Classification and Feature Extraction (Kaur, G. 2024).

Figure 2 provides a detailed representation of a Convolutional Neural Network (CNN) architecture, demonstrating how deep learning models process and classify input images. In the context of crack detection in structural health monitoring (SHM), a CNN follows a hierarchical feature extraction approach, similar to what is depicted in the image. The process begins with an input image of a structural surface, where a convolutional layer applies multiple kernels to detect edge features and texture patterns that might indicate cracks. The output feature maps undergo pooling operations, reducing spatial dimensions while retaining critical information. As the image progresses through additional convolutional and pooling layers, the network extracts higher-level representations, distinguishing fine cracks from normal surface textures. The flattened feature vectors are then processed in a fully connected layer, where the network assigns probabilistic classifications to potential crack patterns. This structured deep learning approach enables CNNs to achieve high precision in detecting microcracks, delamination, and surface deformations in FRP-reinforced structures, allowing for automated, real-time monitoring of bridges, buildings, and aerospace components (Igba et al., 2024). By leveraging CNN-based crack detection, infrastructure maintenance can become more predictive, efficient, and cost-effective, ultimately improving structural safety and longevity.

C. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) for Damage Progression

The application of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks in damage progression analysis has significantly improved the ability to predict long-term structural deterioration in FRP-strengthened infrastructure. These deep learning models excel in processing sequential sensor data collected from structural health monitoring (SHM) systems, enabling the identification of fatigue trends, crack propagation, and delamination patterns (Igba et al., 2024). RNNs are particularly effective in modeling time-series sensor data, making them well-suited for real-time monitoring of strain, vibration, and stress variations in structural components. However, traditional RNNs suffer from vanishing gradient issues, limiting their ability to retain long-term dependencies in sequential datasets. LSTM networks, a specialized variant of RNNs, overcome this limitation by utilizing gated mechanisms to selectively retain relevant past information, making them ideal for predicting damage evolution in high-cycle fatigue conditions (Enyejo et al., 2024). In the structural health monitoring of bridges and high-rise buildings, LSTM models have been successfully deployed to forecast damage accumulation based on historical load fluctuations. These models integrate sensor fusion techniques using accelerometer, fiber Bragg grating (FBG), and acoustic emission (AE) data, enabling a highly accurate representation of progressive structural degradation (Ijiga et al., 2024). Furthermore, the ability of LSTM networks to adapt to changing environmental conditions and operational loads ensures robust damage assessment, reducing the likelihood of false-positive detections and improving proactive maintenance strategies. By leveraging RNN and LSTM-based AI frameworks, engineers can develop predictive maintenance algorithms capable of anticipating critical failures, thus enhancing the long-term resilience of FRP-strengthened structural elements.

D. Hybrid AI Models Combining Machine Learning with Physics-Based Models

The integration of ML with physics-based models has led to the development of hybrid AI models that enhance the predictive capabilities in structural health monitoring (SHM). These models leverage the strengths of both data-driven approaches and traditional physics-based simulations to provide more accurate and reliable assessments of structural integrity as represented in figure 3. Physics-informed machine learning (PIML) is a prominent approach in this domain. PIML incorporates physical laws and constraints into ML models, ensuring that predictions adhere to known physical behaviors. This integration enhances the generalization of models across different operational regimes, which is crucial for lifetime assessment and scenarios where monitoring data may be sparse or not encompass all possible conditions. For instance, in SHM applications, grey-box models that combine simple physics-based models with data-driven components have demonstrated improved predictive capabilities, particularly in generalizing to unobserved conditions (Cross et al., 2022). Another example is the fusion of physics-based performance models with deep learning algorithms for prognostics in complex systems. In this framework, physics-based models are utilized to infer unobservable parameters related to a system's health state. These inferred parameters, combined with sensor data, serve as inputs to a deep neural network that predicts the remaining useful life of components. This hybrid approach has been applied to turbofan engines, where it outperformed purely data-driven models by extending the prediction horizon and reducing sensitivity to limited training data (Chao et al., 2020). The synergy between ML and physics-based models in hybrid AI frameworks offers a robust methodology for SHM. By embedding physical principles into data-driven models, these hybrid approaches enhance predictive accuracy, ensure consistency with known physical behaviors, and provide more reliable tools for the maintenance and safety assessment of critical infrastructure.

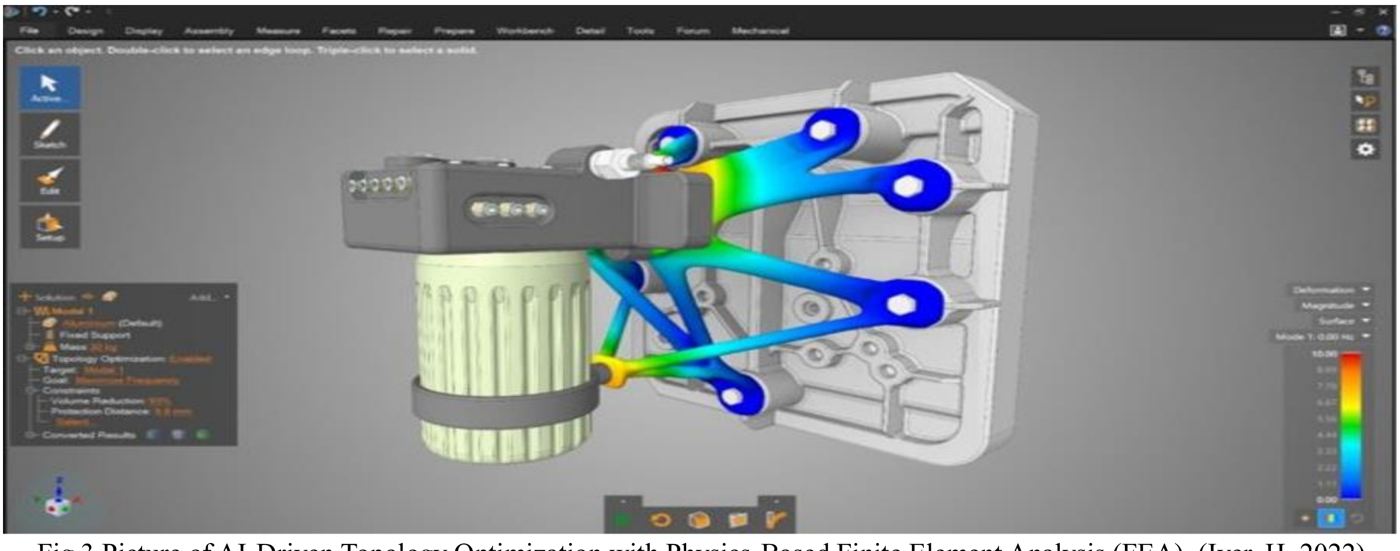

Fig 3 Picture of AI-Driven Topology Optimization with Physics-Based Finite Element Analysis (FEA). (Iyer, H. 2022)

Figure 3 illustrates a Finite Element Analysis (FEA) simulation with topology optimization, showcasing a hybrid AI model that integrates Machine Learning (ML) with physics-based models to optimize structural performance. The color gradient visualization represents stress distribution and deformation analysis, highlighting high-stress regions in red and low-stress areas in blue. This hybrid approach enables AI-driven topology optimization, where ML algorithms analyze vast structural datasets, predicting optimal load paths while physics-based models ensure compliance with engineering constraints and material properties. The combination of AI and physics-informed models enhances predictive accuracy, reduces computational costs, and accelerates the design of lightweight, high-strength components. In structural health monitoring (SHM), such models can predict failure modes in FRP-reinforced infrastructure, optimizing reinforcement strategies. Additionally, reinforcement learning (RL) algorithms can refine load-bearing configurations in real-time, ensuring structures withstand operational stresses efficiently. This hybrid AI-physics framework is crucial in automated aerospace and civil engineering applications, providing resilient, high-performance structural designs while minimizing material usage and environmental impact.

E. Sensor Integration and Data Acquisition Techniques (FBGs, AE, Digital Image Correlation)

Effective structural health monitoring (SHM) relies on advanced sensor integration and data acquisition techniques to detect and assess damage progression in FRP-strengthened structures. Three of the most widely used techniques include Fiber Bragg Gratings (FBGs), Acoustic Emission (AE), and Digital Image Correlation (DIC), each providing unique advantages in real-time monitoring, early fault detection, and predictive maintenance (Idoko et al., 2024). FBG sensors are widely utilized for strain, temperature, and load monitoring in civil and aerospace engineering. These optical sensors embed into FRP composites to detect minute structural deformations caused by external forces, ensuring early detection of stress concentration areas before significant damage occurs (Bao et al., 2019). The high sensitivity and immunity to electromagnetic interference make FBGs ideal for high-voltage transmission lines, bridge structures, and aircraft fuselage monitoring. Acoustic Emission (AE) sensing is another critical technique that detects high-frequency stress waves generated by crack initiation and propagation in FRP composites. AE-based SHM enables real-time failure tracking by capturing sudden energy releases from internal micro-cracks, fiber breakage, or delamination (Ijiga et al., 2024). The ability to localize damage before it becomes externally visible makes AE systems particularly valuable in high-performance aerospace components and offshore structural applications. Digital Image Correlation (DIC) is an optical, non-contact method used for full-field deformation measurement in FRP structures. By analyzing high-resolution image sequences, DIC provides real-time strain mapping and detects surface discontinuities and crack evolution patterns (Yoon et al., 2020). The method is especially effective in large-scale infrastructure projects, where traditional strain gauges may be impractical due to surface irregularities or environmental exposure.

By combining FBGs, AE, and DIC, hybrid sensor networks enhance data accuracy and predictive analytics in AI-integrated SHM systems, ensuring proactive damage assessment and improved structural resilience in FRP-reinforced aerospace and civil engineering applications.

IV. AI-BASED FATIGUE PREDICTION IN FRP STRUCTURAL COMPONENTS

A. Fatigue and Structural Degradation Modeling in Composite Materials

Understanding fatigue and structural degradation in composite materials is crucial for predicting their long-term performance and ensuring structural integrity. Fatigue in composites involves progressive damage accumulation under cyclic loading, leading to stiffness reduction, strength loss, and eventual failure. Modeling these phenomena requires comprehensive approaches that account for the unique behaviors of composite constituents and their interactions (Cheng et al. 2021) as presented in table 2. One effective approach is the progressive fatigue damage modeling, which simulates the residual stiffness, residual strength, and fatigue life of composite laminates under complex loading conditions. This method considers the initiation and growth of damage mechanisms such as matrix cracking, fiber breakage, and delamination, providing a detailed understanding of damage progression. Cheng et al. (2021) developed a fatigue-driven residual strength model that incorporates the effects of low-velocity impact damage and stress ratio, enabling accurate simulation of fatigue damage growth and life prediction in plain-weave composite laminates. Another significant aspect is the modeling of residual strength degradation. Accurately predicting the remaining strength of damaged composites is essential for maintenance and safety assessments. Recent studies have introduced approaches that require less experimental data by integrating computational methods with empirical observations. These models enhance the efficiency of residual strength predictions, facilitating timely decision-making in engineering applications. Additionally, the development of generalized models capable of predicting material property degradation across various stress levels using a single set of parameters has been proposed. Such models streamline the assessment process by reducing the complexity associated with varying loading conditions, thereby improving the reliability of degradation predictions. Incorporating these advanced modeling techniques into the design and analysis of composite structures enhances the ability to predict fatigue life and structural degradation accurately. This integration is vital for optimizing material selection, structural design, and maintenance strategies, ultimately ensuring the safety and longevity of composite material applications.

Table 2 Summary of Fatigue and Structural Degradation Modeling in Composite Materials

Modeling Approach	Description	Key Benefits	Example Applications
Progressive Fatigue Damage Modeling	Simulates fatigue-induced damage accumulation in composite laminates, considering matrix cracking, fiber breakage, and delamination.	Improves failure prediction accuracy, enables optimized reinforcement strategies, and enhances material longevity.	Predicting fatigue life in FRP-reinforced bridges and aerospace components under cyclic loading.
Residual Strength Degradation Models	Estimates the remaining strength of composites post-fatigue exposure, using empirical and computational approaches.	Supports proactive maintenance, reduces catastrophic failure risks, and minimizes unexpected structural failures.	Assessing FRP beam durability in high-rise buildings and marine structures.
Machine Learning-Based Fatigue Prediction	Uses AI and deep learning models to analyze fatigue trends and predict degradation in composite structures.	Enables real-time fatigue monitoring, enhances predictive accuracy, and reduces dependency on physical testing.	AI-driven structural monitoring of FRP wind turbine blades for early fatigue detection.
Multiscale Damage Modeling	Integrates microscopic, mesoscopic, and macroscopic models to simulate damage evolution across different scales.	Captures detailed failure mechanisms, improves composite material design, and enhances structural integrity assessments.	Simulation of micro-crack propagation in FRP-reinforced concrete under variable environmental conditions.

B. Physics-Informed Neural Networks (PINNs) and Reinforcement Learning (RL) for Enhanced Prediction

The integration of Physics-Informed Neural Networks (PINNs) and Reinforcement Learning (RL) offers a robust framework for enhancing predictive capabilities in structural health monitoring (SHM) of FRP composites. PINNs incorporate governing physical laws into the neural network architecture, ensuring that predictions adhere to known physical behaviors. This approach is particularly beneficial in scenarios with limited or noisy data, as it constrains the solution space to physically plausible outcomes. For instance, Cross et al. (2022) demonstrated that PINNs could effectively model structural dynamics by embedding differential equations governing structural behavior directly into the learning process, thereby improving the generalization of models across different operational regimes. In parallel, RL algorithms have been employed to optimize maintenance strategies for FRP composites. By formulating maintenance scheduling as a sequential decision-making problem, RL agents learn optimal policies that balance inspection costs with the risk of structural failure. This dynamic approach allows for adaptive maintenance planning that responds to the evolving condition of the structure, thereby enhancing safety and cost-effectiveness. The synergy between PINNs and RL is exemplified in the predictive modeling of fatigue life in FRP composites. Cheng et al. (2021) developed a progressive damage model that integrates physics-based simulations with data-driven components to predict fatigue damage growth accurately. By incorporating this model into an RL framework, maintenance policies can be continuously updated based on real-time predictions of structural degradation, ensuring timely interventions and prolonging the service life of the composite structures. Moreover, the adoption of Internet of Things (IoT) technologies facilitates the real-time monitoring necessary for implementing these advanced predictive models. Idoko et al. (2024) highlighted the role of IoT in providing continuous data streams that feed into PINN and RL algorithms, enabling dynamic assessment and proactive maintenance of FRP-strengthened structures. In summary, the integration of PINNs and RL, supported by IoT infrastructure, offers a comprehensive approach to enhancing the prediction and management of structural health in FRP composites. This methodology not only improves the accuracy of damage detection and life expectancy assessments but also optimizes maintenance strategies, thereby ensuring the longevity and safety of critical infrastructure.

C. Thermomechanical and Aeroelastic Effects on FRP Strengthened Systems

FRP composites are extensively utilized in structural engineering due to their high strength-to-weight ratio and corrosion resistance. However, their performance under thermomechanical and aeroelastic loading conditions necessitates thorough examination to ensure structural integrity and longevity as represented in figure 4.

➢ *Thermomechanical Effects*:

Elevated temperatures can significantly impact the mechanical properties of FRP composites. The polymer matrix within FRP materials exhibits sensitivity to high temperatures, leading to degradation in bond performance, especially beyond the glass transition temperature (T_g) of the adhesive. This degradation manifests as a reduction in bond strength and potential delamination between FRP and the substrate material, compromising the structural performance of the reinforced system (Salameh et al., 2024). For instance, in FRP–concrete systems, exposure to temperatures above T_g can result in substantial deterioration of the bond integrity, affecting the load-bearing capacity of the structure. Additionally, differential thermal expansion between FRP and substrates like concrete can induce thermal stresses at the interface, leading to microcracking or debonding under cyclic thermal loading. This phenomenon underscores the necessity for selecting adhesives and matrix materials with compatible thermal expansion coefficients to mitigate interface degradation under varying thermal conditions.

➢ *Aeroelastic Effects:*

In aerospace applications, FRP-strengthened components are subjected to aeroelastic phenomena, where aerodynamic forces interact with structural elasticity, potentially leading to instabilities such as flutter. The integration of actuated adaptive wingtips, utilizing stiffness-adaptive aeroelastic hinges, has been investigated to enhance performance. Studies have demonstrated that these adaptive systems can effectively reduce wing root bending moments by up to 7.8% during maneuvering loads, thereby improving the aeroelastic stability of aircraft structures (Aeroelastic Analysis of Actuated Adaptive Wingtips Based on Pressure-Actuated Cellular Structures, 2021).

Moreover, the implementation of pressure-actuated cellular structures (PACS) in wingtips allows for in-flight adjustment of stiffness and shape, facilitating load alleviation and improved aerodynamic efficiency. This adaptability is crucial in mitigating aeroelastic instabilities and enhancing the operational envelope of aircraft equipped with high-aspect-ratio wings.

In summary, understanding the thermomechanical and aeroelastic effects on FRP-strengthened systems is vital for optimizing their design and ensuring their durability across various operational environments. Addressing these challenges through material selection, structural design, and adaptive technologies can significantly enhance the performance and safety of FRP-reinforced structures.

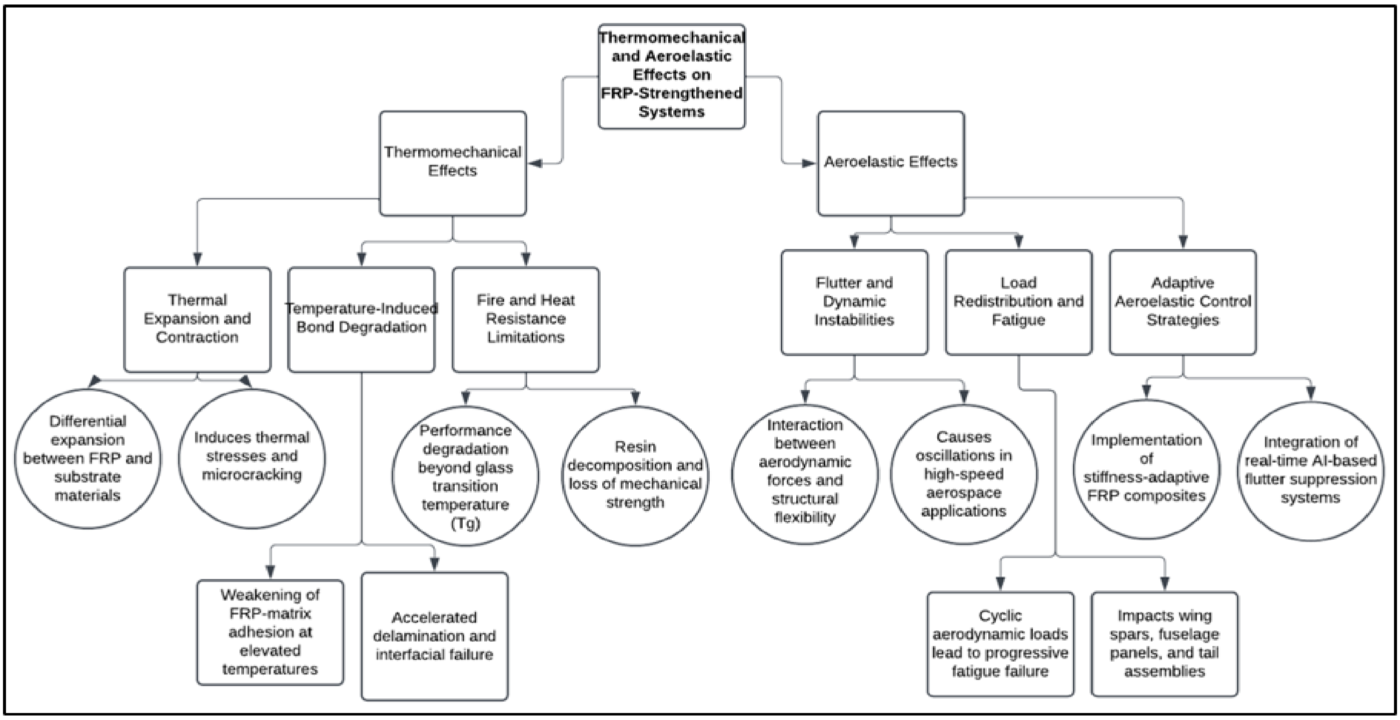

Fig 4 Diagram illustration of Thermomechanical and Aeroelastic Effects on FRP-Strengthened Systems

Figure 4 illustrates the thermomechanical and aeroelastic effects on FRP-strengthened systems, detailing their impact on structural performance and failure mechanisms in aerospace and civil engineering applications. The thermomechanical branch highlights key concerns such as thermal expansion mismatch between FRP composites and substrate materials, leading to internal stresses, microcracking, and interfacial debonding. It also addresses temperature-induced bond degradation, where high operating temperatures weaken matrix adhesion, increasing delamination risks. Additionally, the diagram depicts fire and heat resistance limitations, emphasizing how FRP composites degrade beyond their glass transition temperature (Tg), causing loss of mechanical integrity in extreme environments. The aeroelastic branch showcases dynamic instabilities like flutter, where aerodynamic forces interact with structural flexibility, causing oscillatory deformations in wing spars and fuselage panels. It further explores load redistribution and fatigue, where cyclic aerodynamic loading accelerates fatigue damage in high-performance aerospace structures. The final section illustrates adaptive aeroelastic control strategies, leveraging stiffness-adaptive FRP composites and AI-driven flutter suppression systems to enhance structural resilience and real-time response to aerodynamic forces. This comprehensive framework ensures optimized material performance, extended service life, and increased safety in FRP-reinforced infrastructures.

D. Validation of ML Models with Experimental and Simulation Data

The validation of ML models in structural health monitoring (SHM) is critical to ensure their reliability and accuracy in real-world applications. This process involves corroborating ML predictions with both experimental and simulation data to confirm that the models can generalize effectively across various scenarios. One approach to validation is the integration of physics-informed ML, which embeds physical laws into the learning process. Cross et al. (2022) demonstrated that incorporating structural dynamics equations into ML models enhances their predictive performance, aligning outputs with known physical behaviors. This method reduces reliance on extensive datasets by leveraging inherent system physics. Additionally, the use of simulation data to augment experimental findings has been explored. By transforming simulated data to closely resemble experimental observations, researchers can expand the training dataset, improving model robustness. This technique addresses challenges associated with limited experimental data, enabling ML models to perform accurately under diverse conditions. Furthermore, the application of statistical learning theory provides a rigorous framework for model selection and validation. By estimating generalization bounds, this approach aids in selecting models that are not only accurate on training data but also perform well on unseen data, ensuring reliability in SHM applications.

In summary, validating ML models with a combination of experimental and simulation data, while incorporating physical laws and statistical principles, enhances their credibility and applicability in monitoring the health of structures.

V. STRUCTURAL HEALTH MONITORING (SHM) AND DIGITAL TWIN INTEGRATION

A. Overview of Digital Twin Technology in Structural Engineering

Digital Twin (DT) technology has emerged as a transformative approach in structural engineering, offering dynamic, real-time digital replicas of physical structures. These virtual models integrate data from various sources, enabling continuous monitoring, simulation, and optimization of structural performance. In civil engineering, DTs facilitate predictive maintenance and health monitoring by assimilating sensor data with computational models. For instance, Torzoni et al. (2023) as represented in figure 5 proposed a framework where a probabilistic graphical model integrates real-time data to update the structural state, enhancing decision-making for maintenance and management. This approach allows for dynamic assessment of structural integrity, reducing lifecycle costs and improving safety. The integration of Internet of Things (IoT) devices plays a crucial role in the functionality of DTs. Idoko et al. (2024) highlighted that IoT implementation enables continuous data collection from structures, providing the necessary input for DTs to accurately reflect current conditions and predict future performance. This real-time data acquisition is essential for the effective operation of DTs in monitoring structural health. Moreover, DTs have been applied to enhance resilience in supply chains by modeling infrastructure and identifying potential vulnerabilities. Enyejo et al. (2024) discussed how technology, including DTs, assists companies in navigating disruptions by providing comprehensive models of their structural assets, allowing for proactive risk management and improved operational efficiency.

In summary, Digital Twin technology integrates real-time data and computational models to provide a comprehensive, dynamic representation of physical structures. Its application in structural engineering enhances monitoring, predictive maintenance, and resilience, thereby improving the safety and efficiency of infrastructure systems.

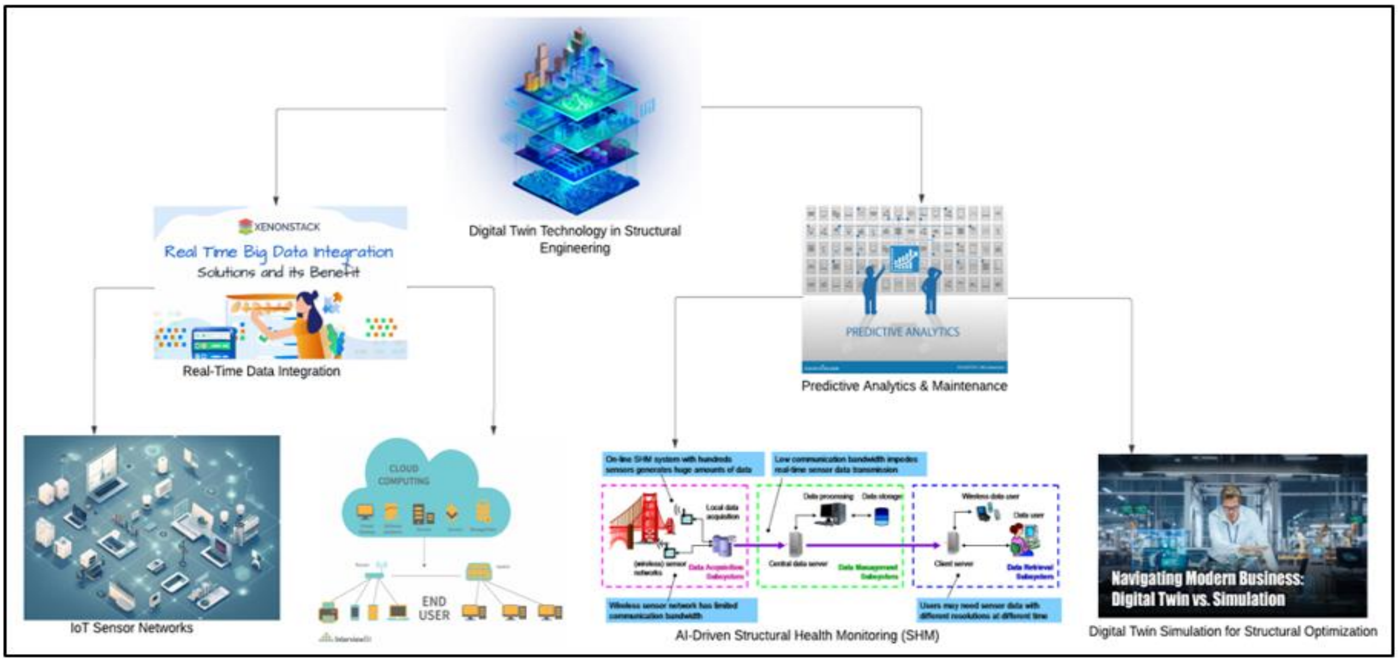

Fig 5 Diagram Illustration of Digital Twin Technology for AI-Driven Structural Health Monitoring.

Figure 5 visually represents Digital Twin Technology in Structural Engineering, demonstrating how real-time data integration and predictive analytics enhance structural monitoring and optimization. On the left branch, IoT sensor networks collect real-time data on stress, vibration, and environmental conditions, transmitting it to cloud-based data processing systems that analyze large-scale structural datasets. This enables immediate anomaly detection and load distribution analysis, ensuring continuous monitoring of bridges, high-rise buildings, and aerospace components. On the right branch, predictive analytics and AI-driven maintenance utilize machine learning algorithms for structural health monitoring (SHM), detecting early-stage fatigue, cracks, and material degradation. Finite Element Analysis (FEA) simulations within the Digital Twin framework optimize structural designs, ensuring resilience against seismic loads, aerodynamic stresses, and environmental aging. The integration of physics-based modeling with AI-driven SHM enhances failure prediction accuracy, reducing maintenance costs and increasing operational safety. This comprehensive Digital Twin ecosystem enables proactive decision-making, improving the lifespan and sustainability of FRP-reinforced infrastructure in civil, aerospace, and industrial engineering applications.

B. Real-Time Monitoring using Federated Learning (FL) and Edge Computing.

The integration of Federated Learning (FL) and Edge Computing has revolutionized real-time monitoring in structural health monitoring (SHM) systems. This synergy enables decentralized data processing and collaborative model training directly at the data source, enhancing both privacy and efficiency

In industrial applications, FL allows multiple edge devices to collaboratively train ML models without sharing raw data, thereby preserving data privacy. For instance, Becker et al. (2022) demonstrated an autoencoder-based FL approach for condition monitoring in the Industrial Internet of Things (IIoT). Their method enabled distributed training on edge devices using vibration sensor data from rotating machinery, facilitating early fault detection while maintaining data confidentiality. This approach not only reduced the need for centralized data storage but also minimized network latency, ensuring timely responses to potential issues.

Moreover, the integration of Internet of Things (IoT) devices plays a crucial role in the functionality of FL and edge computing. Idoko et al. (2024) highlighted that IoT implementation enables continuous data collection from structures, providing the necessary input for FL models to accurately reflect current conditions and predict future performance. This real-time data acquisition is essential for the effective operation of FL in monitoring structural health. In the context of supply chain resilience, Enyejo et al. (2024) discussed how technology, including FL and edge computing, assists companies in navigating disruptions by providing comprehensive models of their structural assets. This approach allows for proactive risk management and improved operational efficiency, as real-time data processing at the edge enables swift adaptation to changing conditions.

In summary, the combination of Federated Learning and Edge Computing offers a robust framework for real-time monitoring in structural engineering. By enabling decentralized, privacy-preserving data processing and collaborative model training, this approach enhances the efficiency and responsiveness of SHM systems, ensuring the safety and longevity of critical infrastructure.

C. Uncertainty Quantification (UQ) and Explainable AI (XAI) for SHM Decision Making.

In structural health monitoring (SHM), the integration of Uncertainty Quantification (UQ) and Explainable XAI is pivotal for enhancing decision-making processes. UQ provides a measure of confidence in AI model predictions, distinguishing between aleatoric uncertainty, arising from inherent data variability, and epistemic uncertainty, stemming from model limitations (Sajedi & Liang, 2020) as represented in figure 6. Accurately quantifying these uncertainties enables engineers to assess the reliability of SHM systems, facilitating informed maintenance and safety decisions. For instance, in deep learning applications for structural damage detection, UQ techniques such as Monte Carlo dropout can be employed to estimate prediction uncertainties. This approach involves performing multiple stochastic forward passes through the network to obtain a distribution of outputs, thereby quantifying the model's confidence in its predictions (Sajedi & Liang, 2020). Such probabilistic assessments are crucial when evaluating critical infrastructure, where overconfidence in flawed predictions could lead to catastrophic failures. Complementing UQ, XAI aims to elucidate the decision-making pathways of AI models, rendering their operations transparent and interpretable. In SHM, XAI techniques can highlight which features or sensor inputs most significantly influence a model's diagnosis of structural integrity. This transparency not only fosters trust among stakeholders but also aids in identifying potential model biases or erroneous data interpretations. The synergy of UQ and XAI in SHM is exemplified in scenarios where AI models detect anomalies in sensor data. By providing both a probabilistic measure of confidence (UQ) and a clear rationale for the decision (XAI), engineers can prioritize inspections and maintenance more effectively, focusing resources on areas with high uncertainty and critical importance.

In summary, the combined application of Uncertainty Quantification and Explainable AI in structural health monitoring enhances the reliability and transparency of AI-driven assessments, thereby improving the safety and maintenance of infrastructure systems.

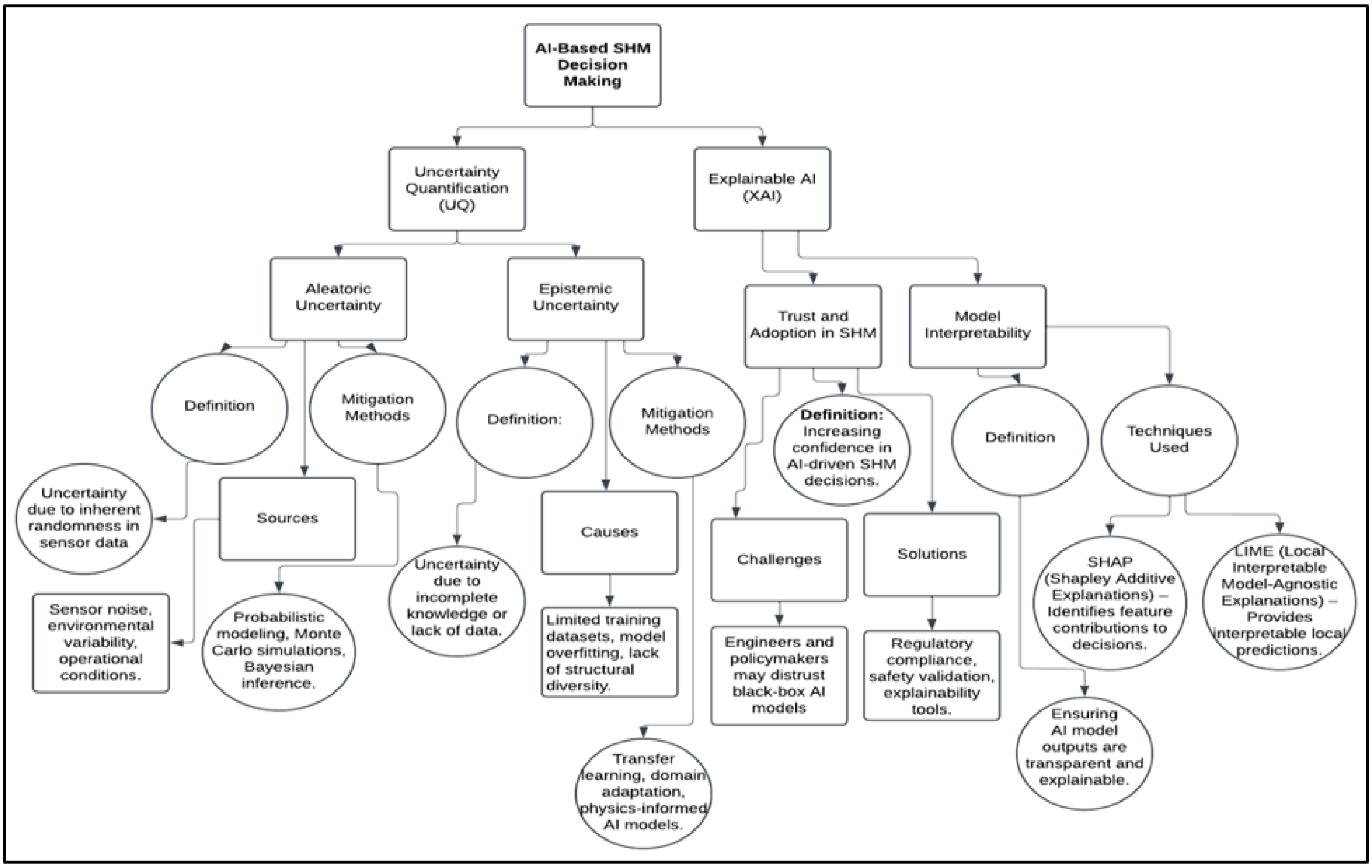

Fig 6 Diagram Illustration of AI-Driven Structural Health Monitoring: Uncertainty Quantification (UQ) and Explainable AI (XAI) Framework

Figure 6 illustrates the integration of Uncertainty Quantification (UQ) and Explainable AI (XAI) in Structural Health Monitoring (SHM) decision-making, detailing how AI models address uncertainty and enhance interpretability in damage detection and predictive maintenance. The central node (AI-Based SHM Decision Making) branches into UQ and XAI, each addressing key limitations in AI-driven SHM systems. UQ consists of Aleatoric and Epistemic Uncertainty, where Aleatoric Uncertainty arises from sensor noise, environmental variability, and operational inconsistencies, mitigated using probabilistic modeling, Monte Carlo simulations, and Bayesian inference. Epistemic Uncertainty stems from incomplete or biased datasets, reduced through transfer learning, domain adaptation, and physics-informed AI models, ensuring robust generalization. XAI focuses on Model Interpretability and Trust & Adoption, where SHAP and LIME techniques help explain AI-driven failure predictions, enhancing transparency for engineers and policymakers. The Trust & Adoption sub-branch highlights regulatory concerns and solutions such as safety validation and compliance frameworks, promoting AI acceptance in civil and aerospace SHM applications. This structured UQ-XAI framework improves AI reliability, failure detection accuracy, and trustworthiness, ensuring proactive, real-time decision-making in FRP-strengthened infrastructure.

D. Case Studies of AI-Driven SHM in FRP-Reinforced Infrastructure

AI has significantly advanced Structural Health Monitoring (SHM) in FRP -reinforced infrastructures, enhancing the detection and assessment of structural anomalies. Azimi et al. (2020) conducted a comprehensive review highlighting the application of deep learning techniques in SHM, emphasizing their effectiveness in processing complex data for damage detection in FRP-reinforced structures. Their study demonstrated that convolutional neural networks (CNNs) could accurately identify and classify damage patterns, thereby improving maintenance strategies. In another study, Enyejo et al. (2024) explored the role of AI in enhancing supply chain resilience, particularly focusing on infrastructure reinforced with FRP materials. The integration of AI-driven SHM systems allowed for real-time monitoring and predictive maintenance, reducing downtime and improving operational efficiency. The study underscored the importance of AI in proactively identifying potential structural issues before they escalate into critical failures. Furthermore, Ijiga et al. (2024) examined the deployment of deep learning models in surveillance systems to combat human trafficking. While the primary focus was on surveillance, the methodologies discussed have direct implications for SHM in FRP-reinforced infrastructures. The study demonstrated that AI models could process vast amounts of data from various sensors, facilitating the early detection of structural anomalies and enhancing the safety and longevity of infrastructures. Additionally, Idoko et al. (2024) provided a comparative analysis of Internet of Things (IoT) implementations, highlighting how AI-integrated IoT devices are utilized in SHM systems for FRP-reinforced structures. The study emphasized that the combination of AI and IoT enables continuous monitoring and data analysis, leading to more informed decision-making regarding structural health and maintenance.

These case studies collectively demonstrate the transformative impact of AI-driven SHM systems in managing and maintaining FRP-reinforced infrastructures, leading to enhanced safety, efficiency, and resilience.

E. Challenges in Implementing AI for Large-Scale SHM Systems

AI in large-scale Structural Health Monitoring (SHM) systems presents several challenges that must be addressed to ensure effective and reliable infrastructure monitoring.

➢ *Data Management and Transmission*:
Large-scale SHM systems generate vast amounts of data, necessitating efficient transmission and storage solutions. Moallemi et al. (2022) highlight that traditional cloud-based approaches may struggle to handle the data volume from numerous sensors, leading to potential bottlenecks. Implementing edge computing can mitigate this by processing data locally, reducing latency and bandwidth requirements as presented in table 3.

➢ *Model Deployment and Scalability*:
Deploying AI models across extensive SHM networks requires careful consideration of scalability and computational resources. Esteghamati et al. (2024) discuss challenges such as model overfitting, underspecification, and ensuring that training data accurately represent the diverse conditions encountered in large-scale applications. Adaptive sampling and physics-informed feature selection are recommended to enhance model generalizability.

➢ *Explainability and Trust*:
The complexity of AI models can hinder their interpretability, making it difficult for stakeholders to trust automated SHM decisions. Enyejo et al. (2024) propose enhancing model explainability on edge devices by integrating computational geometry and advanced database architectures. This approach aims to make AI-driven insights more transparent, facilitating better understanding and acceptance among engineers and decision-makers.

➢ *Environmental and Operational Variability*:
AI models must account for varying environmental conditions and operational loads that can affect sensor data. The importance of thermomechanical and aeroelastic optimization in FRP-strengthened structures ensures that AI models accurately reflect the structural responses under different conditions.

Addressing these challenges requires a multidisciplinary approach, combining advancements in AI, edge computing, materials science, and structural engineering to develop robust, scalable, and trustworthy SHM systems.

Table 3 Summary of Challenges in Implementing AI for Large-Scale SHM Systems.

Challenge	Description	Impact on SHM Systems	Possible Solution
Data Scalability and Management	Large-scale SHM systems generate massive sensor data, leading to storage, processing, and real-time analysis challenges.	Slower decision-making, increased computational load, and high data storage costs.	Federated Learning (FL) and Edge Computing can distribute processing, reducing latency and bandwidth dependency.
Model Interpretability and Trust	AI-driven SHM models, especially deep learning, often function as black-box systems, making results difficult to interpret.	Limits engineering acceptance, increases regulatory challenges, and hinders critical infrastructure applications.	Integration of Explainable AI (XAI) frameworks and Physics-Informed Neural Networks (PINNs) for better interpretability.
Cybersecurity Risks in AI-SHM	AI-based SHM systems are vulnerable to cyberattacks, data breaches, and adversarial attacks that manipulate sensor inputs.	Risk of false alarms, compromised predictive maintenance, and system malfunctions.	Adoption of blockchain-secured data logging, AI-driven anomaly detection, and robust encryption protocols.
High Computational and Hardware Costs	Implementing AI for large-scale SHM requires high-performance computing (HPC), specialized GPUs, and advanced sensors.	Increased deployment costs, limits adoption in developing regions, and high energy consumption.	Use of quantum-assisted AI models and development of lightweight, energy-efficient ML algorithms for SHM applications.

VI. CHALLENGES AND FUTURE DIRECTIONS

A. Limitations in Data Availability and Model Generalization

In Structural Health Monitoring (SHM), the scarcity of comprehensive datasets poses significant challenges to the development of robust and generalizable models. The infrequency of structural failures results in a limited repository of failure data, which is crucial for training predictive models (Bull et al., 2021) as presented in table 4. This data paucity often leads to models that perform well under specific conditions but fail to generalize across diverse scenarios. To address these limitations, researchers have explored domain-generalization techniques. Luleci and Catbas (2022) introduced the Structural State Translation (SST) framework, which estimates the response data of different civil structures based on information from dissimilar structures. By learning domain-invariant representations, SST facilitates condition transfer between structures, enhancing model applicability in varied contexts. Another approach involves probabilistic inference methods that can adapt to incomplete or noisy data. Bull et al. (2021) demonstrated that probabilistic models could effectively handle missing information, allowing for continuous learning as new data becomes available. This adaptability is crucial for maintaining model performance in dynamic environments where data acquisition is challenging. Despite these advancements, ensuring model generalization remains a formidable task. The heterogeneity of structural designs, materials, and environmental conditions necessitates models that can accommodate a wide range of variables. Ongoing research in transfer learning and domain adaptation aims to bridge this gap, striving to develop SHM systems that are both data-efficient and broadly applicable.

Table 4 Summary of Limitations in Data Availability and Model Generalization

Challenge	Description	Impact on AI-SHM Models	Possible Solutions
Limited Failure Data	Structural failures are rare, leading to an insufficient dataset for training AI models effectively.	Reduces model accuracy, increases false positives/negatives, and limits failure prediction reliability.	Use of synthetic data augmentation, physics-based simulations, and transfer learning to supplement datasets.
Data Variability Across Structures	Differences in materials, loading conditions, and sensor configurations create inconsistencies in SHM datasets.	Limits model adaptability, requiring extensive retraining for each new structure.	Implement domain generalization techniques, such as Structural State Translation (SST) and unsupervised learning, to improve transferability.
Incomplete or Noisy Sensor Data	Sensor malfunctions, environmental noise, and missing data affect the integrity of SHM inputs.	Leads to poor decision-making, unreliable damage detection, and model misinterpretations.	Application of probabilistic inference models, data imputation techniques, and robust feature selection methods.
Generalization Across Environments	AI models trained on one structural dataset may not generalize well to different climates, stress conditions, or operational loads.	Decreases real-world applicability, requiring continuous manual tuning and retraining.	Incorporate Physics-Informed Neural Networks (PINNs) and adaptive learning algorithms to enhance generalization.

B. Computational Efficiency and Model Optimization Techniques

In the realm of Structural Health Monitoring (SHM), the deployment of computationally efficient models is paramount for real-time damage detection and assessment. One prominent approach to enhance computational efficiency involves the integration of Model Order Reduction (MOR) techniques with deep learning algorithms. Rosafalco et al. (2021) proposed a simulation-based classification strategy that combines parametric MOR with Fully Convolutional Networks (FCNs) to analyze raw vibration data. This methodology significantly reduces the computational burden, achieving speedups of up to 420 times in complex structural analyses. Another critical aspect of model optimization in SHM is the efficient handling of high-dimensional data. Anaissi et al. (2021) introduced a fast parallel tensor decomposition algorithm utilizing optimal stochastic gradient descent. This technique is particularly advantageous in processing multi-way sensor data, facilitating swift and accurate structural damage identification. The proposed method demonstrated rapid convergence and scalability, making it suitable for large-scale SHM applications.

These advancements underscore the importance of adopting sophisticated computational strategies to enhance the performance and applicability of SHM systems in monitoring and maintaining structural integrity.

C. AI-Driven Smart Infrastructure and Sustainable FRP Design

The integration of AI into smart infrastructure is revolutionizing the design and sustainability of FRP systems. AI enhances the efficiency and resilience of FRP-reinforced structures by optimizing material usage and predicting performance under various environmental conditions. Li et al. (2024) explored the synergy between AI and Building Information Modeling (BIM) technologies in the context of sustainable building within smart cities. Their study highlighted that AI algorithms, when integrated with BIM, can analyze vast datasets to optimize structural designs, leading to more efficient and sustainable FRP applications. For instance, AI can simulate different loading scenarios on FRP-reinforced beams, identifying optimal configurations that minimize material use while maintaining structural integrity. In regions prone to extreme weather events, AI-driven solutions are crucial for enhancing infrastructure resilience. Habib et al. (2024) reviewed AI-based engineering approaches aimed at bolstering infrastructure in arid areas susceptible to sudden, intense rainfall. They found that AI models could predict potential failure points in FRP-reinforced structures, allowing for preemptive strengthening measures. This proactive approach not only extends the lifespan of infrastructure but also aligns with sustainable development goals by reducing the need for frequent repairs and resource consumption.

Moreover, AI facilitates the development of smart monitoring systems for FRP-reinforced structures. By deploying sensors that collect real-time data on stress, strain, and environmental factors, AI can analyze this information to detect anomalies indicative of structural degradation. Such systems enable timely maintenance interventions, thereby preventing catastrophic failures and promoting the sustainability of the built environment.

In summary, the fusion of AI with smart infrastructure design significantly enhances the sustainability and resilience of FRP-reinforced systems, offering promising avenues for future research and practical applications in civil engineering.

D. Emerging Trends: Quantum Computing for Advanced Predictive Modeling

Quantum computing is poised to revolutionize predictive modeling by leveraging principles of quantum mechanics to process complex datasets more efficiently than classical computers. In structural health monitoring (SHM), this advancement enables real-time analysis of high-dimensional data, facilitating early detection of structural anomalies. Alavi and Jayasinghe (2024) introduced a hybrid quantum-classical multilayer perceptron model that utilizes Symmetric Positive Definite (SPD) matrices on Riemannian manifolds for effective data representation in SHM. This approach ensures data integrity within the quantum computational framework, capturing nonlinear relationships and enhancing model performance. Their experiments demonstrated a significant reduction in mean squared error, indicating improved accuracy in structural analysis. In the realm of sensor optimization, San Martin Silva and Lopez Droguett (2023) developed a quantum-based combinatorial optimization framework to address the Optimal Sensor Placement (OSP) problem in civil structures. By formulating the OSP as a Quadratic Unconstrained Binary Optimization (QUBO) problem, they leveraged quantum algorithms to efficiently determine sensor configurations that maximize monitoring effectiveness. This methodology enhances the precision of data acquisition, leading to more reliable predictive models.

These emerging trends highlights the transformative potential of quantum computing in advancing predictive modeling, particularly within SHM. By enabling more accurate and efficient data processing, quantum-enhanced models promise to significantly improve the safety and resilience of critical infrastructure.

E. Future Research Opportunities in AI-Based Structural Analysis

The integration of AI into structural analysis presents numerous avenues for future research, particularly in enhancing the design and performance of composite materials and structures. Liu et al. (2020) as presented in table 5 emphasize the potential of ML models, especially Artificial Neural Networks (ANNs), in addressing complex problems such as nonlinear constitutive modeling, multiscale surrogate modeling, and design optimization. Despite existing applications, challenges persist in achieving robust and accurate data-driven designs, necessitating further exploration into efficient and reliable AI methodologies. Another promising direction involves the fusion of AI with Building Information Modeling (BIM) to revolutionize structural design processes. He et al. (2023) proposes a novel framework that integrates generative AI models, specifically diffusion models, with BIM to automate and enhance structural design tasks. This approach aims to improve the visual quality and detail of generated designs, offering a comprehensive solution that addresses current limitations in application scope and evaluation metrics. Future research could focus on refining this integration to develop intelligent structural design systems capable of assisting or even replacing traditional engineering methods. Additionally, the application of AI in real-time monitoring and predictive maintenance of structures offers substantial benefits. Developing AI-driven models that can process data from various sensors to predict structural health and preemptively identify potential failures is a critical area for future investigation. Such advancements would not only enhance safety but also extend the lifespan of infrastructure, aligning with sustainable development goals.

In summary, future research in AI-based structural analysis should concentrate on developing robust ML models for complex material behavior, integrating AI with BIM for automated design enhancements, and advancing AI applications in structural health monitoring and maintenance. These efforts will collectively contribute to more efficient, reliable, and sustainable structural engineering practices.

Table 5 Summary of Future Research Opportunities in AI-Based Structural Analysis

Research Area	Description	Potential Benefits	Example Applications
AI-Driven Material Modeling	Development of machine learning algorithms to predict nonlinear behavior, stress distribution, and failure mechanisms in composite materials.	Enhanced accuracy in material property prediction, faster computational analysis, and reduced reliance on expensive physical testing.	AI-based constitutive modeling of FRP composites for high-performance aerospace and civil engineering structures.
Generative AI for Structural Design	Integration of Generative AI models with Building Information Modeling (BIM) to automate and optimize structural designs.	Faster design iterations, enhanced sustainability, and cost-effective construction solutions.	AI-powered diffusion models generating optimized FRP-reinforced bridge designs with automated load distribution analysis.
Real-Time AI-Based Monitoring	Use of deep learning models and sensor networks for continuous structural health assessment and predictive maintenance.	Early failure detection, reduction in unexpected structural failures, and proactive reinforcement strategies.	AI-driven real-time monitoring of FRP-strengthened high-rise buildings for seismic performance optimization.
Quantum Computing in SHM	Leveraging quantum-enhanced machine learning for processing large-scale SHM datasets to optimize predictive maintenance.	Increased computational efficiency, superior damage detection accuracy, and improved data processing speeds.	Quantum-assisted optimization of sensor placements in large-scale bridge monitoring networks.

VII. CONCLUSION

A. *Summary of Key Findings*

This study explored the integration of AI in Structural Health Monitoring (SHM), particularly in FRP-strengthened systems, highlighting advancements in predictive modeling, real-time monitoring, and sustainability-driven innovations. The findings indicate that ML-driven predictive analytics, such as Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), significantly improve damage detection, fatigue prediction, and structural degradation modeling. These models facilitate the early identification of defects in FRP-reinforced infrastructure, reducing the likelihood of catastrophic failures. The integration of Digital Twin (DT) technology, Federated Learning (FL), and Edge Computing has enabled real-time monitoring, improving response times and reducing data transmission bottlenecks. Furthermore, Uncertainty Quantification (UQ) and Explainable AI (XAI) have enhanced model transparency, addressing concerns regarding trustworthiness and interpretability in AI-based decision-making. Advancements in thermomechanical and aeroelastic optimization were also reviewed, highlighting the role of quantum computing and AI-augmented smart infrastructure in improving structural resilience and efficiency. Future research opportunities were identified in AI-driven sustainable FRP design, sensor optimization using quantum computing, and generative AI for automated structural analysis. These findings emphasize the transformative impact of AI in SHM, paving the way for next-generation intelligent infrastructure systems.

B. *Contributions of ML to Structural Engineering and FRP Strengthening*

ML has revolutionized structural engineering and FRP strengthening by introducing advanced predictive modeling, automated damage detection, and real-time structural assessment. Traditional finite element modeling (FEM) approaches, while effective, require extensive computational resources and are limited in capturing complex, nonlinear material behaviors. ML algorithms, including Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), have been deployed to predict failure mechanisms, crack propagation, and fatigue life in FRP-reinforced structures with superior accuracy and efficiency. ML-based Structural Health Monitoring (SHM) systems enhance the durability of FRP-strengthened components by integrating sensor-driven anomaly detection and real-time stress-strain analysis. Deep learning architectures, such as CNNs, have been instrumental in automating the detection of delamination and fiber breakage in composite structures using high-resolution image data. Meanwhile, Physics-Informed Neural Networks (PINNs) leverage both data-driven learning and physical laws to improve thermomechanical performance modeling in FRP systems. Additionally, ML-driven predictive maintenance models optimize FRP retrofitting strategies by forecasting structural vulnerabilities under varying load conditions. These contributions facilitate the development of intelligent, resilient, and sustainable FRP-based infrastructure, significantly reducing long-term maintenance costs and structural failures while extending the lifespan of bridges, aerospace components, and high-rise buildings.

C. *Potential Impact on Aerospace and Civil Infrastructure*

The integration of ML and FRP strengthening is set to redefine aerospace and civil infrastructure, enhancing structural resilience, safety, and sustainability. In aerospace engineering, ML-driven models optimize aeroelastic and thermomechanical performance by predicting stress distribution, fatigue accumulation, and delamination in FRP-reinforced aircraft components. AI-powered structural health monitoring (SHM) systems analyze real-time flight data from composite airframes and wing spars, detecting micro-cracks before they escalate into critical failures. These advancements extend the lifespan of composite aerospace structures, improving fuel efficiency and reducing maintenance costs. In civil infrastructure, ML-based FRP strengthening enhances the durability of bridges, tunnels, and high-rise buildings. Deep learning models trained on historical failure data predict load-bearing capacity degradation, enabling proactive reinforcement scheduling. Digital Twin (DT) technology, coupled with edge computing, ensures continuous real-time monitoring of FRP retrofits, adapting to environmental stressors such as seismic activity and extreme weather conditions. Additionally, AI-driven structural optimization algorithms facilitate the lightweight yet robust design of FRP-integrated infrastructure, reducing material waste and enhancing sustainability.

These innovations transform traditional engineering methodologies, ensuring safer, more efficient, and cost-effective aerospace and civil infrastructure systems capable of withstanding complex operational and environmental challenges.

D. Final Thoughts and Policy Recommendations

The integration of ML and FRP strengthening represents a paradigm shift in structural engineering, aerospace, and civil infrastructure. Advancements in predictive modeling, real-time structural health monitoring (SHM), and AI-driven material optimization have demonstrated the potential to extend the lifespan of infrastructure, reduce maintenance costs, and enhance structural resilience. However, to fully realize these benefits, the adoption of standardized AI frameworks, regulatory guidelines, and investment in digital infrastructure is imperative. Policy recommendations must prioritize the development of AI-integrated SHM systems through government and industry collaborations. Legislative bodies should enforce AI-powered safety compliance standards, ensuring that ML-driven predictive maintenance models are adopted in aerospace and large-scale civil projects. Additionally, public and private sector investment in quantum computing for predictive analytics should be encouraged to enhance real-time failure detection capabilities. Infrastructure agencies must implement federated learning-based monitoring systems to ensure secure, scalable, and data-driven maintenance strategies. Furthermore, AI-driven FRP design protocols should be incorporated into sustainability policies, promoting lightweight, energy-efficient materials to reduce carbon footprints. By integrating AI-enhanced FRP solutions into global infrastructure development plans, policymakers can ensure structural integrity, cost efficiency, and long-term resilience in an era of rapid urbanization and climate change challenges.

REFERENCES

[1]. Aeroelastic Analysis of Actuated Adaptive Wingtips Based on Pressure-Actuated Cellular Structures. (2021). AIAA Journal, 59(1), 1-12. https://doi.org/10.2514/1.C037390

[2]. Ahmed, A., Guo, S. C., Zhang, Z. H., Shi, C. J., & Zhu, D. J. (2020). A review on durability of fiber reinforced polymer (FRP) bars reinforced seawater sea sand concrete. Construction and Building Materials, 256, 119484. https://doi.org/10.1 016/j.conbuildmat.2020.119484

[3]. Alavi, A., & Jayasinghe, S. (2024). Leveraging SPD Matrices on Riemannian Manifolds in Quantum Classical Hybrid Models for Structural Health Monitoring. arXiv preprint arXiv:2406.040 55. https://arxiv.org/abs/2406.0405 5

[4]. Almusallam, T. H., Al-Salloum, Y. A., Alsayed, S. H., El-Gamal, S., & Aqel, M. (2012). Tensile properties of glass fiber-reinforced polymer bars embedded in concrete under severe laboratory and field environmental conditions. Journal of Composite Materials, 47(4), 393–407. https://doi .org /10.1177/0021998312440473

[5]. Amer, A., & Kopsaftopoulos, F. (2021). Gaussian Process Regression for Active Sensing Probabilistic Structural Health Monitoring: Experimental Assessment Across Multiple Damage and Loading Scenarios. arXiv preprint arXiv:2106.14841.

[6]. Anaissi, A., Suleiman, B., & Zandavi, S. M. (2021). A fast parallel tensor decomposition with optimal stochastic gradient descent: An application in structural damage identification. arXiv preprint arXiv:2111.02632. https://arxiv.org/abs/2111.02632

[7]. 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.o rg/10.3390/s20102778

[8]. Bakis, C. E., Bank, L. C., Brown, V. L., Cosenza, E., Davalos, J. F., Lesko, J. J., Machida, A., Rizkalla, S. H., & Triantafillou, T. C. (2002). Fiber-reinforced polymer composites for construction—State-of-the-art review. Journal of Composites for Construction, 6(2), 73–87. https://doi.org/10.1061/ (ASCE)1090-0268(2002)6:2(73)

[9]. Balsamo, A., Coppola, L., & Zaffaroni, P. (2012). FRP in construction: Applications, advantages, barriers and perspectives. In Composites in Construction: A Reality (pp. 58–64). American Society of Civil Engineers. https://doi.org/10.10 61/4 0596(264)7

[10]. Bao, Y., Chen, Z., Wei, S., & Xu, Y. (2019). The state-of-the-art in structural health monitoring of cable-stayed bridges. Engineering Structures, 209, 110177. https://doi.org/10.1016/j.engstruct.2019.11 0177

[11]. Becker, S., Styp-Rekowski, K., Stoll, O. V. L., & Kao, O. (2022). Federated learning for autoencoder-based condition monitoring in the industrial Internet of Things. arXiv preprint arXiv:2211.07619. https://arxiv.org/abs/2211.07619

[12]. Bull, L. A., Gardner, P., Rogers, T. J., Cross, E. J., Dervilis, N., & Worden, K. (2021). Probabilistic Inference for Structural Health Monitoring: New Modes of Learning from Data. arXiv preprint arXiv:2103.01676. https://arxiv.org/abs/2103.01676

[13]. Cha, Y.-J., Choi, W., & Büyüköztürk, O. (2017). Deep learning-based crack damage detection using convolutional neural networks. Computer-Aided Civil and Infrastructure Engineering, 32(5), 361–378. https://doi.org/10.1111/mice.12263

[14]. Chao, M. A., Kulkarni, C., Goebel, K., & Fink, O. (2020). Fusing physics-based and deep learning models for prognostics. arXiv preprint arXiv:2003.00732. https://arxiv.org/abs/2003.00732

[15]. Chatzi, E., & Smyth, A. (2012). Particle filter scheme with mutation for the estimation of time-invariant parameters in structural health monitoring applications. Structural Control and Health Monitoring, 19(5), 590–608. https://doi.org/10.1002/stc.463

[16]. Cheng, Z.-Q., Tan, W., & Xiong, J.-J. (2021). Progressive damage modelling and fatigue life prediction of plain-weave composite laminates with low-velocity impact damage. arXiv preprint arXiv:2106.09096. https://arxiv.org/abs/2106.09096

[17]. Cross, E. J., Gibson, S. J., Jones, M. R., Pitchforth, D. J., Zhang, S., & Rogers, T. J. (2022). Physics-informed machine learning for structural health monitoring. arXiv preprint arXiv:2206.15303. https://arxiv.org/abs/2206.15303

[18]. Enyejo, J. O., Adeyemi, A. F., Olola, T. M., Igba, E., & Obani, O. Q. (2024). Resilience in supply chains: How technology is helping USA companies navigate disruptions. Magna Scientia Advanced Research and Reviews, 11(02), 261–277. https://doi.org/10.30574/msarr.2024.11.2.0129

[19]. Enyejo, J. O., Babalola, I. N. O., Owolabi, F. R. A., Adeyemi, A. F., Osam-Nunoo, G., & Ogwuche, A. O. (2024). Data-driven digital marketing and battery supply chain optimization in the battery-powered aircraft industry through case studies of Rolls-Royce’s ACCEL and Airbus's E-Fan X projects. International Journal of Scholarly Research and Reviews, 5(02), 001–020. https://doi.org/10.56781/ijsrr.2024.5.2.0045

[20]. Enyejo, J. O., Balogun, T. K., Klu, E., Ahmadu, E. O., & Olola, T. M. (2024). The intersection of traumatic brain injury, substance abuse, and mental health disorders in incarcerated women: Addressing intergenerational trauma through neuro psychological rehabilitation. American Journal of Human Psychology (AJHP), 2(1), 202-218. https://journals.e-palli.com/home/index.php/ajhp/article/view/383

[21]. Enyejo, L. A., Adewoye, M. B., & Ugochukwu, U. N. (2024). Interpreting Federated Learning (FL) Models on Edge Devices by Enhancing Model Explainability with Computational Geometry and Advanced Database Architectures. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(6). https://doi.org/10.32628/CSEIT24106185

[22]. Esteghamati, M. Z., Bean, B., Burton, H. V., & Naser, M. Z. (2024). Beyond development: Challenges in deploying machine learning models for structural engineering applications. arXiv preprint arXiv:2404.12544. https://arxiv.org/abs/2404.12544

[23]. Ferreira, S. R., Keller, T., Barros, J. A. O., & Sena-Cruz, J. M. (2020). Assessment of flexural crack propagation in FRP-strengthened RC beams using a predictive probabilistic model. Engineering Structures, 213, 110576. https://doi.org/10.1016/j.engstruct.2020.110576

[24]. Habib, M., Habib, A., Albzaie, M., & Farghal, A. (2024). Sustainability benefits of AI-based engineering solutions for infrastructure resilience in arid regions against extreme rainfall events. Sustainable Cities and Society. https://doi.org/10.1016/j.scs.2024.104567

[25]. He, Z., Wang, Y.-H., & Zhang, J. (2023). Generative Structural Design Integrating BIM and Diffusion Model. arXiv preprint arXiv:2311.04052. https://arxiv.org/abs/2311.04052

[26]. Ibokette, A. I., Ogundare, T. O., Anyebe, A. P., Alao, F. O., Odeh, I. I., & Okafor, F. C. (2024). Mitigating maritime cybersecurity risks using AI-based intrusion detection systems and network automation during extreme environmental conditions. International Journal of Scientific Research and Modern Technology (IJSRMT), 3(10), 1-15. https://doi.org/10.38124/ijsrmt.v3i10.73

[27]. Idoko, D. O., Danso, M. O., Olola, T. M., Manuel, H. N. N., & Ibokette, A. I. (2024). Evaluating the ecological impact of fisheries management strategies in Georgia, USA: A review on current practices and future directions. Magna Scientia Advanced Biology and Pharmacy, 12(02), 023–045. https://doi.org/10.30574/msabp.2024.12.2.0041

[28]. Idoko, I. P., Ijiga, O. M., Agbo, D. O., Abutu, E. P., Ezebuka, C. I., & Umama, E. E. (2024). Comparative analysis of Internet of Things (IoT) implementation: A case study of Ghana and the USA-vision, architectural elements, and future directions. World Journal of Advanced Engineering Technology and Sciences, 11(1), 180–199.

[29]. Igba, E., Danquah, E. O., Ukpoju, E. A., Obasa, J., Olola, T. M., & Enyejo, J. O. (2024). Use of Building Information Modeling (BIM) to improve construction management in the USA. World Journal of Advanced Research and Reviews, 23(03), 1799–1813. https://wjarr.com/content/use-building-information-modeling-bim-improve-construction-management-usa

[30]. Ijiga, A. C., Olola, T. M., Enyejo, L. A., Akpa, F. A., Olatunde, T. I., & Olajide, F. I. (2024). Advanced surveillance and detection systems using deep learning to combat human trafficking. Magna Scientia Advanced Research and Reviews, 11(01), 267–286.

[31]. Ijiga, A. C., Aboi, E. J., Idoko, P. I., Enyejo, L. A., & Odeyemi, M. O. (2024). Collaborative innovations in Artificial Intelligence (AI): Partnering with leading U.S. tech firms to combat human trafficking. Global Journal of Engineering and Technology Advances, 18(03), 106-123. https://gjeta.com/sites/default/files/GJETA-2024-0046.pdf

[32]. Iyer, H. (2022). How AI and Machine Learning Accelerate Product Development Workflows in Manufacturing. https://resources.nvidia.com/en-us-modulus-pathfactory/ai-manufacturing-pro

[33]. Kaur, G. (2024) Convolutional Neural Networks (CNN): A Comprehensive Guide. https://www.alm abetter.com/bytes/articles/convolutional-neural-networks#%22Convolutional%20Neural%20Netw orks%20in%20Deep%20Learning%22

[34]. Kumar, B., & Ghosh, S. (2020). Detection of concrete cracks using dual-channel deep convolutional network. arXiv preprint arXiv:2009.10612. https://arxiv.org/abs/2009.106 12

[35]. Li, J., Liu, Z., Han, G., Demian, P., & Osmani, M. (2024). The relationship between artificial intelligence (AI) and building information modeling (BIM) technologies for sustainable building in the context of smart cities. Sustainability, 16(24), 10848. https://doi.org/10.3 390/su162410848

[36]. Liu, X., Tian, S., Tao, F., Du, H., & Yu, W. (2020). How machine learning can help the design and analysis of composite materials and structures? arXiv preprint arXiv:2010.09438. https://arxiv.or g/abs/2010.09438

[37]. Luleci, F., & Catbas, F. N. (2022). Structural State Translation: Condition Transfer between Civil Structures Using Domain-Generalization for Structural Health Monitoring. arXiv preprint arXiv:2212.14048. https://arxiv.org/abs/2212.140 48

[38]. Moallemi, A., Burrello, A., Brunelli, D., & Benini, L. (2022). Exploring Scalable, Distributed Real-Time Anomaly Detection for Bridge Health Monitoring. arXiv preprint arXiv:2203.02380. https://arxiv.org/abs/2203.02380

[39]. Mrázová, M. (2013). Advanced composite materials of the future in aerospace industry. https://www.researchgate.net/figure/Major-monolit hic-CFRP-and-Thermoplastics-applications-11_fig2_269923249

[40]. Rosafalco, L., Torzoni, M., Manzoni, A., Mariani, S., & Corigliano, A. (2021). Online structural health monitoring by model order reduction and deep learning algorithms. arXiv preprint arXiv:2103.14328. https://arxiv.org/abs/2103.1432 8

[41]. Sajedi, S. O., & Liang, X. (2020). Model uncertainty quantification for reliable deep vision structural health monitoring. arXiv preprint arXiv:2004.05151. https://arxiv.org/abs/2004.051 51

[42]. Salameh, A., Hawileh, R., Safieh, H., Assad, M., & Abdalla, J. (2024). Elevated temperature effects on FRP–concrete bond behavior: A comprehensive review and machine learning-based bond strength prediction. Infrastructures, 9(10), 183. https://doi.o rg/10.3390/infrastructures9100183

[43]. San Martin Silva, G., & Lopez Droguett, E. (2023). Quantum-Based Combinatorial Optimization for Optimal Sensor Placement in Civil Structures. arXiv preprint arXiv:2305.08738. https://arxiv.org/ abs/2305.08738

[44]. Torzoni, M., Tezzele, M., Mariani, S., Manzoni, A., & Willcox, K. E. (2023). A digital twin framework for civil engineering structures. arXiv preprint arXiv:2308.01445. https://arxiv.org/abs/2308.0144 5

[45]. Wu, W.-P. (1991). Thermomechanical properties of fiber-reinforced plastic (FRP) bars. Graduate Theses, Dissertations, and Problem Reports, 10052. https://researchrepository.wvu.edu/etd/10052

[46]. Yoon, H., Heo, G., & Kim, J. M. (2020). Deep learning-based crack damage detection using convolutional neural networks. Computers in Industry, 115, 103180. https://doi.org/10.1016/j.co mpi nd. 2019.1 03180

[47]. Zhou, A., Xie, Z., & Bai, Y. (2023). Effects of sustained load and aggressive environmental conditions on failure mechanisms of CFRP-strengthened concrete beams. Journal of Composites for Construction, 27(1), 04022074. https://doi.org/10.1061/(ASCE)CC.1943-5614.000 1266

[48]. Zhu, Q., Dinh, T. H., Phung, M. D., & Ha, Q. P. (2021). Hierarchical convolutional neural network with feature preservation and autotuned thresholding for crack detection. arXiv preprint arXiv:2104.10511. https://arxiv.org/abs/2104.1051 1