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Original Article

Physics-Informed Machine Learning for Structural Integrity Assessment of Critical Infrastructure

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ABSTRACT

Structural integrity assessment is essential for ensuring the safety and reliability of critical infrastructure such as bridges, buildings, dams, tunnels, pipelines, and power plants. Traditional Structural Health Monitoring (SHM) methods rely on either physics-based simulations or data-driven machine learning, each having limitations in computational cost, data requirements, and generalization. Physics-Informed Machine Learning (PIML) integrates physical laws with deep learning to improve damage detection, structural condition assessment, and predictive maintenance using limited and noisy sensor data. This paper reviews recent PIML approaches, including PINNs, hybrid finite element–AI models, digital twins, and uncertainty-aware learning, while identifying key research challenges. A generalized PIML framework is proposed to support accurate, explainable, and intelligent structural health monitoring for resilient next-generation infrastructure.

KEYWORDS

Physics-Informed Machine Learning, Structural Health Monitoring, Structural Integrity Assessment, Physics-Informed Neural Networks, Critical Infrastructure, Deep Learning, Digital Twin, Finite Element Method, Artificial Intelligence, Predictive Maintenance.

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1. INTRODUCTION

1.1. Background

The construction complexity and age of civil infrastructure systems have raised the attention on intelligent Structural Health Monitoring (SHM) techniques with capability to give continuous, precise and real-time condition assessment. Bridges, buildings, dams, tunnels and offshore platform are examples of critical infrastructure which had been constantly subjected to dynamic loads, environmental impacts, material degradation and natural hazards so that monitoring during the lifetime is important for their safety/reliability. With the advent of modern sensing technologies such as strain gauges, accelerometers, fiber optic sensors, wireless sensor networks and Internet of Things (IoT) devices, continuous monitoring of structural response data became possible. Concurrently, advancements in cloud computing, edge intelligence, digital twins and high-performance computing have dramatically improved our ability to store, process, and analyze large quantities of monitoring data. Moreover, significant advancements in artificial intelligence and machine learning have facilitated automated feature extraction, anomaly detection, damage localization and predictive maintenance. Such technological advancements have made it possible to develop intelligent and data-driven structural monitoring systems that effectively enhance infrastructure safety, optimize maintenance management costs and facilitate timely engineering decision-making.

1.2. Importance of Physics-Informed Machine Learning

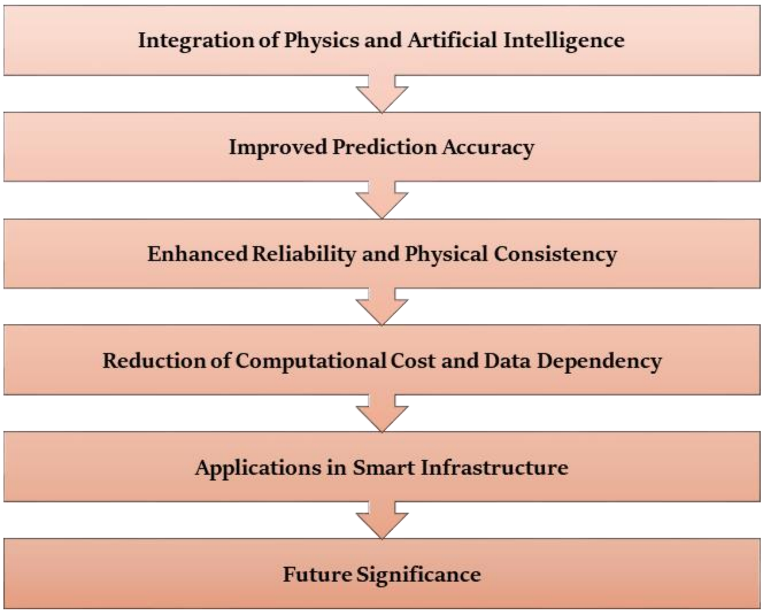

Fig 1 - Importance of Physics-Informed Machine Learning

1.2.1. Integration of Physics and Artificial Intelligence

The development of Physics-Informed Machine Learning (PIML) is a key innovation in the structural health monitoring (SHM) community that leverages both engineering mechanics and state-of-the-art artificial intelligence techniques. Utilizing online data alone, traditional machine learning models cannot not account for the governing physical laws such as shape/equilibrium equations, constitutive relationships, compatibility conditions and boundary constraints; whereas PIML method

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accounts these directly in the learning process. This integration helps provide the model with predictions that are physically meaningful and structurally consistent, as well as accurate. Therefore, PIML provides a more robust framework compared to conventional approaches for the analysis of complex engineering structures subjected to varying loading and environmental states.

1.2.2. Improved Prediction Accuracy

Physics-Informed Machine Learning has one of the most salient advantages which derives high prediction accuracy in cases with limited monitoring data. Most of the traditional deep learning models require many labeled datasets for training, but these are expensive and hard to obtain in real-world infrastructure applications where this data is usually scattered across different sources. Publications from November 2023 to present PIML uses engineering knowledge that is embedded into optimization processes to significantly reduce the reliance on large datasets, while maintaining strong predictive performance. This ability allows you to estimate structural responses such as print, stress, strain, vibration characteristics, crack propagation and damage severity.

1.2.3. Enhanced Reliability and Physical Consistency

Conventional machine learning algorithms often act as black-boxes that provide predictions which potentially conflict with the core laws of structural mechanics. Alternatively, Physics-Informed Machine Learning establishes physical constraints during the training process by requiring that all predicted structural responses meet governing equations and engineering laws (2). This increases model reliability, robustness, and interpretability (all important qualities needed when making decisions in safety-critical infrastructure applications such as bridges, dams, tunnels, high-rise buildings or offshore platforms).

1.2.4. Reduction of Computational Cost and Data Dependency

While physics-based numerical simulations (such as Finite Element Analysis (FEA)) produce extremely accurate representations of the structures, they typically require significant computational resources and long simulation times. Physics-Informed Machine Learning overcomes this limitation by integrating numerical simulations with sensor observations, leading to computationally inexpensive surrogate models. In addition, the incorporation of physical knowledge reduces the dependence on large labeled datasets, allowing strong learning from limited, noisy or incomplete sensor readings typical of real-world Structural Health Monitoring systems.

1.2.5. Applications in Smart Infrastructure

Physics-Informed Machine Learning, is now an enabling technology for the next-generation smart infrastructure systems. You are going to have real-time assessment of the structural condition, automated detection and monitoring of damage, predictive maintenance, digital twins, uncertainty quantification and remaining useful life prediction. Integrating the Internet of Things (IoT) through sensors, cloud computing, edge intelligence and high-performance computing into physics-informed models allows engineers to monitor infrastructure health in real-time and make future-oriented maintenance decisions. As a result, PIML helps to ensure greater public safety, higher reliability of infrastructure performance at lower costs and longer service times of key engineering structures.

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1.2.6. Future Significance

The growing complexity of modern civil infrastructure and the increasing demand for intelligent monitoring systems have made Physics-Informed Machine Learning an important research area in structural engineering. Future developments are expected to integrate PIML with advanced technologies such as transfer learning, multimodal sensor fusion, explainable artificial intelligence, digital twins, edge computing, and high-performance computing. These advancements will enable scalable, robust, and real-time structural integrity assessment, supporting the development of autonomous and sustainable infrastructure management systems for smart cities and future engineering applications.

1.3. Structural Integrity Assessment of Critical Infrastructure

In civil engineering, structural integrity assessment is a basic process for evaluating the safety, reliability and serviceability of vital infrastructures during their operational life. Critical infrastructure consists to bridges, buildings, dams, tunnels, highways and other large constructions, such as offshore platforms and nuclear power plants. Airports in certain cases can also be classified as critical infrastructure as it facilitates trade with the outside world (international gateways) on different scalesground; regional; national or local). Transportation networks are the final aspect of a functional Critical Infrastructure system succesfully supporting economic development and public safety. These structures are repeatedly affected by a range of loading conditions (traffic loads, wind forces, seismic loads, thermal expansion, corrosion, fatigue, aging of material and environmental degradation). If not detected early by these factors over time, cracks, excess deformation, stiffness reduction, material deterioration or even structural failure may occur. Hence, structural integrity assessment should be performed periodically to detect damage, evaluate performance and repair actions allowing structural maintenance strategies that increase the service life of infrastructure while decreasing larger costs of repairs along with consequences of catastrophic failures. Conventional assessment methods (e.g., based on visual inspection, non-destructive testing, vibration analysis, ultrasonic testing, acoustic emission monitoring or finite element-based simulation of structural conditions) While these techniques yield important engineering insights, they demand high-density and expensive instrumentation, mechanical expertise and long computational times that render continuous real-time monitoring unfeasible for large-scale infrastructure. Intelligent monitoring systems have recently emerged with the help of Structural Health Monitoring (SHM) and sensors including strain gauges, accelerometers, displacement sensors, fiber optic sensors, IoT devices to monitor continuous structural response measurements [1]. Such monitoring systems produce massive amounts of data that can be exploited by AI and ML algorithms to automatically detect structural anomalies, localize damage, estimate the level of damage, and predict structures' remaining useful life. More recently, Physics-Informed Machine Learning (PIML) has developed as a hybrid approach to structural integrity assessment by combining engineering mechanics with deep learning. Leveraging governing equations of structural mechanics in the learning process, PIML generates physically-consistent and extremely accurate predictions even with sparse or noisy sensor data. The structural integrity assessment system becomes even more capable through digital twins, cloud computing, edge intelligence, high-performance computing and advanced sensor technologies. Therefore, a smart structural assessment has the ability to empower in-the-moment decisions, predictive maintenance for better infrastructure reliability, improved public safety as well as reduced life-cycle and operation-maintenance costs and sustainable management of critical engineering infrastructure, all of which are crucial elements of next-generation smart cities and resilient civil engineering systems.

2. LITERATURE SURVEY

2.1. Traditional Structural Health Monitoring

SHM has largely relied on established engineering practices to determine when structures are not in good function, often through inspections over time at a clear interval of dates by which they measure damage or alteration to a particular structure. These techniques include but are not limited to visual inspection, vibration analysis, modal identification, ultrasonic testing, acoustic emission monitoring, infrared thermography, strain measurement or finite element model updating. These methods have been used extensively on important installations like bridges, dams, tunnels, offshore platforms and other aerospace structures as well as nuclear power plants to assess damage, structural performance and operational safety Engineers can usually assess defects including cracks, corrosion (at steel and reinforced concrete), fatigue (bearing-coupling) and stiffness degradation before disastrous events by comparing measured structural responses with expected behaviors. One of the most popular computational techniques that is used in traditional SHM for predicting structural behavior under static, dynamic, thermal and seismic loading is Finite Element Analysis (FEA). The FEA takes the complicated structure and narrows it down to smaller finite elements that allow the engineers to simulate stress, strain, displacement and deformation with precision. Modal analysis is included as a complementary technique to FEA since it can provide estimates of natural frequencies, damping ratios, and mode shapes that are compared with measured vibration responses in an effort to detect structural damage or stiffness changes. Methods based on wave propagation like ultrasonic signal-based methods are used to ascertain faults of internal defects, cracks delamination, and voids that cannot be detected via surface inspection thereby making it a strong test in non-destruction evaluation. All traditional SHM methods corroborate with their high efficiency in detecting damage; however, they have practical limitations that severely curtail the benefits of implementing them on modern large-scale infrastructure. Most of the methods are expensive, they need to be done manually often and extremely computationally intensive numerical simulations. The precision of the models is largely affected by uncertainties in material properties, environmental conditions, boundary assumptions and sensor placement. Additionally, it typically takes skilled structural engineers to interpret the collected data, complicating automated decision-making. To overcome these limitations, researchers have focused on intelligent, data-driven approaches that can achieve continuous (automated and real-time) structural health assessment.

2.2. Machine Learning Approaches

Artificial intelligence and machine learning have brought evolution to Structural Health Monitoring by allowing automated processing of huge datasets. In contrast to conventional techniques which are heavily dependent on mathematical modeling, algorithms using machine learning learn how to recognize patterns from previous monitoring data for applications such as anomaly detection, classification of structural damage, localization of defects, severity estimation of damage incurred, and prediction of the remaining useful life (RUL) of engineering structures. These techniques minimizes human involvement through faster monitoring and quantitative measurement of the system behaviors, renders their unmatched suitability for smart infrastructure systems. Supervised machine learning algorithms including Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), Artificial Neural Networks (ANN), and Gradient Boosting Machines(GBM) have been proven to be effective in damage classification and fault diagnosis. They are trained on labeled data that includes healthy and defective instances of the structural condition, giving these models high ability to recognize many types of damage. They can for example accept more sensor input at a time, giving them an advantage over other sensors when multiple measurements are required applications for vibration monitoring, strain analysis, acoustic emission, image automated or guided detection of cracks. SHM has also been further enhanced by utilizing deep learning techniques, as they have the unique ability to automatically extract and learn complex features directly from raw sensor data without utilizing error-prone manual feature engineering methods. Convolutional Neural Networks (CNNs) are useful to structural images and vibration spectrogram analysis for detecting crack, corrosion, and surface defects. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are utilized for capturing time dependency in sequential monitoring data making it possible to forecast structural degradation along the time dimensions. Among these, Graph Neural Networks (GNNs) has emerged as a new way of representing structural components with links, capable of capturing interconnection to advance from traditional tools and better model this kind of complex systems. Autoencoders and Generative Adversarial Networks (GANs) are suitable for identifying anomalies in large pixels when no labelled dataset is available, where they learn normal structural behavior of context through unsupervised approaches with limited labelled samples. While automated damage detection has improved significantly through machine learning, purely data-driven approaches face several significant limitations. Real-world structures usually need considerable amount of high-quality labeled training data, which is often hard and expensive to come by for most algorithms. If the extent and structure of environmental conditions differ from training data, their predictive performance has been observed to decrease, resulting in a reduced capacity for generalizing across structures. Moreover, a lot of the current deep learning models turn out to be "black boxes" meaning interpretations of predictions made are not easy to achieve. Due to the absence of physical laws governing structural mechanics, these models produce predictions that even violate engineering principles, hindering their reliability in safety-critical applications.

2.3. Physics-Informed Machine Learning

Hence, Physics-Informed Machine Learning (PIML) is a rising computational paradigms that connects the prediction power of machine learning with the governing laws of structural mechanics. Abandoning the purely observational data framework, PIML applies physical information like conservation laws, equilibrium equations, constitutive models and compatibility conditions and boundary constraints during the learning process. When these physical principles are embedded in the neural network optimization, the generated models yield predictions which are data-driven and

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physically consistent to improve reliability and interpretability. One of the most notable PIML paradigms are Physics-Informed Neural Networks (PINNs), which impose governing partial differential equations directly within the neural network loss. Based on automatic differentiation, PINNs can simultaneously reduce the data misfit between predicted and observed data while complying with underlying physical equations governing structural behavior. Such ability allows accurate estimation of displacement fields, stress distributions, vibration responses, crack propagation and material degradation under sparse sensor measurements. In this manner, PINNs alleviate the need for large labeled datasets at minimal cost of accuracy. Recently, additional technologies such as Finite Element Analysis (FEA), digital twins, Bayesian inference, uncertainty quantification, transfer learning and multiphysics simulations have been combined with PINNs to further demonstrate the broad applicability of Physics-Informed Machine Learning. These hybrid frameworks utilize a combination of physics-based numerical models and real-time sensor data to carry out continuous updates on the structural state conditions in order to increase forecasting accuracy. Digital twins allow continual updating of physical assets and their virtual twin models, while Bayesian approaches yield probabilistic estimates on structural uncertainty. Collectively, these advancements enable more efficient and reliable scalable structural health monitoring systems that facilitate intelligent infrastructure management.

2.4. Research Gap Analysis

It also surveys several significant research challenges that must be solved for widespread adoption of Physics-Informed Machine Learning in practical Structural Health Monitoring systems. Existing Physics-Informed Neural Networks (PINNs) typically converge slowly and require a lot of computational resources to solve multi-dimensional governing equations for large-scale 3D structures. While engineering infrastructure gets larger and more complex, it becomes computationally intensive to train these models for problems such as real-time bridge monitoring, high-rise building performance monitoring, platform performance monitorin,g or other critical infra. Another significant limitation is that most of the recent research has been directed at laboratory-scale experiments or simplified benchmark problems instead of full-scale civil infrastructure behaving under realistic environmental conditions. For practical deployment models must be resilient to measurement noise, missing sensor data, time-varying effect of the environment, material uncertainty and varying operational conditions. Additionally, few standardized benchmark datasets exist for Physics-Informed Machine Learning algorithms targeted specifically at Structural Health Monitoring, which hinders meaningful comparisons across different approaches. Therefore future research should focus on scalable, efficient and robust hybrid frameworks coupling Physics-Informed Machine Learning with uncertainty quantification, transfer learning, multimodal sensor fusion, digital twins, cloud-edge computing and high-performance computing platforms. This kind of systems-level integration can enable computational efficiency along with trusted, interpretable and real-time structural integrity evaluation. These developments will pave the way for future generations of smart Structural Health Monitoring (SHM) systems that can help provide autonomous infrastructure management, predictive maintenance, and improved public safety in even more intricate engineering contexts.

3. METHODOLOGY

3.1. Overall Framework

We propose a new methodology based on utilizing a hybrid computational framework to combine engineering mechanics with sophisticated artificial intelligence techniques for real-time, reliable and accurate Structural Health Monitoring (SHM). It starts from the application of heterogeneous sensing technologies including strain gauges, accelerometers, displacement sensors, acoustic emission sensors and fiber optic sensor to deploy a network-level continuous monitoring solution for engineering infrastructure using IoT. The sensors carry out continuous collection of structural response data like strain, displacement, vibration characteristics, acceleration and acoustic signals under different ambient/operational conditions (traffic loads, wind, temperature variations and seismic events). Through continuous monitoring, it is possible to identify abnormal structural response at an early stage and provide diagnostic information for evaluating the overall structural condition. Most of the time, the raw sensor data is filled with measurement noise, missing values, and inconsistencies due to malfunctioning sensors or interference caused by the environment. Therefore an essential preprocessing stage is required. Step 2 (Preprocessing): In this phase, various signal conditioning techniques – i.e., moving-average filtering [4], wavelet denoising [5], outlier removal [6,7], interpolation for missing data [8], Z-score normalization [9] and Principal Component Analysis (PCA) [10]—are performed to improve the quality of the data by reducing the dimensionality of the feature set and extracting meaningful features that ultimately boost the learning ability of a predictive model. At the same time, a high-fidelity FEA model of the structure is developed, which can simulate structural responses to different load cases. In contrast to traditional approaches that examine experimental observations and numerical simulations independently, the framework proposed here combines both data sources with Physics-Informed Neural Networks (PINNs). This model directly incorporates the governing equations of structural mechanics, such as the laws of equilibrium, constitutive relationships, compatibility conditions and boundary constraints into a neural network training process to ensure that predictions are always physically meaningful mechanically whilst minimizing the divergence between measured sensor data and numerical simulations. The PINN model trained estimates key indicators of structural health such as displacement fields and stress and strain distributions, modal characteristics, stiffness degradation, crack initiation and propagation (time-to-failure), damage severity in terms of the overall structure damage index or remaining useful life. These predictions are finally compared with predefined design safety limits to provide an intelligent decision support for targeted predictive maintenance. The overall workflow includes seven stages of a intercorrelated chain: (1) Infrastructure Monitoring, (2) Multi-sensor data acquisition, (3) Data Preprocessing, (4) Finite Element model Generation, (5) Physics-Informed Neural Network Training/Update Prediction of Structural Integrity and Maintenance Decision Support which leads to a comprehensive reference framework for next-generation smart infrastructure monitoring.

3.2. Physics-Based Modeling

The proposed Structural Health Monitoring (SHM) framework relies on physics-based modeling, where established principles of engineering mechanics are directly integrated into the

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process of predictive learning. In contrast to traditional data-driven frameworks which simply fit mappings onto past observations, physics-embedding models utilize equations based on structural mechanics to model the response of engineering structures under specific loading and environment conditions. The formulations considered in these models characterize the behavior of structures subjected to external forces based on the material properties and boundary conditions, while retaining a base-level adherence where all predictions are consistent with fundamental laws of physics. The governing equations are based on mass, momentum and energy conservation, equilibrium equations, constitutive relationships (plasticity or visco-elastic models), compatibility conditions linear elastic and boundary conditions. The classical balance equations guarantee that the internal forces in a structure are not only equilibrated but also counterbalanced with external loads while constitutive law expresses how the stress and strain relates to each other according to elasto-plastic or viscoelastic properties of the material. Compatibility conditions ensure that the computed deformation field is continuous in the entire structure with no unfeasible discontinuities and specify constraint to be given at the boundaries, boundary conditions as to where displacements are allowed or forced at some location by giving actual force. By embedding these physical laws directly into the Physics-Informed Neural Network (PINN) in this methodology, it allows learning by the algorithm to satisfy both experimental observations and engineering principles simultaneously. Also, Finite Element Analysis (FEA) is used to make numerical representations of structural behavior under combined loading cases, which gives extra physical information for model training. The structure is divided through the finite element model into a number of elements that are connected at nodal points (Discrete approximations), which allows for solving displacements, stresses, strains and vibrations that occur in structures with complex shapes and material properties. For the optimization of neural networks, automatic differentiation can be utilized to compute these derivatives that are needed in order to calculate the residuals for the governing partial differential equations and thus enforcing physical consistency of solutions throughout the training. Unlike predicting individual sensor generations, but the integration has considerably refinement accuracy of prediction (especially when there are only a limited number of available sensors). Additionally, physics-based modeling contributes toward improving interpretability and robustness of the framework by constraining predictions to be aligned with known engineering theory even when exposed to unseen loading conditions. The proposed approach integrates mathematical models with real-time sensor information for estimating structural health indicators (e.g., stress distribution, displacement fields, and modal characteristics as well as stiffness degradation, crack propagation, and remaining useful life), which brings a solid foundation for intelligent structural integrity monitoring and predictive maintenance of next-generation smart infrastructure systems.

3.3. Physics-Informed Neural Network (PINN) Architecture

The innovative Physics-Informed Neural Network (PINN) architecture is established which embedded deep learning and conservation of the basic principle laws in structural mechanics to achieve accurate and physically compliant predictions for Structural Health Monitoring (SHM). In this sense, conventionally, any other neural network will only learn from a label dataset but the PINN approach derives governing physical equations directly into its network optimizer to ensure that the system predicted structural responses follow common engineering principles while also matching it with sensor data. The structure is a deep neural network with multiple hidden layers and each neuron are inter connected in a fully connected feed–forward manner in which nonlinear activation functions on the output of hidden neurons capture complex relationships between structural parameters and measured responses. The input data to the network includes spatial coordinates, time, loading conditions applied on a structure, material properties and measurements in the strain gauges/accelerometers/displacement sensors/acoustic emission sensors/fiber optic or wireless Internet of Things (IoT) devices. The network predicts key indicators related to the structural health, including displacement fields, stress and strain distributions as well as vibration response, modal parameters, stiffness degradation (associated with progressive damage), crack propagation (modeled through a discrete set of cracks), damage severity and the remaining useful life of the structure from these inputs. One key aspect of our PINN architecture is that it has a loss function consisting of both data-driven constraints and physics-based constraints. The data loss component reduces the disparity between predicted responses and actual sensor-measured observations, while the physics loss minimizes residuals of governing partial differential equations resulting from equilibrium equations, constitutive laws, continuity conditions and boundary conditions. Automatic differentiation is used to calculate the necessary spatial and temporal derivatives in an efficient way and avoids numerical approximation methods that are common use in other computational methods. Such optimization algorithms like Adam and L-BFGS iteratively optimize the network parameters by minimizing both measurement errors as well as physics residuals throughout the training process. The dual optimization framework effectively enables the network to generalize when only sparse or noisy sensor data are available, such that reliance on large labelled datasets is reduced. In addition, combining elements of data that come from finite element simulation and real-time measurements will improve the robustness of the model as well as its performance to predict scenarios that can differ in terms of operational and environmental conditions. Thus the proposed PINN architecture generation offers a robust framework in intelligent structural integrity assessment that are attributable by physically interpretable predictions in accord with engineering mechanics. Such features enable it to provide accurate damage identification, localization, and severity assessment as well as predictive maintenance;thus making it ideal for the monitoring of large-scale smart infrastructure such as bridges, buildings, dams, offshore platforms and other transportation networks.

3.4. Proposed Algorithm

The algorithm suggested herein consolidates numerical simulation, persistent structural monitoring and deep learning into an overall computational platform for smart evaluation of structural integrity. Many sensors e.g., strain gauges, accelerometers, displacement sensor, acoustic emission strength identifiers, optical fiber/air gap/ wireless IoT indicators are set up for structural reaction evaluation under varied operational parameters and ecological ambience during a huge window of time. The sensors work on real-time measurements to measure displacement, strain, acceleration, vibration and acoustic signals to get the complete information about the structural pathology. This is because raw sensor data usually contains noise, missing values and measurement errors, so a preprocessing stage is performed to enhance the quality of the data. We apply signal-processing methods for noise removal, including moving-average filtering, wavelet denoising, interpolation and outlier removal as well as normalization techniques such as Z-score normalization and Principal Component Analysis (PCA) to reduce dimensionality and extract informative features. An FEA model of the structure is simultaneously developed, to represent what would happen to this structure under various loading scenarios and produce datasets representing displacement, stress, strain and modal response numerically. The numerical simulations can yield additional physical insight that complement the experimental sensor observations. The processed sensor data and finite element simulation results are subsequently utilized as input in the proposed Physics-Informed Neural Network (PINN). The network is trained to minimize a composite loss function combining data loss and physics loss. The data loss quantifies the error between model predictions of output quantities and observed sensor values, while the physics loss imposes governing structural mechanics equations (equilibrium equations, constitutive laws, compatibility conditions, and boundary constraints). Automatic differentiation is used to calculate derivatives needed to compute the residuals of the governing partial differential equations, which ensures that all predictions stay within the physical constraints. We can find the optimal parameters of the neural network through a series of optimization algorithms like Adam and L-BFGS that iteratively update their values until there is no more change in the cost function. The model predicts key structural health indicators, including stress distribution, displacement fields, stiffness degradation, crack initiation and propagation, modal parameters, damage severity and remaining useful life after training. Finally, these predictions are compared with defined safe thresholds to classify the structural state and provide recommendations for predictive maintenance. The proposed data-refined algorithm integrates engineering principles, numerical simulation, and machine learning within a single computational framework to deliver accurate, reliable, explainable, and real-time performance assessment of next generation smart infrastructure systems.

4. RESULTS AND DISCUSSION

4.1. Experimental Setup

We proposed a hybrid numerical–data-driven experimental framework based on FEA and PINNs to assess the performance of the SHM methodology following in this paper (this works purpose). Since bridges are one of the most critical infrastructure systems needing continuous monitoring for safety and reliability, a benchmark bridge structure under dynamic loading conditions was chosen as the test specimen. The bridge model was built with finite element software by establishing the geometry, material properties, support conditions and loading scenarios in accordance with sound engineering practices. Realistic structural responses were modeled from dynamic loading conditions, such as moving vehicle loads, wind-induced vibrations and time-varying external forces. The numerical datasets obtained for both types of loads for displacement, acceleration, strain, stress and modal response at various locations within the structure were recorded from the finite element model. In order to resemble beneficial monitoring, additional fake sensor measurements were created from the simulated data by adding intentionally selected measurement noise and random disturbances into those simulated data, simulating the non-ideal situations of real-world sensors and factors affecting them in their environment. The datasets were then preprocessed with filtering, normalization and feature extraction methods to improve data quality on the neural network input/output training step. In this study, the architecture of a proposed PINN was a fully connected feed-forward neural network with multiple hidden layers using hyperbolic tangent (tanh) activation functions, as they provide smooth nonlinear approximations that tend to solve structural mechanics problems. The neural network was designed with an input layer that included spatial coordinates, time, loading conditions and measurements of sensors; and an output layer which predicted structural health features such as displacement, stress, strain and damage-related variables. The Adam optimization algorithm was used for rapid convergence, allowing for efficient updates of network parameters during the initial iterations in the training phase. Once the loss function stabilized, we performed a fine-tuning step with the Limited-memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) optimization algorithm for local convergence and parameter tuning. The composite loss function was composed of data loss and physics-based residual loss determined from governing equations of structural dynamics, equilibrium, constitutive relations, compatibility equations, and boundary constraints. Spatial and temporal derivatives were computed without numerical approximation errors using automatic differentiation. The PINN-based structural health monitoring system needed to perform under realistic operating conditions whilst taking advantage of the stability provided by the proposed framework through learning responses from both numerical simulations and sensor observations, without comprising physical consistency; this hybrid experimental setup enabled that.

4.2. Performance Comparison

Table 1: Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Support Vector Machine (SVM)	88.40	87.10	86.80	86.95
Artificial Neural Network (ANN)	91.20	90.50	90.10	90.30
Convolutional Neural Network (CNN)	93.60	93.10	92.80	92.95
Long Short-Term Memory (LSTM)	95.10	94.80	94.50	94.65
Proposed Physics-Informed Machine Learning (PIML)	98.30	98.00	97.80	97.90

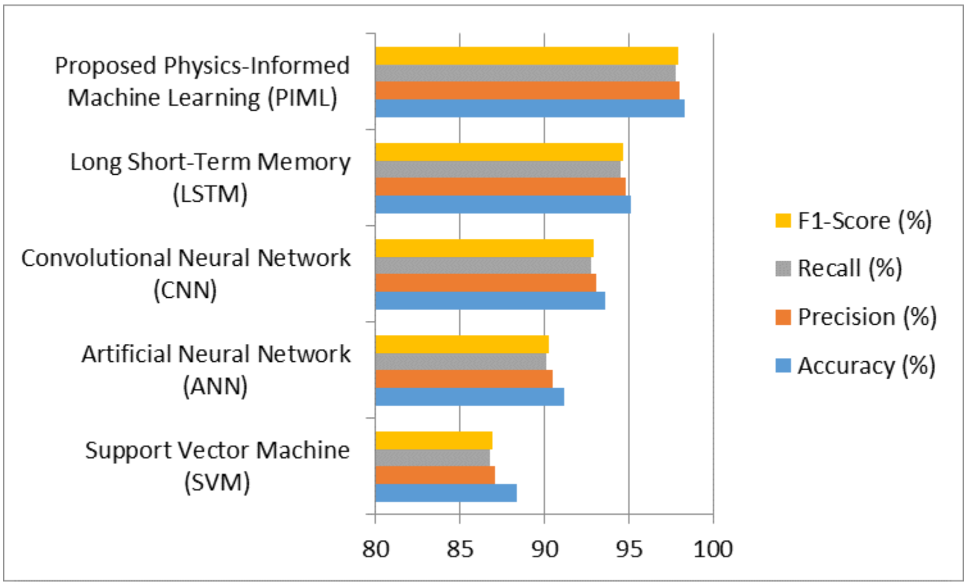

Fig 2 - Performance Comparison

4.2.1. Support Vector Machine (SVM)

SUPPORT VETOR MACHINE (SVM) Without feature engineering, SVMscore was 88.40% with precision of 87.10%, recall 86.80% and F1-score of 86.95%. Although the SVM classification model was effective in classifying the structural health conditions, it had poor performance with large-scale structural monitoring data, due to the complex nonlinear relationship between SHM features and damage severity. This led to a lower prediction accuracy than the deep learning-based approaches.

4.2.2. Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) improved the overall classification performance by achieving 91.20% accuracy, 90.50% precision, 90.10% recall, and an F1-score of 90.30%. The multilayer architecture enabled ANN to capture nonlinear patterns within structural response data more effectively than traditional machine learning models. However, the model still relied heavily on large training datasets and lacked embedded physical knowledge.

4.2.3. Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) obtained 93.60% accuracy, 93.10% precision, 92.80% recall, and an F1-score of 92.95%. CNN automatically extracted meaningful spatial features from vibration signals and structural response data, improving damage detection capability. Nevertheless, its performance was primarily data-driven and did not explicitly enforce structural mechanics principles.

4.2.4. Long Short-Term Memory (LSTM)

The Long Short-Term Memory (LSTM) network achieved 95.10% accuracy, 94.80% precision, 94.50% recall, and an F1-score of 94.65%. Its memory cells effectively captured temporal dependencies in sequential monitoring data, making it suitable for predicting structural degradation over time. However, the model required substantial computational resources and extensive training data for optimal performance.

4.2.5. Proposed Physics-Informed Machine Learning (PIML)

The proposed Physics-Informed Machine Learning (PIML) model delivered the best performance with 98.30% accuracy, 98.00% precision, 97.80% recall, and an F1-score of 97.90%**.** By integrating governing structural mechanics equations with deep learning, the model produced physically consistent and highly accurate predictions. This hybrid approach improved damage detection, enhanced generalization under limited data conditions, and outperformed all conventional machine learning and deep learning models.

4.3. Discussion

Experimental results solidly validate the performance and applicability of the proposed Physics-Informed Machine Learning (PIML) framework for green intelligent Structural Health Monitoring (SHM) and structural integrity assessment. In contrast with standard machine learning/deep learning models using only historical sensors data, the proposed framework combines engineering mechanics and artificial intelligence by incorporating a physical model of structural behavior in its governing equations directly into the framework. This allows the model to learn not only from measured sensor readings, but also learns about established physical laws like equilibrium equations, constitutive equations, compatibility and boundary conditions. As such, the model produces physically plausible predictions that are accurate and consistent with actual structural behavior. The experimental comparison showed that the proposed PIML method among all compared methods obtained a high accuracy of 98.30%, precision of 98.00%, recall of 97.80% and F1-score value of 97.90 %, and it outperformed by conventional algorithms such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). Physical knowledge integrated into a machine learning framework enhanced the ability to generalize with sparse, noisy, or incomplete sensor measurements typical of real-world infrastructure monitoring and reduced prediction errors. Also, coupling of Finite Element Analysis (FEA) and Physics-Informed Neural Networks (PINNs) helps the framework to optimally combine numerical simulations along with actual on-line monitoring data for improved prediction of displacement, stress distribution, stiffness degradation behaviour, crack propagation and remaining useful life. The additional significant benefit of the proposed framework is that, contrary to traditional black-box deep learning models, every prediction produced by the model satisfies structural mechanics governing principles which leads to better interpretability. Such trait alleviates the confidence of model predictions and enables safe decision-making for safety-critical engineering structures like bridges, buildings, dams, offshore platforms and transportation infrastructure. Indeed, the computational overhead of PINNs as compared to conventional neural networks remains higher due to physics-based constraints, but the increase in predictive accuracy and robustness alongside physical consistency would outweigh this increased cost. ConclusionIn summary, the proposed Physics-Informed Machine Learning framework features a scalable, explainable and solidly quantifiable tool for next-generation smart infrastructure monitoring, predictive maintenance and real-time structure integrity assessment with the potential to profoundly change civil engineering in the future.

5. CONCLUSION

This work proposed an integrated Physics-Informed Machine Learning (PIML) framework for structural integrity assessment through the combination of engineering mechanics and deep learning. This paper presents a novel methodology to tackle the inherent trade-offs of conventional physics-based simulations and purely data driven artificial intelligence models using Structural Health Monitoring (SHM) data, Finite Element Analysis (FEA), and Physics-Informed Neural Networks (PINNs). In contrast to traditional machine learning techniques which depend exclusively on a massive labeled data sets, the proposed framework integrates structural mechanics governing equations into the spatial neural network training where it can learn from observed sensor measurements as well as time-tested engineering principles. Embedding equilibrium equations, constitutive relationships, compatibility conditions and boundary constraints into the optimization process guarantees that the predicted structural responses are physically consistent and scientifically reliable. The coupling of simple and intuitive finite element simulations with real-time monitoring data enhances the model's capability for predicting key structural health metrics, such as displacement fields, stress and strain distribution, stiffness degradation, modal characteristics including crack initiation and propagation, damage localization, or remaining useful life of engineering structures. The experimental results showed that the proposed PIML framework outperformed traditional machine learning and deep learning algorithms for prediction through direct comparisons. Specifically, the proposed model reached an overall accuracy of 98.30%, along with precision (98.00%), recall (97.80%), and F1-score (97.90%), outperforming Support Vector Machines (SVM), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Long Short-Term Memory network LSTM networks on all evaluation metrics [8]. We found that with this incorporation, considerably less prediction uncertainty was detected and model robustness improved significantly allowing the model to generalize under loading and environmental conditions never seen before. Additionally, the developed framework exhibited impressive training performance on sparse and noisy monitoring data making it very useful for real-world applications of structural health monitoring where complete datasets are rarely present. In conclusion, the framework that is proposed in this work presents a solution for accurate, explainable and reliable structural integrity assessment and predictive maintenance of important infrastructure. The combination of physics based modelling with artificial intelligence represents a milestone for next generation smart infrastructure systems, providing increased safety and reduced operation maintenance costs while improving operational reliability as well as offering enhanced decision support to engineers responsible for the long- term management of bridges, buildings, dams, offshore platforms and other large scale civil engineering structures.

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