ARTICLE | **OPEN ACCESS**

Indian journal of
Engineering

HESTIA: Hybrid Edge-Supported Twin for Infrastructure Analysis using Graph and Temporal Networks

Melsiline Reeba Melkias[1], Subha Hency Jose Paul[1], Mano Jemila Manoharan Rethnabai[2], Lawrence Kebila Anns Subi[3], Anantha Christu Raj Palayyan[4]*, Sweety Jose Paul[5]

To Cite:
Melkias MR, Paul SHJ, Rethnabai MJM, Subi LKA, Palayyan ACR, Paul SJ. HESTIA: Hybrid Edge-Supported Twin for Infrastructure Analysis using Graph and Temporal Networks. *Indian Journal of Engineering*, 2026, 23, e2ije1708
doi: https://doi.org/10.54905/disssi.v23i59.e2ije1708

Author Affiliation:
[1]Division of Biomedical Engineering, Karunya Institute of Technology and Science, Coimbatore, Tamilnadu, India
[2]Department of Electrical and Electronics Engineering, Dr.N.G.P. Institute of Technology, Coimbatore, Tamilnadu, India
[3]Department of Electronics and Communication Engineering, Ponjesly College of Engineering, Nagercoil, Tamilnadu, India
[4]Division of Robotics Engineering, Karunya Institute of Technology and Science, Coimbatore, Tamilnadu, India
[5]Department of Electrical and Electronics Engineering, PSG College of Technology, Coimbatore, Tamilnadu, India

***Corresponding author:**
Anantha Christu Raj Palayyan,
Division of Biomedical Engineering, Karunya Institute of Technology and Science, Coimbatore, Tamilnadu, India; Email: anantha@karunya.edu

Peer-Review History
Received: 30 July 2025
Reviewed & Revised: 16/August/2025 to 18/January/2026
Accepted: 07 February 2026
Published: 21 February 2026

Peer-Review Model
External peer-review was done through double-blind method.

Indian Journal of Engineering
pISSN 2319–7757; eISSN 2319–7765

DISCOVERY
SCIENTIFIC SOCIETY

ABSTRACT

For ensuring real-time structural health monitoring (SHM), there is a need of reliable framework that balances interpretability, computational efficacy, and adaptability. As an effort, this paper introduces "HESTIA", a novel hybrid edge-supported twin for infrastructure analysis which integrates physics-based reduced-order-models with advanced edge-deployed deep learning. Importantly, the proposed methodology is suitable for monitoring progressive damage such as cracks and fatigue, which are critical indicators of structural weakening. Additionally, The HESTIA approach is highly applicable in areas like lab prototypes, scaled models, and campus SHM testbeds. The embedded digital twin offers state estimation and uncertainty quantification. On the other hand, two AI components – Graph Neural Network (GNN) is utilized for structural topology representation and Temporal Convolutional Network (TCN) aids in effective time-series analysis. This hybrid combination enables accurate modelling of both spatial dependencies & temporal evolution across sensor nodes and structural responses. Next, the outcome of digital twin and networks are fused via the Bayesian ensemble strategy for robust anomaly detection and early damage identification. The HESTIA architecture is optimized with Harris Hawks Optimization (HHO) that leverages feature reweighting and decision threshold tuning. Overall, the suggested model demonstrates its potential in next-generation SHM solution for pro-active infrastructure maintenance through attainment of 85 ms in inference time, 5% in computational overload, and competitive anomaly detection rate of 93%. Further, the approach inhibited a superior recital of specificity 96.2%, precision of 93.1%, and accuracy of 92.6% making it a reliable option for real-time SHM applications.

Keywords: Hybrid digital twin, graph neural network, temporal convolutional network, edge AI, Bayesian fusion, real-time structural analysis, civil infrastructure, digital twin, crack detection, fatigue identification, scaled models, campus SHM testbeds, and structural health monitoring.

1. INTRODUCTION

Structural Health Monitoring (SHM) has emerged as one of the significant areas within current engineering practices for the safety, sustainability, and durability of major infrastructures (Plevris & Papazafeiropoulos, 2024; Mata et al., 2021). With the complexity and size of large civil infrastructures like bridges, aerospace applications, power generation stations, and industrial production facilities rising rapidly, the need for intelligent monitoring systems has grown remarkably (Bado & Casas, 2021; Mardanshahi et al., 2025). Detecting potential structural weaknesses or damage at the earliest can lead to the prevention of dramatic failure and reduce maintenance costs in the long run (Ogunnowo et al., 2024). In such developments, the role of SHM has transformed from being a subordinate to the basic need of design and management in engineering (Wang & Ke, 2024).

There exist some traditional SHM approaches that involve essentially deterministic modeling approaches, signal processing, and a process called visual inspection, which is often not sufficient under complex real-world settings (Mardanshahi et al., 2025). They often consume a significant amount of time and might be costly and inefficient in adapting themselves to different environmental and operational settings in which structures work (Goti, 2025). Moreover, those procedures often lack understanding the interactions between multi-sensor information flows and the behavior of structures dynamically that is a requirement in accurate anomaly identification (Moldovan & Iantovics, 2025). There exists an apparent requirement for an adaptive and intelligent system capable of processing large-scale heterogeneous information and extracting useful patterns out of this information.

To overcome these limitations, recent breakthroughs in SHM communities were introduced by the application of data-driven intelligence enabled by Deep Learning (DL) techniques (Khatir et al., 2025; El-Abbasy, 2025). Compared to conventional models, intelligence-driven techniques, including Deep Learning, are competent enough to capture subtle and non-linear patterns in the large volume of sensed data and ensure high accuracy and adaptive health condition monitoring (Chen et al., 2024; Han et al., 2025). The major demerit with the current models, including Deep Learning, is they are mostly dedicated to analyze either space-related attributes or temporal properties (Kumar et al., 2024). To enable the overall observation, an emerging trend towards the application of hybrid models, considering space-related properties and temporal attributes at the same time, would provide an overall output addressed by structural dynamics (Jadhav et al., 2024; Kumar et al., 2024). To overcome this problem, a methodology involving a combination of a TCN and a GNN is proposed. A GNN captures the spatial interdependence between dispersed sensors as a graph, and a TCN captures changes in sensor readings such as acceleration, strain, and temperatures. Both of these components, when combined, enable the end-to-end modeling of the spatio-temporal aspects of structural behavior.

Finally, the work proposed also highlights the need to integrate graph-based spatial learning, temporal modeling, probabilistic feature fusion, and intelligent optimization in a single paradigm. In the proposed approach, the potential to overcome the difficulties of noisy input, dynamic environment, and large-dimensional inputs has been showcased, which can pave the way for real-time and trustworthy anomaly detection for critical infrastructures. Additionally, the approach has been set up to be applicable for laboratory-scale models or campus-scale testbeds for structural health monitoring.

The outline of this paper is described as follows: The literature survey is described in detail in section 2. This section focuses on modern approaches to spatiotemporal modeling and optimization in SHM and Fault Detection Systems. Section 2 also states the main research gaps that form the basis for this research. Section 3 defines the intended methodology, wherein the functions of GNN and TCN as feature extractors are described, followed by Bayesian Feature Fusion for fusing heterogeneous features and the HHO for optimization of parameters. Section 4 describes experimentation configuration and performance evaluation, where thorough comparisons of the proposed model with existing benchmark techniques using multiple metrics are furnished to validate its efficiency, accuracy, and robustness. Finally, Section 5 concludes the major contributions and results, and it also discusses future research directions for improving scalability, flexibility, and real-world implementation of the proposed framework.

The objectives of the current research are as follows:

- To combine Graph Neural Networks and Temporal Convolutional Networks to achieve efficient spatial–temporal feature learning in detecting cracks and fatigue in laboratory structures and campus SHM testbeds.
- To utilize Bayesian Feature Fusion in the fusion of spatial and temporal features, promoting robustness against noise and uncertainty.
- To optimize model parameter and convergence efficiency with the Harris Hawks Optimizer.
- To test the proposed framework on standard datasets, promoting accuracy, scalability, and real-time suitability.

2. LITERATURE REVIEW

In the domain of civil structure health monitoring, countless research works are carried out at present and this section addresses a few of them. First of all, Anjum et al., (2024) made a comprehensive review of scope of Machine Learning (ML) in Civil SHM. The authors aimed to study different ML-based approaches and their strategies in solving complex problems that rise in civil structures. Similarly, Sakr & Sadhu (2024) investigated the recent progress and future outlook of digital twins (DTs) in SHM of civil infrastructure. The authors reviewed various concepts like 3D representation, surrogate & hybrid modelling, finite element modelling, applications related to DTs in SHM, limitations, and future scope of DTs in SHM.

Bader et al., (2025) examined how AI-ML algorithms work in improving structural health monitoring. Focusing on crack detection and prediction, the authors further developed a framework based on CatBoost and African Vultures Optimizer that was tested on a dataset with 8, 541 rows with diverse attributes. Liu et al., (2025) developed "MA-CNN-BiLSTM", a Multi-head Attention based Convolutional Neural Network (CNN) with Bidirectional Long and Short Term Memory (BiLSTM) model for reconstructing the missing acceleration response data. When compared with baseline LSTM and BiLSTM, the proposed hybrid approach is found to outperform those interms of reconstruction accuracy in both frequency and time domains.

ACNN-based damage classification architecture for multi-part strengthening system was introduced by Holsamudrkar & Banerjee (2024). Through effective usage of image-based waveform data from Acoustic Emission (AE) testing for training of CNN, the waveform is transferred to Discrete Wavelet Transform (DWT) scalogram for analysis. The model yielded an accuracy of 95% in training and 87% in testing phase which was considered a positive attempt as noise was added in testing set. Duran et al., (2024) designed a Transfer Learning (TL)-based CNN approach for detecting and classifying structural damage in civil structures. During the evaluation process, the technique attained a correctness of 1.0 in a ten-label multi-class categorization role but degraded when the model was subjected to different geometry structures.

Ahmadzadeh et al., (2025) utilized multisensory time-series data integrating 1D CNN and LSTM for monitoring structural health and identifying structural damages. The proposed model attained an exactness of 99.6% in identifying damage pattern and 96.6% in localizing damages. A 1D structural damage detection algorithm oriented on Residual Network (ResNet) was built by Xia & Huang (2025). Verified using the numerical simulation of steel truss structure, the designed framework reached an accuracy of 90% proving the superiority in identifying damages in beams.

Singh et al., (2024) developed a hybrid DL model integrating attention mechanisms, GoogleNet, and ResNet50 for improved structural damage recognition. Introduced with primary focus to enhance the recital and accuracy, the suggested model possessed good score in all metrics like F1-score, exactness, recall, and exactitude. At present, transformer-based approaches are becoming popular where the one designed by Wang et al., (2025) based on Bidirectional Gated Current Unit (BiGRU) is a good example. The BiGRU module effectively predicts the deformation data through bidirectional pattern and thereby improving modelling capability inturn. The research works discussed so far are summarized in Table 1.

Table 1. Summary of different research works related to SHM in civil infrastructures

Authors	Description	Limitations
Anjum et al., (2024)	Reviewed the scope of ML approaches in solving complex SHM problems in civil structures.	Review-focused study without proposing lightweight or edge-deployable models.
Sakr& Sadhu (2024)	Investigated digital twins in SHM, covering 3D representation, surrogate/hybrid modelling, FEM, applications, and future scope.	Primarily conceptual with limited emphasis on reduced-order, deployable DT models.
Bader et al., (2025)	Proposed CatBoost with African Vultures Optimizer for crack detection and prediction on a dataset of 8,541 records.	Ensemble-based approach is computationally heavy for real-time edge implementation.
Liu et al., (2025)	Developed MA-CNN-BiLSTM hybrid model for reconstructing missing acceleration response data, outperforming LSTM and BiLSTM.	BiLSTM-based architecture increases computational cost and inference latency.

Holsamudrkar& Banerjee (2024)	Introduced CNN with AE-based waveform scalogram analysis, achieving 95% training accuracy and 87% testing accuracy.	Model performance is sensitive to noise, affecting robustness and limited generalization.
Duran et al., (2024)	Designed TL-based CNN for damage detection with perfect accuracy on 10-label task but degraded on varying geometries.	Performance degrades significantly for unseen structural geometries. Model complexity limits suitability for edge-based deployment.
Ahmadzadeh et al., (2025)	Integrated 1D CNN and LSTM for multisensor SHM, reaching 99.6% damage identification and 96.6% localization accuracy.	Sequential LSTM processing results in higher inference latency. Scalability to lightweight, edge-friendly implementations is limited.
Xia & Huang (2025)	Built ResNet-based structural damage detection framework validated on steel truss simulations with 90% accuracy.	ResNet backbone is computationally intensive for edge deployment.
Singh et al., (2024)	Developed hybrid DL model using attention, GoogleNet, and ResNet50 for structural damage recognition with high F1, recall, and accuracy.	Deep backbone networks demand high computational resources and is not suitable for real-time implementation.
Wang et al., (2025)	Proposed transformer-based BiGRU approach to predict deformation data effectively through bidirectional modeling.	Transformer-based temporal modeling increases computational overhead.

Research Gap

Although various ML/DL techniques based on BiLSTM, CNN, ResNet50, and so on are developed for carrying out structural health monitoring in civil base, many works face generalization issues across varied sensor modalities and structural geometries. Also, the techniques are either computationally heavy or lack edge deployment feasibility making them least choices for real-time implementations. Thus, there is a strong need for a lightweight, edge-friendly and robust architecture that excels in accuracy, computational efficiency, and structural anomaly detection. This is where the proposed model, HESTIA fulfills these research gaps and comes out as a reliable option of detecting cracks and fatigue from small civil structures like lab prototype, and scaled models.

3. METHODOLOGY

A. Proposed Methodology

The suggested methodology starts with the acquisition of raw sensor data, which are fed through a physics-informed digital twin to produce a trusted virtual model of the physical system. The digital twin enables a realistic correspondence of the sensors behavior and removes noise and uncertainty in the process of data gathering. At this stage, the collected information is used as input for DL networks running concurrently and the GNN, which identifies spatial and structural features of the sensors through the use of the graph structure of the sensors information, and the TCN, which identifies the sequence and features of the sensors information as a result of the use of the time-series information.

These extracted features are then merged in a Bayesian Feature Fusion Layer for the first time in the model by the TCN and GNN, and the features are probabilistically merged to form a holistic and discriminatory description. For increased learning efficiency and accuracy, the Harris Hawks Optimizer is employed to tune model parameters for best convergence. Optimized features are passed to the decision layer where final predictions are made based on the optimized representation. Finally, this k-processing produces a correct and sound k-output reflecting the capability of the framework to mutually utilize physics-based modeling, cutting-edge DL structures, and smart optimization for solid decision-making. The block diagram of proposed HESTIA model for damage classification is given in Figure 1.

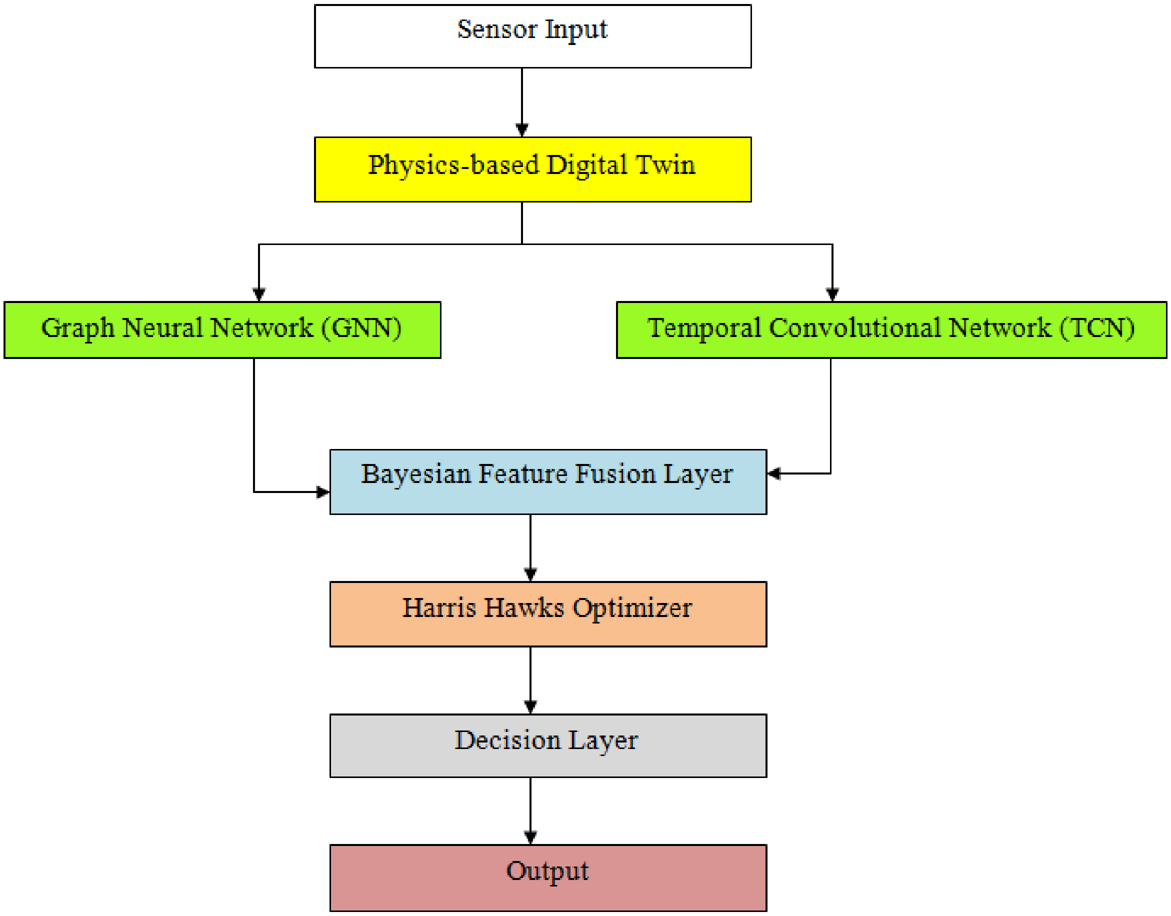


Figure 1. Layered Architecture of HESTIA

The approach starts with the acquisition of multi-modal sensor data, namely acceleration $(a(t))$, strain $(\varepsilon(t))$, and temperature $(T(t))$. These signals are the actual dynamic response of the structure in real time. The obtained signals can be described in a vector form:

$$X(t) = [a(t), \varepsilon(t), T(t)] \tag{1}$$

Where, $X(t)$ is the input of time-varying structural state. This information serves as the basis for the estimation of the monitored structure's physical condition.

The second step is to approximate the state of the structure and represent the uncertainties associated with the noises and environmental variations. The probabilistic state approximation approach, or Kalman Filtering/Bayesian Inference, is expressed as:

$$\hat{X}(t) = X(t) + \omega(t) \tag{2}$$

Where, $\hat{X}(t)$ denotes the state vector estimate and $\omega(t)$, which denotes Gaussian noise, follows $\omega(t) \sim N(0, \sigma^2)$.This will ensure trustworthy feature extraction even when operating in uncertain environments.

The Structural Topology Representation Layer builds a structural topology graph, where the sensor location points are represented by nodes, along with connectivity by edges. The representation mathematically models the graph $G = (V, E)$, where V represents the nodes, while E represents the edges. The adjacency matrix defines $A \in R^{|V| \times |V|}$ models spatial dependencies, where stress or strain diffusion through the structure can be visualized.

Parallel to spatial modeling, the temporal dynamics are extracted using convolution over time-series signals. A TCN or similar method computes features as:

$$h_t = f(\sum_{k=0}^{K} w_k \,.\, X(t-k)) \quad (3)$$

where h_t represents the temporal feature at time t, w_k are learnable convolutional weights, and K is the receptive field size. This picks up both short-term and long-term dependencies in the structural response.

The structural topology and temporal feature outputs are fused into a Digital Twin (DT) augmented representation. The fusion can be represented through weighted feature integration:

$$F = \alpha \cdot F_{spatial} + (1-\alpha) \cdot F_{temporal} \quad (4)$$

Where, $F_{spatial}$ is the feature from the graph-based model, $F_{temporal}$ is the temporal feature, and $\alpha \in [0,1]$ is a weighting parameter. This fusion allows structural integrity and dynamic variability to be modeled together.

In Adaptive Weighting and Threshold Control Layer, adaptive thresholds and weights are optimized for stable classification. A dynamic threshold $\theta(t)$ may be written as:

$$\theta(t) = \mu_F + \lambda \cdot \sigma_F \quad (5)$$

Where, μ_F and σ_F are the mean and standard deviation of the fused features, and λ is a scaling factor that is adaptive. This mechanism preserves the sensitivity of the decision-making process to initial damage without producing false alarms.

The threshold-controlled and fused features are classified into three classes: Normal, Early Damage, and Severe Damage. A softmax classifier is used as:

$$P(y = i|F) = \frac{\exp{(W_i.F + b_i)}}{\sum_{j=1}^{3} \exp{(W_j.F + b_j)}} \quad (6)$$

Where, $P(y = i|F)$ represents the probability of the structural state in class i, with learnable parameters W_i and b_i. The maximum probability is used to determine the final classification result. The purpose or role of each layer in developed SHM technique is illustrated in Figure 2.

Lastly, the classification outputs are converted into actionable recommendations in the forms of real-time alerts and maintenance advice. This process takes the output of the decision layer and converts it into practical advice, e.g., inspection immediately for heavy damage, preventive maintenance for early indicators, or regular monitoring under normal operation.

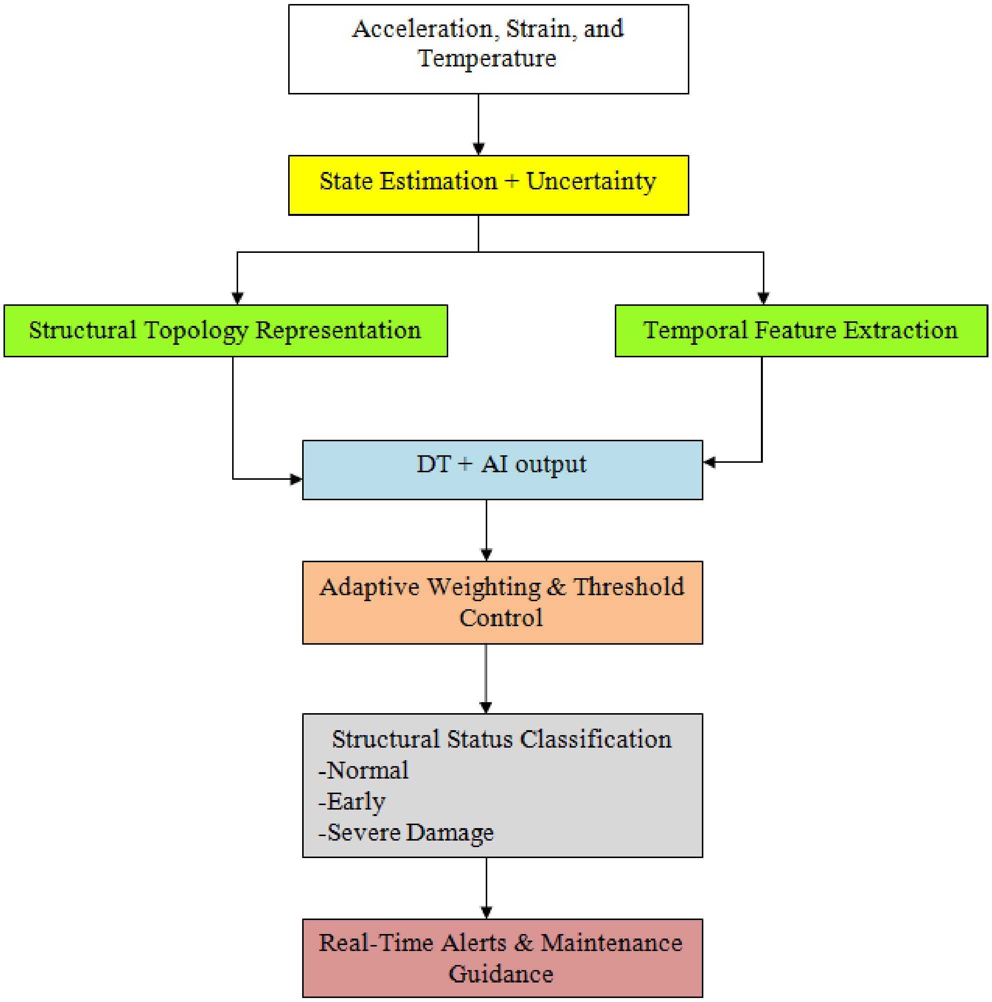


Figure 2. Role of each layer in HESTIA

a. Graph Neural Network (GNN)

A GNN is a DL framework that is specifically designed for graph-structured data, with entities represented as nodes and relationships represented as edges. Unlike traditional neural networks that deal with fixed-dimensional vectors or grid-based data like images, GNN is able to model non-Euclidean structures effectively. This makes them particularly well-fitted to applications where dependencies and relationships go beyond mere sequences or spatial grids. The core mechanism of GNN is the message passing mechanism, in which each node successively updates its feature representation by combining information from neighboring nodes. Because of this, the GNN model has the capability to incorporate the structural information from the graph.

In mathematical terms, the update of the representation of the node at any given layer takes place based on the combination of the representation of the current node along with the representations of the nearby nodes. This update mechanism can be stated generally as:

$$h_v^{(l)} = \sigma\left(W^{(l)}.AGG(\{h_u^{(l-1)} : u \in N(v)\})\right) \quad (7)$$

Here, $h_v^{(l)}$ denotes the feature vector of node v at layer l, $N(v)$ is the set of neighboring nodes, $AGG(\cdot)$ denotes an aggregator function like mean, summation, or attention, $W^{(l)}$ denotes the trainable weights matrix, and $\sigma(\cdot)$ denotes the nonlinear activation function. By stacking multiple layers, it can be ensured that information from far-away nodes is incorporated as well, providing an overall representation of structure.

In the proposed methodology, the role of the GNN is foundational to describe the structural topology of the system under test. The data from distributed acceleration, strain, and temperature sensors are graph-structured inherently, where the sensor nodes and their connections, whether physical or functional, are defined as the edges.

By using the GNN, the model can learn how vibrations, loads, and stresses travel through the structure and, therefore, build up a spatially aware understanding of structural behavior. The role of the GNN further escalates when it is put together with TCN in the model. While the TCN gets to learn temporal relationships in the sensor signals, the GNN assists it in learning spatial interdependencies among sensor nodes. Together, these networks give a full representation considering space and time. This two-perspective feature extraction, coupled with Bayesian feature fusion, ensures anomaly detection more precisely, as anomalies are not considered standalone but part of an effect on the neighborhood structural components.

Finally, the GNN module enhances the DT representation by incorporating structural topology into the virtual model. This helps to replicate real structural dynamics in the DT more closely and improves decision-making during structural status categorization. By placing the sensor data in context within the structural graph, the GNN prevents anomalies from being missed and makes predictions more accurate and effective real-time maintenance recommendations. The graph neural network module employed in HESTIA is shown in Figure 3.

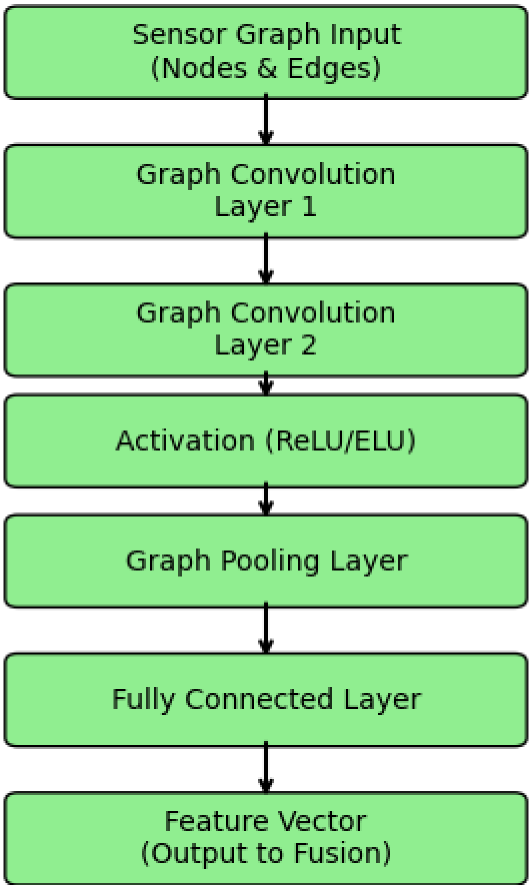


Figure 3. GNN schematic used in HESTIA

b. Temporal Convolutional Network (TCN)

Temporal Convolutional Network is a DL architecture that is specifically designed to capture sequential and time-series data. In contrast to common recurrent structures like LSTMs or GRUs, TCN utilize causal and dilated convolutions to model temporal dependencies. The main strength of TCN is their capacity to process long input sequences in parallel without running into the vanishing or exploding gradients problem, and with high computational efficiency. This renders TCN extremely appropriate for applications where real-time, large-scale, or long-duration temporal patterns need to be well identified, for instance, in structural health monitoring systems.

The basic working of a TCN entails imposing 1-D convolutions over time-series signals with the guarantee of causality, i.e., predictions in time step *t* based on only the current and past inputs and not future information. In order to model long-range dependencies effectively, dilated convolutions are proposed. In mathematical terms, a dilated convolution can be defined as:

$$y(t) = \sum_{k=0}^{K-1} w_k \,.\, x(t - d.k) \tag{8}$$

Where, $y(t)$ is the output at time *t*, *x(t)* is the input sequence, w_k are learnable convolutional weights, *K* is the kernel size, and d is the dilation factor used to regulate the spacing of filter elements. With stacking up numerous layers of growing dilation factor, the TCN is able to capture extremely long-range temporal dependencies with minimal additional computational cost.

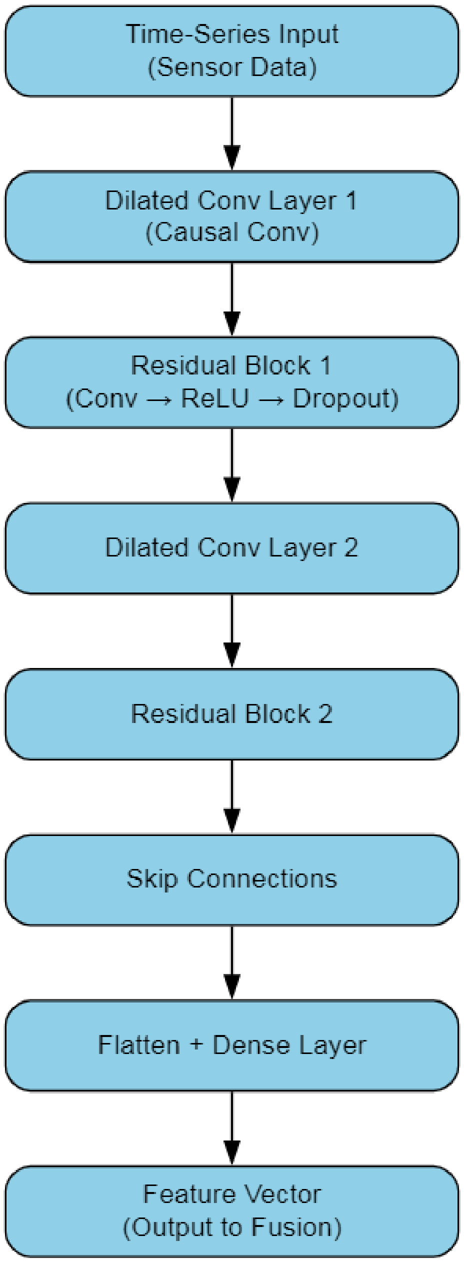


Figure 4. Schematic of TCN module employed in HESTIA

In the methodology adopted here, the TCN is utilized to tap temporal patterns from the structural sensor measurements. Signals like acceleration, strain, and temperature have prominent time-varying behavior that captures the changing condition of the infrastructure under inspection. Through dilated convolution of these sequences, the TCN is able to capture both short-term changes (e.g., transient responses to stress) and long-term changes (e.g., chronic patterns of deterioration). This enables the model to detect early signs of damage that would go unnoticed for models that consider spatial or static features alone (Figure 4).

In addition, the TCN is also essential to advance the DT framework by incorporating temporal evolution modes into the virtual structural model. This allows the DT not only to capture the instantaneous structural state but also to consider its evolution over time. Consequently, the proposed model acquires the capability of performing proactive structural health monitoring, providing accurate status classification as well as on-time maintenance suggestions.

c. Bayesian Feature Fusion

Bayesian Feature Fusion is a probabilistic method employed for the fusion of disparate feature sets into a single representation with explicit accounting of uncertainty in the data. As opposed to simple concatenation or deterministic weighting methods, Bayesian fusion applies the principles of probability theory to put confidence-based weights on different feature sources. For given feature vectors F1 and F2 from the GNN and TCN, the fused feature representation can be represented as a posterior distribution:

$$P(F \mid F_1, F_2) \propto P(F_1 \mid F) \cdot P(F_2 \mid F) \cdot P(F) \tag{9}$$

Where, $P(F \mid F_1, F_2)$ is the posterior probability of the fused feature, $P(F_1 \mid F)$ and $P(F_2 \mid F)$ are the likelihoods of the features with respect to the fused state, and $P(F)$ is the prior. The Prior factor is assumed to follow a zero-mean Gaussian distribution encoding structural regularity achieved from digital twin. Whereas, likelihoods $P(F_1 \mid F)$ and $P(F_2 \mid F)$ are modeled as Gaussian distributors for capturing feature uncertainty. Posterior is calculated by maximizing log-posterior during training analytically. This representation enables the fusion process to adaptively balance features on their reliability in order to be robust under noisy or uncertain sensor situations. Empirically, the Bayesian fusion layer leads to minimal variance across cross-validation folds and increased classification stability.

In the proposed methodology, Bayesian Feature Fusion is the fusion layer that combines the space-related features learned by the GNN with the temporal dynamics learned by the TCN. By the application of probabilistic reasoning, the fusion layer enhances discriminative power without allowing the domination of less-informative features. Such probabilistic fusion is essential for structural health monitoring because sensor observations tend to be subject to environmental variability, noise, or missing information. The combined Bayesian representation therefore gives a more credible input to the following Harris Hawks optimization and decision-making layers, finally allowing precise structural status classification and real-time directions.

d. Harris Hawks Optimizer

The HHO is a population-based, nature-inspired metaheuristic algorithm that imitates the cooperative hunting behavior of Harris hawks in the wild. Harris hawks are renowned for their smart and flexible group hunting strategy in which they dynamically alternate between exploration (searching) and exploitation (exploiting) based on environmental conditions and the escape energy of the prey. Candidate solutions in HHO are modeled as hawks, and the optimization target is analogous to the prey. The exploration-exploitation balance is maintained by the dynamic transition rules, enabling the algorithm to escape local optima and converge to the global solution.

The prey's escape energy is mathematically given as:

$$E = 2E_0\left(1 - \frac{t}{T}\right) \tag{10}$$

Where, $E_0 \in [-1,1]$ is the initial energy of the prey, *t*is the current iteration, and *T* is the maximum number of iterations. When, $|E| \geq 1$, the hawks are interested in exploration, which indicates that they explore the positions in the search space diversely. When,$|E| < 1$, the hawks enter the exploitation stage, in which they perform fast collaborative attack strategies such as soft besiege, hard besiege, and surprise pounce. This way, the optimizer switches between exploration and exploitation efficiently, thereby being highly efficient for complex optimization problems.

In the proposed scheme, HHO is utilized for the optimization of non-gradient parameters of the obtained model, i.e., the weights of the Bayesian feature fusion and classification layers. Owing to the noisy, uncertain, and high dimensional nature of the data in SHM applications, gradient-based optimization techniques tend to converge to local optima. With the use of HHO, the ability to find the optimal parameters dynamically is obtained, resulting in higher accuracy and robustness. Furthermore, the optimizer also encourages appropriate generalization and does not overfit to particular sensor conditions. Lastly, the use of HHO also improves the predictive capability of the proposed scheme to accurately categorize structural health under varying operational environments. Objective function minimized by the HHO block is macro-averaged cross-entropy with an L2 regularization term validated on validation folds. For training the GNN and TCN, gradient-based optimizer (Adam) is employed. HHO is used for performing global hyperparameter refinement, improving generalization on small datasets, and avoiding local minima. Overall, HHO acts as a complementary global optimizer.

Algorithm: Harris Hawks Optimizer (HHO)

Inputs: Population size *N*, maximum iterations *T*, and the objective function *f(x)*.

Outputs: Optimal solution x^* with its corresponding fitness value $f(x^*)$.

*Step 1***:** Generate a population of randomly initial Harris hawks (candidate solutions) within the specified search space:

$$X_i = [x_{i1}, x_{i2}, \dots \dots ., x_{id}], \qquad i = 1,2 \dots \dots N \tag{11}$$

Step 2: Iterative Update Process.

For each iteration $t = 1,2, \dots, T$:

1. **Escape energy of the prey:** Estimate the escape energy of the prey by using:

$$E = 2E_0(1 - \frac{t}{T})$$

Where, E_0 is a random value between [−1,1].

2. **Exploration phase** $(| E | \geq 1)$**:** Hawks explore the search space by modifying their positions with respect to randomly selected hawks:

$$X^{t+1} = X_{rand} - r_1 . |X_{rand} - 2r_2 X_i^t| \tag{12}$$

Where, X_{rand} is a randomly selected hawk, and r_1, $r_2 \in (0,1)$ are random coefficients.

3. **Exploitation phase** $(| E | < 1)$**:** Hawks change attack strategies according to the condition of the prey:

Soft besiege: $$X^{t+1} = \Delta X^t - E . |J . X_{best} - X_i^t| \tag{13}$$

Hard besiege: $$X^{t+1} = X_{best} - E . |\Delta X^t| \tag{14}$$

Soft besiege with rapid dives: $$X^{t+1} = \Delta X^t - E . |J . X_{best} - X_i^t| + S . LF(d) \tag{15}$$

Hard besiege with rapid dives: $$X^{t+1} = X_{best} - E . |\Delta X^t| + S . LF(d) \tag{16}$$

Where, $\Delta X^t = X_{best} - X_i^t$, *J* is a random jump strength in [0,2], *S* is a random step size, and *LF(d)* represents a Lévy flight distribution.

4. **Fitness evaluation:** Compute the fitness of every updated hawk and update X_{best} in case of a better solution is

found.

Step 3: When the number of iterations is reached, return the best solution found:

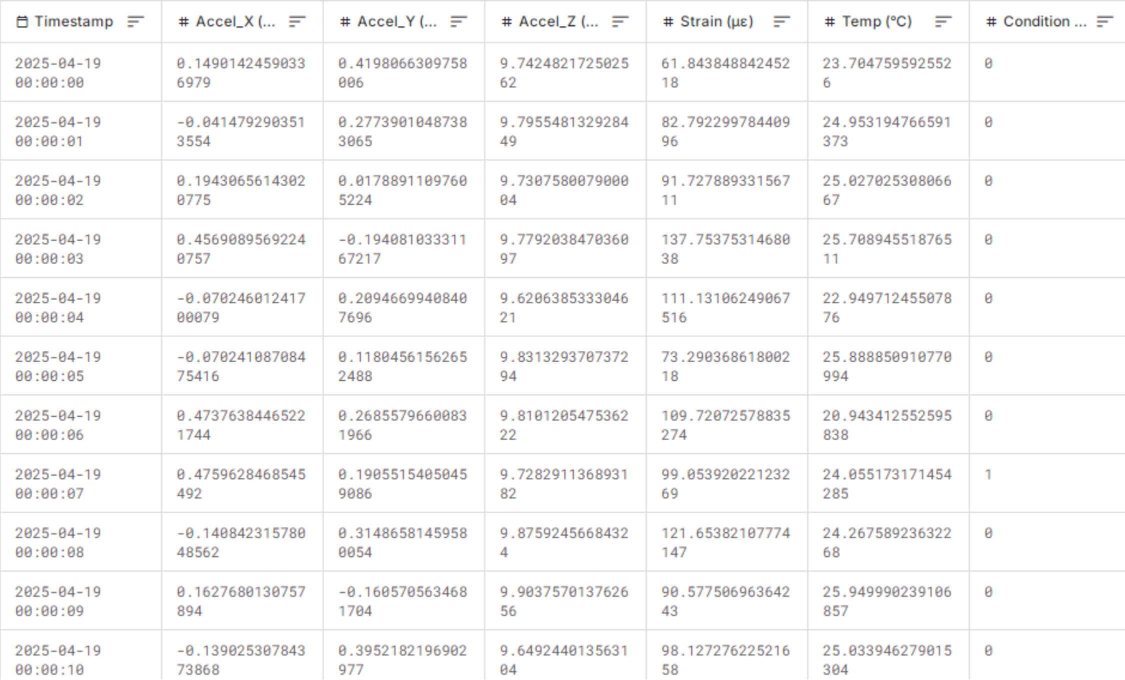
$$x^* = X_{best}, f(x^*) = \min f(X_i) \tag{17}$$

e. Physics-Informed Digital Twin Modelling

Digital Twin in HESTIA is a reduced-order, physics-informed representation of the monitoring structure. It synchronizes structural dynamics with real-time senor measurements. For estimating structural state and uncertainty caused by environmental variations and noise, multi-modal sensor data is used. Reliable correspondence amid virtual counterpart and physical system is ensured by means of probabilistic state estimation. Through digital twin output, state representation is calibrated for improving damage sensitivity and spatial-temporal learning. For real-time SHM applications, digital-twin ensures lightweight and edge-compatible deployment criteria. Mathematical equations governing the process in digital twin are given in eqn. (1-4).

4. RESULTS AND DISCUSSION

For evaluation of the proposed HESTIA approach, an open-source dataset called "Building Structural Health Sensor Dataset" is used. Comprising of 1020 samples, the dataset is a source of time-series data collected from accelerometer, temperature, and strain sensors. Designed especially to carry out research works in developing SHM project works using ML and embedded system techniques, sensor data representing physical state of building structures over different operational and environmental conditions is present. The strain gauge measurements are tabulated in terms of microstrain and temperature interms of degree Celsius. Each sample or record is labeled and timestamped under three conditions: Healthy (0), Minor Damage (1), and Severe Damage (2). Although the dataset seems to have limited samples, it is a controlled set with real-time structural response which is required for evaluating the proposed model. A sample of the employed dataset is given in Figure 5.



Timestamp	# Accel_X (...	# Accel_Y (...	# Accel_Z (...	# Strain (με)	# Temp (°C)	# Condition ...
2025-04-19 00:00:00	0.14901424590336979	0.4198066309758006	9.742482172502562	61.84384884245218	23.7047595925526	0
2025-04-19 00:00:01	-0.0414792903513554	0.27739010487383065	9.795548132928449	82.79229978440996	24.953194766591373	0
2025-04-19 00:00:02	0.19430656143020775	0.01788911097605224	9.730758007900004	91.72788933156711	25.02702530806667	0
2025-04-19 00:00:03	0.45690895692240757	-0.19408103331167217	9.779203847036097	137.7537531468038	25.70894551876511	0
2025-04-19 00:00:04	-0.07024601241700079	0.20946699408407696	9.620638533304621	111.13106249067516	22.94971245507876	0
2025-04-19 00:00:05	-0.07024108708475416	0.1180456156265248	9.831329370737294	73.29036861800218	25.888850910770994	0
2025-04-19 00:00:06	0.47376384465221744	0.2685579660083196	9.810120547536222	109.72072578835274	20.943412552595838	0
2025-04-19 00:00:07	0.4759628468545492	0.1905515405045908	9.728291136893182	99.05392022123269	24.055173171454285	1
2025-04-19 00:00:08	-0.14084231578048562	0.3148658145958054	9.87592456684324	121.65382107774147	24.26758923632268	0
2025-04-19 00:00:09	0.1627680130757894	-0.1605705634681704	9.903757013762656	90.57750696364243	25.949990239106857	0
2025-04-19 00:00:10	-0.13902530784373868	0.3952182196902977	9.649244013563104	98.12727622521658	25.033946279015304	0

Figure 5. Sample data from the Building Structural Health Sensor Dataset

This dataset with multi-modal sensor data is well suited for the HESTIA technique to perform digital twin analysis and AI-based anomaly detection. Additionally, the lightweight data availability is perfect for real-time feasibility testing. In the total of 1020 records, 816 samples are taken for training and 204 are taken for testing phase. A Stratified 5-fold cross-validation is employed for model selection. This stratified 5-fold cross-validation is rigorously applied for mitigating overfitting issues on the entire dataset. In each fold, approximately 80% of data is used for training and 20% for validation. The performance metrics – latency, accuracy, specificity, F1-score, ROC, and sensitivity are calculated as mean and standard deviation across all five folds thus eliminating the bias seen in single-fold evaluation. It is further retained on the 816 records with selected hyperparameters and followed for testing records as well.

The experiment or evaluation process is carried out using an edge-friendly hardware arrangement comprising of Raspberry Pi 4 with 4GB storage. Additionally, a computer with uninterrupted power supply, Windows 10 operating system, high-storage RAM, and GPU configurations is used. Interms of software, Python 3.10 with PyTorch/TensorFlow, and Pandas are used. A unique training setup is established across all modules using an Adam Optimizer with a learning rate of 0.001, batch size of 32, and 50 training epochs. Three message-passing steps and two graph convolutional layers are present in GNN architecture. Whereas, three casual convolutional layers with dilation factors – 1, 2, and 4 are employed in TCN block. Gaussian priors and likelihoods are assumed in Bayesian feature fusion with fusion weights learning for handling uncertainty in training phase. Likewise, for optimization of validation Macro F1-sore, adaptive threshold tuning, and feature reweighting, HHO approach is employed. In this way, stable convergence, reproducibility, and consistent configuration is ensured.

The training vs. testing curve analysis interms of accuracy is given in Figure 6. From the analysis, it can be seen that accuracy in training phase steadily grows and saturates near 95% approximately. Likewise, testing accuracy closely follows the training curve at 92% revealing strong predictive generalization. Throughout the curve analysis, no divergence or sudden drop is seen in the analysis that proves HESTIA as an edge-friendly system even on lightweight datasets.

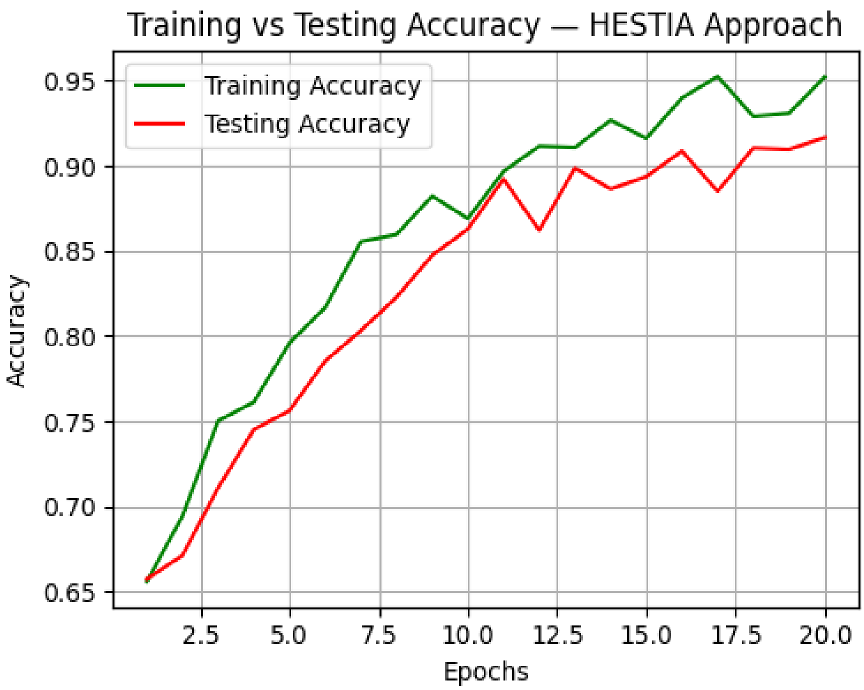


Figure 6. Learning curve analysis of HESTIA model on accuracy

Likewise, Figure 7 shows that loss in training phase decreases steadily and stabilizes at 15 epochs. It is closely followed by the testing curve but with a slight high value highlighting generalization without overfitting. The gap between two curves is small due to robustness of Bayesian fusion and HHO optimizer.

The latency distribution in Figure 8 shows that most of the decisions on the edge devices occur between 75-95 ms with a peak around 85 ms confirming the feasibility of real-time SHM applications. It further pinpoints a Gaussian–like distribution that indicates stable model execution with minimal variance in latency. In the result, outliers are rare demonstrating the effectiveness of model in varying computational loads.

The confusion matrix or heatmap of HESTIA SHM technique is given in Figure 9. Very high classification accuracy is attained matching the true labels and making nearly all predictions correctly. For the healthy condition (class 0), all 118 samples are correctly classified showing strong reliability in normal operation monitoring. Similarly, in class 1 or minor damage and class 2 or severe damage category, the model misclassified one sample confirming robustness in damage classification part as well. This result emphasizes that structural anomalies are consistently detected minimizing the risk of false negatives in safety-critical SHM. This result also states that the methodology is particularly effective in monitoring progressive damage such as the initiation and growth of cracks and fatigue, which are critical signs to structural failure.

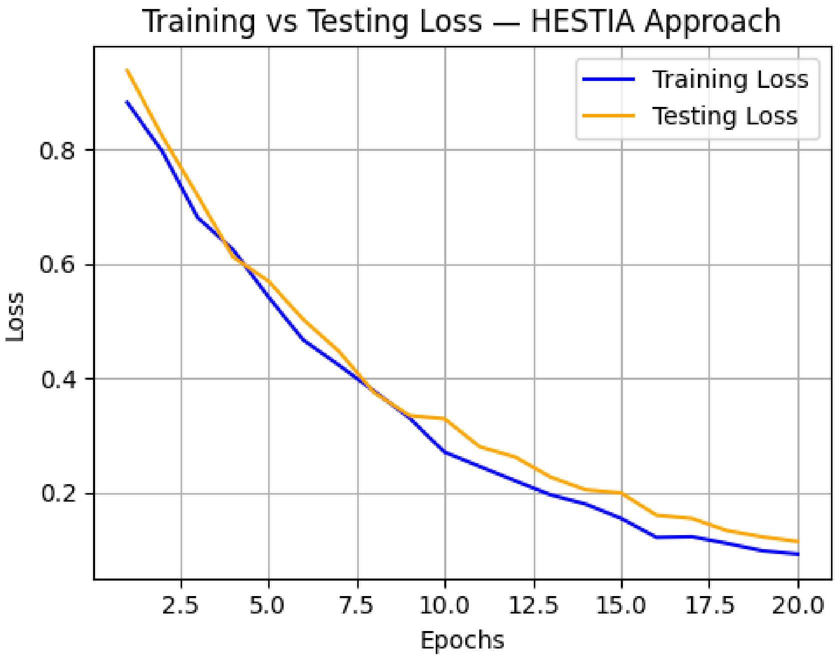


Figure 7. Learning curve analysis of HESTIA model on accuracy

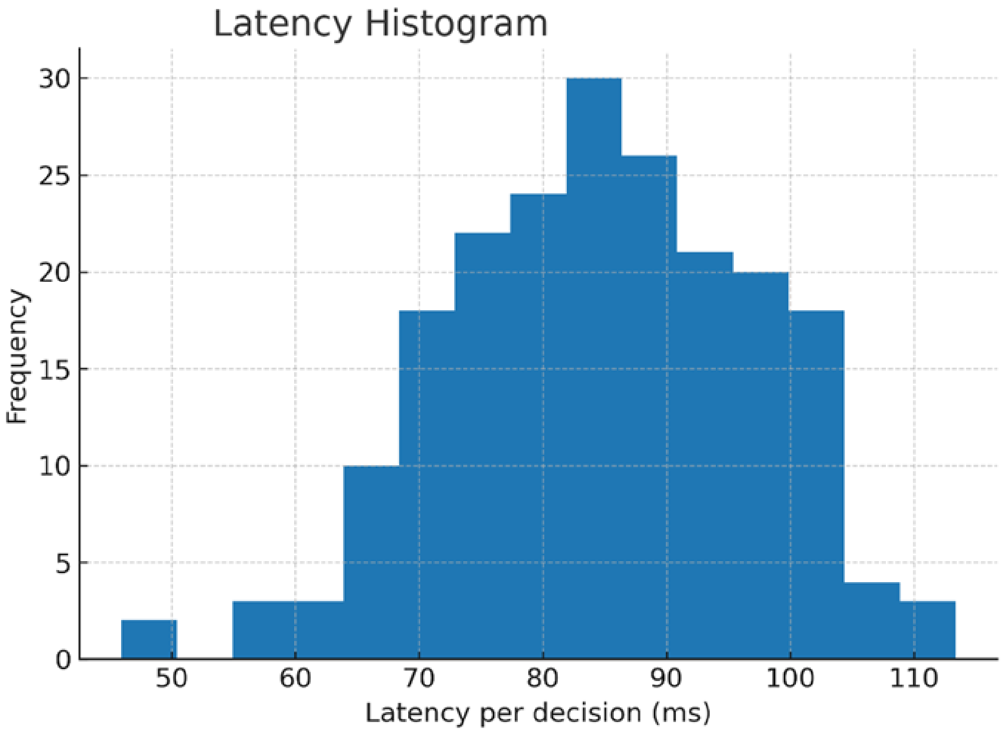


Figure 8. Result of latency histogram analysis

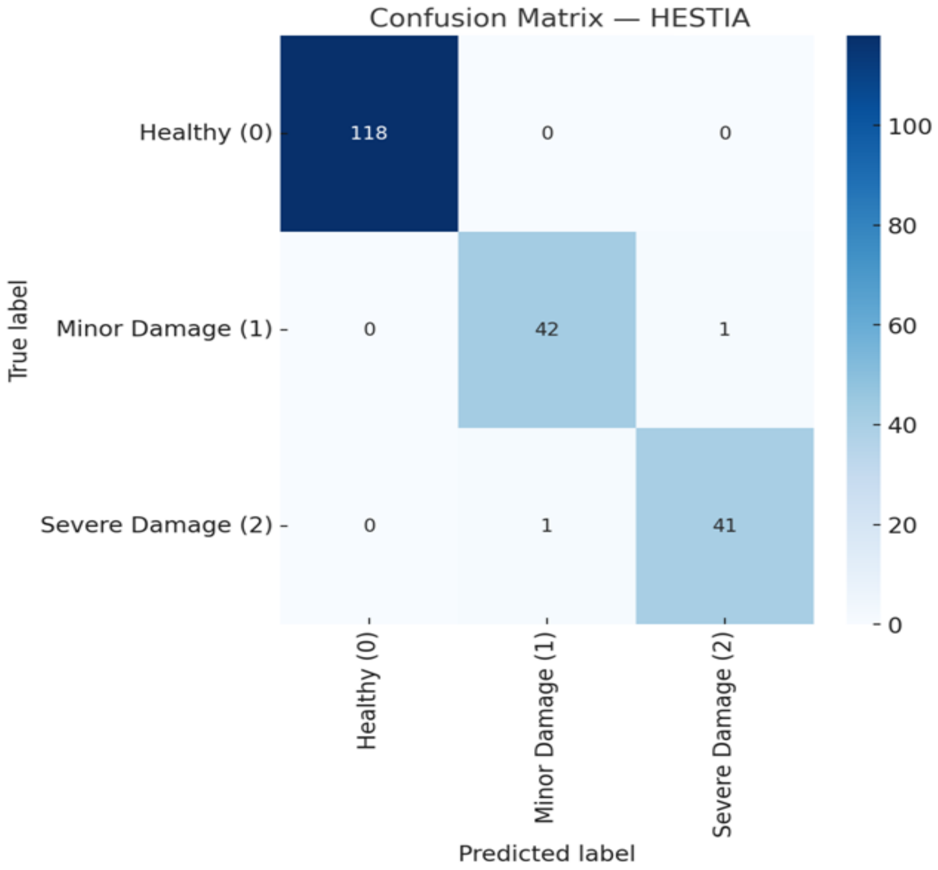


Figure 9. Confusion matrix of HESTIA technique

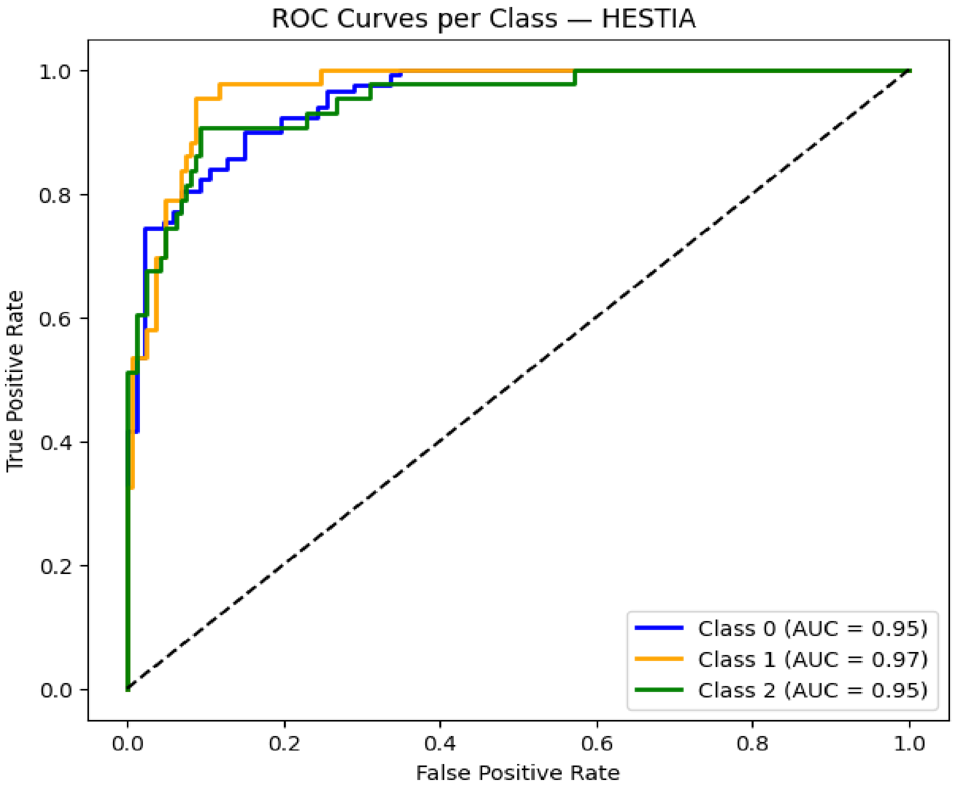


Figure 10. Receiver Operating Characteristics of HESTIA

Figure 10 illustrates the Receiver Operating Characteristics (ROC) of HESTIA technique. AUC score close to 1.0 (0.95-0.97) is seen in all classes revealing strong separability between health states. The steep rise near the Y-axis shows that the proposed approach achieves high sensitivity with low false positive rates. Minor damage category attained the highest ROC with 0.97 highlighting the model's superior ability in capturing early-stage damages.

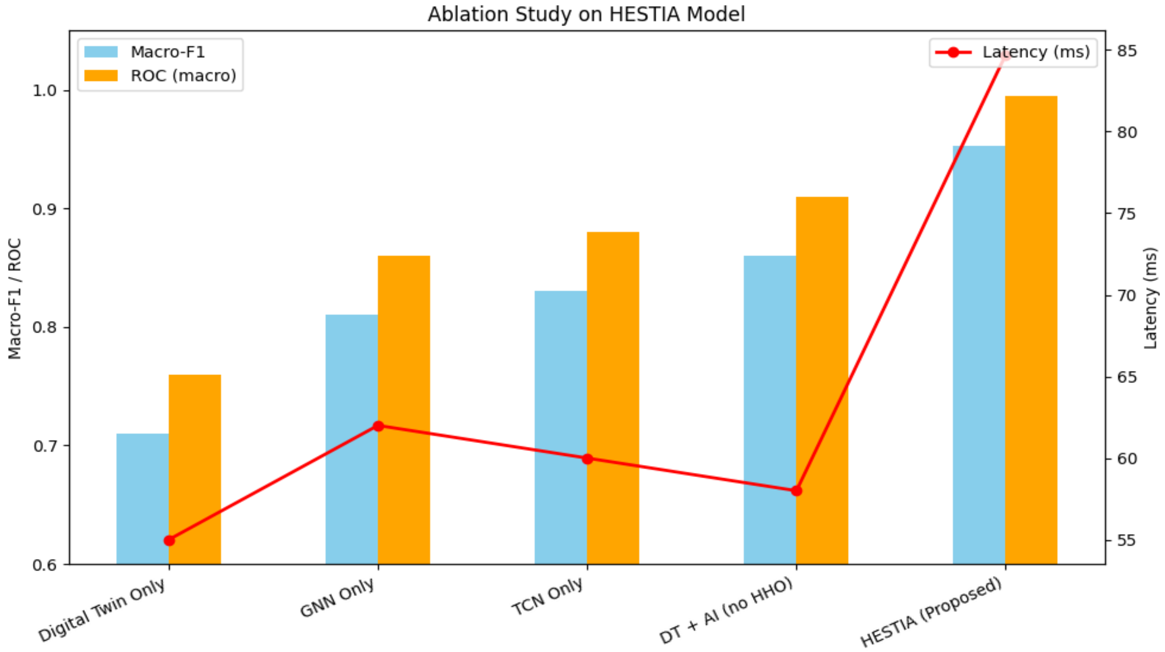


Figure 11. Ablation study results of the proposed **HESTIA** (Hybrid Edge-Supported Twin for Infrastructure Analysis using Graph and Temporal Networks). The performance is evaluated using **Macro-F1** (Macro-averaged F1 score) and **ROC** (Receiver Operating Characteristic, macro-averaged) metrics, along with inference **Latency (ms)**. Comparative analysis is carried out for **DT** (Digital Twin) only, **GNN** (Graph Neural Network) only, **TCN** (Temporal Convolutional Network) only, **DT + AI (no HHO)** (Digital Twin integrated with Artificial Intelligence without Harris Hawks Optimization), and the complete **HESTIA** model

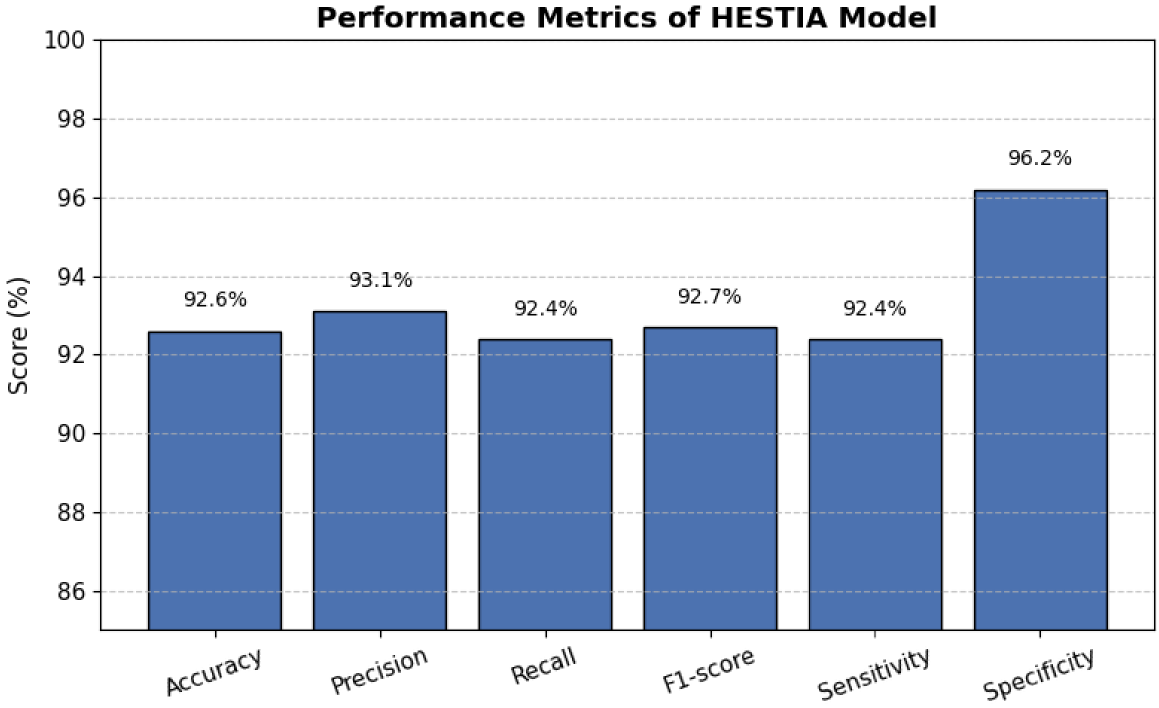


Figure 12. Performance of HESTIA model on different factors

In a machine learning model, performing ablation study is vital to analyze progressive improvement and validate the role of each module. The ablation study results of HESTIA model is graphically represented in Figure 11. Models with only single components like TCN, GNN, and DT performed reasonably while the complete model achieved the best Macro F1 of 0.953, ROC of 0.995 and latency of 84.7 ms approximately. This performance was made possible by HHO and Bayesian techniques.

The HESTIA technique attained specificity of 96.2% demonstrating very high ability in recognizing healthy structures correctly. The model classified health states with strong ability leading to 92.6% in accuracy. With 92.7% in F1-score, balanced trade-off between precision and recall and precision is accomplished showing its robustness under varied operational scenarios. Finally, sensitivity of 92.4% and precision of 93.1% is achieved by HESTIA illustrating false alarm reduction that is crucial for SHM in avoiding unnecessary inspections and maintenance costs. This superior performance of HESTIA is graphically represented in Figure 12.

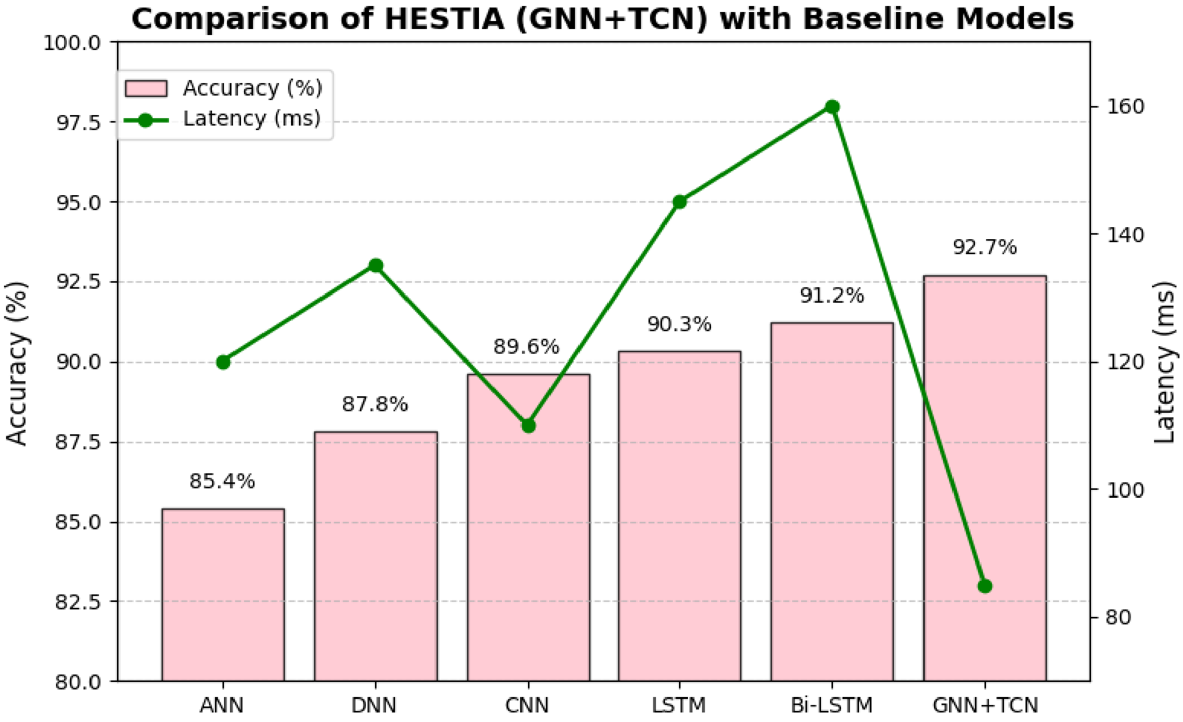


Figure 13. Performance analysis of the proposed **GNN + TCN** model with baseline network architectures. **GNN** denotes Graph Neural Network and **TCN** represents Temporal Convolutional Network. The comparison is conducted against **ANN** (Artificial Neural Network), **DNN** (Deep Neural Network), **CNN** (Convolutional Neural Network), **LSTM** (Long Short-Term Memory), and **Bi-LSTM** (Bidirectional Long Short-Term Memory) models using **Accuracy (%)** and inference **Latency (ms)** as evaluation metrics

From Figure 13, it is evident that HESTIA yielded the best trade-off between accuracy and efficacy. Interms of exactness, the combination of GNN and TCN surpassed other models with 92.7%. It is then followed by Bi-LSTM with 91.2% due to its bidirectional temporal feature learning ability. Next, CNN and LSTM stands on the list with 89.6% and 90.3% with their effectiveness in extracting temporal and spatial patterns. Similarly, in latency or computational cost, LSTM and BiLSTM suffer high latency of 145-160 ms making them least suited for real-time SHM. CNNs are relatively faster with 110 ms but still lacks back due to its deep sequential context. Finally, the combination of GNN & TCN once again prove best with lowest latency of 85 ms making it ideal for real-time and edge-friendly implementation.

Finally, the proposed HESTIA technique is compared with few of the models discussed in literature section based on three factors (Latency, Computational Overload, and Structural anomaly detection) and the results are represented from Figure 14 to Figure 17. Upon analysis of Figure 14, it can be seen that HESTIA occupies the first place with fast inference time of 85 ms. It is then followed by CNN-AE (Holsamudrkar and Banerjee, 2024) with 115 ms and TL-CNN (Duran et al., 2024) due to convolutional depth and TL overhead. MA-CNN-BiLSTM (Liu et al., 2025) and BiGRUformer (Wang et al., 2025) gets the highest delay of 150 ms and 140 ms due to their complex and attention heavy architecture making them last on the list.

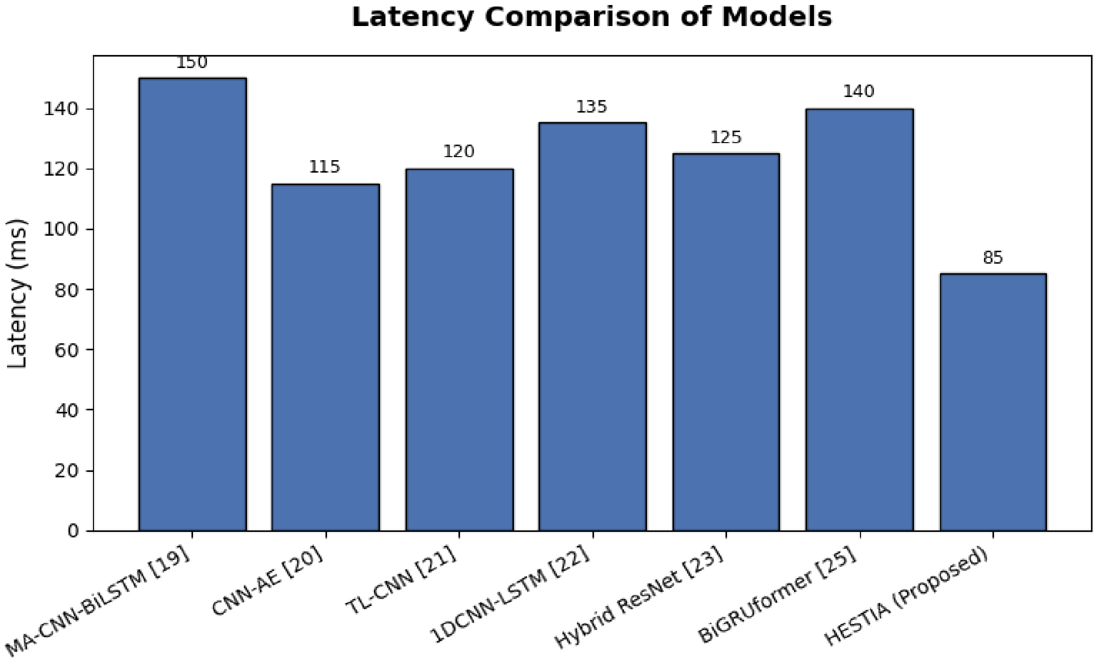


Figure 14. Latency comparison of different models, where **Latency (ms)** represents the average inference time measured in milliseconds. The evaluated models include **MA-CNN-BiLSTM** (Multi-Attention Convolutional Neural Network with Bidirectional Long Short-Term Memory), **CNN-AE** (Convolutional Neural Network–Autoencoder), **TL-CNN** (Transfer Learning-based Convolutional Neural Network), **1DCNN-LSTM** (One-Dimensional Convolutional Neural Network with Long Short-Term Memory), **Hybrid ResNet** (Hybrid Residual Network), **BiGRUformer** (Bidirectional Gated Recurrent Unit with Transformer architecture), and the proposed **HESTIA** (Hybrid Edge-Supported Twin for Infrastructure Analysis using Graph and Temporal Networks) model.

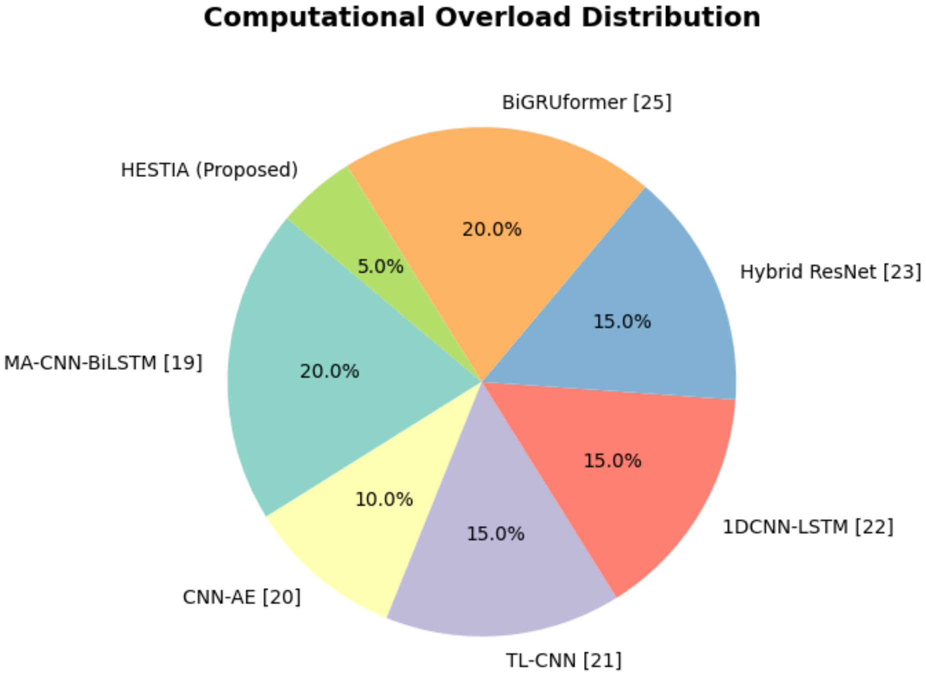


Figure 15. Computational overload comparison between the proposed **HESTIA** (Hybrid Edge-Supported Twin for Infrastructure Analysis using Graph and Temporal Networks) model and existing deep learning (DL) approaches. The compared methods include **MA-CNN-BiLSTM** (Multi-Attention Convolutional Neural Network with Bidirectional Long Short-Term Memory), **CNN-AE** (Convolutional Neural Network–Autoencoder), **TL-CNN** (Transfer Learning-based Convolutional Neural Network), **1DCNN-LSTM** (One-Dimensional Convolutional Neural Network with Long Short-Term Memory), **Hybrid ResNet** (Hybrid Residual Network), and **BiGRUformer** (Bidirectional Gated Recurrent Unit with Transformer architecture). The percentage values indicate the relative computational overload contribution of each model

Similarly, interms of computational overload, HESTIA once again comes superior with the lowest overload of 5% while the other models like BiGRUformer and MA-CNN-BiLSTM stands last with 20%. Due to few convolutional layers, CNN-AE gets a medium-to-low load score of 10%. This performance of HESTIA proves it as a lightweight and edge-friendly architecture compared to other reviewed SHM models. Finally, interms of structural anomaly detection, 1DCNN-LSTM attained highest detection score of around 98-99% due to damage pattern identification and localization abilities. The proposed model stands third on the list with score of 93% but still being a competitive and reliable option with best overall trade-off.

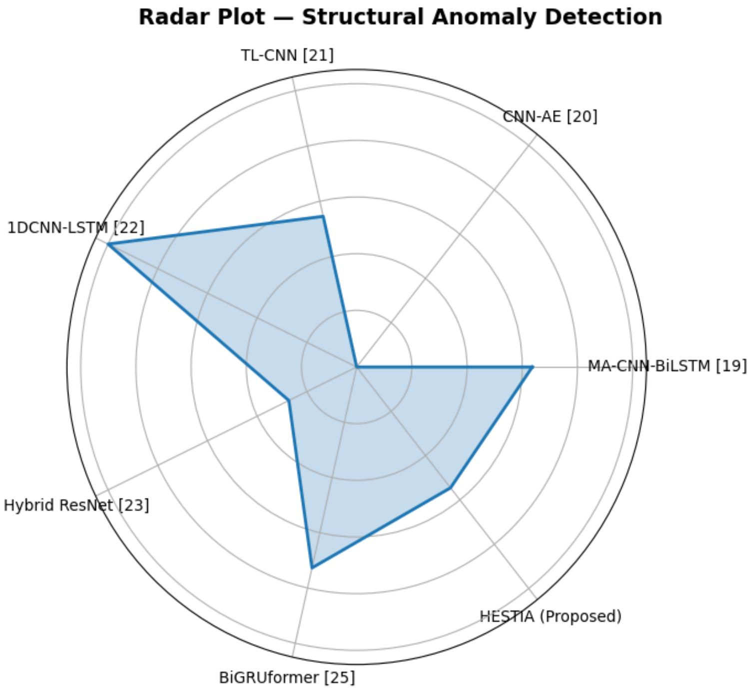


Figure 16. Radar representation comparing various artificial intelligence–based techniques for structural anomaly detection

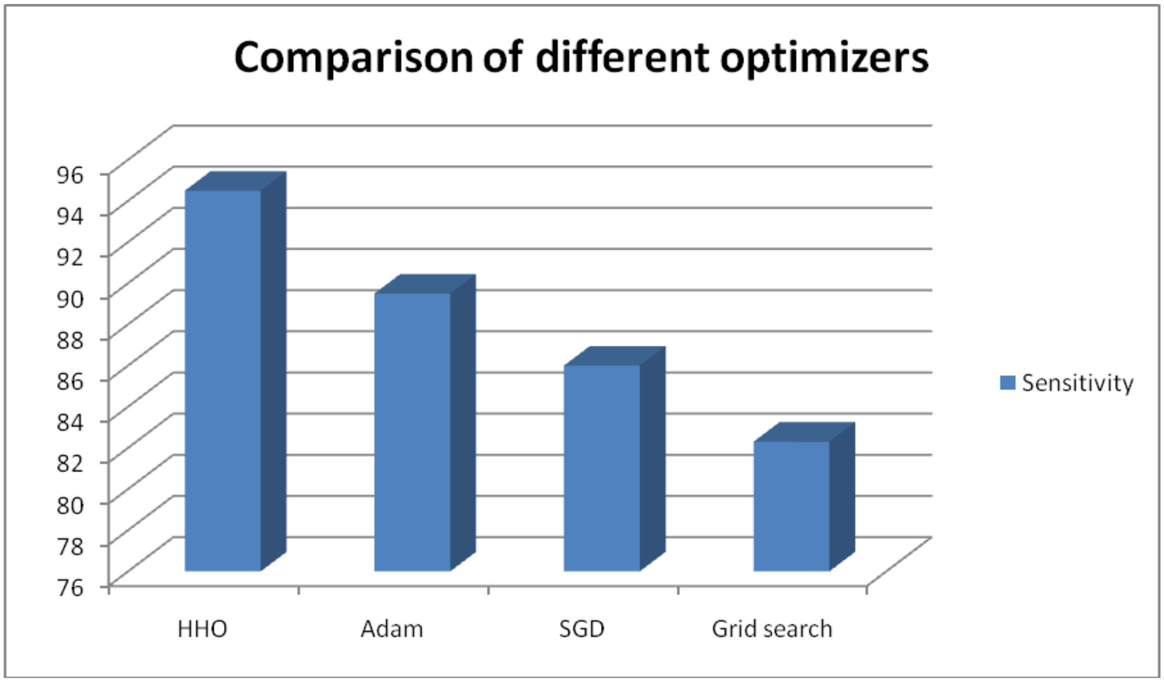


Figure 17. Comparison of Harris Hawk Optimizer with Adam, SGD, and grid search based on sensitivity

In the developed HESTIA model, HHO optimizer is used for refining non-gradient parameters. When compared to other options like SGD, Adam, and grid search, high sensitivity of 94% is attained as it is highly resistant to noisy data regions which are common in SHM. It acts as a global optimizer and robust overall configuration compared to the other techniques. It is further followed by Adam with 89.5%, SGD with 86%, and grid search with 82.3%.

Table 2 demonstrates on how the developed HESTIA model maintains its F1-score when Gaussian noise is injected into sensor data. It includes 95% confidence Intervals (CI) derived from 5-fold cross-validation for quantifying prediction uncertainty. From analysis, it can be seen that high Macro F1-score of 88.6% is noticed under moderate noise (10 dB) highlighting noise-dampening capabilities of Bayesian fusion layer. When compared with CNN baseline, significant statistical p-value ($p < 0.05$) is attained under all four noise levels.

Table 2. Robustness analysis under varying noise levels

Noise Level (SNR in dB)	Mean F1-Score (%)	95% Confidence Interval (±)	p-value (vs. Baseline CNN)
No Noise (Clean)	92.7	0.82	< 0.001
20 dB (Light Noise)	91.4	1.15	< 0.01
10 dB (Moderate)	88.6	1.42	< 0.05
5 dB (Heavy Noise)	84.1	2.05	0.08

Limitations of Proposed HESTIA approach

Although the model came out as a reliable option in monitoring structural health in civil structures, few constrains persists as detailed in this section. Primarily, the model is evaluated on a small dataset size of only 1020 records that limits the model's scalability. Secondarily, moderate structural anomaly detection accuracy of 93% is possessed by the HESTIA model that needs to be improved. Next, as the model was dependent on Raspberry Pi as edge hardware, recital could degrade in varying low-power hardware environments. Finally, testing on real-world civil infrastructure under dynamic operational conditions is required.

5. CONCLUSION

This paper presented HESTIA as a novel Hybrid edge-supported twin for structural health monitoring in civil infrastructures. Through integration of GNN & TCN with Bayesian feature fusion and HHO optimizer, the proposed SHM technique effectively processed data from different sensor data (accelerometers, strain gauge and temperature). Moreover, the adaptability of this work makes it highly suitable for experimental and practical environments, including laboratory prototypes, scaled models, and campus SHM testbeds. Such applicability confirms that the framework can be validated under controlled conditions before being scaled to large infrastructure systems. Designed especially to classify damaged and normal structures, the HESTIA model was trained and tested on an open-source dataset – "Building Structural Health Sensor Dataset" with 1020 records labeled with different classes.

Through experimental evaluation, it is revealed that the suggested SHM approach attained consistent results with specificity of 96.2%, exactness of 92.6%, and precision of 93.1%. This superior result demonstrated its reliability in identifying healthy structures and minimizing false alarms. The learning curve analysis is evident for strong generalization with 95% accuracy in training and 92% in testing. Next, HESTIA achieved fast inference of around 85 ms with Gaussian-like stability outperforming baseline models like BiLSTM, CNN, and LSTM. When compared with other state-of-the-art techniques like CNN-AE, BiGRUformer, and MA-CNN-BiLSTM, HESTIA emerged as a lightweight and edge-friendly model with lowest computational overload of 5% and competitive anomaly detection of 93%. These key findings underscore HESTIA as the highly recommended option for identification of cracks, damages and fatigue from small civil prototypes.

Further, to address the limitations and boundaries of the developed approach, the model evaluation can be extended to a large-scale and real-world SHM dataset. Further, integrating attention-based mechanism and ensemble learning could leverage structural anomaly detection. Finally, employing the model in diverse edge or IoT-based hardware would help in validating the robustness of HESTIA in varied environmental conditions.

Acknowledgement

I would like to express my sincere gratitude to all those who supported me throughout the course of this research.

Author Contributions

All authors contributed equally to the conceptualization, methodology, data analysis, implementation, and manuscript preparation of this study. All authors reviewed, revised, and approved the final version of the manuscript.

Ethical issues

Not applicable. This study does not involve any experiments on humans or animals. Hence, ethical approval was not required.

Informed consent

Not applicable.

Funding

Not applicable. This research did not receive any external funding like specific grant from funding agencies in the public, commercial, or nonprofit sectors.

Conflict of Interest

The authors declare that they have no conflicts of interest, competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data and materials availability

Data that support the findings of this study are embedded within the manuscript.

REFERENCES

1. Ahmadzadeh M, Zahrai SM, Bitaraf M. An integrated deep neural network model combining 1D CNN and LSTM for structural health monitoring utilizing multisensor time-series data. Struct Health Monit 2025; 24(1):447–465. doi: 10.1177/14759217241239041
2. Anjum A, Hrairi M, Aabid A, Yatim N, Ali M. Civil structural health monitoring and machine learning: a comprehensive review. Fract Struct Integr 2024; 18(69):43–59. doi: 10.3221/IGF-ESIS.69.04
3. Bader A, Shtayat A, Al-Mistarehi B. Enhancing structural health monitoring with AI-ML algorithms: a focus on crack detection and prediction. Asian J Civ Eng 2025; 26(5):1907–1918. doi: 10.1007/s42107-024-01261-z
4. Bado MF, Casas JR. A review of recent distributed optical fiber sensors applications for civil engineering structural health monitoring. Sensors 2021; 21(5):1818. doi:10.3390/s21051818
5. Chen L, Xia C, Zhao Z, Fu H, Chen Y. AI-driven sensing technology. Sensors 2024; 24(10):2958. doi:10.3390/s24102958
6. Duran B, EftekharAzam S, Sanayei M. Leveraging deep learning for robust structural damage detection and classification: a transfer learning approach via CNN. Infrastructures 2024; 9(12):229. doi: 10.3390/infrastructures9120229
7. El-Abbasy AAA. Artificial intelligence-driven predictive modeling in civil engineering: a comprehensive review. J Umm Al-Qura Univ Eng Archit 2025; 1–24. doi: 10.1007/s43995-025-00166-5
8. Goti A. AI-driven PCB reliability testing for IPC-9701 compliance. Int J Sci Res Manag 2025. doi: 10.18535/ijsrm/v13i03.ec03
9. Han X, Li Z, Cao H, Hou B. Multimodal spatio-temporal data visualization technologies for contemporary urban landscape architecture: a review and prospect in the context of smart cities. Land 2025; 14(5):1069. doi: 10.3390/land14051069
10. Holsamudrkar N, Banerjee S. Damage classification using CNN-based model for multi-part strengthening system. Procedia Struct Integr 2024; 64:580–587. doi: 10.1016/j.prostr.2024.09.312
11. Jadhav S, Durairaj M, Reenadevi R, Subbulakshmi R, Gupta V, Ramesh JVN. Spatiotemporal data fusion and deep learning for remote sensing-based sustainable urban planning. Int J Syst Assur Eng Manag 2024; 1–9. doi: 10.1007/s13198-024-02583-6
12. Khatir A, Capozucca R, Khatir S, Magagnini E, Le Thanh C, Riahi MK. Advancements and emerging trends in integrating machine learning and deep learning for SHM in mechanical and civil engineering: a comprehensive review. J Braz Soc Mech Sci Eng 2025; 47(9):1–34. doi: 10.1007/s40430-025-05697-5
13. Kumar R, Bhanu M, Mendes-Moreira J, Chandra J. Spatio-temporal predictive modeling techniques for different

domains: a survey. ACM Comput Surv 2024; 57(2):1–42. doi: 10.1145/3696661

14. Liu Y, Di S, Ji W, Li J. Enhancing SHM data reconstruction with MA-CNN-BiLSTM: a deep learning approach for missing acceleration responses. Structures 2025; 75:108693. doi: 10.1016/j.istruc.2025.108693
15. Mardanshahi A, Sreekumar A, Yang X, Barman SK, Chronopoulos D. Sensing techniques for structural health monitoring: a state-of-the-art review on performance criteria and new-generation technologies. Sensors 2025; 25(5):1424. doi: 10.3390/s25051424
16. Mata J, Santos J, Barateiro J. Using emergent technologies on the structural health monitoring and control of critical infrastructures. In: Ind 4.0 Built Environ: Methodol Technol Skills. Cham: Springer; 2021; 541–567. doi: 10.1007/978-3-030-82430-3_23
17. Moldovan SC, Iantovics LB. Review on information fusion-based data mining for improving complex anomaly detection. WIREs Data Min Knowl Discov 2025; 15(2):e70017. doi: 10.1002/widm.70017
18. Ogunnowo E, Ogu ELEMELE, Egbumokei P, Dienagha I, Digitemie W. Conceptual model for failure analysis and prevention in critical infrastructure using advanced nondestructive testing. Iconic Res Eng J 2024; 7(10):2456–8880
19. Plevris V, Papazafeiropoulos G. AI in structural health monitoring for infrastructure maintenance and safety. Infrastructures 2024; 9(12):225. doi: 10.3390/infrastructures9120225
20. Sakr M, Sadhu A. Recent progress and future outlook of digital twins in structural health monitoring of civil infrastructure. Smart Mater Struct 2024; 33(3):033001. doi: 10.1088/1361-665X/ad2bd7
21. Singh V, Baral A, Kumar R, Tummala S, Noori M, Yadav SV. A hybrid deep learning model for enhanced structural damage detection: integrating ResNet50, GoogLeNet, and attention mechanisms. Sensors 2024; 24(22):7249. doi: 10.3390/s24227249
22. Wang G, Ke J. Literature review on the structural health monitoring of sustainable civil infrastructure: an analysis of influencing factors in the implementation. Buildings 2024; 14(2):402. doi: 10.3390/buildings14020402
23. Wang X, Xie G, Zhang Y, Liu H, Zhou L, Liu W, Gao Y. The application of a BiGRU model with transformer-based error correction in deformation prediction for bridge SHM. Buildings 2025; 15(4):542. doi: 10.3390/buildings15040542
24. Xia H, Huang X. Research on structural damage identification based on multiple model deep ResNet. In: Proc 3rd Int Conf Green Build Civ Eng Smart City (GBCESC 2024). Paris: Atlantis Press; 2025; 868–887. doi:10.2991/978-94-6463-728-1_80