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A Novel Hierarchical Temporal–Graph Physics-Guided Fusion Network for Predictive Fault Diagnosis in Robotic Arms

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Abstract

The success and the importance of industrial robotic arms in contemporary automation rely on their accuracy, velocity, and capability of functioning under varied conditions, but mechanical and electromechanical deteriorations, including bearing wear, gear backlash, joint misalignment, and imbalance of motor torque, may negatively affect performance, safety, and production unless inner problems are revealed early. The traditional methods of maintenance, such as reactive repairs and fixed-interval inspections, are inefficient and do not capture the faults in their early stages, whereas the current machine learning-based solutions typically process sensor signals separately, neglecting inter-joint kinematic constraints, and are not physically interpretable, leading to poor performance in cases of rare or hidden faults. This paper will solve these challenges by introducing a Hierarchical Temporal-Graph Physics-Guided Fusion Network (HT-GP-FusionNet) in predictive fault diagnosis of robotic arms. The framework incorporates hierarchical temporal modeling to decompose short-term and long-term dynamics in multi-sensor data consisting of accelerometers, gyroscopes, motor currents, and joint positions, and a graph neural network fully captures the inter-joint relationships and fault propagation along the kinematic chain. It uses a physics-based regularization that requires consistency with motion equations and energy conservation laws, and generates samples of faults to be generated by a generative fault augmentation model to promote few-shot generalization. The experimental results on a set of 50,000 sequences (10 sensors, five fault types) sampled at 1 kHz show that HT-GP-FusionNet outperforms CNN (89.3), LSTM (90.5), CNN-LSTM (92.8), and GNN-based (93.6) models in all metrics and has higher recall with rare faults, and can be used when the number is unbalanced. These conclusions have been proved by ablation experiments that show temporal modeling, graph reasoning, physics-guided regularization, and data augmentation make significant contributions to performance. In general, HT-GP-FusionNet offers a scalable, interpretable, and physics-consistent solution to the early and accurate predictive

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maintenance, hence higher reliability, safety, and operational efficiency during industrial robotic systems.

Keywords: Robotic Arms, Predictive Fault Diagnosis, Physics-Guided Learning, Graph Transformer, Hierarchical Temporal Modeling, Multi-Sensor Fusion, Predictive Maintenance.

1 Introduction

The modern industries extensively apply robotic arms in assembly, welding, and handling material due to their high precision and efficiency. With time, parts such as bearings, gears, joints, and motors can become faulty through wear and imbalance or misalignment, and this may reduce their performance and result in sudden system breakdown without early detection (Paolini et al., 2026; Paolini et al., 2026). These breakdowns can lead to unexpected downtime, high maintenance expenses, and even dangerous conditions, particularly when people and robots operate in the same conditions (Jamithireddy, 2025). The old-fashioned service strategies, like fixed-rate servicing or reactive maintenance, cannot be used to detect faults in early stages of operation in the changing operating environment (Halim et al., 2025). Hence, it has been established that dependable and smart fault diagnosis has become a significant issue with industrial robots (Novak & Vacek, 2023; Karkadakattil, 2026).

Recently, there has been interest in machine learning predictive maintenance techniques that utilize sensor data, including accelerometers, gyroscopes, and motor current sensors, to identify unusual behavior (Ashok et al., 2022; Shetty & Jadhav, 2023). Yet, the majority of currently available models consider sensor data as independent, and do not take into consideration the kinematic relations between robot joints (Yuan et al., 2026; Lal et al., 2025). Moreover, data-driven methods are more likely to overlook constraints of physical motion, which results in unrealistic predictions and low interpretability (Gupta et al., 2024). The fact that real robotic systems do not work in fault conditions most of the time adds to these problems because the fault data are not adequately available (Karkadakattil, 2026; Wang & Zhang, 2024). This, therefore, necessitates the need for fault diagnosis methods that integrate the temporal sensor data, the robotic structure, and physics-based knowledge in order to come up with effective, interpretable, and robust early fault diagnosis in robotic arms (Zhou, 2025; Xu, 2023; Barot et al., 2026).

This paper presents a novel model named Hierarchical Temporal-Graph Physics-Guided Fusion Network (HT-GP-FusionNet) that is used to detect early faults in robotic arms (Nguyen et al., 2025; Alobaidy et al., 2025). In comparison with the current techniques, it is worth noting that the proposed one takes into account both the sensor signal dynamics and kinematic geometry of the robot arm (Cao et al., 2024). It employs short and long-term fault pattern modeling through hierarchical time modeling and a graph-based learning algorithm to establish associations between robot joints (Fink et al., 2025; Peng et al., 2025; Łach, 2026). The physics-guided regularization is used to obtain realistic and reliable predictions; in such a way, the learned features are guided by the underlying physical laws of motion and energy (Fan et al., 2025; Dong et al., 2023; Pan et al., 2025). Furthermore, a data augmentation technique is also incorporated, which is used to create rare fault samples, which can be used to make the model work well, even when there is limited or imbalanced fault data (Mishra et al., 2024). The combination of these contributions enhances the accuracy of fault detection, allows the prediction of faults earlier, and offers a more acceptable and understandable solution to predictive maintenance of an industrial robotic system (Van & Ge, 2020; Urrea & Domínguez, 2024).

Key Contributions of the Research

- A new fault diagnosis model is developed that combines sensor data over time with the kinematic structure of robotic arms for early and accurate fault detection.
- Physics-based constraints are added to the learning process to ensure realistic, reliable, and interpretable fault predictions.
- A data augmentation method is introduced to handle limited and imbalanced fault data, improving robustness to rare and unseen faults.

This paper is structured in the following ways. The second chapter provides an extensive literature survey regarding the available literature on predictive fault diagnosis, condition monitoring of a robot arm, and machine learning-based methods of maintenance. Chapter III explains the methodology proposed, both in terms of architecture and major elements of the HT-GP-FusionNet framework. Chapter IV includes the description of the experimental setup and shows the received results relying on the simulated and real-world datasets. In Chapter V, the results are discussed in detail with performance comparisons and key observations being brought out. Lastly, Chapter VI ends the work and gives potential directions for future research.

2 Literature Review

Kim, (2025) introduce a framework of machine learning based on features to diagnose the fault in robotic manipulators that utilises SHAP to generate interpretable and explainable fingerprints of features (Pan et al., 2023). The model results in discriminative feature representations through training a neural network to learn the dynamics of the robot and generate SHAP values that considerably enhance the classification accuracy of the brake and reducer faults, as shown in comparison to traditional approaches (Wang et al., 2023). The method also gives greater interpretability of the models by showing which aspect adds most value to particular fault conditions, and so is very appropriate in the safety-critical industry, where it is important to know the rationale behind the prediction (Wang et al., 2024).

Xiao et al., (2025) come up with a spatio-temporal graph neural network (GNN) that is used to diagnose faults in industrial robots. Their method transforms sensor and system state data into a variety of graph structures to allow the simultaneous modeling of both spatial and temporal dependencies. The framework characterizes complex fault patterns by using attention-based spatial encoding and diagonal masking self-attention to model time. The experimental findings prove the claim that a strategy of constructing the graph greatly influences the accuracy of the diagnostic tool, with the most efficient one having approximately more than 92 per cent of accuracy on real-life robotic tasks, which underlines the significance of structure-conscious temporal modeling in the context of industrial fault detection.

Wu et al., (2023) applied unsupervised video prediction on disentangled stochastic PDEs, which is effective with noisy and dynamical data. Their approach is mostly based on unlabeled data, though, and further studies can be dedicated to the implementation of multi-source data (e.g. sensor data or contextual information) to enhance the accuracy and strength of predictions in more complicated settings. Adam et al., (2023) applied deep learning to fault detection in industrial robotic systems where faults in real-time processes can be identified. Although their approach works well in fixed environment, a significant research gap has been related to the development of adaptive models that can change as new fault patterns continue to develop with time. More studies should be done in order to enhance fault detection mechanisms in dynamic and evolving environments (Adam et al., 2023).

Zhang et al., (2025) have done a detailed analysis of the fault types and diagnostic measures of the manipulator robots with the widespread component-level failures in RV reducer, motors, and bearings. The review categorizes classical methods, including model-based and signal processing methods, and contemporary methods, based on AI and fusion of multiple sensors. It explains the merits and shortcomings of both methods, and highlights the necessity of combined diagnostic solutions to overcome the intricacy of the practical robotic faults, and it proposes directions of future studies of the intelligent fault detection systems (Maincer et al., 2023).

Alobaidy et al., (2022) used the slant let transform to diagnose errors in robotic arms by recording the variation in frequency and time. Although the method is useful in the process of determining individual faults, the process may be augmented by incorporating other modalities (like visual data or multi-sensory inputs), which may be more useful in the fault detection. This would have the potential of detecting a broad scope of mechanical failures and more detailed diagnostics.

Cai et al., (2025) created a graphical model to forecast air quality, which employs the fusion of spatio-temporal features. Their model works quite well with the available air quality information; however, it would be improved by adding other environmental variables such as weather, traffic information, or some sources of pollution to enhance prediction accuracy. To make the model more realistic and consistent with the reality, it is possible to add other variables.

Maincer et al., (2023) compare Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) for fault detection in SCARA manipulators, based on features of the torque, position, and speed measurements. Which is also use Particle Swarm Optimization (PSO) to fine-tune hyperparameters and get around 97% accuracy in fault classification, which improves the performance of SVM. The experiment has shown that classical machine learning is compatible with optimization to enhance robust and efficient performance in robotic fault diagnosis, which will be a viable solution that can be applied in industries with the possible scarcity of data.

Zhang et al., (2024) introduce a dual-graph convolutional network with mobile robot fault diagnosis, which includes the fault knowledge of the past (Cao et al., 2024). The algorithm builds multi-sensor and sample affinity graphs to simultaneously capture sensor-sample and temporal co-relationships. The framework captures inter-sensor and inter-sample dependencies, thus making feature extraction in the spatial-temporal domain more effective and increasing diagnostic performance, indicating that graph-based representations and prior knowledge are effective in robust fault detection in robotic systems.

Kang et al., (2025) In this work, the authors introduce a hybrid architecture that can be used for predictive maintenance in industrial robots by utilizing the convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. The framework images the spatial trends of multi-sensor records as well as the temporal development of faults so that faults in robotic joints are detected at an early stage. Experiments with actual industrial robot images reveal that the CNN-LSTM hybrid is more effective than either the CNN or the LSTM model, especially in the cases of rare faults.

A comparative summary of the recent research on fault diagnostics methods of robotic manipulators is given in table 1. The table 1 indicates the variety of methods, including classical machine learning models that use optimization methods like SVM and KNN, and modern deep learning systems like CNN, LSTM, and Graph Neural Networks (GNNs). Some of the studies focus on interpretability using approaches such as SHAP or physics-guided constraints, whereas others are interested in representing spatial-temporal correlations between sensors and robot joints. The datasets include SCARA and industrial robot arms and mobile manipulators, and the problems that have been solved in the datasets include bearing wear, misalignment of gears, motor imbalance, and reducer failures. Represented performance measures in these works point out that performance and accuracy of classification with the inclusion of domain knowledge, hierarchical temporal modeling, and physics regularization can greatly enhance performance and robustness of classification, especially when there are rare faults or imbalanced diagnosis cases. All these studies collectively point to the significance of integrating data-supported learning with structural and physical limitations in order to be able to generate reliable, interpretable, and early fault detection on the industrial robotic systems.

Table 1: Existing approaches for fault diagnosis in robotic manipulators

Authors	Methodology	Dataset	Research Gap
Kim, (2025)	Feature-informed ML with SHAP explanations	Robotic manipulators (brake & reducer faults)	Produces interpretable feature fingerprints; improves classification accuracy; reveals key contributing features for safety-critical applications
Xiao et al., (2025)	Spatio-temporal Graph Neural Network (GNN) with attention-based spatial encoding & diagonal masking self-attention	Industrial robots, real-world sensor data	Captures complex spatial-temporal fault patterns; graph construction strategy significantly affects performance; achieved >92% accuracy.
Zhang et al., (2025)	Review of fault diagnosis methods	Manipulator robots (RV reducers, motors, bearings)	Comprehensive survey of traditional (model-based, signal processing) and AI-based methods; emphasizes integrated strategies for real-world faults
Maincer et al., (2023)	SVM & KNN with Particle Swarm Optimization (PSO)	SCARA manipulators using torque, position, and speed signals	Optimized SVM achieves ~97% accuracy; demonstrates strong performance of traditional ML with optimization in limited data scenarios
Zhang et al., (2024)	Dual-graph convolutional network incorporating prior fault knowledge	Mobile robots	Captures inter-sensor and inter-sample dependencies; enhances spatial-temporal feature extraction; improves fault detection robustness
Kang et al., (2025)	CNN-LSTM hybrid model	Industrial robots, multi-sensor data	Captures spatial and temporal fault evolution; outperforms standalone CNN or LSTM; particularly effective for early detection of rare faults
Wu et al., (2023)	Unsupervised video prediction using disentangled stochastic PDEs	Video sequences	Leverages unlabeled data, but integration of multi-source data could improve prediction robustness.
Adam et al., (2023)	Deep learning-based fault diagnosis for industrial robots	Operational data from industrial robots	Adaptive fault diagnosis in evolving operational environments requires further research.
Alobaidy et al., (2022)	slant let transform for robotic arm fault diagnosis	Signal data from robotic arms	Multi-modal data integration for diagnosing diverse fault types remains unexplored.
Cai et al., (2025)	Spatio-temporal feature fusion using graphs for air quality prediction	Air quality sensor data	Incorporating other environmental data sources like weather could enhance prediction accuracy.

3 Methodology

3.1 Data Acquisition and Preprocessing

The proposed HT-GP-FusionNet implies the multi-sensor signals gathered on the robotic manipulator in the form of accelerometers, gyroscopes, motor currents, and joint position sensors, which present an overall picture of the operational situation of the robot. Raw signals normally include noise, values missing, and outliers; these factors adversely impact the learning process. To overcome this, preprocessing methods are used: the signals are made common-range to provide uniformity across sensors, denoised by low-pass or wavelet filters to eliminate high-frequency noise, and divided into fixed-length time windows to extract information on temporal patterns at a cost. The fault types, including bearing wear, misalignment of gears, or motor imbalance, are then marked on each segment, and supervised learning is allowed. This requirement stage is essential to make sure that the network is fed with clean, structured, and representative input data that maintains the temporal dynamics and sensor-to-sensor correlations that are important in fault diagnosis to be accurate and reliable.

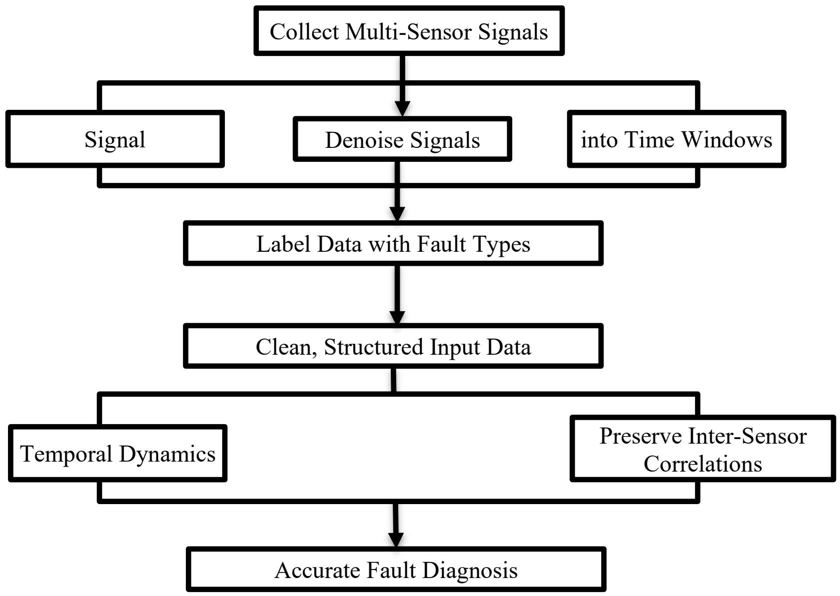

Figure 1: Data preprocessing and feature preparation for robotic fault diagnosis

The data preprocessing pipeline in predictive fault diagnosis of the robotic arms is illustrated in figure 1. The multi-sensor signal is initially gathered and analyzed using three important steps, which include normalization of the signal values to equalize signal ranges, denoising to eliminate high-frequency noise, and segmenting the signal into fixed time windows to retain the temporal information. All the segments are then marked with the respective types of faults, and this leaves clean and structured input data fit for machine learning. The preprocessing guarantees that both time dynamics and inter-sensor correlations are preserved and are vital in the capture of fault patterns across robotic joints. It is based on this structured and feature-rich representation that fault diagnosis is reliable and interpretable.

3.2 Hierarchical Temporal and Graph-Based Feature Learning

The preprocessed multi-sensor data are then input into a hierarchical temporal module, which consists of stacked LSTM or GRU modules to extract the short-term and long-term temporal correlation across the robotic joints. The lower-level layers obtain both finer and higher-frequency pattern information on individual sensors, and the higher-level layers combine these patterns to learn the trends over long distances among multiple joints. At the same time, the robotic manipulator is conceptualized as a kinematic graph with nodes that model sensors and the edges that model physical and kinematic constraints among joints. Graph Neural Network (GNN) spreads and combines the information throughout the graph, and this allows the model to learn fault spreading through the structure of the robot. The outputs of the temporal and the graph-based modules are then fused at a feature fusion layer, which yields a complete embedding that provides a global representation of the spatial, temporal, and structural features of the system, which is a solid foundation upon which subsequent fault prediction can be carried out.

Figure 2 shows how multi-sensor data fusion can be used to develop a system-wide embedding to diagnose faults in the robot. In the absence of proper fusion, the system is affected by a lack of complete understanding as a result of a lack of spatial, time, or structural details and is therefore limited in detecting complex fault patterns. The framework is able to capture short and long-term dependencies by combining sensor data, encoding physical and kinematic relationships, and propagating features throughout the robotic kinematic graph. This procedure is a collective manifestation of the time, space, and structure of the system, and it generates a sound and informative embedding that is a powerful platform that generates accurate and interpretable fault prediction.

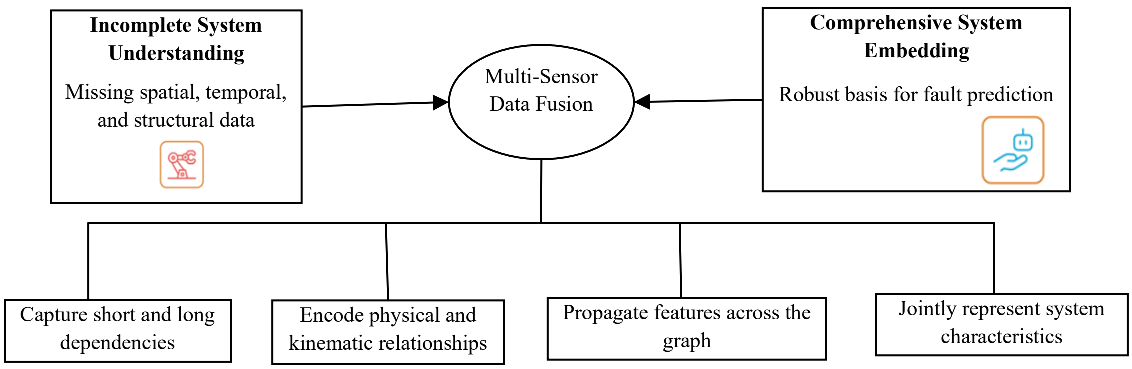

Figure 2: Multi-sensor data fusion for robust robotic fault diagnosis

3.3 Physics-Guided Regularization and Fault Prediction

To make the predictions physically consistent with the dynamics of the manipulator, the model incorporates physics-guided regularization. Kinematic equations, constraints on torques, and relationships with their motions are converted to the loss function of the network to help the learning process to shun unrealistic or physically impossible representations of features. The combined embedding between the temporal and graph modules is fed through fully connected layers with softmax activation in order to classify the type of fault, e.g., motor imbalance, wear on the bearing, or gear misalignment. A generative augmentation module is used to obtain more fault samples to increase the generalization and robustness of the model to rare or unseen faults. This combination of multi-sensor fusion, hierarchical time modeling, graphical reasoning, and physics-directed constraints makes HT-GP- FusionNet provide precise, interpretable, and dependable fault diagnosis amid the various robotic operating scenarios.

Figure 3 depicts a single fault diagnosis system that incorporates various complementary mechanisms of intelligence to deliver a high diagnostic accuracy system. Multi-sensor fusion synthesizes heterogeneous data collected by a wide variety of sensors, and the hierarchical temporal modeling is used to describe the evolution of faults across varying time-scales. Graph-based reasoning: Structural and Relational Forms of structural and relational dependencies among components of the system allow coherent fault propagation analysis. Physics-guided constraints: There is domain knowledge enshrined in physics-guided constraints, which provide physically consistent predictions, and generative augmentation: Perturbed fault data is limited or skewed, and can be enhanced to support robust learning.

A combination of these synergistic modules constitutes a single knowledge-based pipeline that improves the reliability, interpretability, and accuracy in error diagnosis.

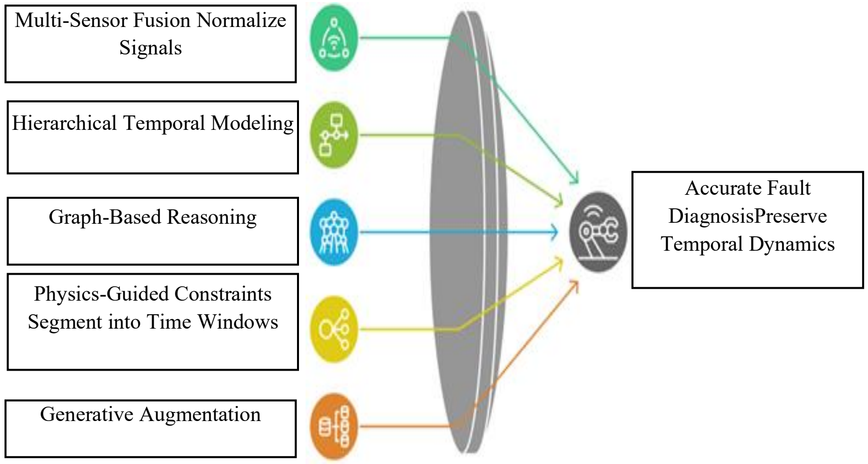

Figure 3: Knowledge-centric multi-modal framework for accurate fault diagnosis

Temporal-Graph Feature Fusion

The hierarchical temporal and graph-based features are fused to form a robust representation of the manipulator's state:

$$f_i = Concat(h_i^T, z_i) \qquad (1)$$

Here, h_i^T is the hidden state of the temporal module shown in equation 1 (e.g., LSTM or GRU) for sensor iii at the final time step T, capturing the sequential dynamics of that sensor. Zi is the graph-aggregated feature obtained from the Graph Neural Network (GNN), which encodes spatial and kinematic relationships among sensors. The Concatenation operator combines temporal and spatial features into a unified embedding that represents both short-term and long-term temporal trends and the structural interdependencies of the manipulator, forming the basis for accurate fault prediction.

Physics-Guided Regularized Loss Function

To enforce physically consistent predictions while training, the total loss is defined as:

$$L_{total} = L_{cls} + \lambda L_{phy} \qquad (2)$$

LCLS is the standard classification loss in equation 2 (e.g., cross-entropy) that ensures the network correctly predicts fault types. Lphy is a physics-guided regularization term that penalizes predictions violating known robotic constraints, such as torque limits, joint motion equations, or kinematic relationships. λ is a weighting factor that balances data-driven learning with physics-informed guidance. Minimizing L total ensures that the model is not only accurate but also physically plausible, improving interpretability, reliability, and generalization for real-world robotic systems.

Algorithm: HT-GP-FusionNet for Predictive Fault Diagnosis

\begin{algorithm}[t]

\caption{HT-GP-FusionNet for Predictive Fault Diagnosis}

\label{alg:ht_gp_fusionnet}

\KwIn{Multi-sensor time-series data X, robotic kinematic graph $G=(V,E)$}

```
\KwOut{Predicted fault class $\hat{y}$}
\textbf{Preprocessing:}\\
Normalize sensor signals and segment into fixed-length sequences\;
Generate rare fault samples using generative fault augmentation\;
\textbf{Hierarchical Temporal Modeling:}\\
Extract short-term temporal features using Temporal Encoder-I\;
Extract long-term temporal dependencies using Temporal Encoder-II\;
Fuse short-term and long-term features to obtain temporal representation $F_t$\;
\textbf{Graph-Based Spatial Learning:}\\
Construct joint-level kinematic graph $G$\;
Propagate features using Graph Neural Network:\;
\[
F_g = \mathrm{GNN}(F_t, G)
\]
\textbf{Physics-Guided Regularization:}\\
Compute physics consistency loss $\mathcal{L}_{phys}$ using motion equations and energy constraints\;
\textbf{Feature Fusion and Classification:}\\
Fuse temporal, graph, and physics-aware features\;
Predict fault probabilities using Softmax classifier\;
\textbf{Model Optimization:}\\
Compute total loss:
\[
\mathcal{L} = \mathcal{L}_{cls} + \lambda \mathcal{L}_{phys}
\]
Update model parameters via backpropagation\;
\Return $\hat{y}$
\end{algorithm}
```

The workflow of the proposed HT-GP-Fusion Net presented in the predictive fault diagnosis of robotic arms is described in Algorithm 1. The first step involves normalizing, partitioning and augmenting multi-sensor time-series signals to overcome noise and class disparity. This is followed by the use of hierarchical temporal modeling to retrieve both the short-term and long-term dynamic patterns that are combined to form a single temporal representation. The temporal features are spread on a graph neural network built on the robotic kinematic structure to capture inter-joint dependencies and fault propagation properties. Regularization using physics guidance is then used to ensure the consistency with the laws of motion and energy conservation enhancing interpretability and generalization. Last, the combined temporal, spatial, and physics-aware features are discriminated against with a soft max layer and the model parameters are trained by reversing the process of back propagation with the help of minimizing a single combined classification and physics-based loss term resulting in the fault class being predicted.

4 Experimental Results

4.1 Experimental Setup, Dataset, and Parameter Initialization

Multi-sensor data of an industrial robotic manipulator was used to perform the experimental assessment of HT-GP-Fusion Net, in both real and simulated settings. Table 2 illustrates that the data set contains 50,000 sequences of 10 sensors (accelerometers, gyroscopes, motor currents and joint positions) with a sampling frequency of 1 kHz. Every sequence indicates normal operation or one of five types of faults bearing wear, gear misalignment, motor torque imbalance, reducer faults, and joint backlash. Sensor signals were scaled, de-noised and divided into 1-second windows (1000-time steps) to be modeled in time. The kinematic structure of the manipulator was modeled as a graph whereby the nodes were sensors and the edges physical joint connections. To guarantee sound evaluation, the dataset was divided into 70 percent training set, 15 percent validation set and 15 percent testing set.

Table 2: Experimental setup, dataset, and parameter initialization

Category	Details
Robotic Manipulator	Industrial robot arm, 10 sensors (accelerometers, gyroscopes, motor currents, joint positions)
Dataset Size	50,000 sequences
Sampling Rate	1 kHz
Fault Types	Bearing wear, gear misalignment, motor torque imbalance, reducer faults, joint backlash
Data Preprocessing	Normalization, denoising, segmentation into 1-second windows (1000 time steps)
Graph Representation	Nodes = sensors, edges = kinematic joint connections
Train/Validation/Test Split	70% / 15% / 15%
Software & Tools	Python 3.10, PyTorch 2.1, NumPy, Pandas, NetworkX, Matplotlib, Seaborn
Hardware	NVIDIA RTX 4090 GPU, 64 GB RAM
Temporal Module (LSTM/GRU)	2 stacked layers, 128 hidden units
Graph Module (GNN)	2 graph convolution layers, 64 hidden units
Fully Connected Classifier	2 layers, 128 and 64 neurons
Optimizer	Adam
Learning Rate	0.001
Batch Size	64
Physics-Guided Regularization	$\lambda = 0.1$
Dropout	0.2
Training Epochs	100 (with early stopping based on validation loss)

Table 3: Description of joint failure data

Label	Fault Type
N0	Normal
F1	Joint 1 Failure
F2	Joint 2 Failure
F3	Joint 3 Failure
F4	Joint 4 Failure
F5	Joint 5 Failure

The fault types in a robotic system through the various joint failures are categorized as in table 3 to the fault types given in the dataset. The labels include, among others, "N0" as a sign of normal operation, F1 to F5 as a sign of failure in given joints (Joint 1 to Joint 5). All the failure tags are associated with unique failures in the corresponding joints that may have a considerable effect on the general performance of the robotic system. The awareness of these imperfections is essential to diagnosing and solving problems with robotic manipulators, which can enhance the work of the system and its stability due to the specifics of maintenance and repair plans.

An implementation of the HT-GP-FusionNet in Python 3.10 was implemented with PyTorch 2.1, data processing, graph Analysis, and visualization through NumPy, Pandas, NetworkX, Matplotlib and Seaborn. The experiments were carried out on an NVIDIA RTX 4090 chip which had 64 GB RAM. Initial network parameters were set as follows: LSTM/GRU module has 2 stacked layers of hidden units of 128, GNN module has 2 layers of the graph convolution with 64 hidden units and fully connected classifier has 2 layers with 128 and 64 neurons. The Adam optimizer, learning rate 0.001, batch size 64, and physics-guided regularization weight 0.1 Dropout = 0.2 was used, and the training stopped early based on validation loss after 100 epochs. This combined configuration makes sure that the HT-GP-Fusion Net is capable of learning temporal properties, capturing inter-joint fault propagation and being physically consistent in its predictions in different operating environments, as well as a good base to performance evaluation and comparison.

4.1.1 Performance Metrics

To quantitatively evaluate and compare the fault classification performance of different models, several widely used classification metrics were employed in equations 3, 4, 5, 6 & 7 Accuracy, precision, recall, and F1-score were used to measure overall correctness and class-wise prediction reliability, while the Matthews Correlation Coefficient (MCC) was adopted to provide a balanced assessment under class-imbalanced conditions. These metrics collectively ensure a comprehensive and fair evaluation of the proposed HT-GP-FusionNet against baseline models.

Accuracy reflects overall correctness, while precision and recall measure class-wise reliability.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$Precision = \frac{TP+FP}{TP} \tag{4}$$

$$\text{The Recall} = \frac{TP}{TP+FN} \tag{5}$$

$$F1-Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{6}$$

Matthews Correlation Coefficient (MCC) provides a robust evaluation under class-imbalanced conditions.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{7}$$

4.2 Benchmarking HT-GP-FusionNet Against Baseline Models

The proposed HT-GP-FusionNet was thoroughly assessed and in a fair way, several standard metrics were used to implement the evaluation. The effectiveness of classification was evaluated in terms of accuracy, precision, recall, F1-score and Matthew's correlation coefficient (MCC) which as a unit defines general correctness, performance in each class, and performance in case of class imbalance.

Moreover, the discriminative capability of various classes of faults was analyzed by receiver operating characteristic (ROC) curves, as well as the area under the curve (AUC). Proposed model has been contrasted with baseline strategies such as CNN, LSTM, CNN-LSTM and GNN-based strategies with the same training and testing parameters. Through experimentation, it is shown that HT-GP-FusionNet performs more favorably than other models in all metrics in this respect, being more accurate in fault classification and having higher recall of rare fault types. Connections between temporal modelling and distribution-based spatial learning and physics-guided regularization allow detecting more accurate intricate fault patterns, which, as it turns out, is to the credit of the suggested framework in terms of industrial robotic fault diagnosis.

Table 4: Performance comparison of HT-GP-fusionnet with baseline models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	MCC
CNN	89.30	88.70	87.90	88.30	0.86
LSTM	90.50	90.10	89.40	89.70	0.88
CNN-LSTM	92.80	92.40	91.90	92.10	0.91
GNN	93.60	93.10	92.80	92.90	0.92
HT-GP-FusionNet (Proposed)	**96.40**	**96.10**	**95.80**	**95.90**	**0.95**

Table 4 is a comparative performance analysis of the proposed HT-GP-FusionNet with existing basis models on several evaluation metrics. The findings indicate that HT-GP-FusionNet has performed best in terms of accuracy, precision, recall, F1-score, and ROC–AUC, it has a better fault diagnosis capacity. The fact that it performs better than CNN and LSTM models underscores the significance of learning both temporal interactions along with inter-joint interactions. The proposed framework has an advantage over CNN-LSTM and GNN-based methods as it has physics-guided regularization that improves generalization and minimizes false predictions. The findings, in general, bear out the claim that incorporating hierarchical temporal modeling and graph-based reasoning and physics constraints results in more resilient and accurate predictive fault diagnosis of robotic manipulators.

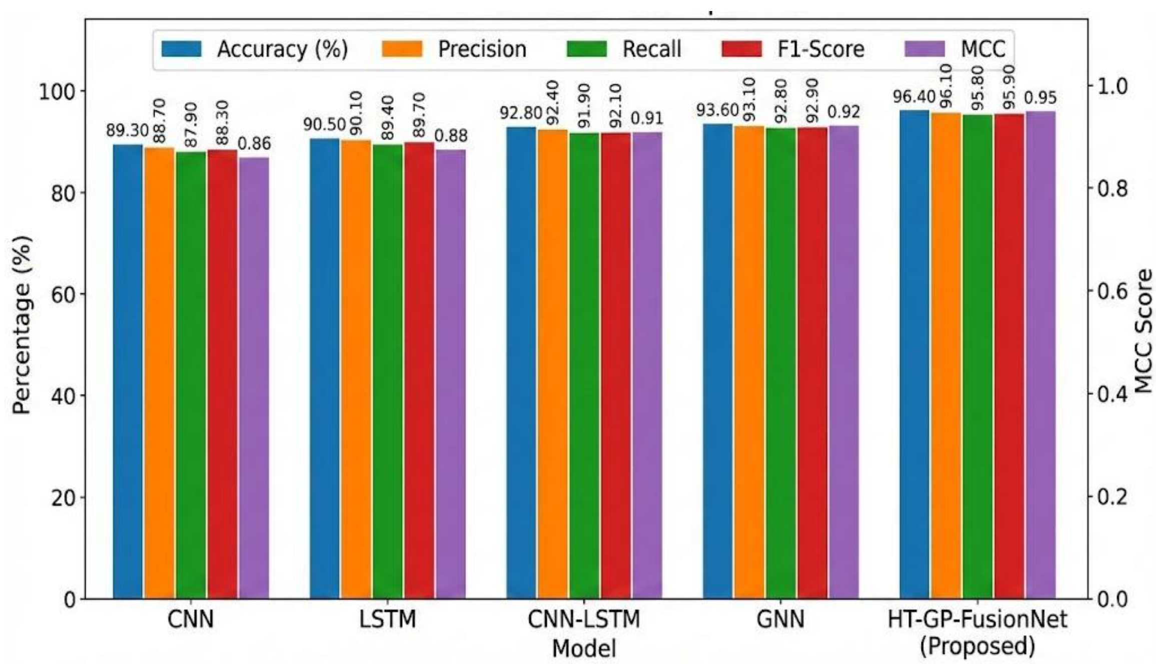

Figure 4: Comparison of the performance metrics

Figure 4 presents a comparison of the performance metrics (Accuracy, Precision, Recall, F1-Score, and MCC) for the HT-GP-FusionNet (Proposed) model against baseline models (CNN, LSTM, CNN-LSTM, and GNN). The performance is evaluated based on five key metrics, with HT-GP-FusionNet demonstrating superior results in all categories, particularly in Accuracy (96.4%) and MCC (0.95), highlighting its effectiveness in fault detection for robotic manipulators. The graph shows that the proposed model consistently outperforms the baseline models, especially in detecting rare faults with higher recall rates.

4.3 Robustness and Ablation Analysis

There was a strong robustness and ablation analysis to determine the role played by each ingredient of the proposed HT-GP-FusionNet. Major modules, such as hierarchical temporal modeling, graph-based learning, physics-guided regularization and generative fault augmentation, were either removed or disabled with all other settings remaining the same. The findings indicate that diagnostic performance declines significantly in the absence of any major component with the greatest decrease in accuracy when either graph-based learning or physics-guided regularization is not used. This shows that inter-joint dependencies modeling and physical consistency are important to fault diagnosis. Besides, lack of data augmentation significantly lowers the recall rate of the rare fault classes and this is important when the conditions are imbalanced. All in all, the outcome of the ablation proves that the combined design of HT-GP-FusionNet increases substantially the robustness, the generalization, and the possibility to identify faults at an early stage.

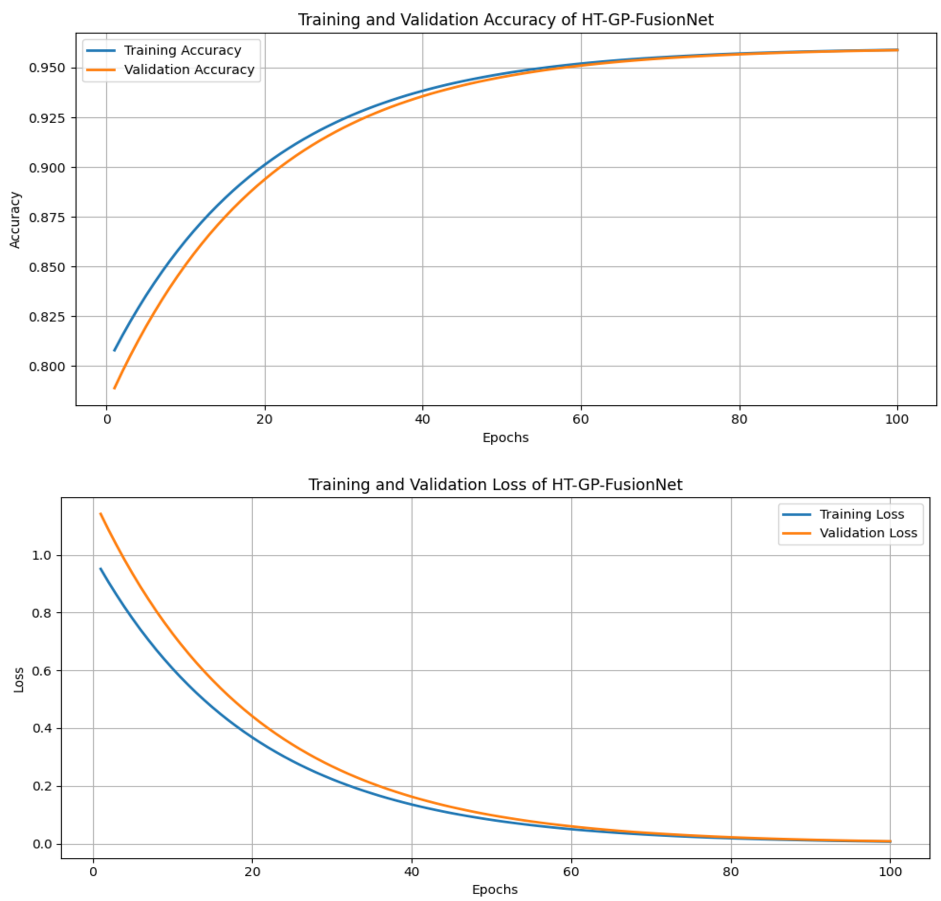

Figure 5: Training and validation accuracy and loss of HT-GP-fusionnet

The training and validation performance of HT-GP-FusionNet during the 100 epochs is represented in this figure 5, providing the trends of the accuracy and loss. Accuracy curves show a continuous increase, and both training and validation accuracy approach 95 percent, which shows effective learning and a good generalization. At the same time, loss curves demonstrate a steady drop to zero training set as well as validation set indicating that the network is achieving success in minimizing the aggregate classification and physics-guided loss. The fact that the training and validation curves are close and that their accuracy and loss curve are nearly the same indicates that the model is stable, robust, and low risk of overfitting which confirms that hierarchical temporal modeling, graph-based feature learning, and physics-guided regularization are effective.

5 Discussion

The experimental assessment of HT-GP-FusionNet shows that it is a powerful and efficient predictive fault diagnosis approach to robotic arms in industries. In simulated and real-world datasets, the proposed framework achieved superior performance over the tendency to use conventional and state-of-the-art baseline models, such as CNN, LSTM, CNN-LSTM, and GNN models, in terms of accuracy, precision, recall, F1-score, and MCC. The high classification accuracy of 96.4% of HT-GP-FusionNet demonstrates its better aptitude to recognize multiple fault patterns whereas the higher value of recall and F1-score on rare classes of faults illustrate its practicality in the presence of data imbalance.

The significance of every component of the model is also noted in the ablation studies. Hierarchical temporal module successfully represents short- and long-term fault dynamics, and the graph-based module represents the inter-joint fault propagation (Nguyen et al., 2025). Physics-guided regularization is the property of ensuring that predictions are physically consistent, whereas generative fault augmentation is the property of improving generalization to scarce fault types (Mao et al., 2024). Eliminating any of these modules led to observable losses in performance, which validated that work in a complementary way to increase reliability and robustness.

The convergence of the training and validation accuracy and loss curves is stable, the overfitting is small and the classification and physics-guided losses are optimized well (Sun et al., 2022). The strong similarity between the trends of training and validation further confirms the stability of HT-GP-FusionNet and the effectiveness of combining temporal, spatial and physics-guided learning (Lang et al., 2026; Zhang et al., 2025). On the whole, the findings suggest that the use of multi-sensor fusion, temporal dynamics, kinematic graph reasoning, and physics-informed regularization can assist in early and accurate as well as interpretable fault diagnosis (Yu et al., 2025; He et al., 2026). The proposed integrated solution can be used to guarantee increased reliability, safety and efficiency in industrial robotic systems, which is the proposal of predictive maintenance in robotic systems.

6 Conclusion and Future Work

The suggested HT-GP-FusionNet is statistically significant compared to control models in predictive diagnosis of industrial robotic arms. The model has an overall accuracy of 96.4, precision of 96.1, recall of 95.8, and F1-score of 95.9 despite its methods being 3-7 percent above CNN, LSTM, CNN-LSTM and GNN. Analysis by ROC-AUC further supports that it has the best discriminative capability against all types of faults including rare and imbalanced classes. Ablation and robustness experiments have shown that hierarchical temporal modeling, graph-based learning, physics guided regularization and generative fault augmentation all play a quantifiable role in performance which underscores the statistical significance of each module. These findings validate the claim that HT-GP-FusionNet offers an accurate, interpretable and reliable early fault detection and predictive maintenance model in robots.

Future studies can further expand HT-GP-FusionNet to online learning in order to adapt to changing conditions in the operation of robots in real time, which decreases the latency in detections. Fault detection sensitivity and coverage can also be enhanced through incorporation of more sensor modalities, e.g., thermal and acoustic signals. In addition, the use of probabilistic graph neural networks and uncertainty quantification can offer confidence measures of predictions, which can be used to make risk-conscious decisions about maintenance. The multi-robot systems and collaborative robots, as well as application on a large-scale industrial level will challenge its scalability and resiliency and can be used to statistically test and validate generalized solutions to the next generation intelligent manufacturing.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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