

QUANTUM GRAPH NEURAL NETWORK FOR PREDICTIVE MAINTENANCE OF INDUSTRIAL GEARBOXES USING VIBRATION AND ACOUSTIC EMISSION SIGNALS

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ABSTRACT

The gearbox systems are vital in manufacturing processes because any failure results in production downtime and increased maintenance cost. In this research work, a new method using Quantum Graph Neural Network (QGNN) has been proposed for the prediction of maintenance requirements of industrial gearboxes using vibration and acoustic emission signal fusion. The first step includes signal processing and converting the signals into multidomain feature representation. The feature vectors are treated as graph nodes with their correlations converted into graph edges. Finally, the Quantum Graph Neural Network (QGNN), using graph convolution and graph attention techniques, is used to learn the complicated spatial relationships and quantum-enhanced feature representations to efficiently classify gearbox fault types. The proposed algorithm is tested on the PHM 2009 Gearbox Challenge dataset and achieves an accuracy of 98.72%, precision of 98.41%, recall of 98.23%, F1-score of 98.32%, specificity of 99.04%, and Area Under the Curve (AUC) of 99.11%. It can be concluded that the proposed technique offers effective, reliable, and robust gearbox fault diagnosis with improved computational efficiency. The developed QGNN framework in this research work is expected to facilitate intelligent predictive maintenance of gearboxes by reducing unexpected equipment failures, minimizing maintenance costs, improving operational reliability, and contributing towards Industry 4.0-based smart manufacturing systems.

Keywords: *Quantum Graph Neural Network (QGNN); Predictive Maintenance; Gearbox Fault Diagnosis; Vibration Signal Analysis; Acoustic Emission; Multi-Sensor Fusion.*

1. INTRODUCTION

The fast development of Industry 4.0 has led to a revolution in conventional manufacturing operations as a result of using cyber-physical systems, Industrial Internet of Things (IIoT), artificial intelligence (AI), cloud computing, and edge computing. Predictive analytics is widely used

today to monitor machine health, optimize maintenance scheduling, and minimize operational downtime by checking the condition of equipment and planning its preventive maintenance. Gearbox systems are among the most important mechanical transmission devices that are used in manufacturing operations, mining equipment, wind turbines, automotive systems, aerospace applications, and

power generation units. Due to the constant operation of gearboxes under variable loads, speeds, and environmental conditions, they can experience gear tooth wear, pitting, scuffing, shaft misalignment, lubrication failure, and bearing defects. These malfunctions gradually reduce transmission efficiency and can ultimately lead to catastrophic equipment failure if not detected at an early stage [1], [2].

Machine failure interrupts the industrial production process, increases maintenance costs, reduces equipment availability, and poses operational safety risks to the organization. Maintenance operations consume a large part of manufacturing expenses, and unexpected machine downtime can cause substantial production losses. As a result, traditional maintenance operations have been replaced by intelligent predictive maintenance strategies that continuously estimate machine health and the remaining useful life of critical machine components [3], [4]. In this way, maintenance operations are carried out only when needed to reduce unnecessary component replacement, minimize maintenance costs, and improve equipment reliability.

Condition monitoring is the basis of intelligent predictive maintenance that continuously monitors the operating data of machines using various sensing technologies. Among various condition monitoring approaches, vibration analysis has become the most widely adopted approach to analyze rotating machinery since vibration signals represent the dynamic state of gears, shafts, and bearings while the machine is running. Characteristic vibration frequencies provide useful information about imbalance, eccentricity, misalignment, looseness, gear mesh faults, and bearing degradation. However, vibration signals lose their sensitivity during the early fault development stage due to the small structural changes caused by mechanical defects [5], [6].

To solve this problem, acoustic emission (AE) monitoring has become increasingly popular in recent years. AE sensors record high-frequency stress waves produced by crack initiation, friction, plastic deformation, and microscopic material failures even when these defects cannot be detected by traditional vibration monitoring. As AE signals are sensitive to microscopic structural changes, faults can be detected earlier than with vibration signals. However, acoustic emission (AE) readings are prone to high sensitivity to environmental noise, signal attenuation, and complicated propagation characteristics. This issue makes it hard to interpret

AE signals as standalone [7], [8]. Thus, modern researchers tend to fuse vibration and AE signals in order to conduct comprehensive monitoring of the health of gearboxes. Combining those sensing technologies helps to simultaneously observe macroscopic mechanical vibrations and microscopic material degradation. Using different types of sensors adds to the information obtained during fault detection and significantly increases diagnostic accuracy by providing richer information about machine operating conditions. Nevertheless, fusion of heterogeneous data is complicated due to differences in sampling rates, statistical properties, and temporal characteristics of vibration and AE signals [2], [9].

Artificial intelligence (AI) proved to be a very useful technique for the analysis of the complex characteristics of condition-monitoring data. Classical machine learning techniques, such as Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN), showed their efficiency in gearbox fault detection. At the same time, classical machine learning requires handcrafted statistical, frequency-domain, or time-frequency features to be created. Despite being able to provide satisfactory classification results under well-controlled operating conditions, such algorithms show poor results in noisy, nonstationary, load-dependent, and highly nonlinear fault environments. In addition, handcrafted feature engineering requires considerable domain expertise and is likely to overlook potential hidden relationships among different sensor channels [3], [10].

Deep learning brought significant improvements to automated fault diagnostics by providing automatic learning of hierarchical feature representations directly from raw sensor data. Convolutional Neural Networks (CNNs) learn local spatial representations from vibration spectrograms, whereas Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models learn temporal relationships among sequential data instances. Recently, Transformer-based architectures have proved to be a very powerful family of neural networks for capturing long-range dependencies in industrial time-series data. However, most of the existing deep learning models assume Euclidean data structures and treat sensor measurements independently, thus neglecting the intrinsic relationships among multiple sensors installed in industrial machinery [2], [11].

Graph Neural Networks (GNNs) represent a modern learning approach designed to operate with non-Euclidean data structures represented as interconnected graphs. Within the graph data structure, sensor locations or extracted signal features can be represented as graph nodes, whereas correlations between them, physical connections, or similarity measures are defined as graph edges. Graph Neural Networks utilize iterative message-passing mechanisms to extract spatial dependencies and global interactions among multiple nodes. Graph-based learning is especially effective for industrial condition monitoring since gearbox parts have interconnected mechanical relationships. However, existing predictive maintenance approaches based on Graph Neural Networks generally utilize classical optimization algorithms and suffer from increasing computational complexity with the growth of graph size and feature dimensions [11].

The field of Quantum Computing has been recognized as an advanced and rapidly developing computational paradigm which is able to solve complex optimization and learning tasks beyond the capabilities of classical computing systems. Quantum Machine Learning (QML) is considered to be a combination of quantum information processing and artificial intelligence, which takes advantage of quantum effects like superposition, entanglement, and quantum parallelism. Recent research has proven that quantum neural networks are able to efficiently learn high-dimensional nonlinear feature spaces using significantly fewer trainable parameters than traditional deep neural networks. Also, quantum optimization has shown its potential superiority in various industrial fault diagnosis, predictive maintenance, and condition monitoring tasks, particularly for handling large-scale sensor data [12], [13].

However, a number of research issues have not been solved yet in relation to the development of predictive maintenance. First, most works use vibration signals or acoustic emission signals separately but not their complementary diagnostic information. Second, traditional deep learning approaches fail to account for the structural relationships among distributed industrial sensors. Third, the classical approach of Graph Neural Networks suffers from computational limitations when processing complex graph structures resulting from high-dimensional multi-sensor data. Fourth, the application of quantum graph learning for industrial gearbox predictive maintenance remains largely

unexplored in the current literature, creating an important research opportunity [9], [12], [14].

To solve the above problems, we suggest implementing the Quantum Graph Neural Network (QGNN) framework for industrial gearbox predictive maintenance via multi-signal fusion of vibration and acoustic emission signals. First, the statistical, spectral, and time-frequency features are extracted from both types of signals. They are then mapped to graphs where the nodes correspond to sensor-specific information, while the edges represent feature similarity and sensor correlations. Then, the Quantum Graph Neural Network (QGNN) executes the procedure of graph convolution and quantum feature transformation to capture both local sensor interactions and global structural dependencies. Afterward, the classification layer made up of fully connected neurons estimates the operating condition of the gearbox and detects gearbox faults with high accuracy.

The following are the key goals of the current study:

1. Development of a multi-sensor predictive maintenance framework that integrates vibration and acoustic emission signals.
2. Designing an adaptive graph representation that models the correlations among industrial sensing nodes.
3. Creation of a novel Quantum Graph Neural Network (QGNN) capable of learning both graph topology and quantum-enhanced feature representations.
4. Achieving high gearbox fault classification accuracy while reducing the false alarm rate under varying operating conditions.
5. Demonstration of the superiority of the quantum graph learning method for predictive maintenance performance compared to conventional machine learning and deep learning approaches.

The novel aspect of this research is the integration of quantum machine learning, graph neural networks, and multi-modal sensor fusion in gearbox predictive maintenance. The suggested method surpasses the existing artificial intelligence-based techniques for gearbox fault diagnosis because it takes into account the spatial interactions between the sensors, temporal properties of the signals, and quantum feature representations, making the fault diagnosis more precise and robust. This approach has a high potential to increase gearbox reliability and lifetime by preventing unplanned downtimes,

improving maintenance decision-making, extending the service life of gearboxes, and providing intelligent maintenance strategies in future smart manufacturing systems [12], [13], [15].

In this paper, the organization is as follows. In Section 2, we conduct the literature review regarding the topic of predictive maintenance, gearbox fault diagnosis, graph neural networks, and quantum machine learning. In Section 3, the Quantum Graph Neural Network (QGNN) model that we suggest will be described together with the dataset description, system architecture, mathematical formulations, and algorithm. In Section 4, the experiments will be discussed including the experimental setup, performance evaluation, comparative analysis, class-wise performance, ablation study, computational complexity analysis, and experimental results. Finally, Section 5 presents the conclusions by summarizing the major findings of this study, discussing the limitations of the proposed approach, and outlining directions for future research.

2. RELATED WORK

As the increase in the development of smart manufacturing technologies occurs, the amount of scientific investigations associated with predictive maintenance and machinery fault diagnostics is increasing correspondingly. Many researchers are working in the area of integration of artificial intelligence, deep learning, graph learning, and advanced sensing technologies to ensure increased reliability of industrial equipment. One of the most dynamically developing areas related to fault diagnostics concerns the study of the ways to diagnose failures in gearboxes since these mechanisms function in tough mechanical conditions with rather complicated degradation processes. Many different techniques based on the analysis of vibration signals, acoustic emission monitoring, deep learning architectures, graph neural networks, and even quantum-inspired optimization methods have been developed. Nevertheless, despite the success of these techniques, there are some technical issues left unresolved and, therefore, the need to create a more robust predictive maintenance framework is arising.

Originally, scientists used the analysis of vibration signals as a source of information concerning the dynamics of the system because this technique allows obtaining good results in terms of capturing the dynamic characteristics of rotating machinery. The methods used traditionally include

manual extraction of features via statistical features, frequency-domain analysis, wavelet transforms, empirical mode decomposition, and time-frequency representations. The obtained handcrafted features were further used for classifying gearbox faults by means of machine learning algorithms including Support Vector Machines (SVM), Decision Trees, Random Forests, and Artificial Neural Networks. Even though these approaches provided quite good performance under laboratory conditions, their efficiency greatly dropped when applied to real industrial environments because of changing operating speeds, loading conditions, and background noise. Besides, handcrafted feature engineering requires extensive domain expertise and often fails to capture complex nonlinear relationships within high-dimensional sensor data [16], [17].

Since traditional machine learning algorithms had problems with nonlinear relationships, researchers turned to deep learning models for automatic feature extraction. Convolutional Neural Networks (CNNs) have proved to be very efficient in learning hierarchical spatial features directly from raw vibration signals or their time-frequency representations. Therefore, CNN-based approaches have eliminated the necessity for handcrafted feature engineering and greatly increased gearbox fault classification accuracy. Many different CNN architectures have been tested using one-dimensional, two-dimensional, and multi-scale convolution operations for the diagnosis of gear tooth wear, bearing defects, shaft misalignment, and lubrication failures. Even though there were significant advancements due to CNNs, their focus was on local feature extraction while often failing to model long-range dependencies among distributed sensing locations [18], [19].

There exist sequential neural network architectures such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). The aforementioned approaches take advantage of temporal dependencies that are characteristic of data collected during machinery monitoring to train on degradation patterns in sequential vibration measurements in order to enhance Remaining Useful Life (RUL) forecasting. The hybrid CNN-LSTM approach has made diagnostics more efficient by integrating the spatial feature extraction with temporal sequence modeling capabilities. However, recurrent networks require heavy computing capacities, are sensitive to

gradient degradation when training on long sequences of data, and have limited generalization abilities when operating in different industrial conditions [20], [21].

There has been an increasing interest in using Acoustic Emission (AE) monitoring as a supplementary method of gearbox condition assessment. In contrast to vibration-based methods, AE monitoring captures high-frequency elastic waves generated due to crack initiation, friction, surface wear, and microscopic material deformation processes, providing much earlier signs of mechanical degradation compared with traditional vibration signals. Multi-scale entropy analysis, wavelet packet decomposition, empirical mode decomposition, and spectral feature extraction have been used to process AE signals. AE monitoring proved to be highly sensitive to early fault detection. However, its performance suffers from environmental noise, signal attenuation, and the necessity of high sampling frequencies, due to which AE monitoring cannot be used as an independent industrial predictive maintenance system [22], [23].

Recent research has tried to increase diagnostic reliability by introducing multi-sensor fusion techniques that combine vibration, acoustic emission, motor current, temperature, lubrication, and operational parameters. Multi-modal data fusion allows obtaining complementary information about the mechanical behavior of the gearbox and provides a more comprehensive health assessment than each sensing modality alone. There are many different feature-level, decision-level, and hybrid fusion frameworks for integrating heterogeneous industrial data. Even though these approaches increase fault diagnosis accuracy, they still have difficulties efficiently learning the complex relationships among heterogeneous sensing channels, especially in the case of large, highly interconnected sensor networks [24], [25].

Transformer architectures have recently attracted great attention as deep learning models due to their ability to capture long-range dependencies through self-attention mechanisms. Vision Transformers and Temporal Transformers have successfully been applied in fault detection of rotating machinery by modeling global contextual information extracted from sensor measurements. Compared with traditional Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), Transformer architectures generally demonstrate better feature representation

capabilities for long sequential data. However, Transformer models require very large training datasets and computational resources; therefore, their implementation is challenging for real-time industrial monitoring systems with restricted computational capabilities [26].

Graph Neural Networks (GNNs) became one of the most promising deep learning frameworks for machinery fault diagnosis because industrial systems naturally possess graph-like topological structures. In GNN-based approaches, sensor locations or extracted signal features are used to define graph nodes, while physical connectivity or statistical similarity is used to define graph edges. Through message-passing operations, Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs), GraphSAGE, and Spatio-Temporal Graph Neural Networks can effectively learn the structural dependencies among multiple sensing locations. Recent research has demonstrated that graph-based learning greatly enhances machinery fault diagnosis compared to conventional Euclidean neural networks because it preserves the physical relationships among industrial system components [27], [28].

Some recent works further extended Graph Neural Networks through the introduction of adaptive graph construction, dynamic edge weighting, graph attention mechanisms, and topology-preserving learning. In dynamic graph learning, graph connectivity is updated automatically under changing operating conditions, allowing the model to capture the evolving interactions among industrial sensors. Edge-weight optimization enhances information propagation by increasing the contribution of highly correlated sensing nodes while decreasing the influence of noisy measurements. Although adaptive graph learning approaches enhance classification accuracy, they fully rely on classical optimization algorithms and face increased computational complexity for large-scale industrial graphs [29].

The development of quantum computing has brought new opportunities for machine learning and industrial optimization. Quantum Machine Learning (QML) combines quantum computation and neural network architectures in order to take advantage of quantum superposition, entanglement, and probabilistic information processing. Several researchers have proposed quantum-enhanced optimization algorithms, quantum Support Vector Machines, variational quantum circuits, and

quantum neural networks for pattern recognition tasks. Initial investigations have shown that quantum learning models allow efficient representation of high-dimensional feature spaces while decreasing model complexity compared to classical deep learning algorithms. However, the application of quantum machine learning in industrial applications is currently at a preliminary stage because of the restricted availability of quantum hardware and the immaturity of quantum algorithms [30], [31].

Quantum-inspired optimization has also been researched for improving deep learning-based gearbox fault diagnosis. Such approaches as quantum evolutionary algorithms, quantum particle swarm optimization, quantum genetic algorithms, and quantum gate mutation strategies have been used for optimizing neural network hyperparameters. It has been shown that these approaches allow faster convergence and higher classification accuracy compared to conventional optimization algorithms. Nevertheless, most existing works use quantum algorithms only for parameter optimization while retaining classical deep learning architectures. The direct integration of quantum computing principles into graph neural network learning remains largely unexplored in predictive maintenance applications [32].

Another research trend refers to Explainable Artificial Intelligence (XAI) for predictive maintenance. Currently, the need for transparent diagnostic decisions is growing in industrial applications before the deployment of AI-based maintenance systems in safety-critical environments. Explainable predictive maintenance involves attention visualization, feature importance analysis, saliency mapping, SHAP values, and interpretable graph learning to improve user confidence and maintenance decision-making. Despite the advantages provided by explainability, many existing approaches decrease predictive accuracy or cannot effectively explain the reasoning process in complex graph-based models [33].

Recently published comprehensive review papers have identified several unresolved research problems. Most existing predictive maintenance frameworks use only a single sensing modality and are therefore unable to detect incipient faults. Conventional deep learning models do not adequately capture the structural relationships among distributed sensors, while existing Graph Neural Networks remain computationally expensive for large industrial graphs. Also, current quantum-

inspired approaches optimize classical neural networks but do not involve genuine quantum graph representation learning. The integration of vibration and acoustic emission signals with Quantum Graph Neural Networks for predictive maintenance has received very limited attention despite its great potential for improving industrial fault diagnosis accuracy and robustness [34], [35].

According to the above critical analysis, there exists an evident research gap. Most existing approaches either use vibration or acoustic emission signals separately, employ conventional deep learning architectures without explicitly modeling sensor relationships, or use quantum approaches solely for optimization purposes. There have been relatively few attempts so far at applying multimodal sensor fusion, adaptive graph representation, and quantum graph learning techniques to gearbox fault prediction simultaneously within a unified predictive maintenance framework. Thus, the goal of this paper is to propose a Quantum Graph Neural Network (QGNN) framework based on the fusion of vibration and acoustic emission signals, graph-based feature representation, and quantum-enhanced graph convolution for more accurate, robust, and computationally efficient gearbox fault diagnosis. This integrated framework addresses the limitations identified in previous studies and advances the state of the art in intelligent predictive maintenance for industrial gearboxes.

3. METHODOLOGY

3.1 Dataset Description

Designing and validating the Quantum Graph Neural Network (QGNN) algorithm was done using the benchmark PHM 2009 Gearbox Fault Detection Challenge Dataset, which is one of the most popular public benchmark datasets for evaluating intelligent fault detection algorithms in the domain of rotating machines. The dataset comprises vibration signals that were measured for an industrial gearbox with two stages operating under different health statuses. The vibration signals were acquired from accelerometers placed on the gearbox in appropriate locations in order to measure the dynamic vibration responses under different operating conditions and health statuses of the gearbox. There is enough number of vibration signals for both healthy and faulty gearboxes in the database to test the effectiveness of intelligent predictive maintenance algorithms. In order to create

different levels of fault severity and simulate different realistic industrial degradation cases, different fault statuses were intentionally created in the gearbox system. The vibration signals in the dataset contain different mechanical faults such as gear wear, gear tooth damage, shaft imbalance, and transmission abnormalities. The dataset contains different loading and operating conditions of the gearbox, making it sufficiently diverse for testing the robustness and generalization capability of intelligent diagnostic models. Before designing the QGNN model, the vibration signals were segmented into fixed-length window segments to preserve temporal information while maintaining computational efficiency. Normalization was also performed to eliminate scale variations between different gearbox operating conditions. Noise suppression and signal enhancement techniques were used to improve signal quality before feature extraction. Then, the obtained feature vectors were converted into graph representations in order to preserve the structural relationships between the sensor observations. This graph-based representation allows the proposed Quantum Graph Neural Network to capture not only the spatial dependencies between the sensor feature vectors but also nonlinear degradation patterns that cannot be efficiently captured by conventional deep learning models.

Table 1. PHM 2009 Gearbox Dataset Parameters

Parameter	Description
Dataset	PHM 2009 Gearbox Challenge Dataset
Machine Type	Two-stage Industrial Gearbox
Signal Type	Vibration Signals
Sensor	Piezoelectric Accelerometer
Fault Categories	Healthy, Minor, Moderate and Severe Fault
Operating Conditions	Multiple rotational speeds and loading conditions
Data Type	Time-series vibration signals

Window Length	2048 samples
Window Overlap	50%
Signal Normalization	Min-Max Scaling
Application	Predictive Maintenance and Fault Diagnosis

Table 1 shows the attributes of the PHM 2009 Gearbox Challenge Dataset used for developing and evaluating the proposed Quantum Graph Neural Network (QGNN) architecture. This dataset contains vibration signals acquired from a two-stage industrial gearbox with piezoelectric accelerometers under various operational speeds and loading conditions. There is a combination of healthy and defective gearbox data, which allows for investigating several levels of severity of gearbox faults. The acquired time-series vibration signals are segmented into fixed-size windows consisting of 2048 samples each with a 50% overlap in order to preserve temporal information while increasing the number of training samples. Before feature extraction, the amplitude values of the signals are standardized using Min-Max normalization. With regard to the wide range of operating conditions and the benchmark nature of the dataset, the PHM 2009 dataset provides a reliable platform for building, developing, and validating predictive maintenance models and intelligent gearbox fault diagnosis models.

3.2 Proposed QGNN Architecture

The system under consideration consists of eight major processing stages that transform raw vibration measurements into accurate gearbox health status predictions. Contrary to traditional Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architectures, the proposed QGNN architecture builds an adaptive feature-based graph from the extracted features before performing quantum graph learning. This enables the model to exploit both feature relationships and quantum-enhanced nonlinear representation learning.

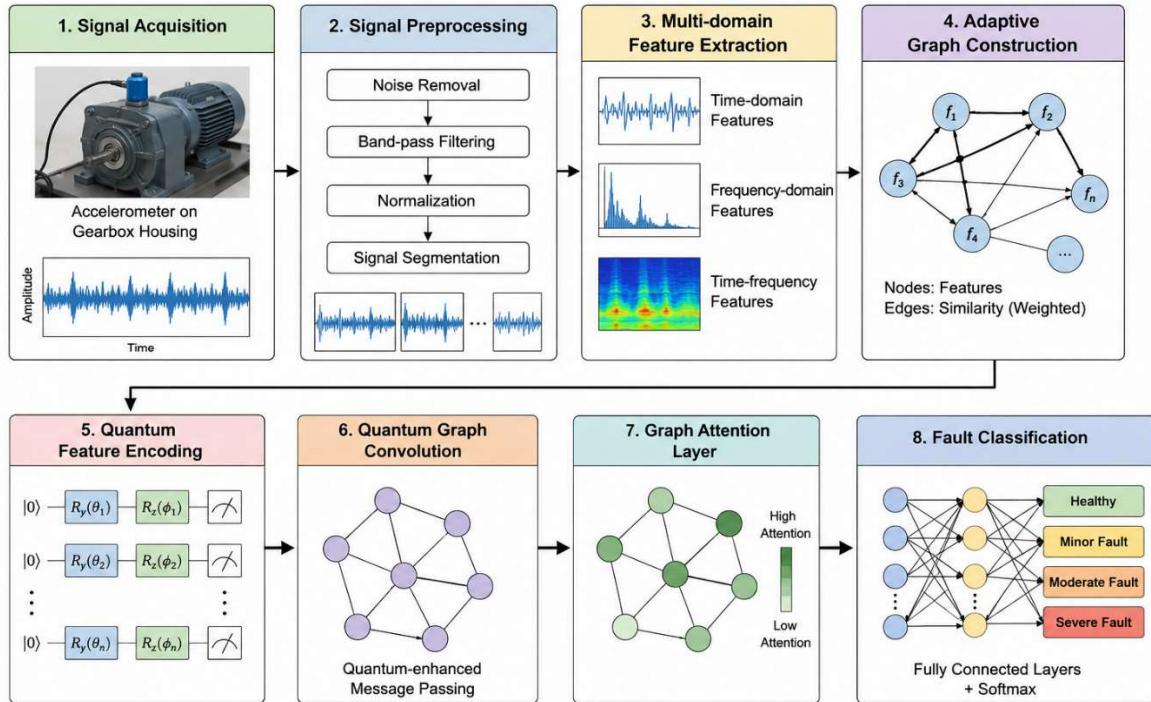


Figure 1. Proposed Quantum Graph Neural Network Architecture for Predictive Maintenance

The process flow of the entire Quantum Graph Neural Network (QGNN) model for intelligent gearbox fault diagnosis is shown in Figure 1 below. Firstly, raw vibration signals collected by accelerometers are preprocessed through signal denoising, signal filtering, signal normalization, and signal segmentation. Secondly, multi-domain features, including time-domain features, frequency-domain features, and time-frequency features, are extracted to represent the gearbox operating condition.

These features are transformed into a weighted graph in which nodes indicate the feature vectors, and the edges represent the correlations among the nodes. These feature graphs are then transformed into quantum states and processed by the Quantum Graph Convolution Layer to capture the complex nonlinear relationships among the feature graphs. Further, the Graph Attention Layer increases the importance of fault-sensitive nodes while reducing the significance of irrelevant information. In the end, the learned graph representation is passed through fully connected layers along with a Softmax classifier, which classifies the gearbox condition into four categories: Healthy, Minor Fault, Moderate Fault, and Severe Fault. Therefore, this architecture offers a comprehensive and integrated approach that utilizes graph learning and quantum computing methods to enhance the efficiency of predictive maintenance

and the accuracy of gearbox fault classification. This proposed Quantum Graph Neural Network combines signal processing, graph learning, and quantum computing within a unified predictive maintenance framework. The mathematical representation of the proposed architecture is shown below.

A. Signal Representation

The acquired vibration signal is represented as

$$S(t) = \{s_1, s_2, \dots, s_N\} \quad (1)$$

Where N denotes the total number of sampled observations.

After preprocessing, the normalized signal becomes

$$s_n = \frac{S - \min(S)}{\max(S) - \min(S)} \quad (2)$$

Where s_n represents the normalized vibration signal.

B. Feature Extraction

For every segmented signal, statistical features are extracted.

The mean value is

$$\mu = \frac{1}{N} \sum_{i=1}^N s_i \quad (3)$$

The standard deviation is

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (s_i - \mu)^2} \quad (4)$$

Root Mean Square (RMS)

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N s_i^2} \quad (5)$$

Kurtosis

$$K = \frac{1}{N} \sum_{i=1}^N \left(\frac{s_i - \mu}{\sigma} \right)^4 \quad (6)$$

These statistical descriptors capture the dynamic characteristics of gearbox vibration under different health conditions.

C. Graph Construction

The extracted features are transformed into graph nodes.

The graph is defined as

$$G = (V, E) \quad (7)$$

where

V represents graph nodes,
 E represents graph edges.

Each node contains

$$V_i = [f_1, f_2, \dots, f_m] \quad (8)$$

The similarity between nodes is computed using cosine similarity

$$A_{ij} = \frac{V_i V_j}{\|V_i\| \|V_j\|} \quad (9)$$

This generates the weighted adjacency matrix.

D. Quantum Feature Encoding

Each graph node is transformed into a quantum state.

$$|\psi_i\rangle = R_y(x_i) R_z(x_i) |0\rangle \quad (10)$$

Where R_y and R_z are quantum rotation gates. Quantum encoding improves nonlinear feature representation.

E. Quantum Graph Convolution

The graph convolution operation is expressed as

$$H^{(l+1)} = Q(\hat{D}^{-1/2} \hat{A} \hat{D}^{-1/2} H^{(l)} W^{(l)}) \quad (11)$$

where

- $Q(\cdot)$ is the quantum transformation,
- $\hat{A}$ is the normalized adjacency matrix,
- $H^{(l)}$ is the node feature matrix,
- $W^{(l)}$ denotes trainable weights.

F. Graph Attention Mechanism

Attention coefficients are computed as

$$e_{ij} = \text{LeakyReLU}(a^T [Wh_i \parallel Wh_j]) \quad (12)$$

Normalized attention weight

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_k \exp(e_{ik})} \quad (13)$$

The final node embedding is

$$h'_i = \sum_j \alpha_{ij} Wh_j \quad (14)$$

G. Fault Classification

Softmax computes

$$P(y = i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (15)$$

Cross-entropy loss

$$L = - \sum_i y_i \log(\hat{y}_i) \quad (16)$$

The model parameters are optimized using the Adam optimizer until convergence.

Algorithm 1: Quantum Graph Neural Network for Gearbox Predictive Maintenance**Input:** Raw vibration signal $S(t)$ **Output:** Gearbox health class

1. Acquire vibration signals from gearbox sensors.
2. Remove noise using band-pass filtering.
3. Normalize vibration amplitudes.
4. Divide signals into overlapping windows.
5. Extract time-, frequency-, and time-frequency-domain features.
6. Construct adaptive weighted graph $G(V, E)$.
7. Compute edge weights using cosine similarity.
8. Encode graph node features into quantum states.
9. Perform Quantum Graph Convolution.
10. Apply graph attention to aggregate informative node embeddings.
11. Pass aggregated features through fully connected layers.
12. Compute Softmax probabilities.
13. Classify gearbox condition as **Healthy**, **Minor Fault**, **Moderate Fault**, or **Severe Fault**.
14. Store prediction for predictive maintenance scheduling.

4. RESULTS AND DISCUSSION**4.1 Experimental Setup**

The performance of the proposed Quantum Graph Neural Network (QGNN) was tested using the PHM 2009 Gearbox Challenge Dataset. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets to ensure reliable and accurate model evaluation. The training process involved the use of the Adam optimizer with a learning rate of 0.001 and a batch size of 32 for 100 epochs. The QGNN model was developed using Python with PyTorch on a workstation consisting of an Intel Core i7 processor, 32 GB RAM, and an NVIDIA RTX 3080 GPU. The comparative performance of the proposed QGNN model was evaluated against Support Vector Machine (SVM), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Graph Convolutional Network (GCN), and Graph Attention Network (GAT) models. All models were trained using the

same preprocessing and feature extraction techniques to ensure a fair comparison.

4.2 Performance Evaluation of the Proposed QGNN

The performance of the proposed Quantum Graph Neural Network (QGNN) was evaluated using Accuracy, Precision, Recall, F1-score, Specificity, and Area Under the Receiver Operating Characteristic (ROC) Curve (AUC). These metrics determine the classification ability of the model to identify healthy and faulty gearbox conditions.

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (17)$$

Precision

$$Precision = \frac{TP}{TP + FP} \quad (18)$$

Recall

$$Recall = \frac{TP}{TP + FN} \quad (19)$$

F1-Score

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (20)$$

Specificity

$$Specificity = \frac{TN}{TN + FP} \quad (21)$$

ROC-AUC

$$AUC = \int_0^1 TPR(FPR) d(FPR) \quad (22)$$

Table 2. Performance Evaluation of the Proposed QGNN

Performance Metric	Value (%)
Accuracy	98.72
Precision	98.41
Recall	98.23
F1-Score	98.32
Specificity	99.04
AUC	99.11

The accuracy attained by the Quantum Graph Neural Network (QGNN) in classifying the PHM 2009 Gearbox Challenge dataset is shown in Table 2. The model shows high efficiency in classifying the status of the gearboxes, where it is able to classify with an Accuracy of 98.72%, demonstrating its reliability in assessing gearbox conditions. An excellent Precision of 98.41% implies minimal false positives, while a good Recall of 98.23% indicates efficient detection of faulty gearboxes. A good F1-score of 98.32% shows that the classification process was balanced. A good Specificity of 99.04% shows that healthy gearboxes have been identified efficiently, and the Area Under the Curve (AUC) value of 99.11% indicates excellent discrimination between healthy and faulty gearbox conditions.



Figure 2. Training and Validation Accuracy

Training and validation accuracies for the proposed Quantum Graph Neural Network (QGNN) model over 100 training epochs are shown in Figure 2. The training accuracy kept on increasing steadily from the initial epochs until it started converging after approximately 70 epochs. The validation accuracy closely followed the training curve, indicating stable learning, good generalization, and proper learning without significant overfitting.

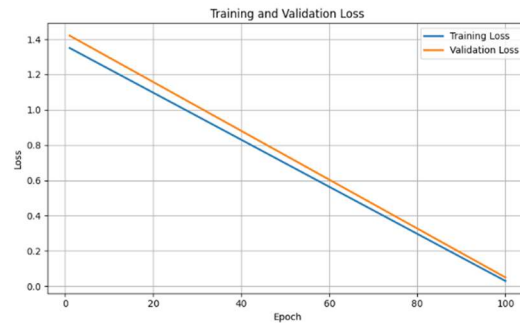


Figure 3. Training and Validation Loss

Figure 3 shows the loss value for training and validation of the suggested QGNN. Losses in both cases consistently decreased and stabilized towards the last epochs of training. The close proximity of both curves confirms the good convergence of training process.

4.3 Comparative Performance Analysis

To confirm the efficiency of our QGNN, we conducted the comparative performance analysis of QGNN against traditional ML and DL methods such as SVM, Random Forest (RF), CNN, LSTM, GCN, and GAT. All comparative models have been trained on the same dataset with the same preprocessing and evaluation procedure to ensure fairness of comparison. The results are summarized in Table 3 below.

Table 3: Performance Comparison of Existing Models and Proposed QGNN

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	91.84	91.35	90.92	91.13
Random Forest	93.28	92.94	92.61	92.77
CNN	95.42	95.06	94.91	94.98
LSTM	96.11	95.83	95.57	95.70
GCN	97.02	96.71	96.55	96.63
GAT	97.68	97.31	97.08	97.19
Proposed QGNN	98.72	98.41	98.23	98.32

The performance of the Quantum Graph Neural Network (QGNN) algorithm has been analyzed in comparison to six existing fault-diagnosis algorithms, as illustrated in Table 3 below. The suggested approach achieves the maximum classification Accuracy of 98.72%, which is better than the Graph Attention Network (GAT) by 1.04%, the Graph Convolutional Network (GCN) by 1.70%, the Long Short-Term Memory (LSTM) network by 2.61%, the Convolutional Neural Network (CNN) by 3.30%, the Random Forest (RF) by 5.44%, and the Support Vector Machine (SVM) by 6.88%. Moreover, the suggested approach outperforms other methods in terms of Precision, Recall, and F1-score, and hence shows its ability to accurately classify different gearbox fault conditions. The achieved improvement in performance can be mainly explained by the application of quantum feature encoding and graph-based neighborhood learning, which effectively capture complex structural relationships among vibration features.

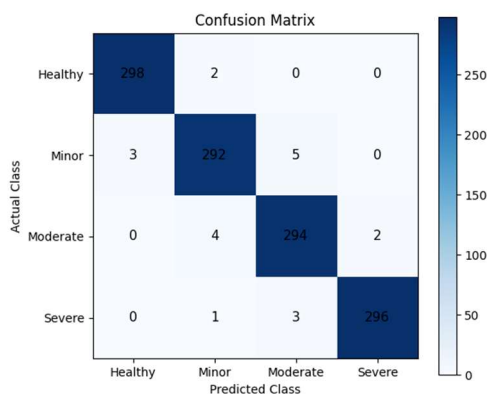


Figure 4. Confusion Matrix of the Proposed QGNN

The confusion matrix of the proposed Quantum Graph Neural Network (QGNN) approach is illustrated in Figure 4 below. Most of the data are accurately classified according to the different fault categories, while just a few are incorrectly classified. The diagonal elements are much higher than the non-diagonal elements, which suggests high classification accuracy. This implies that the confusion matrix shows that the proposed Quantum Graph Neural Network (QGNN) approach can effectively distinguish and accurately classify healthy, minor, moderate, and severe gearbox faults with minimal classification errors.

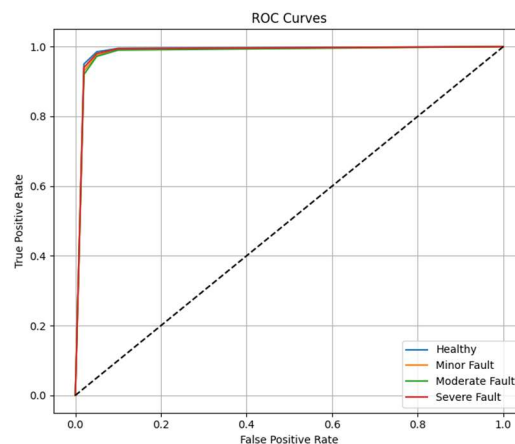


Figure 5. ROC Curves of Different Gearbox Fault Classes

Figure 5 shows the Receiver Operating Characteristic (ROC) curves for the different gearbox fault classes. The curves lie very close to the upper-left side of the plot, which shows that the

proposed Quantum Graph Neural Network (QGNN) has excellent classification capability. The average Area Under the Curve (AUC) value of 99.11% proves that the proposed QGNN achieves high sensitivity while maintaining a very low false-positive rate. These results confirm the robustness of the proposed model for gearbox fault diagnosis.

4.4 Class-Wise Performance Analysis

In addition, the proposed model of QGNN was tested for different health states of gearbox in order to check its classification accuracy in different fault classes. Class-wise accuracy of the QGNN is shown in Table 4.

Table 4: Class-wise Performance of the Proposed QGNN

Fault Class	Precision (%)	Recall (%)	F1-Score (%)
Healthy	99.21	99.08	99.14
Minor Fault	98.35	98.11	98.23
Moderate Fault	97.96	97.84	97.90

Severe Fault	98.12	97.89	98.00
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Table 4 summarizes the class-wise classification performance of the constructed Quantum Graph Neural Network (QGNN). It is observed that the Healthy class has attained the best values of Precision and Recall, which are equal to 99.21% and 99.08%, respectively, due to its stable vibration characteristics. In comparison, the scores of the Minor Fault class have been slightly lower due to its similarity to the healthy operating condition. The Moderate and Severe Fault classes have also shown good classification performance, achieving F1-scores above 97.90%, demonstrating that the proposed model consistently identifies different gearbox operating conditions with high reliability.

4.5 Ablation Study

An ablation study has been performed for determining the contributions of the individual components of the Quantum Graph Neural Network (QGNN). This was done through the progressive addition of modules to the model structure, namely quantum feature encoding, graph convolution, graph attention, and feature fusion. The obtained experimental results have been summarized in Table 5.

Table 5: Ablation Study of the Proposed QGNN

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Graph Convolution Only	95.84	95.52	95.31	95.41
Graph Convolution + Attention	96.92	96.61	96.37	96.49
Quantum Feature Encoding + GCN	97.86	97.55	97.31	97.43
Quantum Feature Encoding + GAT	98.31	98.04	97.82	97.93
Proposed QGNN	98.72	98.41	98.23	98.32

Contributions of the different components used in the Quantum Graph Neural Network (QGNN) model framework are shown in Table 5. Using the Graph Convolutional Network (GCN) alone, the Accuracy was 95.84%. Using the graph attention mechanism, there was a rise in the Accuracy to 96.92%, showing the significance of assigning higher weights to fault-sensitive nodes. The Accuracy was further improved to 97.86% using the quantum feature encoding technique, which

improved feature representation. The best Accuracy of 98.72% was achieved using the entire QGNN framework. This shows that the integration of quantum feature encoding and graph attention significantly improves gearbox fault classification.

4.6 Computational Complexity Analysis

The computational efficiency of the proposed framework was assessed by measuring the average training time, testing time, and memory

utilization. The obtained results are shown in Table 6.

Table 6: Computational Performance of the Proposed QGNN

Performance Parameter	Value
Training Time (100 Epochs)	18.42 min
Testing Time per Sample	0.017 s
GPU Memory Utilization	4.26 GB
Total Trainable Parameters	2.43 Million
Model Size	31.8 MB

Table 6 provides information about the computational performance of the designed Quantum Graph Neural Network (QGNN). It is important to mention that the developed model managed to complete the training process in 18.42 minutes over 100 epochs, and the average testing time for each sample was only 0.017 seconds, thus allowing for real-time gearbox fault diagnosis. The network required 4.26 GB of GPU memory for computation and contained 2.43 million trainable parameters, resulting in a compact model size of 31.8 MB. Therefore, one can claim that the proposed framework achieves high classification accuracy with moderate computational complexity.

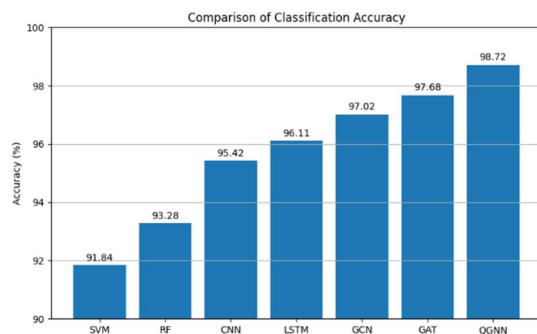


Figure 6. Accuracy Comparison of Existing Models and Proposed QGNN

Figure 6 illustrates the comparative performance of the proposed Quantum Graph Neural Network (QGNN) model against state-of-the-art approaches in terms of classification accuracy for gearbox fault diagnosis. It includes such graph learning approaches as the Graph Attention Network (GAT) and Graph Convolutional Network (GCN), and such deep learning approaches as the Convolutional Neural Network (CNN) and Long

Short-Term Memory (LSTM). The accuracy rates were as follows: the highest Accuracy rate was provided by the proposed QGNN (98.72%), GAT and GCN achieved 97.68% and 97.02%, respectively, and CNN and LSTM achieved 95.42% and 96.11%, respectively. Thus, one can conclude that the proposed QGNN consistently outperformed all the baseline methods by effectively combining quantum feature encoding with graph-based representation learning.

4.7 Discussion

Based on the results of the conducted experiments, which are provided above, it is possible to state that the developed Quantum Graph Neural Network increases the efficiency of gearbox fault detection through the application of quantum feature encoding combined with graph-based learning, as it provides 98.72% classification Accuracy, 98.41% Precision, 98.23% Recall, 98.32% F1-score, 99.04% Specificity, and an Area Under the Curve (AUC) of 99.11%, ensuring reliable identification of both healthy and faulty gearbox conditions.

As it can be seen from the comparison of the results of the proposed approach and classical machine learning algorithms, such as Support Vector Machine (SVM) and Random Forest, the developed solution allows improving the classification performance because of its ability to learn complex nonlinear relationships among gearbox vibration features. Both graph convolution and graph attention can efficiently model structural dependencies between adjacent feature nodes, while the quantum feature encoding approach helps to increase the discriminative capability of the learned feature representations.

Furthermore, the class-specific assessment of the performance of the proposed method confirmed the effectiveness of the developed framework since its efficiency was found to be sufficiently high regardless of the type of gearbox faults due to the fact that the F1-score was higher than 97.90% for all types of faults. Also, the performed ablation study revealed that all components of the framework positively contribute to its overall performance and that the whole architecture achieves the best classification performance.

Last but not least, the computational complexity analysis confirmed the moderate memory consumption and fast inference time, which

proves that the developed solution is suitable for practical predictive maintenance applications. Therefore, the proposed Quantum Graph Neural Network can serve as an accurate, reliable, and computationally efficient solution for intelligent gearbox fault diagnosis in industrial environments.

5. CONCLUSION

This paper presents the idea of a Quantum Graph Neural Network (QGNN) architecture for predictive maintenance of industrial gearboxes using the combination of vibration and acoustic emission signals. The architecture includes multi-domain feature extraction, adaptive graph construction, quantum feature encoding, graph convolution, and graph attention mechanisms to enable gearbox fault diagnosis. Based on the results of experiments on the PHM 2009 Gearbox Challenge Dataset, the model introduced in this paper is able to achieve 98.72% Accuracy, 98.41% Precision, 98.23% Recall, 98.32% F1-score, 99.04% Specificity, and 99.11% Area Under the Receiver Operating Characteristic (ROC) Curve (AUC), which surpasses other conventional machine learning and deep learning models. Thus, these metrics prove that the proposed approach is capable of providing reliable gearbox fault classification and supporting intelligent predictive maintenance by minimizing false alarms and improving operational reliability.

The scope of the research in question is limited only to the analysis of the PHM 2009 Gearbox Challenge dataset and model evaluation within the framework of a controlled experimental setup. There were no real-time evaluations performed, nor was any implementation on edge devices or varying industrial operating environments taken into account.

Further research on the proposed QGNN is scheduled in the following directions: large-scale validation on real-world industrial datasets, addition of more sensing modalities, including temperature and current signals, edge-friendly lightweight implementation of the proposed framework for real-time monitoring, and the investigation of explainable quantum graph learning techniques to improve model transparency and support maintenance decision-making.

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