Improving Mechanical Fault Diagnosis Using Graph Neural Networks with Dynamic and Multiscale Features

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ABSTRACT

Mechanical systems face a major drawback to fault diagnosis, as class imbalance greatly undermines it since minority class instances (critical faults) are underrepresented, resulting in biased predictions. This paper introduces a new Multiscale Receptive Fields and Dynamic Edge Weighting (MRS-GNN) framework, which fuses MRF and Dynamic Edge Weighting (DEW) on a GNN to improve classification performance in imbalanced datasets. Graph edge strengths are dynamically weighted with the learned node embeddings during training according to the DEW mechanism, and MRF allows the model to aggregate information from different neighborhood scopes for robust feature representation. In addition, a graph-specific oversampling algorithm, MR-SMOTE, was used to generate synthetic minority class nodes respecting and preserving the topology of the graph. The proposed model was evaluated through experiments on the 2009 PHM gearbox dataset and was found to have an accuracy of 92.1% and an AUC-ROC score of 0.95, better than traditional oversampling methods such as SMOTE, LR-SMOTE, and Graph-SMOTE. The results of an ablation study indicate that 3.7% and 2.4% accuracy drops occur in DEW and MRF removals, respectively, highlighting their importance. This study proposes a scalable and topology-preserving solution to the imbalanced fault diagnosis problem and makes substantial improvements compared to existing GNN-based methods.

Keywords-fault diagnosis; class imbalance; dynamic edge weighting; graph neural networks; predictive maintenance

I. INTRODUCTION

Fault diagnosis is vital for the safe and efficient operation of mechanical systems, especially as industries increasingly depend on complex machinery for energy, transport, and manufacturing [1]. Failures can lead to serious accidents, downtime, and financial losses, making early detection essential for predictive maintenance [2]. Rotating components, such as bearings, gears, and motors, are particularly prone to wear due to constant use. For example, bearing failure can severely disrupt system performance. Accurate diagnosis improves reliability, extends the life of the equipment, and reduces maintenance costs. Traditional methods use physics-based models to analyze vibration, acoustic, and temperature data [3-5] but often struggle with the complexity and variability of modern machines. As systems become more interconnected and data-rich, there is a growing demand for advanced, data-driven fault diagnosis techniques capable of handling high-dimensional data effectively.

Class imbalance, where certain fault types (majority classes) greatly outnumber others (minority classes), poses a major challenge in ML-based fault diagnosis [6]. In practice, mechanical systems generate abundant data under normal conditions, whereas fault data is rare [7]. This skew leads traditional models, often optimized for overall accuracy, to favor majority classes, reducing their ability to detect rare but critical faults. Misclassifying such faults can have serious consequences. Common solutions include data-level techniques, such as oversampling and undersampling [8], and algorithm-level methods, such as cost-sensitive learning. However, these approaches often fall short in handling the high-dimensionality, temporal dependencies, and complex feature interactions typical of fault diagnosis datasets.

Graph Neural Networks (GNNs) have emerged as a powerful ML tool to analyze non-Euclidean data such as graphs [9]. Unlike traditional models designed for tabular or grid data, GNNs effectively capture complex dependencies in graph-structured inputs. This ability suits fault diagnosis, where sensor and operational data can be modeled as nodes, with edges representing correlations or spatial relations [10]. Each node may represent a time segment of vibration signals, enabling GNNs to uncover patterns often missed by conventional methods. By integrating both structural and feature data, GNNs enhance diagnostic accuracy through tasks such as node classification [11]. Despite their promise, GNNs are still in the early stages of application to fault diagnosis, with key challenges remaining, particularly in handling class imbalance [12]. However, GNN models assume balanced data and struggle when minority classes are underrepresented. Techniques such as oversampling and cost-sensitive learning are hard to apply in graphs, as adding synthetic nodes or modifying loss functions can disrupt graph topology and learning balance. Overcoming these challenges is essential for the broader adoption of GNN in this domain. This paper proposes an enhanced GNN-based fault diagnosis framework tailored to address class imbalance, aiming to increase predictive maintenance and mechanical system reliability.

Imbalanced datasets remain a major hurdle in intelligent fault diagnosis, often leading to poor accuracy for minority classes. In [13], the need for scalable solutions was highlighted, addressing gaps such as intraclass imbalance. To address this, LR-SMOTE [14] generates synthetic samples near the core of the minority class and uses SVM and K-means for noise filtering, enhancing data quality. In healthcare, K-Means SMOTE was applied in [15] to improve ACS classification, combining clustering, noise removal, and oversampling for better accuracy. In [16], FSDR-SMOTE was introduced, using the Tukey rule and feature deviation to generate high-quality samples and achieve strong results in F-measure and G-mean. Although SMOTE variants effectively address class imbalance in standard datasets, most are designed for independent, identically distributed data, posing challenges for direct use in graph-structured datasets due to their complex topology and node relationships.

In [17], a Multi-Receptive Field GCN was proposed to improve feature representation by aggregating data from multiple neighborhood scopes, overcoming the limitations of the static receptive field of standard GCNs. Expanding on this, GCN-SA [18] combines structural analysis with GNNs to enhance the accuracy of fault diagnosis, especially with limited labeled data and imperfect association graphs. In [19], a Fast Deep GCN (FDGCN) was developed using wavelet packet transforms to convert vibration signals into graphs, achieving high fault recognition and strong noise resistance in wind turbine diagnostics. In [20], varying operational conditions were addressed with a Domain Adversarial GCN, applying unsupervised domain adaptation and structural data to improve classification without relying heavily on class or domain labels.

In [21], Dynamic Weighted GNN (DWGNN) was introduced for rotating machinery fault diagnosis, optimizing edge weights through energy spectrum and distance metrics to enhance learning from noisy data. To address overfitting and improve accuracy with limited labeled samples, multiscale weighted visibility graphs were combined with a Multi-Channel GNN (MCGCN) in [22], effectively capturing local features and global topology for robust fault detection.

In [23], an automated GCN architecture used layer-wise propagation to optimize node embeddings and improve fault diagnosis. In [24], Interaction-Aware GNNs (IAGNNs) were proposed, which use separate GNN blocks for different edge types and fuse them into comprehensive embeddings, enhancing the interpretation of sensor signals. GEDBLS [25] is a graph-based deep broad learning system that integrates category and structure information through progressive encoding and decoding. By incorporating category weights and intraclass compactness into its loss function, GEDBLS effectively addresses data imbalance and improves the detection of rare faults.

Recent studies have advanced fault diagnosis using GNNs and deep learning. In [26], RAA-GNN was proposed, which addresses GNN over-smoothing by combining attention mechanisms and skip connections, preserving key node features. MixUp augmentation further boosts generalization. Tested on social and citation networks, RAA-GNN improved accuracy by 1%, especially in heterophilic graphs where traditional GNNs often fail. In [27], a hybrid model used BLSTM and an undercomplete autoencoder for the detection of wind turbine gearbox faults. This model reduced feature dimensions and achieved 98.68% accuracy, while reducing testing and training times by over 70% and 65%, respectively, showcasing its efficiency for predictive maintenance in renewable energy systems. In [28], the Minutiae algorithm, adapted from image processing, was applied to classify faults in rotating machinery using vibration signal recurrence plots. This method achieved high accuracy, 100% for combined faults, 98.33% for loose, and 95% for unbalanced, showing strong potential for industrial early fault detection.

This study introduces a GNN architecture for imbalanced fault diagnosis by integrating Dynamic Edge Weighting (DEW) and Multiscale Receptive Fields (MRF). This method differs from current ones by employing an adaptive edge weighting mechanism for training because it adjusts weights to match relationship changes in nodes and performs multiscale feature aggregation. MR-SMOTE is implemented as a topological structure-preserving method to improve the effectiveness of minority class sampling. The proposed framework operates at a robust level of scalability to outperform traditional graph-based methods alongside classical methods in imbalanced classification systems.

II. METHODOLOGY

The MRS-GNN framework addresses class imbalance in graph-structured data, a common issue in tasks such as fault diagnosis. It balances class representation by generating synthetic nodes for underrepresented classes, enhancing connectivity without disrupting the graph's structure. These nodes are crafted to resemble minority class features, allowing the model to improve generalization while maintaining the graph's original properties.

The graph construction process starts with vibration signals collected from sensors attached to the mechanical system. To ensure data quality and consistency, signals undergo preprocessing, which involves noise removal to eliminate unwanted disturbances. Following this, the data is normalized using min-max scaling, ensuring that all values are scaled within a defined range to facilitate accurate analysis and model performance. Following normalization, features are extracted from the vibration signals using techniques such as Fourier transforms, which capture critical frequency and time-frequency characteristics of the data. These extracted features are then represented as nodes in a graph. Edges between nodes are established using the KNN algorithm, which calculates the Euclidean distance (1) between features to determine the most closely related nodes, thus preserving the relationships within the dataset. Here, x_i and x_j represent the feature vectors of nodes i and j, respectively, while d denotes the number of dimensions in the feature space.

$$\mathrm{Dist}(x_i, x_j) = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k}\right)^2} \quad (1)$$

A notable drawback of traditional graph construction methods is the uniform weighting of edges, which fails to capture the varying importance of connections between nodes. A static weighting strategy is employed to address this. In this approach, edge weights are calculated to be inversely proportional (2) to the distances between nodes, ensuring that closer nodes are assigned higher weights, thus reflecting their stronger relationships more accurately.

$$w_{ij} = 1 - \frac{Rank(j)}{k} \quad (2)$$

In this context, $Rank(j)$ indicates the position of node j within the set of i's k-nearest neighbors, where k represents the total number of neighbors. During the training phase, a dynamic weighting strategy is introduced to adjust edge weights based on high-level features extracted by the GNN. The revised weights are calculated using (3), where h_i and h_j represent the features of nodes i and j, respectively. The node embeddings are denoted by $f(\cdot)$, which corresponds to a similarity function, such as cosine similarity, to measure the relationship between nodes. Additionally, the variable α serves as a weighting factor, enabling fine-tuned adjustments to the edge weights.

$$w_{ij}^{(t+1)} = \alpha w_{ij}^{(t)} + (1-\alpha) f\left(h_i, h_j\right) \quad (3)$$

The proposed method utilizes GCN to enable the efficient propagation of information across nodes and edges within the graph. Each node's representation is iteratively updated by aggregating information from its neighboring nodes. This iterative process ensures that the graph captures both local and global relationships effectively. The standard update rule for a GCN, as outlined in (4), governs this aggregation and update process, ensuring accurate and consistent representation learning.

$$h_i^{(t+1)} = \sigma\left(\sum_{j \in \mathcal{N}(i)} \frac{1}{\sqrt{d_i d_j}} A_{ij} W^{(t)} h_j^{(t)}\right) \quad (4)$$

In the GNN framework, each node i is described by a feature vector $h_i^{(t)}$, which is iteratively updated at layer t by aggregating information from its neighboring nodes. The neighbors of node i are denoted as $N(i)$, while the degree of node i, representing the number of connections it has, is expressed as d_i. The influence of one node on another during the aggregation process is determined by the edge weight, denoted A_{ij}, which defines the strength of the connection between nodes i and j. The model incorporates a trainable weight matrix $W^{(t)}$ at each layer t, which is adjusted during training to enhance the learning and representation of node features. To introduce non-linearity and capture complex relationships within the graph, an activation function, denoted as $\sigma(\cdot)$, is applied to the aggregated information. This combination of aggregation, trainable parameters, and non-linear activation enables the GNN to effectively model intricate interactions and dependencies among nodes.

The method integrates a weighted loss function to effectively address the issue of data imbalance. This involves assigning higher penalties to misclassifications of minority class samples, ensuring that the model prioritizes these underrepresented classes during training. The traditional cross-entropy loss function is modified by introducing class-specific weights, as outlined in (5). These weights amplify the contribution of minority class errors to the overall loss, encouraging the model to learn features that improve the classification accuracy for the minority class. This tailored approach ensures balanced performance across all classes, even in imbalanced datasets.

$$\mathcal{L} = -\sum_{c=1}^{C} w_c y_c \log(\hat{y}_c) \quad (5)$$

The loss function incorporates class weights to address the issue of data imbalance, ensuring that the model focuses more on minority classes. The total number of classes is denoted by C, and the class weight for each class, w_c, is calculated as the ratio of the total number of samples to the number of samples in class c, defined as

$$w_c = \frac{Total\ Samples}{Number\ of\ Class\ c\ Samples}$$

The true label for a given class is represented by y_c, while the predicted probability for that class is denoted by $\hat{y}_c$. By incorporating these weighted penalties into the loss calculation, the model gives greater importance to correctly classifying samples from underrepresented classes, thus enhancing its performance on imbalanced datasets.

Figure 1 outlines a method to balance datasets by generating synthetic samples for the minority class. It begins by calculating the minority class center x_c, which is the average position of its samples in feature space. Then, the Euclidean distances from each sample to x_c are calculated to determine the sample radius d_m, defining the boundary for generating new points. The algorithm randomly selects k minority samples, forms vectors v_i from x_c to these points, and computes a resultant vector to guide sample placement. New samples are drawn from a normal distribution around these vectors, preserving the class structure. This process repeats until the minority class matches the majority class in size. The result is a balanced dataset that retains the original distribution, improving classification performance and reducing model bias.

The MR-SMOTE algorithm focuses on generating synthetic samples predominantly concentrated around the sample radius, ensuring their validity and alignment with the minority class natural distribution. By leveraging k selected samples relative to the calculated sample center, this algorithm preserves the inherent characteristics of the minority class more effectively than traditional methods. To demonstrate the spatial distribution of synthetic samples, comparisons are made between various oversampling techniques, including SMOTE, LR-SMOTE, and MR-SMOTE. Each method employs a unique approach to sample generation, leading to distinctive patterns in the resulting data distribution. These differences are visualized through two-dimensional feature representations, as depicted in Figure 2.

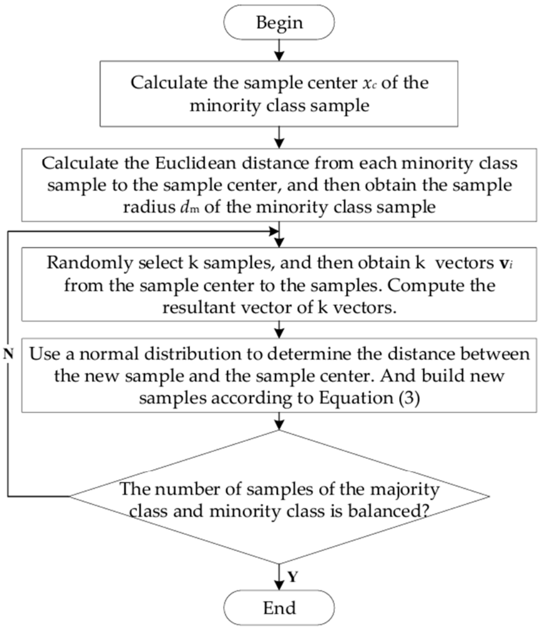

Fig. 1. Workflow of the MR-SMOTE algorithm for minority class oversampling and feature space balancing.

As the DEW and MEF components in the proposed MRS-GNN play a crucial role in the performance of the model, their hyperparameters should be carefully tuned. For DEW, the weighting factor α was empirically set to 0.7 to balance the influence of original edge weights and the learned similarities between node embeddings. Cosine similarity was used as the similarity function and effectively worked as a semantic closeness between nodes in the feature space. For MRF, three receptive field levels ($k = 4, 8, 12$) were used to aggregate features from successively larger neighborhoods. The multiscale design of this GNN allowed it to learn both local and global structural patterns. A dropout rate of 0.5 was applied to prevent overfitting, and the number of GCN layers was set at 3. Grid search on cross-validation was used to select all hyperparameters.

III. RESULTS AND DISCUSSION

A. *Dataset Used*

This study employed the 2009 PHM Data Challenge dataset [29] for fault diagnosis [30], which is a highly regarded industrial benchmark. It features a gearbox system with three shafts, four gears, and six bearings, covering two gear types: spur gears and helical gears. The spur gear data includes eight distinct health states, while the helical gear data features six health states. The dataset provides measurements from two accelerometer channels and one tachometer channel, sampled at a frequency of 66.67 kHz. The tachometer signals are recorded at 10 pulses per revolution, enabling precise tracking of the rotational speed. Additionally, the dataset captures data across five shaft speeds: 30 Hz, 35 Hz, 40 Hz, 45 Hz, and 50 Hz, under both high and low load conditions. For this experiment, the focus was on the low-load spur gear operating at 30 Hz. Vibration data from the two accelerometer channels were used for feature extraction, ensuring that critical signal characteristics were captured. Table I summarizes the details of the eight health states for spur gears. The comprehensive range of conditions and measurements in this dataset provides a solid foundation for developing and evaluating fault diagnosis methods, offering a realistic representation of industrial gearbox operations.

TABLE I. DATASET FAULT CLASS DESCRIPTION

Label	Description
Label 1	Good
Label 2	Gear chipped and eccentric
Label 3	Gear eccentric
Label 4	Gear eccentric and broken, bearing ball fault
Label 5	Gear chipped, eccentric, and broken
Label 6	Gear broken, bearing inner, faults; shaft imbalance
Label 7	Bearing inner fault
Label 8	Bearing ball and outer fault

B. *Performance of MRS-SMOTE GNN Model*

Figure 2 illustrates an assessment of multiple methods for dealing with data imbalances, quantified through the AUC-ROC metric over a spectrum of imbalance rates. The x-axis illustrates the imbalance rate, ranging from 0.4 to 1.0, whereas the y-axis displays the AUC-ROC score, which reflects classification performance. The comparison comprises techniques including oversampling, reweighting, SMOTE, graph-SMOTE, MRS-GNNs, and MRS-GNNt. The results indicate that MRS-GNNs and MRS-GNNt consistently exceed the performance of alternative methods, achieving the highest AUC-ROC scores across all the imbalance rates evaluated. This demonstrates their enhanced ability to effectively manage imbalanced datasets. As the imbalance rate increases from 0.4 to 1.0, a general improvement in performance is observed for most methods, indicating a reduction in classification difficulty at higher imbalance rates. However, the degree of improvement differs among the various techniques employed. For instance, techniques such as Reweight and Graph-SMOTE demonstrate only slight enhancements in performance as the imbalance rate escalates, whereas MRS-GNNs and MRS-GNNt reveal more significant advances. The results show that the proposed MRS and GNN frameworks are better at dealing with datasets that are not balanced and still do a good job of classifying data, even when things get tough.

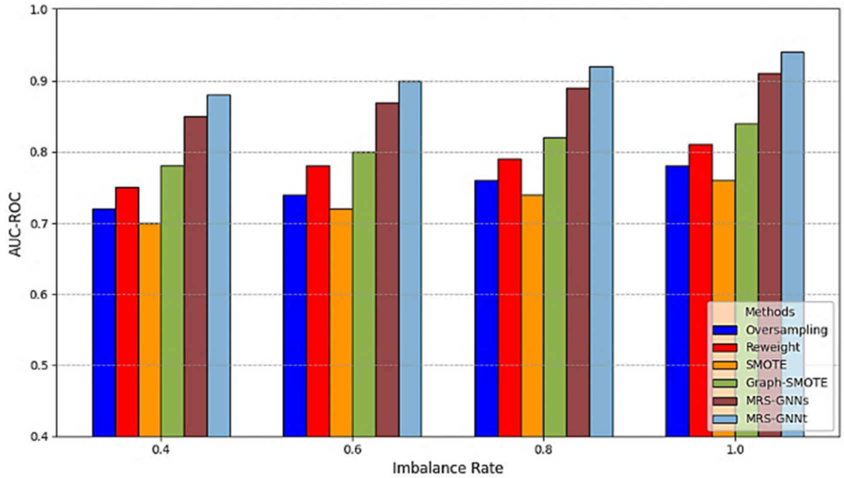

Fig. 2. AUC-ROC scores of the proposed model under varying class imbalance ratios.

C. Ablation Study

An ablation study was carried out to evaluate the contribution and significance of the novel components in the proposed method, with the findings summarized in Table II. This analysis involved systematically removing specific features or components from the model and assessing the impact on its performance. These studies were carried out using a dataset characterized by an imbalance rate of 0.6, chosen for its ability to represent a balanced test scenario. This dataset allowed for a thorough assessment of the challenges associated with imbalanced data and the need for effective fault classification. The study focused on two key components: DEW and MRF. These components are central to the model's ability to effectively manage imbalanced data and enhance classification accuracy. By isolating and removing these features individually, the study sought to determine their specific contributions to the model's overall performance.

TABLE II. ABLATION STUDY SUMMARY

Model Configuration	Accuracy (%)	AUC-ROC
Without DEW	88.4	0.92
Without MRF	89.7	0.93
Complete model	92.1	0.95

DEW dynamically adjusts the edge weights between nodes during the training process, ensuring that the graph structure reflects the actual relationships between nodes more accurately. This iterative refinement improves the quality of graph-based feature representations, particularly for minority-class samples. The removal of this component led to a 3.7% decrease in accuracy and a 0.03 reduction in the AUC-ROC score, underscoring its critical role in improving the model's classification capabilities. These findings highlight the importance of dynamically updating edge weights to ensure that the model captures relevant relationships effectively and mitigates the effects of data imbalance.

Five-fold cross-validation was used to assess the performance of the proposed MRS GNN and reduce overfitting. Data were randomly divided into five equal parts, and in every fold, four were used for training and one for testing. The values of accuracy and AUC-ROC are reported as averages across all folds. The MRF component further allowed the model to extract the local and global graph features, helping to capture subtle patterns. MRF removal resulted in a 2.4% reduction in accuracy and a 0.02 reduction in AUC-ROC, indicating the benefit of MRF. Combining MRF and DEW, the full model achieved 92.1% accuracy and 0.95 AUC-ROC, showing their combined ability to improve classification performance.

IV. CONCLUSION

This study presented a new GNN-based framework for fault diagnosis in mechanical systems that operates in a class-imbalance regime. Integrating DEW, which dynamically refines graph connectivity during learning, and MRF, which allows the model to learn features of local and global structural patterns, improves its feature learning and generalization. Moreover, the MR-SMOTE algorithm introduces a graph-aware oversampling scheme that creates synthetic minority class nodes while maintaining the topology of the graph, which is one of the major advances against traditional oversampling techniques. Experiments on the PHM 2009 gearbox dataset show that the proposed model has an accuracy of 92.1% and AUC-ROC of 0.95, which are better than other methods. This was further confirmed by ablation studies of the individual contributions to each novel component. The innovations addressed here offer a generic, high-performance approach to fault diagnosis that works even in real-world situations that are challenging in terms of class imbalance and complexities in the relationships among faults. Future work will focus on real-time deployment and adaptation across different industrial settings.

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