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MeanRadius SMOTE Based Graph Neural Network for Imbalanced Node Classification in Fault and Intrusion Detection

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***Abstract*—Data-driven approaches are also extremely important to intelligent diagnosis systems, which are critical to complex mechanical monitoring (fault detection) as well as network security (intrusion detection), but are seriously impaired by the challenge of class imbalance. A semi-supervised Graph Neural Network (GNN) is highly biased towards the minority classes (faults or intrusions) data thus the minority data is skewed in the classification process and historical oversampling methods are ineffective as they do not specify the required graph topology.**

As a solution to the unbalanced node classification problem, the present paper introduces a new framework, called MeanRadius-SMOTE Graph Neural Network (MRS-GNN), which aims to generate trustworthy node representations in GNNs. The MRS-GNN combines the MeanRadius-SMOTE oversampling method with interpolation in the intermediate embedding space obtained out of a GNN feature extractor. This process generates stronger synthetic samples and improves the ability of the model to learn in a case of under-represented classes. Specialized edge generator is then presented to create links between these newly created nodes and in effect maintain the topological integrity and structural continuity of the augmented graph.

The superiority and strength of the MRS-GNN is validated with the largest publicly available fault diagnosis datasets (CWRU, JNU, PU) against traditional approaches, such as SMOTE, Oversampling, and Reweight. Under extreme imbalance conditions (IMR of 0.4), the structure attained an AUC-ROC of 0.904 and enhanced the accuracy of the classification by more than 18 percentage points. MRS-GNN is able to preserve both node attributes and connectivity structure, which increases the overall diagnostic reliability. This framework does not only enhance fault diagnosis, it also provides a scalable solution to complicated systems proving it to be very useful and bendable to parallel problems like network intrusion detection.

Keywords— Class Imbalance, Graph Neural Networks (GNNs), MeanRadius-SMOTE (MRS-SMOTE), Fault Diagnosis, Oversampling Techniques, Intrusion Detection, Imbalanced Node Classification

I. INTRODUCTION

The blistering pace of modern industry and the development of the most important infrastructure facilities, including manufacturing, transport, and power plants, require a high level of reliability and fault-free functioning. In the case of a mechanical system, the performance is greatly affected by items such as bearings, and therefore, they need to be diagnosed with the appropriate accuracy and at the right time to avoid failure that is catastrophic and minimizing the cost of maintenance. The effective monitoring and diagnosis of the rotating machines should therefore be developed by developing a reliable prognostics health management (PHM) system[1].

A. Background & Motivation

Traditionally, the model-based approach was used in the diagnosis of faults but new systems are increasingly using data-driven approaches, which take advantage of the large volumes of data produced by measurement devices and the Internet of Things (IoT) [2]. The deep learning-based fault diagnostic models are strong at feature and pattern detection as well as nonlinear data of high dimensions without prior knowledge that is intensive. More importantly, GNNs have attracted interest as powerful non-Euclidean data processing tools and complex spatial topology system-level interaction capturing tools. GNNs have also been demonstrated in the multifaceted area of intelligent diagnosis, such as sensor-signal interaction modeling in industry processes or Wavelet Packet-Enhanced Deep Graph Contrastive Learning to fault diagnose rolling bearings[3]. This analytical method based on graphs is also essential in the key areas of technology, especially in the field of cyber risk management and security. The network layer attacks are susceptible to complex networks, like IoT networks and smart grids. Such security risks are usually modeled in terms of topology networks, such as attack graphs and fault trees, and their control needs powerful security

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frameworks. These challenges are quickly being addressed with GNNs, which are used in deep learning systems in IoT networks based on communication graphs, to detect botnet attacks, to detect anomalies in multivariate form, and detect network layer attacks in mobile ad hoc networks[4]. Although GNNs are effective to model complex topological relationships, a common issue in the real-world setting is classified as a critical detriment to the success of both fault diagnosis and intrusion detection systems: class imbalance. In mechanical systems, rotating machinery normally works under the normal conditions that, faults are uncommon hence a high imbalance of data between the normal and faulty state is very high due to the majority state of normal and minority state of fault. The same thing happens in network security where both malicious intrusion attempts and rare attacks are far outnumbered by benign traffic [5]. In such disproportional scenarios of node classification, the predominant class of the nodes strongly impacts the loss of the GNN and causes the concentration on the normal data when the individual, the minority, and rare, yet, fault or the attack category is underrepresented (and the opposite as well)[6]. This is a weakness that limits practical use of GNNs in high stakes contexts where failure to identify a rare event whether a mechanical failure or a cyber attack may result in major economic costs. This is a challenge that should be addressed by means of special GNN schemes that should be capable of dealing with imbalanced node classifications in graph-structured data[7].

B. The Need for Graph Neural Networks (GNNs)

Although traditional deep learning models, e.g. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are quite efficient to process structured data, e.g. grids or sequences, they are not as effective with data that has non-Euclidean properties. Intelligent fault diagnosis and network security systems are complex systems that inevitably generate structurally complex data, with a large number of interacting components, variables, and failure modes. Graph Neural Networks (GNNs) have received extensive interest to model these interactions because they have a special ability to work with graphical data, which has an inherent spatial topology. GNNs are the key to any system that is supposed to examine, understand the intricate system topology, and interactions[1]. Within the framework of the present study, one-dimensional signals (data of vibration in mechanical systems) are carefully translated into a massive topological graph, represented by G. Under this representation every sample is represented by a unique node and the connections between these nodes are determined by the statistical linear correlations between the nodes e.g. the Pearson correlation coefficient. Such transformation enables the model to facilitate potential relationships and implicit connection among various faults or conditions that otherwise would not be considered in a traditional analysis[7]. The main advantage of GNNs is that they are performing well on semi-supervised node classification. In this architecture, the GNN is trained using a limited set of labeled nodes however uses the topological data of the full graph (including unlabeled nodes) to label all the other entities. This is crucial to PHM systems and security applications since it offers a powerful way to extract feature information and the model captures local structure information and in general is effective generalisation. The development of GNNs proves that they are more and more able to cope with complexity[8]: Graph Convolutional Networks (GCNs) were extended versions of traditional convolutional operations to graph structures. Graph Attention Networks (GATs) expanded on this ability by adding an attention mechanism, which means that the network can give different weights to different neighbors, which leads to the enhanced ability to process complex data and process variations between nodes better. • GraphSage provides high scalability and flexibility, where sampling and aggregation functions are employed to learn local topologies, which is appropriate in processing large graphs in complicated tasks. GNNs are trained to encode both node features and graph topology to a continuous embedded representation space so that downstream tasks, such as the classification of faults or intrusions, can be run on features in which intraclass similarities and interclass differences can be effectively modeled. It is such an advanced feature encoding ability that is the precondition to formulate strong solutions to the issue of asymmetrical node classification.

C. Problem Statement

The idea of deep learning and Graph Neural Networks (GNNs) is a very promising and efficient model utilizing data to solve various tasks and problems, such as intelligent fault diagnosis and network security, but the widespread problem of class imbalance severely worsens the process of practical implementation. When data is needed to monitor mechanical systems or identify cyber threats, data acquisition overwhelmingly supports the majority class (e.g. healthy components or benign network traffic) compared to the minority class (e.g. rare faults or malicious intrusions). This imbalance causes massive data imbalance that can be difficult to determine using deep learning models to specify the correct decision boundaries. The classifiers that are trained with such data put a premium on the general accuracy, and the resulting ability to single out the minority samples that are rare and difficult to predict defines the misguided prediction of the minority samples. Such an unbalanced node classification is a particular problem to existing GNN models that are designed to work on graph-structured data. The loss function of the GNN is highly dependent on the size of the majority class, which also makes the model biased, therefore, performing poorly and making incorrect predictions in the minority classes. Since the inability to identify infrequent mechanical failures or security violations may lead to serious losses to the economy, it is essential to focus on the creation of special GNN mechanisms to combat this. The suboptimal results of applying the conventional solutions like resampling methods to the graph data is that they address individual sample independently and thus are incapable of handling the topography of the graph. In particular, the addition of synthetic samples into the graph structure gives rise to two key issues: Producing Trustworthy Relational Information: The traditional oversampling techniques, such as standard SMOTE, are based on interpolating among samples. Nevertheless, edge relationships are generally no longer suitable to be interpolated when used with graph data because of its discrete and sparse character, which may break topological integrity between the samples. Weakened Quality of Synthetic Samples: When oversampling is directly applied in the original feature space, which can be of a high dimension, then the synthetic samples can be out of distribution, or they may have noise, which is bad news to train the GNN classifier. A new methodology is needed to address these structural and data quality issues. The study thus aims to investigate synthetic minority class over-representation in GNNs to the problem of imbalanced node classification, namely, synthesizing node representations in a low-level embedding space and maintaining topological accuracy and precision by means of robust edge generation.

D. Contributions

This study proposes the MeanRadius-SMOTE Graph Neural Network (MRS-GNN), a new framework, whose main goal is to synthesize node representations in GNNs to alleviate the issue of the imbalance in the classes of the topologically complicated data. The key findings of this research paper include the following: New MeanRadius-SMOTE Hybrid: We suggest that the MeanRadius-SMOTE algorithm should be directly integrated into the GNN network, with the minority sample-generation done on the embedding space in between. This technique takes advantage of the lower dimensionality and localized distribution of features in the embedded space to improve the trustworthiness and quality of the produced synthetic samples to improve the tradeoff between minority and majority classes. Topological Integrity: The framework contains a special edge generator module, which is concerned with the very important issue of connectivity of newly created nodes. The edge generator keeps the topology and structural integrity of the graph constant by ensuring the creation of new edges between synthetic and existing samples, which is vital in ensuring robust performance in the node classification. High Performance and Strength: Numerous experiments prove that the MRS-GNN is more effective than other popular, conventional strategies, not only in terms of classification accuracy but also class imbalance. The MRS-GNN was also found to be more robust in extreme imbalanced conditions (IMR of 0.4) with an AUC-ROC of 0.904 and making a larger improvement of 18 percentage points against certain baseline approaches. Scalability and Utility of Complex Systems: Scalability and versatility The MRS-GNN is a scalable and general solution, and it confirms its utility as well as adaptability beyond fault diagnosis of mechanical systems. The presented robustness justifies its use in various complex fields, like systems such as power grids and transport networks, and further proves its applicability to analogous problems, such as intrusion detection that involve imbalanced classification on network graphs which are more complex.

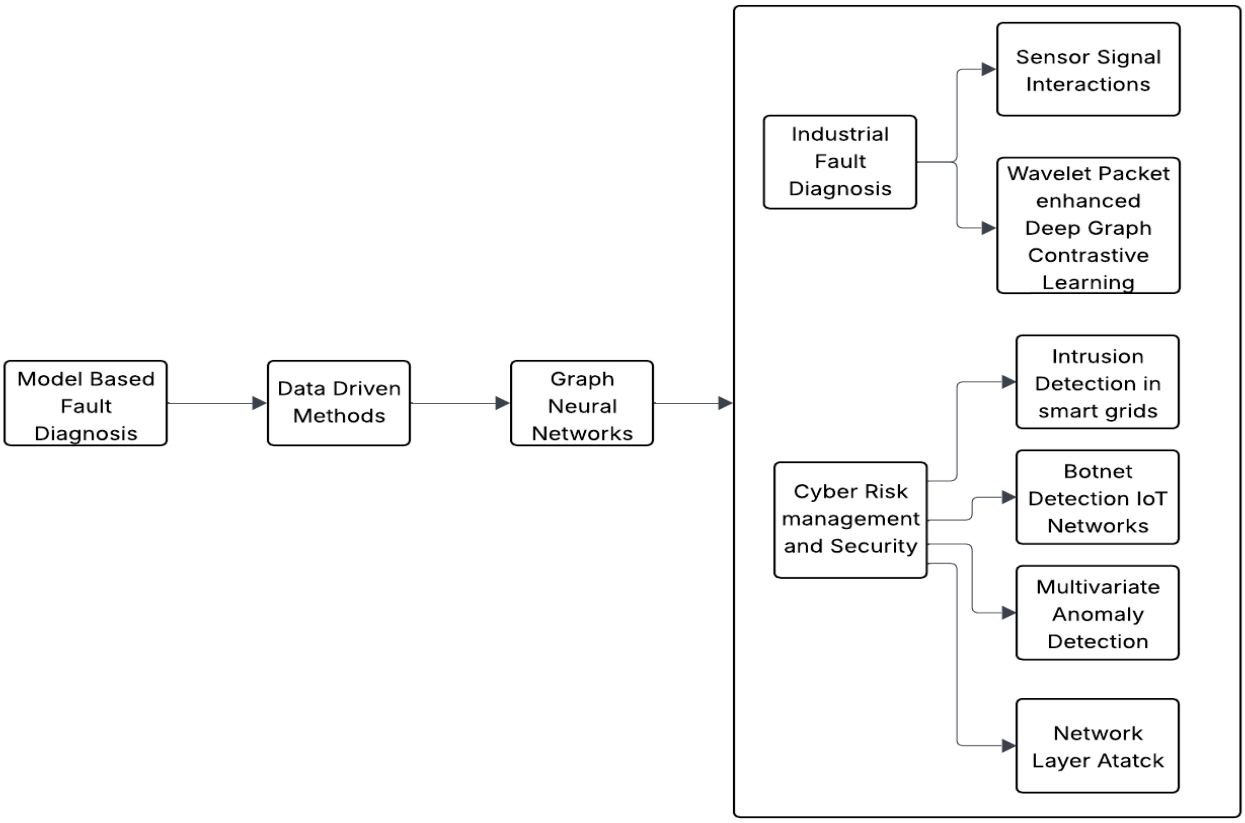


Fig. 1. Evolution GNN-Based Fault Diagnosis and Intrusion Detection

E. Organisation of the Paper

The rest of this research article is organized in such a way that it gives a complete review of the available methods of imbalance, describe the design of the proposed MRS-GNN framework, and strictly justify its functionality. Section 2 presents the Related Work that is relevant to this study. This part initially examines traditional solutions to the issue of class imbalance, which are divided into data-level solutions (e.g. oversampling and undersampling), algorithm-level solutions (e.g. sample weighting or objective function), and a combination of both. A particular focus is put on one of the most popular algorithms called SMOTE and its variants, and the challenges it brings when attempting to apply it directly to non-Euclidean graph data are outlined because of the topology constraints. This section then goes further to examine the current developments in Graph Neural Networks (GNNs) and explores the fundamental models (like Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs)) and their implementation in more challenging areas, like intelligent diagnosis. The Problem Modeling is

officially described in Section 3. This part determines the graph topological data representation G(V,A,X) required in the semi supervised node classification task. It also provides important parameters, such as the total number of categories of faults (K) and the Imbalance Rate (IMR) which is the parameter that measures the extent of sample imbalance in the training subset (LS). Section 4 elaborates on the Proposed Methods, as it will describe how the MRS-GNN system will be structured and work. This architecture is described in sequence, beginning with the Graph Data Generation process, which applies the Pearson correlation coefficient to make up the adjacency matrix, and then a sparsification step that will reduce oversmoothing. This would then be followed by an explanation of the Feature Extractor (where GraphSage is used to illustrate) which converts the information into an intermediate embedding space. The algorithmic steps of constructing balanced samples through the MeanRadius-SMOTE algorithm in this embedding space are then described and so is the construction of the Edge Generator, which creates the connections of the newly created nodes to hold the graph together structurally. Lastly, the Classifier design which will use the improved balanced graph data is given. The Experimental Results and Comparisons are provided in Section 5. The section will describe the validation environment with three publicly available datasets (CWRU, JNU and PU) and varying imbalance rates (IMR) and imbalanced classes. To establish the superiority and resilience of the system in extreme imbalances, the variants of MRS-GNN (MRS-GNNS and MRS-GNNT) are presented in a systematic comparison with the popular methods, including Oversampling, SMOTE, Reweight, and GraphSMOTE, in terms of such metrics as AUC-ROC and classification accuracy. Section 6 includes the Conclusions, which indicate the contributions of the MRS-GNN framework and supports its higher diagnostic accuracy and wider versatility. It ends with the fact that the framework can be useful in many other complex systems, such as power grids and transport networks, and defines future work opportunities, such as incorporating unsupervised learning methods.

II. Related Work

The evolution of the suggested MRS-GNN architecture is based on the large body of knowledge in tackling the issue of class disproportion, the benefits of the Graph Neural Networks (GNNs), and their application to topological systems of real-world problem such as fault identification and security surveillance.

A. Class Imbalance Solutions

The well-known problem in practice is known as class imbalance, which is a traditional field of research in deep learning. When the data is limited to infrequent faults, as in the case of mechanical fault diagnosis, the trained sample classifier can not accurately predict such an event, even though the general accuracy of the prediction of majority class samples. As unbalanced datasets are prone to serious economic losses due to occasional faults, there is an urgent need to study these problems when diagnostic machine faults. Typically, the approaches to the imbalanced dataset are divided into two main groups: data-level approaches and algorithm-level approaches, with a few combining both[1].

B. Data-Level Techniques (Resampling)

These techniques are used to modify the data distribution directly using resampling techniques to synthesize, duplicate, or eliminate original samples to obtain sample size balance. ◦ Oversampling can be done by increasing the amount of samples of the minor classes in order to achieve balance in the classes, either by copying (which may recreate the noise samples) or by synthesizing new samples. Synthetic Minority Over-sampling Technique (SMOTE) is a traditional oversampling algorithm which produces new samples by interpolating along the line between two existing samples of the minority class. Nevertheless, SMOTE remains prone to the production of noisy samples, and the new samples will be prone to the effect of the original sample distribution, which may lead to the production of a different sample distribution[3] [4]. Later improvements have also been suggested e.g. LR-SMOTE and BorderlineSMOTE which depends on reducing noise and better generation algorithms[1] [2]. ◦ Undersampling balances the classes by reducing the number of samples of the majority classes. ◦ Oversampling methods are taken as a research direction of prime importance because the samples of minority classes are practically scarce in most imbalanced datasets.

C. Algorithm-Level Techniques

Algorithm-Level Techniques Such strategies include changing the algorithm of the learning process e.g. changing the sample weights to focus on rare samples or changing the decision boundaries. By way of example, the Reweight technique can fix the imbalance by giving the samples of the minority classes more weight or the samples of the majorities class less weight, allowing the classifier to pay more attention to the minorities class. The most important aspect noticed is that most of the available studies on SMOTE have been carried out on independent and identical data points. This attribute makes it difficult to transfer it immediately to graph data because of the distinctive graph topology[1] [2] [3]. In particular, when interpolation in SMOTE versions creates new nodes, they do not have any links to the original graph, and they create isolated islands which are less beneficial to the GNN classifier. Additionally, synthetic generation of nodes in the source domain usually ignores intrinsic topology and high dimensionality of the node features in the source graph, which may lead to poor sample quality and poor training of classifiers.

D. Graph Neural Networks (GNNs)

GNNs are proven to be powerful graphical and non-Euclidean data processing tools. The general principle of GNNs has been researched widely, resulting in a number of important variations: Johnson et al. (2020) note that the models are known as Graph Convolutional Networks (GCNs): They generalize convolutional operations on grid data to graphical data, providing a new way to process graph structures [1] [2]. They can be used to capture local structural information, especially with the combination with

powerful sampling methods. Graph Attention Networks (GATs): GATs are the networks that improve the representational complexity with an attention mechanism that enables the network to put a different level of importance by weighting the neighbors of the node. This flexibility offers a better way of dealing with imbalanced data which gives it a better performance as opposed to GCNs and the GraphSage when it comes to different imbalance rates. • Graph Isomorphism Networks (GINs): The networks improve the representational power of GNNs by adding the graph isomorphism test. GraphSage: It is characterized by the capacity to efficiently acquire different local topologies with the help of sampling and aggregation operations. GraphSage is highly scalable and can accommodate variability in nodes and can work with large graphs although its localization approach can impair its performance in some imbalanced situations [3]. GNNs have been very widely used in various domains such as social network analysis, and bioinformatics. More to the point in terms of this study, they are becoming more applied in the complicated field of intelligent diagnosis. Since real engineering systems have many interacting components, variables, and failure modes, then modeling these interactions using topologically structured graphs data can be useful.

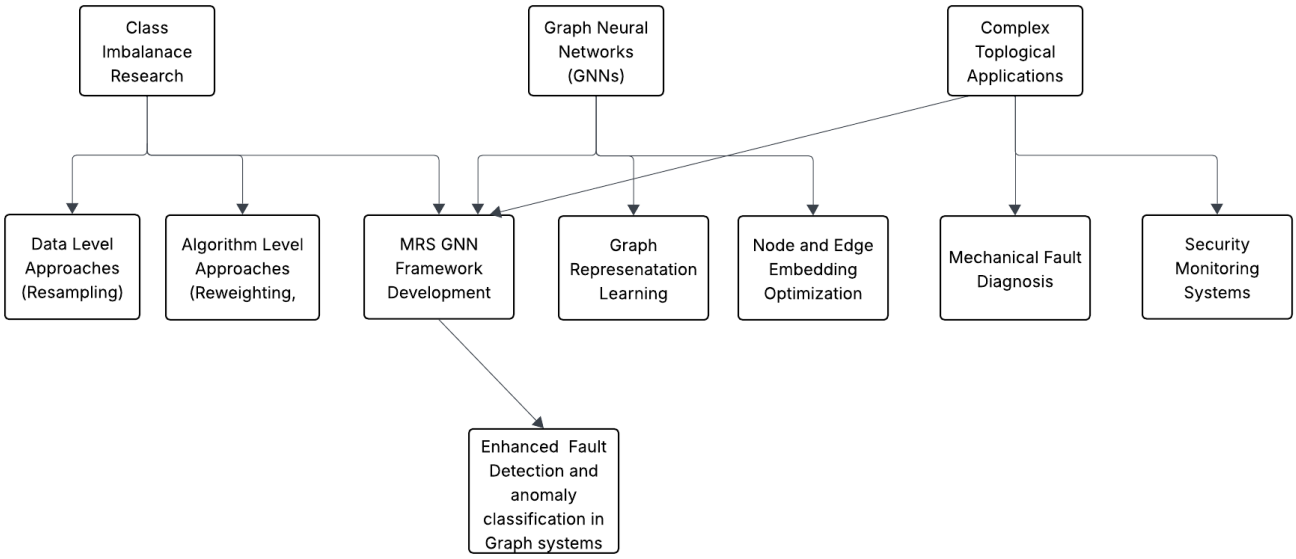


Fig. 2. Conceptual foundation of the proposed MRS-GNN framework

E. Graph-based Fault and Intrusion Detection

This has direct applications to predicting faults and to security analysis since the usefulness of GNNs to complex topological systems is versatile. Fault Diagnosis: GNNs are useful in representing and interacting with system topology and interactions in order to obtain valuable feature information of Prognostics Health Management (PHM) systems.

The introduction of a graph neural network, the interaction-aware (IAGNN) to predict sensor-signal interactions in a complex industrial process, which would further increase the accuracy of fault diagnosis. A wavelet packet-enhanced Deep Graph Contrastive Learning approach (i.e. wavelet packet decomposition with graph convolutional networks) to extract the node-level fault information to diagnose rolling bearings.

The introduction of a graph-guided collaborative convolutional neural network (GGCN) to explore the common features among multi-source signals, which enables the effective fault diagnosis of electromechanical systems. Intrusion Detection: Intrusion Detection is the basic problem of detecting infrequent activities on a complicated network topology which is identical to fault diagnosis. Complex networks that have intrusion detection system (IDS) (i.e. smart grids and IoT networks) are based on GNNs to compute traffic features and communication graphs. The source material highlights the fact that the MRS-GNN structure that has demonstrated its effectiveness in imbalanced classification in mechanical systems can also be used to provide a scalar solution to a wide range of complex systems, such as a power grid, and a transport system[5] [6]. This supports the usefulness of the methodology of MRS-GNN in addressing the imbalanced node classification issues common in network intrusion detection. The gap in this review is that, even though different types of GNNs have been successfully used in intelligent diagnosis, no studies have explored the research aiming to synthesize a small number of classes using oversampling methods specifically designed to work with graph-structured data. It was this need that shaped the creation of the MRS-GNN, which is based on resolving the problem by utilizing the MeanRadius-SMOTE method to increase the use of GNNs to tackle the problem of node classification with unequal classes [7].

III. PROBLEM MODELING

The purpose of this section is to clearly describe the data format and the semi-supervised classification problem of nodes that will be studied in the work to expose the difficulties posed by the problem of class imbalance in graph topological networks. Graph Data Representation In this work, the complicated data of operations (vibration signal of the mechanical system or network

characteristics of the log of intrusions) is converted into a large-scale topological graph. This representation does not only reflect the specifics of individual data samples, it also represents how these might have potential relationships and interconnections.

The graph topological data is formally represented by a

$$G = (V, A, X). \quad (1)$$

• *Nodes:* VV = {v1, v2, etc., vn} indicates the set of all nodes, with each sample (e.g. a particular slice of operational data) being considered a node.

• *Feature Matrix (X)*

X = {x1, x2, ... xn} is the feature matrix and its dimension is n x d, n is the total number of nodes and d is the dimension of node feature vector.

• *Adjacency Matrix (A)*

A accounts the relationship of connection of nodes: Use of adjacency matrix of G, A, represents the relationship of connection between a node, i, and node, j. There is an edge (i.e., aij=1) when there is a connection relationship between node i and node j: otherwise aij=0. This matrix represents the relationship between neighborhood and reflects the relationship between various samples in the complex system topology. The Semi-Supervised Task of Classification. The system has the purpose of addressing the issue of semi-supervised node classification. Assume that the true attribute information (labels) of the nodes in the graph are denoted by L L in R n. Partial subset of this label information which is referred to as LS is only available to the model during the training period. The aim of the classification is to classify the unlabeled nodes based on the samples and the structure of the graph. Although unlabeled samples do not explicitly contain any labeling information in the case of graph topological networks, this is essential, since they may be used to provide the model with more topologic data when the similarity between samples is being investigated. The total of fault or status categories is denoted by: c1, c2, c3, c4, c5, c6, c7, c8, c9... ck where ck is the size (number of samples) of the ck th category. Measurement of the Challenge of Imbalance. The fundamental challenge is the disparity in classes in the marked set $LS. As an example, in fault classification, the majority class (healthy bearings, denoted by green nodes) has a large number of representatives as compared to the minority class (faulty bearings, denoted by purple nodes). This skew is tendent to be extended in a semi-supervised configuration since the little labeled information only further diminishes the quantity of labeled minor samples to train with. In order to measure the extent of this imbalance, this paper will use the Imbalance Rate (IMR) which can be defined as:

$$IMR = \min(ci) / \max(ci) \quad (2)$$

A lower IMR implies an increase in the level of imbalance in the dataset in terms of classes. In general, the IMR of LS in task setting is small.

The general training goal of the sample task of the imbalance in the classroom is as follows: The objective is to learn and train a classifier (also referred to as f (V, A, X) to L) that can specifically perform extremely well at the task of labeling the majority and the minority classes, given the information regarding the graph (in terms of its inherent node class imbalance) and the labels information (in terms of the accessible subset of the nodes) denoted by G and LS respectively. The latter goal directly implies the need to use specific techniques to reduce the impact of the majority class on the loss of the GNN that would cause incorrect predictions of the minority one.

IV. Proposed Methodology

This section gives a detailed look at the MeanRadius-SMOTE Graph Neural Network framework, called MRS-GNN. It gets designed especially to handle class imbalance problems in graph data. The MRS-GNN works to balance classes by using node interpolation in the embedding space. It also uses a policy-driven edge generator that keeps the graph topology intact. All this leads to a better balanced graph for classification tasks through a GNN classifier. The setup combines automatic graph encoding with node classification. It relies on the same feature extractor for both parts. Plus, it does oversampling right in the module's output space to make the generated node samples more reliable.

The framework moves forward through several clear modules. Those get described in more detail right here.

A. Graph Data Generation

In section 4.1, graph data generation comes first. The MRS-GNN needs graph data to start with. That includes the feature matrix X and the adjacency matrix A. The raw input often shows up as one-dimensional time signals. Think vibration data for mechanical fault diagnosis, for example. Turning those signals into a graph structure G takes some careful thought.

First off, node and feature creation happens like this. The raw signal data gets broken into sample points for each fault type. It uses a sliding time window of a set length, say 256. Every segment that comes out turns into its own unique node in the graph.

Next, adjacency matrix construction follows. The matrix A has to show neighborhood relationships. It also needs to capture interconnections among samples in the system topology. To spot potential links and hidden ties between faults or samples that direct connections might miss, this work turns to the Pearson correlation coefficient. That coefficient measures linear correlation between two sample nodes. Values go from -1 to 1. Once fault samples get segmented, the node Pearson correlations between different fault samples get calculated. Those help build the adjacency matrix A.

Then, a sparsification step kicks in. The undirected dense graph from the Pearson correlation often has noisy or useless edges. That creates too much density in connections. Such density can cause oversmoothing issues during GNN training. To cut that risk, sparsification prunes the adjacency matrix A. It drops connections based on a threshold from correlation values. In the end, only the key relationships stay. Those are the real, meaningful interactions between faults.

B. Feature Extractor

After turning one-dimensional temporal signals into graph data G, a GNN feature extractor steps up. This proves important because oversampling straight in the original feature space does not work well. The original space might feel sparse and high-dimensional. That makes interpolation tough for finding similar nodes. Direct oversampling also skips the built-in graph topology.

The main job of the GNN feature extractor is to grab feature representations for nodes. It encodes node info and graph topology into a continuous embedded space.

One big plus of this embedded space is how it grabs node features and their relationships. Similar nodes end up close together. Dissimilar ones stay far apart. So, doing interpolation on a small group of nodes and their nearest neighbors here creates embedded reps that better stand for new, solid samples from the same limited classes.

For model choice, lots of GNN models could work as the feature extractor. But GraphSage gets picked as the base architecture in the original work for showing how it goes. GraphSage shines because it learns well from different local topologies. It also generalizes nicely to new structures.

GraphSage runs through two key processes. Those are sampling and aggregation. It samples neighbor nodes using connection info. Then it keeps blending in neighbor information via a multi-layer aggregation function. This gives the node's embedded representation h_v^l at layer l. That comes from concatenation and nonlinear transformation.

C. Generation of New Sample Nodes

The process requires embedded representation calculation for each node before performing minority class sample oversampling in the embedding space. The MeanRadius-SMOTE algorithm serves as the main oversampling tool because it maintains decision boundaries while reducing noise and enhancing sample diversity.

The process to create new minority class sample nodes follows these steps:

- Center Calculation: The geometric center (Z) of the minority class samples in the embedding space is calculated.
- Radius Calculation: The minority class sample radius (R) is computed by calculating the average Euclidean distance between each minority class sample and the sample center Z.
- Synthetic Vector Generation: A random selection of M minority class samples is made, and a synthetic vector V is computed by synthesizing the vectors extending from the sample center Z to these M samples.
- New Sample Generation: The distance between the new sample and the sample center is determined using a normal distribution based on the radius R, and the new sample (z_{new}) is generated according to Equation (7).
- Iteration: Steps 3 and 4 are repeated until the number of samples in the minority class matches that of the majority class, thus achieving a balanced distribution of various class sizes.

The number of new samples produced for each minority class can be controlled through hyperparameter adjustments of m and θ which leads to better classification results for minority classes.

D. Edge Generator

The oversampling process creates new nodes which become disconnected from the original input graph data G because they lack connections to the graph structure. The GNN faces a challenge because it cannot perform edge-based node representation updates and aggregation and propagation operations.

The edge generator function creates new connections between synthetic nodes and the original graph structure of G.

- Function: The edge generator learns the authentic edge distributions among the node samples and utilizes the embedded representations and topological information to generate new edges. The new edges connect synthetic nodes to the original graph structure while maintaining its structural characteristics.
- Implementation: The edge generator receives training from real node and edge connections to predict neighborhood information for new sample nodes. The edge generator uses a weighted vanilla design to predict edge weights between nodes i and j based on their embedded representations.

Augmented Adjacency Matrix Ă

- The predicted new edge relationships together with sample nodes get added to the original neighborhood matrix A to create the updated neighborhood matrix $\breve{A}$. The GNN classifier receives $\breve{A}$ as its input.

Two Edge Generation Strategies: The research implemented two different methods to insert predicted edges into the adjacency matrix A which resulted in two distinct MRS-GNN models.

- The predicted edges $\check{A}$ for the synthesized new nodes are continuous values (0 to 1), representing connection strength; this is the strategy we propose. The first benefit of our method is that the gradient loss of the augmented adjacency matrix could be computed through the classifier module. It enables the edge generator to be optimized by the loss from the node classifier and also from the edge re-prediction task.
- The process involves setting a threshold ε to convert predicted edges into binary values (0 or 1). An edge connection is established when the connection strength exceeds this threshold. In this formulation, the edge generator is optimized solely using the loss derived from the edge prediction task.

E. Classifier Design.

The end result of these operations will be the augmented graph data $\check{G}$, which consists of the upgraded node representation $\check{H}$ and the augmented adjacency matrix $\check{A}$ and the upgraded node label set $\check{V}$_L. The sample data in this augmented graph is evenly distributed by class.

- The softmax function gives the probability distribution of class labels (P_v) at a node v.
- The cross-entropy loss function is used to optimize classifier
- During testing, the predicted label $\check{V}$_L will be that class with the highest probability.

This framework offers an effective method to address the challenge of class imbalance through an improved representation of the graph and synthesizing more samples of the minority class by preserving their topological properties.

V. Experiments and Results.

This part explains how we tested the MRS-GNN framework to see how well it fights class imbalance. The assessment compares the two proposed variants against several traditional approaches by means of three public datasets concerning bearing fault diagnosis.

A. Dataset Descriptions.

In this work, three publicly available bearing datasets are used to validate across multiple faults.

- The CWRU dataset created by Case Western Reserve University is one of the most popular datasets[9]. It contains bearing test data collected under normal conditions and various fault conditions. For the experiment, the selected types of faults were: Normal (N), Inner Ring Fault (IF), Outer Ring Fault (OF), and Ball Fault (BF).
- The Jiangnan University dataset is maintained by Jiangnan University and is useful for fault diagnosis[10]. Data on the running of rolling bearings on different speeds (600 rpm, 800 rpm, 1000 rpm) and under various faulty conditions is provided. The four fault types which were chosen to test the fault recognition accuracy were normal (N), inner ring fault (IF), outer ring fault (OF) and ball fault (BF) at the rotating speed 800 rpm in CWRU dataset.
- The PU data set was released by the University of Paderborn[11]; it makes use of motor current signal to monitor damage to bearing of electromechanical drive systems. The experiment was conducted with five fault types which are Normal (N), Artificial Outer Damage (AOF), Artificial Inner Damage (AIF), Real Outer Damage (ROF) and Real Combined Damage (RCF).

B. Dataset Preprocessing.

To make the data usable for GNN processing, a sliding time window of length 256 was applied to raw signal data to segment them into sample points. Using this sample, the Pearson correlation coefficient was computed to create a graph from node pairs.

The data was partitioned in a way that 70% of the signal data for each fault type is randomly assigned as training set while the rest is the test set. To this end, we constructed multiple imbalanced datasets by adjusting two metrics, namely, the imbalance rate (IMR) and the number of imbalance classes (IC). A larger IMR shows that the data set has a bigger classific imbalance.

The GNN-based experimental framework did not ensure that all comparison methods and proposed MRS-GNN variants did not utilize the same learning strategies and environments.

Comparison of some Popular Methods

The MRS-GNN framework has been compared with four representative approaches for handling class imbalance problems and its two variants in our experiments.

- Oversampling is a baseline data-level technique that balances the dataset by copying minority class nodes along their existing edges in the original space.
- The classical oversampling algorithm which creates new minority class samples through interpolation between sets of minority class observations and their neighbors.
- Reweight is an algorithm level technique that accomplishes the same task by either the increasing weight of minority class samples or decreasing the weight of majority class samples in order to concentrate the classifier on the under-represented classes.

- GraphSMOTE is an improved version of SMOTE that is used on graphical data which uses graph structure to find similarity and create synthetic samples.
- The method presented this year allows for a continuous value representation of predicted edges (values between 0 and 1). This allows the edge generator to be optimized using losses from both the node classification task as well as the edge prediction task.
- The sixth method is called MRS-GNNT or Thresholded Edge Generation. In this method, edges generated are changed to binary values, (0 or 1), with the help of a threshold. Furthermore, the edge generator is optimised using only the loss from the edge prediction task.

C. Experimental Results and Analysis.

Performance Validation of the MRS-GNN Model.

- In our first experiments comparing MRS-GNN variants with the popular methods on three bearing datasets, we showed that MRS-GNN variant beat the conventional methods in almost all cases.
- Superiority in Extreme Imbalance.
- MRS-GNNS and MRS-GNNT methods showed significant improvements when IMR was at its highest, showing a higher robustness of these methods under extremely imbalanced conditions.
- On the CWRU dataset with an IMR of 0.4, the classification accuracy of the MRS-GNNS improved by more than 18% over that of the baseline oversampling method.
- For AUC-ROC, a metric very informative for assessing discriminative power when the positive categories are few, both variants of MRS-GNN deliver outstanding performance. At the IMR = 0.4 position, MRS-GNNS achieved an AUC-ROC of 0.904 while MRS-GNNT was 0.8953, thereby proving their effectiveness in combating high imbalance issues.

Robustness to Increasing Imbalanced Classes:

- The MRS-GNN variants showed relatively stable performance with the increase in the number of imbalanced classes from 1 to 2, which means that they are suitable for complex imbalance situations.
- On the contrary, traditional methods, such as SMOTE and Reweighting, show more severe degradation in performance when the number of imbalanced classes increases.
- Most notably, the GraphSMOTE method, considering the underlying graph structure, improved significantly over standard SMOTE and thus showed great potential for graph-based methods when dealing with highly complex class relationships in imbalanced datasets.

However, the key findings pointed out that multiple measures, such as accuracy and AUC-ROC, come into play when dealing with an imbalanced dataset. Variants of MRS-GNN outperformed other methods in terms of superior performance and increased robustness, highlighting the potential this approach based on graph neural networks has for tackling class imbalance problems.

D. Exploring the Effect of Different Base Models

To further investigate the adaptability of the MeanRadius-SMOTE method, it was compared to various GNN base models—GCN, GAT, and GraphSage—when combined with these state-of-the-art sampling techniques.

- Graph Attention Networks: GAT had consistently yielded better performance than GCN and GraphSage for all imbalance rates. It is due to the attention mechanisms in GAT that provide an edge over the others by learning node importance weights, which develop better ways of handling class imbalance. The improvement of GAT was quite significant when used in conjunction with the MRS-GNNS method.
- GraphSage: This model has shown outstanding scalability and adaptiveness to node variability. In its performance, GraphSage was comparable to GAT and GCN while at the equilibrium state, where IMR = 1. However, GraphSage's localization strategy led to limited global awareness in certain imbalanced scenarios, occasionally resulting in inferior performance compared to GAT.
- Graph Convolutional Networks: The model showed a significant improvement on the baseline when applying GCNs and MRS-GNNT methods, respectively, indicating its strong ability in learning local structure information and increasing its power by integrating an advanced sampling technique. However, due to a lack of consideration for internode variabilities in GCN development, it does not perform as well as GAT on highly imbalanced heterogeneous graphs.

The results confirmed the effectiveness of generating new minority samples by means of the specialized techniques under different conditions of imbalance, but also pointed out that the choice of the GNN variant should be guided by specific application scenarios and dataset characteristics.

VI. Conclusion and Future Work

A. Conclusions

The current study successfully proposed the MeanRadius-SMOTE Graph Neural Network framework as a significant methodological improvement in the implementation of GNNs for problems featuring severe class imbalance, which widely occur in mechanical fault diagnosis and network security. Its core objective was to effectively synthesize node representations in GNNs and thereby mitigate the inherent difficulty in addressing the imbalanced data challenge common in fault diagnosis in mechanical systems.

The proposed MRS-GNN framework tackles two major challenges of traditional oversampling methods applied on graph data: the difficulty of generating reliable relational information, and the poor quality of synthetic samples due to high dimensionality. Overall, key conclusions that this work supports are:

The proposed framework embeds the MeanRadius-SMOTE oversampling technique within the GNN architecture, which enables interpolation in the intermediate embedding space. This enhances the model's learning capability regarding under-represented classes by leveraging the reduced dimensions and concentrated distribution features in the embedded space for the generation of more coherent and reliable synthetic minority samples.

The framework includes a critical edge generator module, which forms new edges between the generated synthetic nodes and existing samples to preserve the topology and structural integrity of the graph. Preserving such topological information is very essential to maintain high node classification performance and ensure the capacity for propagation and aggregation of the GNN.

Superior Performance and Robustness: Intensive testing on three benchmark fault diagnosis datasets showed that the MRS-GNN outperformed famous methods, including Oversampling, standard SMOTE, Reweight, and GraphSMOTE. To be more specific, the framework demonstrated higher robustness in extremely imbalanced situations. For example, when the IMR was up to 0.4, it recorded an AUC-ROC of 0.904 for the MRS-GNN. Besides, the MRS-GNN increased the classification accuracy by more than 18% compared with some baseline methods.

This MRS-GNN extends the fault diagnosis accuracy and, in addition, is scalable for diverse complex systems. The utility and adaptability shown hence support its application to the most challenging topological domains, such as power grids and transport networks, which further asserts its suitability for the complex and imbalanced classification task of intrusion detection discussed in the context of this paper.

In summary, MRS-GNN has successfully coupled node interpolation with policy edge generation in order to solve the complex class distribution problem in a simple and effective way. It advances the development of reliable and efficient diagnostic systems.

B. Future Work

Based on the promising results and established framework, there are several avenues along which future research and development can occur. Future research should be directed to the integration of unsupervised learning techniques that would enhance the ability of the MRS-GNN framework in processing unlabeled data, thus widening its industrial applicability where it is substantially challenging to obtain large volumes of labeled data. Though this work presented the foundational work using GraphSage, further research should be focused on improving GNN models to tackle challenging imbalance problems. In particular, further research on how to exploit the ability of GNNs in capturing rich information about heterogeneous graphs would be of utmost importance for further improvement of accuracy and efficiency in diagnosis. Drawing upon the framework's demonstrated utility in complex systems, extensive experimental validation will be conducted with real-world intrusion detection datasets. This will especially test the performance of the MRS-GNN on network security problems that are imbalanced and tap into the full potential of this framework to transform the maintenance strategies and operational reliability of critical infrastructure.

The two edge generation strategies pursued in this work, namely MRS-GNNS and MRS-GNNT, could lead to optimized combinations for specific dataset topologies and imbalance rates when extended to other variants of GNNs like GAT, GCN, and GraphSage; thus, providing precise guidance for model selection.

References

[1] Lu,W et al. “Enhancing Fault Diagnosis in Mechanical Systems with Graph Neural Networks Addressing Class Imbalance.” Mathematics 2024, 12, 2064. https://doi.org/10.3390/math12132064

[2] Oudina, Zina and Makhlouf Derdour. “Hybrid Security Framework for Critical Systems: Combining Attack Graph and Intrusion Detection, Deep Learning.” 2025 7th International Conference on Pattern Analysis and Intelligent Systems (PAIS) (2025): 1-6.

[3] Nagaraju, Vidhyashree et al. “A survey of fault and attack tree modeling and analysis for cyber risk management.” 2017 IEEE International Symposium on Technologies for Homeland Security (HST) (2017): 1-6.

[4] Mehta, Vaibhav et al. “Ranking Attack Graphs.” International Symposium on Recent Advances in Intrusion Detection (2006).

[5] Basheer, Liloja and Ranjana P. “A deep learning framework for intrusion detection system in smart grids using graph convolutional network.” Engineering Research Express 7 (2025): n. pag.

[6] Qi, Panpan et al. “MAD-SGCN: Multivariate Anomaly Detection with Self-learning Graph Convolutional Networks.” 2022 IEEE 38th International Conference on Data Engineering (ICDE) (2022): 1232-1244.

[7] Muñoz, David Concejal and Antonio del-Corte Valiente. “A novel botnet attack detection for IoT networks based on communication graphs.” Cybersecurity 6 (2023): 1-17.

[8] Narayanan, Sivanesan and K. S. Archana. “Auto metric graph neural network optimized with woodpecker mating algorithm for detecting network layer attacks in mobile ad hoc networks.” Smart Science 12 (2024): 305 - 318.

[9] Case Western Reserve University Bearing Data Center. Bearing vibration data set. Case Western Reserve University; 2000. https://engineering.case.edu/bearingdatacenter.

[10] Jiangnan University. JNU bearing fault data set. 2012. https://github.com/ClarkGableWang/JNU-Bearing-Dataset.

[11] C. Lessmeier, J. K. Kimotho, D. Zimmer, and W. Sextro, "Condition monitoring of bearing damage in electromechanical drive systems by using motor current signals of electric motors: A benchmark data set for data-driven classification," in Proc. European Conf. Prognostics and Health Management Society (PHM Europe), 2016. [Online]. Available: https://mb.uni-paderborn.de/en/kat/research/bearing-datacenter/data-sets-and-download.

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Not applicable. This study did not involve human participants, human data, human tissue, or animals; therefore, ethical approval, informed consent to participate, and consent for publication were not required.

Data Availability Statement

The datasets analysed during the current study are publicly available in the following repositories: the CWRU bearing dataset in the Case Western Reserve University Bearing Data Center (https://engineering.case.edu/bearingdatacenter); the Jiangnan University bearing dataset at https://github.com/ClarkGableWang/JNU-Bearing-Dataset; and the Paderborn University bearing dataset in the KAt Research Data Center (https://mb.uni-paderborn.de/en/kat/research/bearing-datacenter/data-sets-and-download). No new datasets were generated during the current study.