

# Few-shot Message-Enhanced Contrastive Learning for Graph Anomaly Detection

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**Abstract**—Graph anomaly detection plays a crucial role in identifying exceptional instances in graph data that deviate significantly from the majority. It has gained substantial attention in various domains of information security, including network intrusion, financial fraud, and malicious comments, et al. Existing methods are primarily developed in an unsupervised manner due to the challenge in obtaining labeled data. For lack of guidance from prior knowledge in unsupervised manner, the identified anomalies may prove to be data noise or individual data instances. In real-world scenarios, a limited batch of labeled anomalies can be captured, making it crucial to investigate the few-shot problem in graph anomaly detection. Taking advantage of this potential, we propose a novel few-shot Graph Anomaly Detection model called FMGAD (Few-shot Message-Enhanced Contrastive-based Graph Anomaly Detector). FMGAD leverages a self-supervised contrastive learning strategy within and across views to capture intrinsic and transferable structural representations. Furthermore, we propose the Deep-GNN message-enhanced reconstruction module, which extensively exploits the few-shot label information and enables long-range propagation to disseminate supervision signals to deeper unlabeled nodes. This module in turn assists in the training of self-supervised contrastive learning. Comprehensive experimental results on six real-world datasets demonstrate that FMGAD can achieve better performance than other state-of-the-art methods, regardless of artificially injected anomalies or domain-organic anomalies.

**Index Terms**—graph anomaly detection, few-shot, Deep-GNN

## I. INTRODUCTION

Graph serves as a versatile representation of structured data, facilitating systematic modeling of complex dependencies among instances. It has been widely used in diverse domains like social networks, finance, biology, and transportation [1]–[3]. The rapid progress of industrial and internet technologies has led to a surge in the frequency of anomalous instances, encompassing fraudulent activities within social networks and the unauthorized disclosure of sensitive corporate information.

Consequently, graph anomaly detection has garnered substantial attention from both industrial and academic communities.

Graph neural networks (GNNs) [4] have made significant advancements in graph representation learning by extending deep learning methods to graph-structured data, and they have found wide applications in graph anomaly detection. Unlike traditional anomaly detection methods that focus on vector data, graph anomaly detection requires the simultaneous exploration of both node attribute information and graph structure information, which is challenging for conventional approaches [5]. While, leveraging GNNs for modeling complex graph-structured data allows for the joint encoding of intricate interactions among instances and their respective attribute features, thereby facilitating the identification of anomalous nodes.

Due to the labor-intensive and time-consuming nature of acquiring labeled anomaly data, most existing models in graph anomaly detection are developed in an unsupervised manner. For instance, DOMINANT [6] proposed a deep autoencoder that utilizes graph convolutional networks (GCNs) to reconstruct attributes and structure, thereby enhancing detection performance. GAAN [7] employs generative adversarial networks and generates pseudo-anomalies by utilizing Gaussian noise for discriminative training. Furthermore, with the rise of self-supervised learning, graph anomaly detection methods based on contrastive learning have gained popularity. For example, CoLA [8] employs random walks for graph augmentation, constructs positive and negative pairs, and designs proxy tasks for contrastive learning. Research findings have demonstrated that contrastive learning-based graph anomaly detection methods have achieved state-of-the-art performance in unsupervised settings.

However, due to the complexity and diversity of anomalies, as well as the lack of guided supervision from prior knowledge, unsupervised methods may suffer from local optima or

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exhibit biased anomaly detection performance. Nowadays, domain experts have provided feedback indicating that obtaining a limited number of labeled anomalies is feasible [9]. These labeled anomalies can serve as prior knowledge to guide model training and have great potential for improving graph anomaly detection performance. However, detecting anomalies in a few-shot setting remains a significant challenge. Existing semi-supervised and positive-unlabeled (PU) learning methods [10] have not yielded satisfactory results in this task. They rely on a sufficient number of labeled anomaly samples, making it difficult to effectively utilize supervised information in few-shot scenarios. Recently, some methods utilize meta-learning [11] and cross-domain transfer learning approaches [12] to address the few-shot setting. For instance, GDN [13] incorporates a meta-learning algorithm across networks to transfer meta-knowledge from multiple auxiliary networks for few-shot network anomaly detection. However, these methods have requirements for auxiliary networks or datasets, which are often difficult to obtain in real-world scenarios.

To address the aforementioned challenges, we propose a Few-shot Message-enhanced Contrastive-based Graph Anomaly Detector (FMGAD) that combines the rational utilization of few-shot labels with self-supervised contrastive learning. FMGAD consists of two main modules: (i) Multi-view contrastive learning module adopts the core idea of multi-view contrastive learning to facilitate both intra-view and cross-view contrastive learning. (ii) Deep-GNN message-enhanced reconstruction module leverages spectral high-pass filtering to design a deep message-passing network, effectively utilizing the few-shot label information. This module assists the Multi-view Contrastive Learning Module in learning tailored representations for the anomaly detector. The framework of our approach is illustrated in Fig 1. To summarize, our main contributions are summarized as follows:

- To ensure that the self-supervised module can learn an optimal representation, we employ graph augmentation to obtain multiple views, enabling contrastive learning within and across views.
- To effectively utilize the few-shot label information and leverage it to assist the training of contrastive learning, we propose a Deep-GNN Message-Enhanced Reconstruction Module that provides a sufficiently large receptive field for the few-shot labeled nodes.
- We conduct extensive experiments on six real-world datasets with synthetically injected anomalies and organic anomalies. The experimental results demonstrate the effectiveness of our approach in few-shot graph anomaly detection.

## II. RELATED WORK

In this section, we briefly describe the related work on (1) Graph Anomaly Detection; (2) Few-shot Graph Learning and (3) Graph Augmentation.

### A. Graph Anomaly Detection

Like other graph-based methods, semi-supervised learning is the most common graph representation learning mode and is also used in the field of graph anomaly detection. SemiGNN [14] utilizes a hierarchical attention mechanism to better associate different neighbors and different views. BWGNN [15] designs a band-pass filter kernel function satisfying Hammond’s Graph Wavelet, transmitting information in corresponding frequency bands separately. Since anomalies are difficult to obtain, most existing methods are based on unsupervised modes and are mainly divided into two types: graph autoencoder and self-supervised contrastive learning. GAE (Graph Autoencoder) [16] reconstructs node features using an Encoder-Decoder architecture and defines nodes with high reconstruction loss as anomalous. DOMINANT [6] simultaneously reconstructs both structural information, such as the adjacency matrix, and node attributes to calculate anomaly scores. In recent years, with the rise of self-supervised learning and proxy tasks, various contrastive learning strategies have been widely applied. CoLA [8] utilizes random walk sampling to perform graph augmentation and subsequently constructs positive and negative node-subgraph pairs for contrastive learning. GraphCAD [17] employs a global clustering algorithm to partition the entire graph into multiple parts, where nodes injected from other parts are regarded as pseudo-anomalies, forming negative pairs. GRADATE [18] adopts edge modification graph augmentation technique and incorporates three types of contrastive learning strategies: node-node, node-subgraph, and subgraph-subgraph.

### B. Few-shot Graph Learning

In most real-world scenarios, only very limited labeled samples are often available due to expensive labeling costs. In view of this, graph few-shot learning and cross-network meta learning are proposed to solve the problem of performance degradation when facing limited labeled data to a certain extent. For instance, GDN [13] is equipped with a cross-network meta-learning algorithm that utilizes a small number of labeled anomalies to enhance statistically significant deviations between abnormal nodes and normal nodes on the network. Meta-PN [19] infers high-quality pseudo-labels on unlabeled nodes via a meta-learning label propagation strategy while achieving a large receptive field during training. However, cross-domain auxiliary datasets are not always available, thus many non-meta-learning strategies have been explored. ANEMONE-FS [20] contains two multi-scale comparison networks, where the consistencies between nodes and contextual embeddings are maximized for unlabeled node while minimized for labeled anomalies in a mini-batch.

### C. Graph Augmentation

Similar to the vision domain, there are numerous augmentation methods in the field of graph representation learning. Specifically, graph augmentation techniques alter the attribute and structural characteristics of graph datasets within a certain

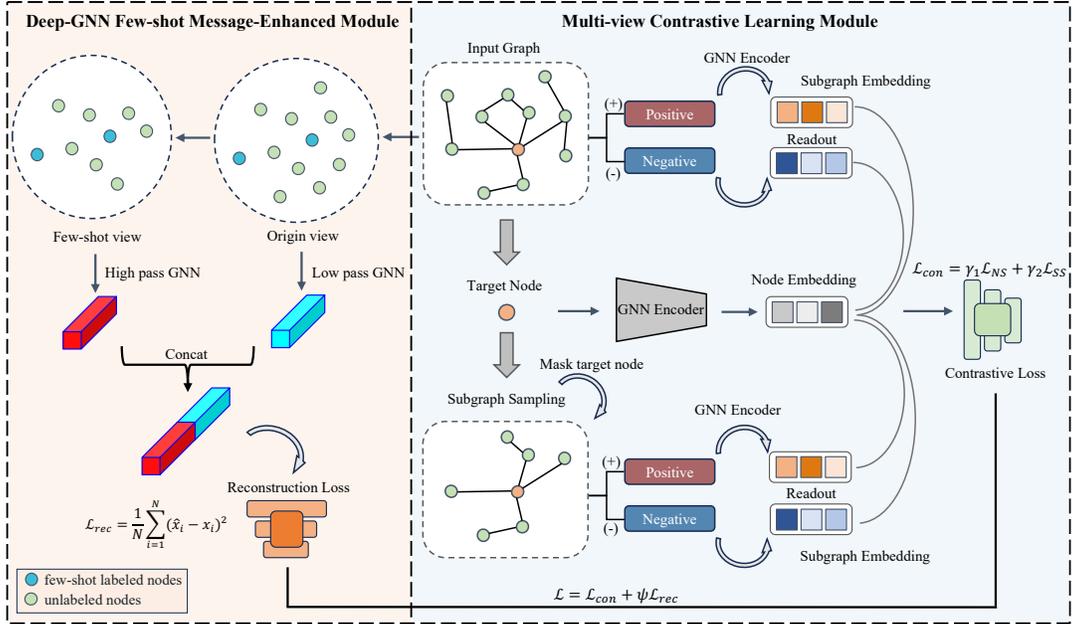


Fig. 1. The above image presents an overview of our model FMGAD, where the architecture demonstrates the details of the multi-view contrastive learning module(Right) and Deep-GNN few-shot message-enhanced module(Left) respectively.

range, providing convenience for self-supervised learning. The majority of existing methods focus on manipulating nodes or edges within the graph. These methods include: (i) enhancing by modifying or masking node features [21], (ii) adapting the adjacency matrix or adjusting edge weights [22], and (iii) utilizing Restarted Random Walk (RoSA) [23] to generate augmented local views.

### III. PROBLEM DEFINITION

In this section, we first introduce the notations mentioned in this paper, and then give the formal problem definition. Given an attributed graph  $\mathcal{G} = (X, A)$ , we denote its node attribute (i.e., feature) and adjacency matrices as  $X \in \mathbb{R}^{n \times d}$  and  $A \in \mathbb{R}^{n \times n}$ , where  $n$  and  $d$  are respectively the number of nodes and feature dimensions. It can also be defined as  $\mathcal{G} = (V, E, X)$ , where  $\mathcal{V} = \{v_1, v_2, \dots, v_n\}$  and  $\mathcal{E} = \{e_1, e_2, \dots, e_n\}$  represent node and edge sets respectively.

The definition of Few-shot GAD is to use the attribute and structure information of the graph to detect anomalies when a few-shot abnormal labeled nodes are known. We have a small set of labeled anomalies  $\mathcal{V}^L$  and the rest set of unlabeled nodes  $\mathcal{V}^U$ , where  $|\mathcal{V}^L| \ll |\mathcal{V}^U|$ , since the labeled anomaly nodes are difficult to obtain and few of them can be actually used. Then, our goal is to learn a model  $\mathcal{F}(\cdot) : \mathbb{R}^{N \times D} \rightarrow \mathbb{R}^{N \times 1}$  on  $\mathcal{V}^L \cup \mathcal{V}^U$ , which measures node abnormalities by calculating their anomaly scores  $y$ .

### IV. METHODOLOGY

In this section, we present the details of our proposed approach FMGAD for detecting graph node anomalies in few-shot scenarios. As shown in Fig 1, our approach mainly

consists of two modules, including multi-view contrastive learning module and Deep-GNN message-enhanced reconstruction module. Graph anomalies are typically categorized as attribute-context anomalies and structural anomalies, and our method addresses both aspects. Firstly, we employ suitable graph augmentation techniques to construct different views and perform subgraph sampling for each target node. Next, to fully explore structural anomalies, we utilize proxy tasks and design a multi-view contrastive learning framework. Subsequently, to investigate features at the attribute-context level and leverage existing few-shot labels, we build a deep information augmentation reconstruction module. In all, our model starts from the essence of graph anomalies, designs self-supervised learning objectives, and incorporates supervised constraints using few-shot labels. In the rest of this section, we demonstrate the details of the whole framework respectively.

#### A. Graph Augmentation

The self-supervised strategy based on contrastive learning enables not only differentiation learning within the same scale, such as "node vs. node," but also discrimination across different scales, such as "node vs. subgraph." As discussed in related work, to ensure that the self-supervised learning module can extract rich attribute and structural information, it is necessary to design augmentation strategies and proxy tasks tailored to the current task. For graph anomaly detection, according to [reference], anomalies in graph nodes often manifest as a mismatch with their surrounding environment.

For several popular graph augmentation strategies in current graph representation learning, such as node feature pertur-

bation or masking and edge modification. Including Graph Diffusion, it essentially involves perturbing the adjacency matrix and modifying the target edges. We argue that these strategies are not suitable for graph anomaly detection because they may alter the underlying logic or semantic features of the data. This could particularly have negative effects on detecting naturally occurring anomalies rather than artificially injected anomalies. Hence, we utilize random walks with restart (RWR) to obtain augmented views. Specifically, for each selected target node, we sample subgraphs of fixed size  $p$ . Unlike standard random walks, RWR introduces a restart probability, where there is a certain probability of restarting from the initial node at each step. Therefore, using RWR to sample subgraphs does not introduce additional anomalies.

### B. Multi-view Contrastive Learning Module

Furthermore, we constructed a multi-view contrastive learning module. This module utilizes GNN encoders and decoders to perform contrastive learning between the target node and two views, simultaneously learning discriminative attribute and structural topological information. It consists of two parts: Node-Subgraph and Subgraph-Subgraph, capturing features within each view and across different views respectively.

**Node-Subgraph Contrast.** In each view, a target node  $v_i$  forms a positive pair with its located subgraph and forms a negative pair with a random subgraph where another node  $v_j$  is located. We first adopt a GCN encoder that maps the features of nodes in the subgraph to the embedding space. The hidden-layer representation can be defined as:

$$H_\omega^{\ell+1} = GNN(A_\omega, H_\omega^\ell) = \sigma(D_\omega^{-\frac{1}{2}} A_\omega D_\omega^{-\frac{1}{2}} H_\omega^\ell W^\ell), \quad (1)$$

where  $H_\omega^{\ell+1}$  and  $H_\omega^\ell$  denote the  $(\ell + 1)$ -th and  $\ell$ -th layer hidden representation in view  $\omega$ ,  $\tilde{D}_\omega^{-\frac{1}{2}} \tilde{A}_\omega \tilde{D}_\omega^{-\frac{1}{2}}$  is the normalization of the adjacency matrix in view  $\omega_i$  and  $W^\ell$  is the network parameters. It is noteworthy that the networks operating under two views employ identical architecture and parameter sharing. Then we take the average pooling function as the readout module to obtain the subgraph-level embedding vector  $e_\omega$ :

$$e_\omega = READOUT(H_\omega) = \frac{1}{K} \sum_{j=1}^K (H_\omega)_K, \quad (2)$$

where  $K$  denotes the number of remaining nodes in the subgraph. Given that the target node is masked within the subgraph, we utilize the weight matrix of the GCN encoder to project the features onto a shared embedding space. Mathematically, this can be formulated as follows:

$$h_\omega^{\ell+1} = \sigma(h_\omega^\ell W^\ell). \quad (3)$$

In each view, the anomalous degree of a target node depends on its similarity to the paired subgraph embedding. Therefore, we choose a Bilinear model to quantify the relationship:

$$s_\omega = \text{sigmoid}(e_\omega W_s h_\omega^T), \quad (4)$$

where  $W_s$  is a learnable matrix. We employ the binary cross-entropy loss to measure the contrastive loss in a single view that can be demonstrated as:

$$\mathcal{L}_{NS}^\omega = - \sum_{i=1}^N (y_i \log(s_{\omega i}) + (1 - y_i) \log(1 - s_{\omega i})), \quad (5)$$

where  $y_i$  is equal to 1 when  $s_{\omega i}$  denotes a positive pair, and is equal to 0 when  $s_{\omega i}$  denotes a negative pair. The same operations and model architecture are used on the second view, and both views share model parameters. Thus the final node-subgraph contrast loss is:

$$\mathcal{L}_{NS} = \alpha \mathcal{L}_{NS}^1 + (1 - \alpha) \mathcal{L}_{NS}^2, \quad (6)$$

where  $\alpha \in (0, 1)$  is a trade-off parameter to balance the importance between two views.

**Subgraph-Subgraph Contrast.** Instead of intra-view contrast, subgraph-subgraph contrast implements cross-view contrastive learning. It aims to learn more representative subgraph embeddings, thereby enhancing the neighborhood representations of target nodes. Specifically, a subgraph establishes a positive pair with the subgraph formed by its target node  $v_i$  in another view, while it forms negative pairs with two subgraphs where another node  $v_j$  is located in both views. Inspired by [], we employ a loss function to optimize the contrast:

$$\mathcal{L}_{SS} = - \sum_{i=1}^n \log \frac{\exp(e_{1i} \cdot e_{2i})}{\exp(e_{1i} \cdot e_{1j}) + \exp(e_{1i} \cdot e_{2j})}, \quad (7)$$

where  $e_{1i}$  and  $e_{2i}$  denote the embeddings of the subgraphs that the target node  $v_i$  belongs to in two views,  $e_{1j}$  and  $e_{2j}$  represent the embeddings of the subgraphs of another node  $v_j$  separately. Then the final multi-view contrastive loss is:

$$\mathcal{L}_{con} = \gamma \mathcal{L}_{NS} + (1 - \gamma) \mathcal{L}_{SS}, \quad (8)$$

where  $\gamma \in (0, 1)$  balances the influence of two contrastive learning modes.

### C. Deep-GNN Message-Enhanced Reconstruction Module

In the context of few-shot scenarios, the availability of anomaly label information is severely limited. Conventional semi-supervised graph anomaly detection methods suffer from the issue of over-smoothing, making it challenging to extend the receptive field and effectively propagate label information to deeper neighborhoods. To address this challenge, we propose leveraging the concept of AutoEncoder from unsupervised methods to reconstruct attributes. Additionally, we introduce a scalable deep graph neural network (GNN) architecture to enhance the utilization of few-shot labels and their associated features, thereby improving the performance of anomaly detection in graph data.

Initially, we extract a few-shot environmental subgraph from the original graph, comprising a subgraph originating from the few-shot labeled node and encompassing its  $M$ -order neighbors. To facilitate the sparse message enhanced feature reconstruction process, distinct graph neural network (GNN) architectures are employed for encoding the original graph and the few-shot environment subgraph. In particular, for the original view, GNN encoder is with low-pass filtering characteristics, such as GCN, GAT, GIN. These GNN models effectively capture and propagate information within the graph, enabling accurate attribute reconstruction and subsequent anomaly detection. The transform of corresponding GNN encoder is as follows:

$$H_r^{\ell+1} = \sigma(D^{-1/2}AD^{-1/2}H_r^\ell W_r). \quad (9)$$

To leverage the specific attributes of sparse anomaly samples within the few-shot environment subgraph and their high-order correlation with the surrounding context, we propose a scalable deep graph neural network (Deep-GNN) [24] architecture that enables long-range propagation. This approach allows for the consideration of a broader range of context nodes, thereby expanding the receptive field of sparse anomaly samples. To address the challenge of over-smoothing that arises when increasing the propagation step size in GNN, we introduce a high-pass filtering GNN [25] that operates in the spectral domain:

$$\mathcal{F}_H = \varepsilon I - D^{-1/2}AD^{-1/2} = (\varepsilon - 1)I + L, \quad (10)$$

$$H_f^{\ell+1} = \sigma(\mathcal{F}_H H_f^\ell W_f). \quad (11)$$

According to [25], high-pass filtering GNN can overcome the over-smoothing problem to a certain extent, and therefore can be extended to more layers. Then we concatenate the node embeddings obtained from the original graph and the few-shot environmental subgraph:

$$H = \text{CONCAT}(H_r, H_f), \quad (12)$$

for nodes that do not appear in the few-shot environment subgraph, their  $h_f$  is padded with 0. Then a layer of MLP is applied to obtain the reconstructed node embeddings:

$$\hat{X} = \text{MLP}(H). \quad (13)$$

The reconstruction loss of the original graph is calculated by MSE loss:

$$\mathcal{L}_{rec} = \frac{1}{N} \sum_{i=1}^N (\hat{x}_i - x_i)^2. \quad (14)$$

#### D. Anomaly Detector

To jointly train the multi-view contrastive learning module and the Deep-GNN message-enhanced reconstruction module, we optimize the following objective function:

$$\mathcal{L} = \mathcal{L}_{con} + \psi \mathcal{L}_{rec}, \quad (15)$$

where  $\psi$  is a controlling parameter which balances the importance of the two modules. By minimizing the above objective function, we can compute the anomaly score of each node.

### V. EXPERIMENTS

In this section, we conduct empirical evaluations to showcase the efficacy of the proposed framework. Our primary objective is to address the following research inquiries:

- **RQ1.** Can our method perform well in extreme few-shot scenarios?
- **RQ2.** How our model behave when changing the degree of label availability and the number of Deep-GNN layers?
- **RQ3.** How do the key designs and components influence the performance of our method?

#### A. Experimental Settings

**Dataset.** To thoroughly evaluate our method’s performance in identifying both naturally occurring organic anomalies and artificially injected anomalies, we selected two categories of datasets. The first category consists of two authentic datasets: Cora [26] and Citeseer [27], that do not inherently contain organic anomalies but require manual injection of anomalies. The second category comprises three authentic datasets: Wiki [28], Reddit [29] and YelpChi [30], that inherently contain organic anomalies. For anomaly injection, we followed the same approach as DOMINANT by injecting the same number of feature and structural anomalies into the three datasets that previously did not have any organic anomalies.

TABLE I  
STATISTICS OF DATASETS

Dataset	Nodes	Edges	Features	Anomaly	Ratio(%)
Cora	2,708	5,429	1433	150	5.54
CiteSeer	3327	10,154	3703	150	4.51
Wiki	9,227	18,257	64	217	2.35
Reddit	15,860	136,781	602	796	5.02
YelpChi	23,831	98,630	32	1,217	5.11

**Compared Methods.** We compare our proposed method FMGAD with other three categories of methods. (i) Conventional semi-supervised GNN models: GCN [4], GAT [31], and semi-supervised methods designed for GAD: SemiGNN [14], BWGNN [15]. (ii) Unsupervised GNN-based graph anomaly detection methods: DOMINANT [6], CoLA [8], GraphCAD [17] and GRADATE [18]. (iii) Few-shot methods on graph anomaly detection: GDN [13], Meta-PN [19] and ANEMONE-FS [20].

TABLE II  
PERFORMANCE COMPARISON RESULTS (10-SHOT) W.R.T. AUC-ROC AND AUC-PR ON FIVE DATASETS.

Methods	Cora		Citeseer		Wiki		Reddit		YelpChi	
	AUC-ROC	AUC-PR								
GCN	0.5239	0.0427	0.4128	0.055	0.4324	0.0239	0.4975	0.0826	0.3371	0.0725
GAT	0.5473	0.0495	0.4645	0.062	0.4373	0.0284	0.5184	0.1225	0.3564	0.0834
SemiGNN	0.6637	0.1293	0.5322	0.074	0.4785	0.0332	0.6249	0.1953	0.4146	0.1378
BWGNN	0.6855	0.1876	0.5421	0.081	0.4668	0.0295	0.5863	0.1634	0.5473	0.2161
DOMINANT	0.7483	0.2741	0.8279	0.2415	0.4488	0.0227	0.7429	0.3185	0.4872	0.1652
CoLA	0.7515	0.2398	0.8738	0.2942	0.5373	0.0319	0.7257	0.2474	0.3985	0.1579
GraphCAD	0.7674	0.2892	0.8521	0.2787	0.5282	0.0249	0.7536	0.2643	0.4238	0.1843
GRADATE	0.7786	0.2973	0.8872	0.3471	0.5471	0.0322	0.7472	0.2879	0.4994	0.2164
GDN	0.7736	0.1965	0.7963	0.1826	0.5248	0.0326	0.8136	0.3084	0.7281	0.2785
Meta-PN	0.8537	0.2817	0.8127	0.2273	0.4663	0.0276	0.8064	0.3126	0.7549	0.2698
ANEMONE-FS	0.8836	0.3062	0.9028	0.3294	0.5317	0.0348	0.8123	0.3352	0.7729	0.2977
FMGAD	<b>0.8928</b>	<b>0.3187</b>	<b>0.9193</b>	<b>0.3981</b>	<b>0.6133</b>	<b>0.0438</b>	<b>0.8326</b>	<b>0.3561</b>	<b>0.8052</b>	<b>0.3338</b>

**Evaluation Metrics.** We employ two popular and effective metrics for evaluation, the Area Under Receiver Operating Characteristic Curve (AUC-ROC) and the Area Under Precision-Recall Curve (AUC-PR) [32]. AUC-ROC quantifies the ability of a binary classifier by measuring the area under the receiver operating characteristic curve. AUC-PR captures the trade-off between the two metrics and is particularly useful when the dataset is imbalanced or when the focus is on positive instances.

#### Implementation Details.

All our experiments are conducted with a 24 GB 3090 GPU, and the proposed FMGAD is mainly implemented through pyg library. In our implementation, the size  $K$  of subgraph of each target node and the dimension of hidden layer are fixed to 8 and 128, respectively. In the contrastive learning module, the GNN network is set to 2 layers; in the reconstruction module, the low-pass and high-pass GNN Encoder are set to 2 and 5 layers. For each dataset, we set the number of few-shot labeled anomalies as 10, and the trade-off parameters  $\alpha, \gamma_1, \gamma_2, \psi$  are chosen as 0.7, 0.6, 0.4, and 0.5 separately.

#### B. Experimental Results (RQ1)

In this subsection, we consider semi-supervised, unsupervised and other few-shot baseline methods for comparing with our methods in terms of AUC-ROC and AUC-PR. To ensure few-shot scenarios, for all few-shot GAD methods, we use 10 annotated anomalies during model training. Tab II shows the overall performance comparison on both artificially injected anomaly and organic anomaly datasets. FMGAD consistently outperforms all baseline methods on all six real-world datasets, thereby validating the effectiveness of our approach in addressing anomaly detection in few-shot scenarios. Based on the experimental results, we have the following observations:

- Conventional semi-supervised graph anomaly detection methods (i.e., GCN, GAT, SemiGNN, and BWGNN) generally do not exhibit competitive performance, indicating their limited ability to exploit label information. It performs even worse than unsupervised methods on

almost all datasets. This discrepancy can be attributed to the reliance of conventional semi-supervised methods on sufficient label information for message propagation, which exacerbates the over-smoothing issue in few-shot scenarios and hinders the learning of abnormal features. However, unsupervised methods leverage AutoEncoder or contrastive learning strategies to uncover deep data distributions based on local features and structures. Thus, they can achieve strong discrimination capabilities when it comes to identifying artificially injected anomalies.

- On datasets with artificially injected anomalies, the unsupervised methods achieve performance that matches existing few-shot graph anomaly detection methods. However, on organic anomaly datasets, unsupervised methods generally underperformed compared to few-shot methods. In particular, compared to the GRADATE, on YelpChi dataset, our FMGAD has 60.35% and 54.25% improvement w.r.t. AUC-ROC and AUC-PR, respectively. This is most likely because real data often possesses numerous expert priors, and unsupervised methods tend to blindly map and partition features.
- In comparison to existing few-shot graph anomaly detection methods, our approach has demonstrated notable advancements. To be specific, on Wiki dataset, our method FMGAD outperforms GDN by 16.86% and 34.36% in terms of AUC-ROC and AUC-PR, respectively. The three methods we compared are all founded on meta-learning principles, and the efficacy of meta-learning methods relies heavily on the quality of the auxiliary network or dataset. However, in many real-world scenarios, datasets often do not meet such stringent requirements.

#### C. Sensitivity & Robustness Analysis (RQ2)

In order to verify the effectiveness of FMGAD in different few-shot anomaly detection settings, we change the number  $k$  of anomalous samples for model training to form  $k$ -shot learning settings for evaluation. Specifically, we perform experiments on all five datasets and select  $k$  from  $\{1, 3, 5, 10, 15, 20\}$ . The experimental results are summarized in Tab III.

TABLE III  
FEW-SHOT PERFORMANCE ANALYSIS OF FMGAD.

Setting	Cora	Citeseer	Wiki	Reddit	YelpChi
1-shot	0.8681	0.9039	0.5854	0.8216	0.7667
3-shot	0.8843	0.9126	0.6003	0.8244	0.7786
5-shot	0.8906	0.9177	0.6078	0.8263	0.7928
10-shot	<b>0.8946</b>	<u>0.9193</u>	<u>0.6133</u>	<u>0.8326</u>	<u>0.8052</u>
15-shot	<u>0.8921</u>	<b>0.9225</b>	<b>0.6158</b>	<b>0.8367</b>	<b>0.8127</b>

As observed, even in scenarios where only 1-shot anomalies are provided, FMGAD can still outperform other baseline methods, demonstrating its superior performance. For instance, on Reddit dataset, the FMGAD with 1-shot anomaly outperforms GraphCAD by 9.02% in terms of AUC-ROC. When compared with ANEMONE-FS, it achieves improvements of 6.52% in terms of AUC-ROC with 5-shot anomalies. This demonstrates the effectiveness of the FMGAD method for extremely limited anomalous labels. Furthermore, we also observe that as the number of few-shot anomaly labels increases, FMGAD’s performance generally improves, which further confirms the effectiveness of our method.

Subsequently, we investigated the effects of varying the number of Deep-GNN layers in the reconstruction module and adjusting the number of nodes through RWR sampling in the enhanced subgraph sampling of the contrastive learning module on model performance. The corresponding experimental results are shown in Fig 2.

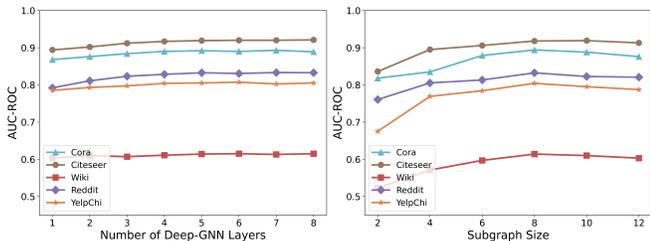


Fig. 2. Performance with different number of Deep-GNN layers and the size of subgraph sampled by RWR.

Analyzing the image on the left, we observe a trend where the model performance initially improves with an increasing number of sampling subgraph nodes. However, beyond a certain threshold, further increments in the number of nodes lead to a diminishing effect on the model’s performance. This is because insufficient sampling of the target node subgraph makes it challenging for the model to capture the local structural characteristics of the data, leading to subpar performance. Conversely, if the sampled subgraph is excessively large, it may contain redundant information, thereby adversely affecting model performance. Observing the graph on the right, we note that with an increase in the number of Deep-GNN layers, the model performance exhibits a slight improvement initially, followed by a subsequent decline. We attribute the performance improvement to the Deep-GNN

network effectively propagating label information to more distant neighbors within the graph. However, an excessive number of layers will inevitably introduce the challenge of over-smoothing, which can negatively impact the model’s performance. Hence, finding an optimal balance in the size of the sampled subgraph and the number of Deep-GNN layers is crucial for achieving optimal results.

#### D. Ablation Study (RQ3)

In order to verify the effectiveness of each key component of FMGAD, we conduct an ablation study on the variants of the proposed approach. Concretely, we introduce three variants of our approach: FMGAD-ns and FMGAD-ss, which individually exclude the node-subgraph and subgraph-subgraph contrastive learning sub-modules, and FMGAD-re, which omits the Deep-GNN few-shot message-enhanced module. The detailed results are shown in Fig 3.

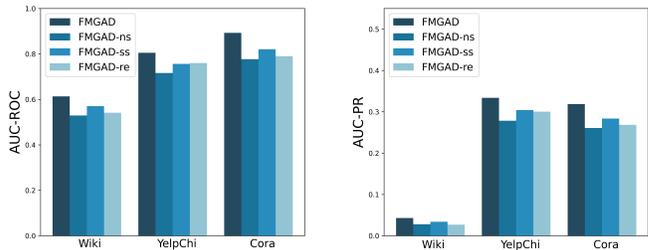


Fig. 3. Ablation Performance on different variants.

As observed above, for each variant that excludes a specific module, there has been a noticeable degradation in the model’s performance. Among these variants, FMGAD-ns stands out as the most significantly impacted, as it eliminates the node-subgraph contrastive sub-module. Specifically, it drops by 8.62% and 13.17% on YelpCHI datasets in terms of AUC-ROC and AUC-PR. In summary, through ablation studies, we affirm the robustness and efficacy of our proposed technique in addressing graph anomaly detection under few-shot scenarios.

## VI. CONCLUSION

In this paper, we investigate the problem of graph anomaly detection in few-shot scenarios. Through a comprehensive analysis of existing semi-supervised, unsupervised, and customized few-shot methods, we propose FMGAD, a novel anomaly detector that combines few-shot message enhancement with multi-view self-supervised contrastive learning. Our model effectively utilizes the self-supervised contrastive learning strategy to capture local structures and features within the graph. Additionally, we introduce a deep message-passing mechanism that incorporates high-pass convolutional filtering functions to enable deep propagation of few-shot node information. Extensive experiments conducted on multiple real-world datasets demonstrate the outstanding performance of FMGAD.

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