Meta Learning Enhanced Graph Transformer for Robust Smart Grid Anomaly Detection

Layth Almahadeen[1], Aseel Smerat[2a,b], Dr. Sandeep Kumar Mathariya[3], Dr. G. Indra Navaroj[4],
Dr. Vuda Sreenivasa Rao[5], Kamila Ibragimova[6], Osama R.Shahin[7a,b]

Department of Financial and Administrative Sciences, Al- Balqa' Applied University, Jordan[1]
Faculty of Educational Sciences, Al-Ahliyya Amman University, Amman, 19328, Jordan[2a]
Department of Biosciences-Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, 602105, India [2b]
Assistant Professor, Department of Computer Science and Engineering, MEDICAPS University Indore, MP, India[3]
Assistant Professor (SG), Department of Information Technology, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India[4]
Associate Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India[5]
Department of Computer Engineering, Tashkent University of Information Technologies, Uzbekistan[6]
Department of Computer Science-College of Computer and Information Sciences, Jouf University, Saudi Arabia[7a]
Faculty of Engineering-Physics and Mathematics Department, Helwan University, Helwan, Egypt[7b]

Abstract*—The increasing complexity of modern smart grids and the heterogeneity of multi-sensor data make anomaly detection extremely challenging, as existing techniques struggle to capture long-range spatial dependencies, cross-sensor interactions, and unseen anomaly patterns. Conventional models such as Isolation Forest, Random Forest, GCAD, AT-GTL, CVTGAD, and hybrid CNN-Transformer approaches often suffer from limited generalization, weak multimodal fusion, and strong dependence on labeled anomalies. To address these limitations, this study introduces a novel Multimodal Graph Transformer with Contrastive Self-Supervised Learning and Model-Agnostic Meta-Learning (MGT-CGSSML), a uniquely integrated framework designed to learn structural, attribute, and cross-modal relationships simultaneously. The proposed method stands out by combining multimodal graph encoding, dual-view contrastive learning, and fast meta-adaptation, enabling the model to rapidly identify new anomaly types with minimal labeled data. Implemented in Python using PyTorch, the model is evaluated on a multimodal smart grid dataset containing time-stamped voltage, current, power factor, frequency, temperature, and humidity measurements recorded at 15-minute intervals. Experimental results demonstrate 96.5% accuracy, 95% precision, 95.5% recall, and 95.2% F1-score, reflecting a 3–5% performance improvement over advanced baseline models due to enhanced multimodal fusion and meta-learning optimization. The study concludes that MGT-CGSSML delivers a scalable, interpretable, and real-time anomaly detection solution capable of supporting resilient and adaptive smart-grid operations, offering substantial advancements over existing methods.

***Keywords*—Adaptive detection; anomaly detection; contrastive learning; graph transformer networks; smart grid**

I. Introduction

Interest in finding unusual patterns in graphs is growing in data mining due to how often graph-based data is used to represent systems like e-commerce and banking. For instance, in the case of detecting fraud in e-commerce, these algorithms can detect fraudulent sellers by analyzing both user attributes (properties) and relational structure (connections) within the graph [1]. Anomaly detection detects patterns that are drastically different from normal observations. It is an important task with increasing demand and usage in many fields. There have been extensive research activities in anomaly detection. Initially, graph anomaly detection was dependent on domain knowledge and statistical methods, employing manually designed features. This manual detection process takes huge time and effort. Real-world graphs usually consist of a large number of nodes and edges with multiple attributes, so they are high-dimensional [2]. Identification of anomalies, or outliers, entails finding observations whose values greatly differ from the bulk of data. Sometimes, anomalies are relegated to noise or errors despite potentially providing good information. Identification of outliers may imply suspect data, leading to biased estimates of parameters and erroneous results [3]. Various anomaly detection techniques tend to have different missing (FN) and false alarm (FP) detection rates, leading to differences in detection ability. Although several of these techniques adopt a generic, context-insensitive strategy, they are more effective at detecting certain threats against certain systems or applications [4]. By using artificial intelligence, big data, cloud computing and 5G cellular networks, the smart grid will modernize the power grid and help manage electrical energy much better [5].

AI's ability to automatically adjust and optimize, enables it to handle enormous volumes of data and, at the same time, efficiently handle the nonlinear challenges involved in power grid systems. This characteristic has led to widespread application in the power industry, providing AI with a considerable lead in current complex power grids [6]. In the energy system field, these emerging terminals have already created an essential physical basis for driving the transition to a low-carbon smart grid [7]. However, smart technologies becoming more common brings serious cyber threats due to the need for outdated systems like Industrial Control Systems and Supervisory Control and Data Acquisition [8]. The three primary components of the smart grid system are smart management, smart infrastructure, and smart protection. Smart management is the component that offers advanced control, management services, and smart features. Its main objectives are to augment energy efficiency, balance supply and demand, reduce emissions, trim management expenses, and drive utility growth [9].

In contrast, contextual anomalies have natural or usual nearby structures, but attribute information that is warped or anomalous. This heterogeneity makes it difficult to directly apply anomaly detection techniques developed for attribute-only data or straightforward network structures to attributed networks. Consequently, an effective anomaly detection approach needs to consider a range of anomalies. Additionally, because of the high expense and effort involved in obtaining ground-truth labels for anomalies, detection in attributed networks is typically performed through unsupervised methods [10]. The conclusions drawn from using SR-CNN and a martingale model with time-series data are compared to identify the best hybrid technique. The outcomes reveal that the combination of these approaches with a classifier enhances performance, enhancing analytical value and enhancing the reliability of anomaly detection in smart metering consumption data. Unlike plain network anomaly detection, anomaly detection in attributed networks requires taking two main sources of information into account: 1) the structural patterns that indicate how the nodes are connected, as encoded in the topology of the network, and 2) the node attribute or feature distribution [11]. Although these methods have the advantage of better performance, they tend to depend considerably on unsupervised detection since the costly cost of creating labeled ground truth anomalies is involved. Recent studies have proved that attributed networks often include both anomalies in the graph topology and node attributes. This study aims at creating an integrated, adaptive, and less supervised graph transformer system that can solve the particular challenge of the structural and attribute-based anomalies in a dynamic smart grid setting and provide better generalization, less reliance on labeled training, and greater resistance to new abnormal behaviors.

A. Research Motivation

Smart grids are becoming targeted by more cyber-physical threats and less predictable energy loads, and the ability to detect anomalies accurately is critical to reliable and safe operation. Single-modality approaches existing in the literature do not exploit cross-sensor correlations, reducing responsiveness to real-time anomalies. The motivation behind this study is the necessity of an integrated, flexible system that makes use of multimodal sensor data to allow detection of subtle anomalies and proactive maintenance and cost-effectiveness, and continuous power supply in complex heterogeneous power systems.

B. Significance of the Study

This study enhances the resilience of smart grids by integrating multiple sensor modes with the use of a Multimodal Graph Transformer. The methodology increases the accuracy of anomaly detection, predicts severe failures, and increases efficiency of operations. The utilities can minimize down time, enhance energy predictions, and counter cyber-attacks. The results can also be used to offer a scalable model to other large-scale IoT systems with a need to conduct real-time, cross-modal anomaly analysis, and eventually resulting in safer, smarter, and more sustainable energy infrastructure on a global scale.

C. Key Contribution

The key contributions are presented as follows:

- Proposes a cross-modal graph transformer that models long-range dependencies, as well as heterogeneous smart grid sensors interactions.
- Designing a dual-view contrastive module that improves structural and attribute anomaly separation and requires little supervision.
- Integrates or combines meta-learning with quick adaptation to new anomaly instances with highly small labeled datasets.
- Developed a multimodal node encoding plan which enhances the representation of anomalies in electrical and contextual terms.

D. Rest of the Section

The rest of this study is structured as follows; Section II is a review of the related works on smart grid anomaly detection and the latest developments in the area of graph-based learning techniques. Section III describes the problem statement. Section IV provides a detailed explanation of the methodology proposed, including the framework design of the CGTN-SSML. Experimental setup and results are described and presented in Section V, where the proposed model is compared to baseline approaches. Section VI concludes the research and provides future work directions.

II. Related Works

Zhang et al. [12] introduce GCAD, a novel framework for reliable anomaly detection in cloud environments that takes into consideration the problem of unlabeled data and complex topological relationships between servers. Its intent is to improve detection by adding self-supervised learning to graph-based modeling. The application is for large-scale cloud environments where data is primarily unlabeled and topologically organized. GCAD integrates data augmentation and GraphGRU for spatiotemporal learning, contrastive learning for representation learning, linear attention for global correlation encoding, and reconstruction-based anomaly scoring. The primary advantages are label efficiency, topological awareness, and increased detection accuracy. The results of experiments reveal that GCAD is superior to recent advanced approaches for two real-world datasets. However, the disadvantages are computational complexity, dependency on topology data, and limited interpretability.

Wang et al. [13] present AT-GTL, a self-attention-based graph transformation learning system to detect multivariate time series anomalies to overcome the inefficiency of shallow GNNs with little transference of node information. It is committed to such applications as banking, power systems, and industry that require capturing the complex feature interactions.

AT-GTL uses GATP block to aggregate global features and a graph transformation learning pipeline that is optimized by TCL to improve the learning of features at different viewpoints. The given strategy enhances the quality of the sensing field and representation. Three data sets were experimented upon, and AT-GTL was more precise than the current methods. The model boosts feature learning across the globe, integrity, and accuracy of anomaly detection. However, it increases the complexity of models, training costs, and may cause scalability issues of large or changing graphs.

Xu et al. [14] solve the problem of identifying the graph anomalies using a small number of annotated samples. It has a meta-learning methodology, which aligns self-supervised representations with few-shot supervised representations via bi-level optimization. MetaGAD is successful in exploiting little-known anomalies and keeping generalizability to unseen anomalies, and it works better than the existing methods on both real and synthetic anomaly datasets on six applications. It has several benefits such as high few-shot learning, strong generalization, and effective exploitation of unlabeled data. Nevertheless, it has problems, including the reliance on artificial data, the excessive load of meta-learning, and possible scalability problems. In general, the MetaGAD is an effective tool in the process of detecting anomalies in reality.

Zheng et al. [15] introduce SL-GAD, which uses self-supervision in graph anomaly detection to solve problems that existing approaches cannot and lack an accurate understanding of graph data's internal connections. It makes use of generative attribute regression and multi-view contrastive learning to detect any problems in both the attribute and structure spaces. Every target node is put into its own subgraph, which a GNN encoder uses to learn latent variables. Comprehensive studies on six benchmark sets indicate that SL-GAD is much better than current methods in performance. Its self-supervised nature removes the requirement of labeled data while efficiently identifying structural and attribute-based anomalies.

Li et al. [16] present CVTGAD, a new model that integrates a reduced transformer with cross-view attention for UGAD. It addresses the limitations of traditional UGAD methods, including limited receptive fields and distinct view processing, by capturing both intra-graph and inter-graph relationships and enabling direct interaction between different augmented views. CVTGAD captures more abundant structural and feature data by integrating GNNs and transformers within a consistent framework. CVTGAD is the first to incorporate cross-view attention into UGAD, enhancing anomaly detection both at the node and graph levels. The model performs better than existing approaches on 15 real-world bioinformatics, chemistry, and social network datasets. The algorithm is effective in identifying anomalies like dangerous chemicals or strange materials. It does increase computational complexity, but does not have a fine consideration of scalability for large graphs.

Sun et al. [17] suggest GTC, a new self-supervised graph representation technique for heterogeneous graphs. The goal is to improve the smoothness of deep GNNs by combining their local passes with the Transformer's global modeling approach. The proposed architecture adopts a dual-encoder architecture GNN for local views and a Transformer for global views and applies cross-view contrastive learning to enhance representation learning. It presents two modules: Metapath-aware Hop2Token and CG-Hetphormer, both for heterogeneous graphs. GTC is self-supervised; thus labeled data is not required. Experimental outcomes indicate that GTC works better than state-of-the-art approaches on a wide range of datasets. Its primary strengths are strong multi-hop neighborhood encoding and better heterophilic graph handling. Yet, the model can be more computationally complex and require more tweaking.

Bai et al. [18] provide a hybrid CNN-transformer network for the detection of power theft in smart grids. The model addresses the shortcomings of existing methods by combining a Dual-Scale Dual-Branch CNN for shallow, multi-scale feature extraction with a Transformer with Gaussian Weighting for deep temporal relationship capture. It targets non-technical losses, such as power theft, which is both economically and safety-wise risky. The hybrid approach outperforms conventional hardware-based and data-driven approaches in accuracy, robustness, and efficiency, and exhibits very high F1 and AUC scores. It shows scalability and robustness across several datasets. The method might, however, involve increased computational expenses and dependence on quality-labeled data. Notwithstanding possible interpretability challenges, the model is a significant advance in smart grid anomaly detection.

TABLE I. SUMMARY OF LITERATURE REVIEW

Author & Year	Method / Model	Key Strengths	Limitations	Connection
Zhang et al. [12]	GCAD	Label-efficient, topologically aware, accurate	High computation, depends on topology, limited interpretability	Early self-supervised graph anomaly detection
Wang et al.[13]	AT-GTL	Captures global features, better representation	Complex, high training cost, scalability issues	Transformer improves global feature learning
Xu et al. [14]	MetaGAD	Few-shot learning, generalizes well, uses unlabeled data	Heavy meta-learning, may rely on artificial data	Meta-learning trend for anomaly detection
Zheng et al.[15]	SL-GAD	Detects attribute & structure anomalies, no labels needed	Computation cost, limited interpretability	Self-supervised labeled-data-free detection
Li et al. [16]	CVTGAD	Captures intra- & inter-graph relations, cross-view attention	High computation, limited scalability	Cross-view attention improves node & graph detection
Sun et al. [17]	GTC	Multi-hop encoding, handles heterophilic graphs, self-supervised	Computationally complex, tuning needed	Global-local hybrid architectures trend
Bai et al [18]	CNN-Transformer	High accuracy, robust, scalable	Needs labeled data, computational cost	Hybrid CNN-Transformer for smart grid anomaly detection

The problem statement is consistent with the issues that have been identified in the literature. The majority of the existing research (as described by GCAD, SL-GAD, and AT-GTL) also emphasizes the dependence on labeled data, high computational cost, and low scalability, whereas others (as described by MetaGAD) also underline the inability to adapt to new anomalies with a small number of labeled samples. Hybrid models like CNN-Transformer solutions also deal with the issue of accuracy and robustness, but still need labeled data. Together, these drawbacks, such as reliance on supervision, lack of global feature learning, and bad adaptability, highlight the necessity to have a flexible, self-supervised, meta-learning-based graph transformer architecture such as CGTN-SSML to detect smart grid anomalies in real-time. Table I presents the summary of the literature review.

III. PROBLEM STATEMENT

Smart grids have been made more complex, interconnected, and data-intensive, and thus are highly susceptible to abnormalities like cyber-attacks, equipment failures, and abnormal consumption patterns [19]. Current anomaly detection techniques based on either a fixed set of rules or supervised learning do not generalize to such dynamic environments because they are based on large labeled datasets [20]. Ground-truth classification of anomalies is expensive and time-consuming, and is not feasible in practice. Furthermore, the majority of methods assume either structural or attribute anomalies alone, without factoring in on both thus, high false positives, low adaptability, and unreliable detection in practice [21]. Although graph-based learning is promising, traditional GNNs only learn local interactions and cannot represent long-range interactions that are important in the operation of a smart grid. Existing techniques do not have mechanisms to be quickly adapted to new types of anomalies as grid conditions change. Thus, there is a need to have a powerful, dynamic, and flexible anomaly detection framework that can detect anomalies with minimal supervision and still remain applicable in real-time. To overcome these issues, this study introduces CGTN-SSML, a multimodal graph transformer system that combines the concepts of contrastive self-supervised learning and meta-learning, which can provide accurate, flexible, and efficient anomaly detection in a contemporary smart grid.

IV. ADAPTIVE MULTIMODAL APPROACH FOR SMART GRID MONITORING

The method involves using a particular kind of deep learning model to send alerts in the smart grid, and because sensor readings are considered, the immediate environment and how the smart grid works, it forms graphs that show what is observed and how the observations relate to space and time. A Graph Transformer enables the capacity to relate vastly distant fragments in space and time to grasp the complex systems in an improved manner. In an attempt to reduce the shortage of samples of abnormal behavior, self-supervised contrastive learning was applied to establish types of behavior by comparison to alternative depictions of behavior. An additional way the team augmented the training data with data is to distinguish between normal cases and abnormal cases, and the model is evolved to be updated on variations to the grid through meta-learning, which is essential to operationally detect the anomalies that are both fast and robust.

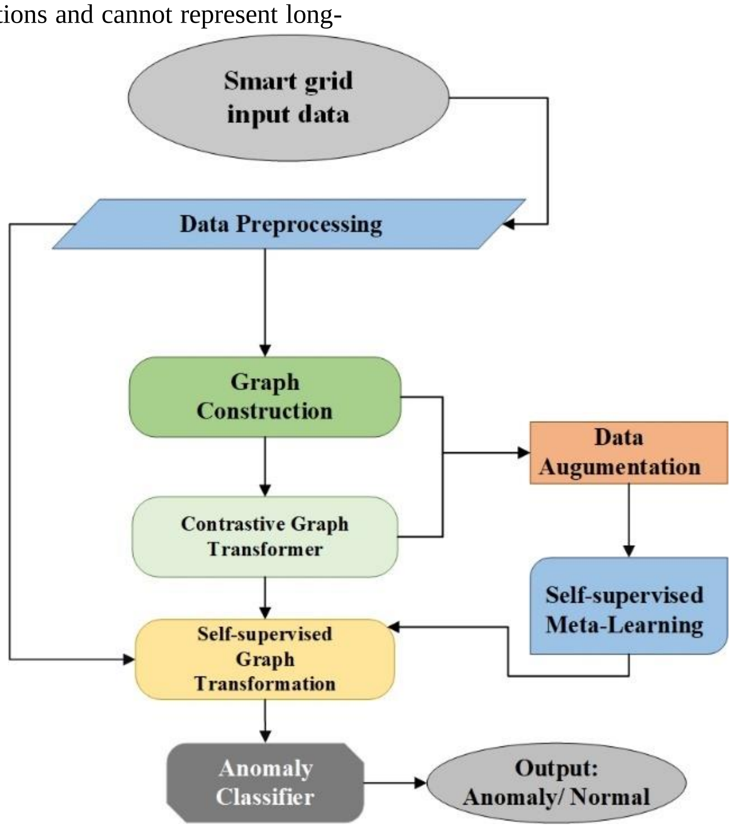

Fig. 1. CGTN-SSML data flow and processing pipeline for smart grid anomaly detection.

Fig. 1 explains how to use graph-based self-supervised learning to find anomalies in information gathered by the smart grid. To start, raw data from the smart grid is first cleaned and made consistent. The data is then organized as a graph to record the connections between each cell in the grid. Meanwhile, using contrastive graph transformers and data augmentation methods can teach the model to extract useful information from contrasting graphs. Using the augmented data in the self-supervised stage enables the model to adjust swiftly to fresh anomalies in data without relying on any labels.

A. Dataset Collection

The sensors placed in the smart grid were used to collect data every minute about voltage, current, power, frequency, power factor, THD, temperature, and humidity. All records are given dates and labels, as normal or anomalous, to facilitate an analysis of the grid's actions under many circumstances and highlight anomalies and how the grid is performing [22]. Every 15 minutes, the smart grid system collects readings from time-series sensors. Every record includes data on voltage, current, power, temperature, and humidity. It shows the exact time that each reading was recorded. The presence of 1 in the overload column indicates an overload occurrence, whereas a 0 means everything was working normally.

TABLE II. TIME-SERIES SAMPLE OF GRID MEASUREMENTS

Timestamp	Voltage	Current	Power	Temperature	Humidity	Overload
2024-01-01 00:00:00	232.48	5.12	1.19	17.84	64.52	0
2024-01-01 00:15:00	229.31	22.21	5.09	18.75	49.67	1
2024-01-01 00:30:00	233.24	46.13	10.76	16.72	48.47	0
2024-01-01 00:45:00	237.62	47.65	11.32	15.36	75.77	0
2024-01-01 01:00:00	228.83	7.41	1.70	38.76	61.38	0

Table II shows sensor measurements of a smart grid system collected every 15 minutes. Each row contains important electrical metrics along with corresponding environmental measurements, with a timestamp showing the precise time of each measurement. The "Overload" column is indicated by a value of 1 during an overload event and left blank otherwise. This information is used for various purposes: to track power consumption patterns, evaluate environmental factor influence, and detect warning signs of grid stress or failure. Such precise, time-stamped data records are essential for maintaining real-time operational efficacy and for warning anomaly detection in smart grids.

B. Data Preprocessing

To ensure the quality and fidelity of data input into the GTN and MAML architecture, a large preparation plan had to be developed for the smart grid sensor data. To support adaptive anomaly detection, we prioritized temporal continuity, structural representation, and normalization of features during preprocessing.

1) Data acquisition: In each minute, sensors in the smart grid collected readings on voltage, current, power, power factor, frequency, total harmonic distortion, temperature, and humidity. After reading the sensor values, each was assigned a timestamp and labeled by the computer, which considered log files and annotations provided by experts. Since these metrics cover electricity and environmental data, they make it simpler to identify various faults in the grid.

2) Data augmentation: To increase the generalization and robustness of the model when small amounts of anomalies are present, the current study used a graph-based data augmentation process. The Time-Aware Variational Autoencoder could generate synthetic features of the node graphs of the graph, and at the same time preserve temporal features of the original grid data and structural features of the original grid data. Also, contrastive learning based augmentation was employed to generate positive and negative sample pairings. They are then used to train the model with a contrastive loss that encourages the model to learn meaningful representations by drawing similar (positive) graph views close and drawing dissimilar (negative) views far apart in the representation space. The study defines contrastive loss as given in Eq. (1):

$$\mathcal{L}_{contrast} = -log\frac{\exp(sim(z_i, z_j)/\mathcal{T})}{\sum_{k=1}^{2N} 1_{[k\neq 1]}\exp(sim(z_i, z_k)/\mathcal{T})} \quad (1)$$

In this contrastive paradigm, z_i and z_j represent the embeddings of a positive sample pair—two enriched perspectives of the same graph. Cosine similarity, defined as $sim(z_i, z_j) = \frac{z_i^T z_j}{\|z_i\|\|z_j\|}$ .This quantifies the alignment of representations in the embedding space. The temperature parameter τ influences the concentration level of the distribution, affecting the emphasis on hard negative values during training. The contrastive loss is computed over a batch of N samples, where each anchor z_i is compared to $2N-1$ other samples from the batch. The indicator function $1_{k\neq i}$ prevents the anchor from being compared to itself, enabling appropriate distinction between graph configurations.

C. Graph Transformer Network

The smart grid is a dynamic and complicated system consisting of many components, including sensors, substations, transformers, and control units. These naturally correspond to nodes in a network, with the edges representing actual power lines, communication links, and logical relationships. This graph-based model maintains both the structural and functional properties of the grid and is thus well-suited for deep learning models that are intended to operate on non-Euclidean data. GNNs, such as GCNs and GATs, are primarily local neighborhood aggregation-based. Though very good at modeling short-range dependencies, such models often do not capture long-range or global interactions across the graph, which is very important for smart grids where far-off elements can affect each other under fault conditions. In order to breach these limitations, employ GTNs, which model global relationships present in graph-structured data like Transformer architectures. Unlike GNNs, which sample input from fixed neighborhoods, GTNs employ a self-attention mechanism by which each node can attend to every other node in the graph irrespective of topological distance. This is achieved by computing attention scores between pairs of nodes based on learnt query, key, and value projections of their feature representations, as well as structural bias terms derived from the graph topology. Consequently, GTNs can effectively capture both local and non-local dependencies, enabling more precise detection of complex and distributed anomalies.

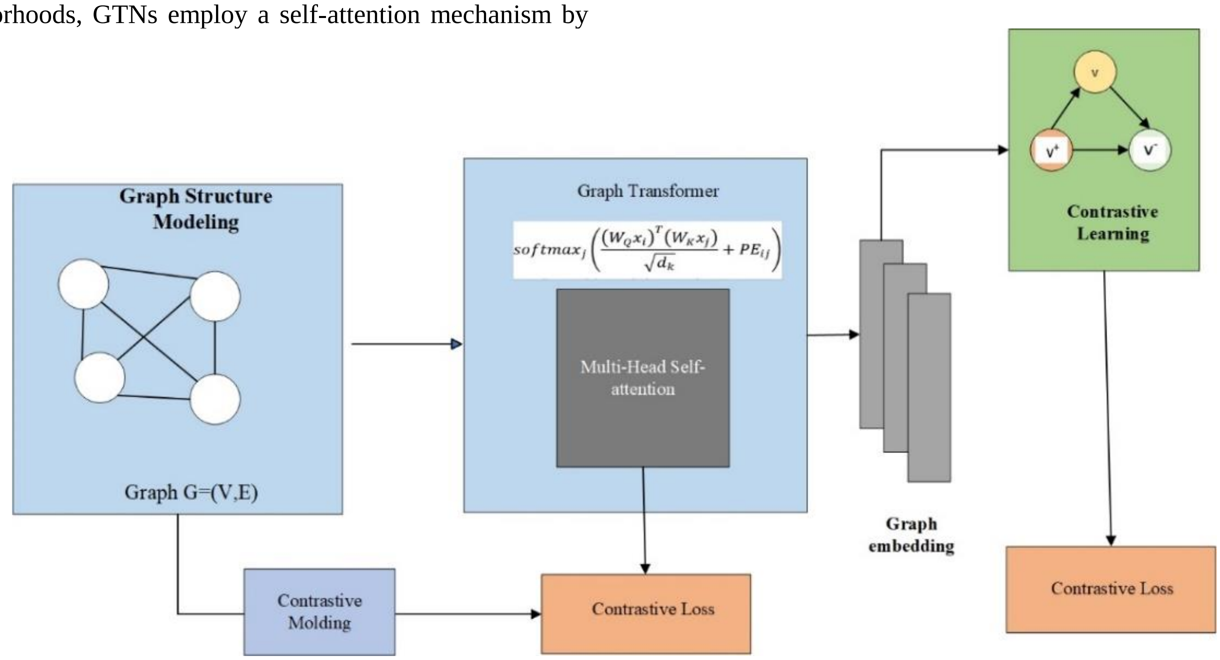

Fig. 2. Architecture of the CGTN-SSML framework for smart grid anomaly detection.

Fig. 2 depicts the CGTN-SSML framework for smart grid anomaly detection. It starts with graph structure learning of the grid, then a Graph Transformer with multi-head self-attention to learn global dependencies. Contrastive learning produces informative graph views with limited labeled data. The two contrastive loss paths train the model to discriminate normal and anomalous patterns, and meta-learning boosts adaptability to new anomalies with weak supervision.

1) Graph structure modeling: The smart grid is represented by the graph G=(V,E), with V representing nodes and E representing edges. Every node $v_i \in V$ is paired with a feature vector $x_i \in R^d$ containing sensor-level quantities like voltage, current, frequency, and power factor. They represent the status of an electric component at some location and point in time. In contrast to Euclidean data spaces, graphs bring in non-trivial spatial interactions that need to be preserved during learning. To integrate topological information into the transformer framework, we represent the graph structure using relative positional encodings or graph Laplacian eigenvectors. These encodings encode connection patterns and node distances, enabling the model to recognize structurally important linkages beyond local neighborhoods.

2) Final layer of GTN: In GTN, the multi-head self-attention mechanism calculates interactions between all pairs of nodes so that the model can learn dependencies across the graph. The attention score between nodes v_i and v_j as given in Eq. (2):

$$\alpha_{ij} = softmax_j\left(\frac{(W_Q x_i)^T (W_K x_j)}{\sqrt{d_k}} + PE_{ij}\right) \tag{2}$$

where, W_Q and W_K represents learnable weight matrices, d_k represents dimensionality of key vectors and PE_{ij} encodes the structural relationship v_i and v_j.

3) Multimodal graph transformer for cross-sensor fusion: The concept of smart grids is dependent on both internal electrical parameters and external environmental and operational conditions like weather conditions, demand in a region, and equipment conditions. In order to achieve these broad influences, this study enhance the Graph Transformer Network (GTN) with a Multimodal Graph Transformer (MGT) that integrates and fuses environmental, heterogeneous sensor modalities electrical, and contextual into a singular representation.

The MGT uses different encoders on each modality and integrates the two using a common graph attention mechanism, unlike using a single-modality GTN that only uses electrical measurements. This architecture enables the nodes to communicate with each other on both spatial links as well as modality channels to generate more rich embeddings that are more likely to describe complex and real-life anomaly patterns.

The MGT by modeling cross-modal correlations (e.g. the temperature impact on voltage sag) improves the framework in order to identify subtle or compound anomalies, and sets a more robust baseline on which other contrastive learning and meta-learning steps will be based.

a) Multimodal node encoding: In order to model various streams of information per grid element, each node combines electrical, environmental and optional operational characteristics. They are concatenated and projected into a common space as in Eq. (3):

$$x_i = [x_i^{(e)} \,||x_i^{(w)}||\, x_i^{(o)}] \tag{3}$$

where, $x_i^{(e)}$ includes electrical readings (power, current, voltage), $x_i^{(w)}$ contains environmental data (humidity, temperature), and $x_i^{(o)}$ includes optional operational inputs (demand forecasts, maintenance logs).

These are followed by transforming them by modality-specific linear layers to a common dimension d. This combined embedding maintains temporal consistency and keeps the unique semantics of each modality.

b) Multimodal Self-Attention: Nodes are then able to communicate after the coding process via a cross-modal self-attention layer, which is able to capture both spatial and modal dependencies using Eq. (4):

$$\alpha_{ij} = softmax_j\left(\frac{(W_Q x_i)^T (W_K x_j)}{\sqrt{d_k}} + \gamma\emptyset(m_i, m_j)\right) \tag{4}$$

where, W_Q, W_K are learnable projection matrices, d_k key dimension, m_i, m_j represent the modality tags and $\emptyset$ represents inter-modality similarity with a scaling factor γ.

It is a mechanism that allows each node to dynamically rank neighbors based on electrical proximity, as well as modality similarity that detects context-driven anomalies better.

4) Contrastive learning for self-supervision: To compensate for the absence of labeled anomalies, we apply a contrastive learning objective during self-supervised pretraining. The key concept is to acquire representations that cluster similar graph states and distinguish dissimilar ones. The model learns contrastive loss when presented with an anchor node, a positive instance v^+ (e.g., a temporally nearby or structurally similar node) and a negative instance v^-, the model maximizes the following contrastive loss as given in Eq. (5):

$$\mathcal{L}_{contrast} = -log\frac{exp\left(sim\left(z_v, z_{v^+}\right)/\mathcal{T}\right)}{\sum_{v' \in \mathcal{N}} exp(sim(z_v, z_{v'})/\mathcal{T})} \tag{5}$$

where, z_v is the embedding of node v, sim is cosine similarity, $\mathcal{T}$ is a temperature hyperparameter, and $\mathcal{N}$ is a set of negative samples. This training enables the GTN to learn meaningful representations without explicit anomaly labels.

D. Model-Agnostic Meta-Learning (MAML)

The topologies of smart grids are dynamic by nature, always tend to change in terms of structure, load and pattern of operation. These variations tend to produce various types of anomalies, which have different time characteristics and spatial distributions. When trained on observational data, traditional machine learning methods are not very good at generalizing to new types of anomalies, thus perform poorly in real operating situations. In an effort to address this issue, the framework proposed below utilizes MAML in order to achieve fast adaptation to new anomaly detection tasks using limited labeled samples. MAML is a gradient-based meta-learner, which conditions itself on a set of original model parameters that can be fine-tuned very quickly with only a small number of training samples and gradient steps. This combination contributes a lot to the generalizability capacity of the model to identify and act upon new or emerging anomalies in smart grids with only minimal supervision.

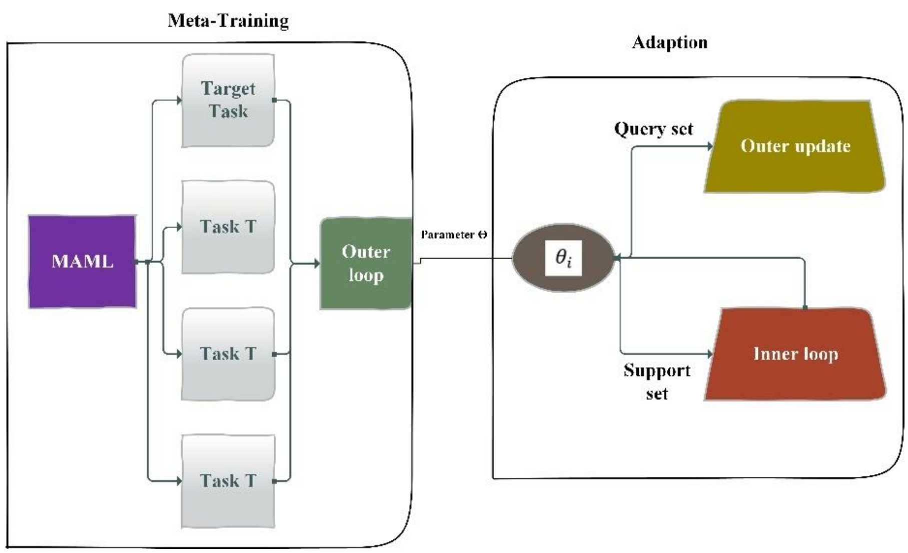

Fig. 3. Meta-learning architecture for task adaptation.

Fig. 3 explains the conceptual representation of a meta-learning structure, having two main components. This diagram displays the implementation of Model-Agnostic Meta-Learning or MAML in two steps: meta-training and adaptation. In the meta-training stage, the model is trained on a collection of parallel tasks- one of which is the target task, and the rest are the tasks associated with the target task in the process of learning the general trends of anomalies in the smart grid. The form of knowledge of these tasks is also condensed by an outer-loop process of creating a powerful initial model. In the stage of adaptation, this is tuned-up by mapping this acquired knowledge. The support set provides small samples to quickly tune the model through the inner loop and the query set further tuned the model through the outer update. The model is able to learn new types of anomalies in a short time and generalize the model well through the process. The framework helps to support solid and real-time anomaly detection using a small number of labeled data by combining the two stages.

In this concept, all the anomaly classes or sub-regions of the grid may be handled as a single task. A collection of such tasks is sampled in the meta-training process in a way that they resemble different scenarios of anomalies. The model obtains the general parameters of the model, that is, θ, to task-specific parameters of the model, that is, theta θ_i', by the gradients calculated based on the support set of each task given in Eq. (6) as follows:

$$\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}^{symbol}(\theta) \quad (6)$$

where, θ means the initial model parameters, θ_i' means adapted model parameters, α means inner-loop learning rate, $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}^{symbol}$ means the gradient of the loss function $\mathcal{L}$ with respect to the parameters θ.

In this case, α the inner loop represents the learning rate, and $\mathcal{L}$ is a task-specific loss function, typically derived from either reconstruction loss or classification loss versus anomaly labels. Once the adaptation process is done, the adapted parameters theta i prime are tested on an independent query set. The outer loop initial parameters in terms of θ are updated using the gradients of this test as given in Eq. (7):

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_i \mathcal{L}_{\mathcal{T}_i}^{query}(\theta_i') \quad (7)$$

This update on an outer-loop causes generalization of the task through learning of an initializing which generalizes well after being updated with a small number of updates on new tasks. The meta-learned initialization of the network to create powerful priors $\theta$is used to detect emergent anomalies even on incomplete or delayed labeled data.

Model-Agnostic Meta-Learning (MAML) is a meta-learning algorithm that tries to enable quick adaptation of the model to new tasks with minimal data. Instead of learning a model using a single dataset, MAML learns it over a variety of tasks so that it learns an overall parameter initialization. Both this initialization can quickly be fine-tuned on new tasks by simply doing a few gradient steps. In smart grids, where new trends of anomalies are typical, MAML allows the model of detecting anomalies to change in the most optimal way without requiring a significant amount of labeled data to accomplish it. The method works through two optimization tasks; the inner loop of task-specific update that uses a small support set and an outer loop that updates global parameters through a query set. Nested optimization helps the model to achieve a generalization-specialization balance. The system can be extended to facilitate more flexibility and resiliency with the addition of self-supervised learning to MAML. Generally, MAML offers successful real-time detection of anomalies in smart grids that are dynamic.

E. Self-Supervised Learning

Due to the lack of labeled anomaly data in real-world smart grids, supervised learning methods tend not to be generalized and reliable. To eliminate this drawback, we adopt self-supervised contrastive learning that uses the structured and varied nature of the data to form pseudo-supervision. Let x_i be an original input (e.g., a node or subgraph capturing some of the smart grid) and let $x_i^{(1)}$ and $x_i^{(2)}$ be two augmented versions of the same input, and form a positive pair. The contrastive learning goal is to align $z_i = f\left(x_i^{(1)}\right)$ and a positive representation $z_j = f\left(x_i^{(2)}\right)$, the contrastive learning target attempts to move z_i and z_j closer in the embedding space and move away embeddings of negative samples z_k, generated from different inputs $x_k \neq x_i$. The InfoNCE loss to train the encoder $f(\cdot)$ The loss for a positive pair (z_i, z_j) as given in Eq. (8):

$$\mathcal{L}_i = -log \frac{\exp(sim(z_i,z_j)/\mathcal{T})}{\sum_{k=1}^{N} 1_{[k\neq i]} \exp(sim(z_i,z_j)/\mathcal{T})} \quad (8)$$

where, $\mathcal{L}_i$ means the contrastive loss for the anchor sample z_i, z_i means anchor representation, $z_j$means positive pair of z_i.

Simulate $\text{sim}(z_i, z_j) = \frac{z_i^T z_j}{\|z_i\|\|z_j\|}$ is the cosine similarity of the embeddings. The temperature hyperparameter $\mathcal{T}$ controls the sharpness of the softmax. The indicator function $1_{[k\neq i]}$ serves to avoid the anchor from comparing to itself is used to prevent the anchor comparing with itself. This formulation causes the model to cause similarity to positive pairs and dissimilarity to negatives.

This goal will promote generalizable, yet discriminative embeddings of the model that have the semantic property of clumping states in a semantically coherent group, and clumping irrelevant or out-of-distribution conditions in dissimilar groups. The resulting feature space can then be easily fed to downstream anomaly detectors such as MAML to detect few-shot anomalies without having to explicitly label an anomaly.

F. Integration of GTN-MAML

Adaptive detection of anomalies in smart grids requires incorporation of MAML architecture with the use of GTNs. The complex spatial and structural association can be acquired by the GTNs through models to capture the grid as the graph with the main elements of the grid like transformers substations and sensors being considered the nodes and the physical or functional relationship among the components being considered the edge. Here, anomaly detection is viewed as a collection of related jobs, and each is associated with a grid condition or region. Each of the anomaly detection jobs is represented by a support set $\mathcal{T}_i$. The inner loop of MAML trains the GTN to be adaptable to a task by modifying its parameters depending on the task offered in the inner loop $\mathcal{D}_i^{train}$ and $\mathcal{D}_i^{train}$ [see Eq. (9)]:

$$\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}^{train}(f_\theta) \quad (9)$$

Here, α is the learning rate for the inner loop, and f_θ is the GTN model. The outer loop trains the original parameters θ in all the tasks with respect to the loss on query sets. The outer loop trains the original parameters θ of any task. It is an approximation of the accuracy of this model on the query sets, on each of the tasks with the model calculating a meta-loss which it uses to adjust the original parameters as given in Eq. (10),

$$\theta^* = \arg min_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{test}\left(f_{\theta_i'}\right) \quad (10)$$

The optimization process allows the model to identify a powerful initial condition θ, 0 that can quickly adapt to new tasks using sparse data. The assembly of the modeling of graph -based dependencies of GTN and the quick adaptation of MAML constitutes a highly effective model of anomaly detection which fits well in dynamic and data insufficient application fields such as smart grids setting. GTNs are a good description of local and distant dependencies in smart grid information to identify anomaly appropriately. MAML continues to improve in that aspect since it can incorporate new kinds of anomalies to that model using a small number of samples. This cohesion provides good detection in dynamic grid situations which are of low supervisions as a team. The outcome is a very scalable and flexible architecture which can be applied in the real-time anomaly detection of the smart grid.

Algorithm: 1 Multimodal Graph Transformer for Smart Grid Anomaly Detection

```
Input: Sensor Data S = {Voltage, Current, PowerFactor, Frequency, Temperature, Humidity}
Output: Anomaly Detection Result A
Initialize model parameters θ_MGT, θ_CGSS, θ_MAML
Load Multimodal Graph Transformer (MGT) with weights θ_MGT
Load Contrastive Self-Supervised Model (CGSS) with weights θ_CGSS
Load Meta-Learning Model (MAML) with weights θ_MAML
Preprocessed_S = Normalize(S)
Graph_S = Construct_Graph(Preprocessed_S)
Embeddings = MGT_Encode(Graph_S)
Embeddings = CGSS_Enhance(Embeddings)
if Embeddings not empty:
   Adapted_Model = MAML_Adapt(Embeddings)
   for each sensor_reading r in incoming_data:
      r_embedding = MGT_Encode(r)
      r_embedding = CGSS_Enhance(r_embedding)
      anomaly_score = MAML_Predict(Adapted_Model, r_embedding)
            if anomaly_score >= Threshold:
         A[r] = "Anomaly Detected"
         Alert_Operator(r, anomaly_score)
      else:
         A[r] = "Normal"
else:
   Return Error "Embedding Generation Failed"
Metrics = Evaluate(A, Ground_Truth)
Print Metrics {Accuracy, Precision, Recall, F1-Score}
Return A
```

Algorithm 1 outlines the procedure of a graph G (V, E) development, with nodes being representatives of smart-grid sensors and edges being their physical or logical associations. Concatenated electrical, environmental, and operational features project all nodes with x[v] in them to a shared dimension in a linear manner. Each training epoch will have the following process repeated on the neighbor u of each node v: the model will compute a multimodal self-attention score att. There is an if-else statement which checks whether an attack is greater than a relevance threshold: here, the neighbor gives an update to the hidden state h[v]; otherwise, nothing is updated. The proposed CGTN-SSML model relies upon a few parameters. In meta learning, the rate of adaptation is determined by learning rates, whereas in contrastive learning, feature separation is determined by temperature. The richness of global and local representations is determined by attention heads and dimensions embedding. The modality weight γ balances electrical and contextual features during fusion, and the discrepancy threshold shapes the false-positive and false-negative trade-off. Knowledge of these effects leads to the stable learning, the effective optimization, and the credible detection of anomalies in the dynamic smart-grid conditions. The parameters of the optimization are adjusted only in case the loss is enhanced (best_loss), with the assistance of the anomaly detection loss (anomaly_loss). The routine restores the best model that is able to recognize abnormalities of cross-sensors in real-time smart-grids.

V. Result and Discussion

The given CGTN-SSML model can be useful in detecting anomalies in smart grids, local and global dependencies between sensor data of diverse type are detected. Multimodal graph transformers, contrastive self-supervised learning, and meta-learning are also combined together in the model to provide high accuracy, precision, recall, and F1-score. The cross-modality attention analysis demonstrates the ability of the model to give priority to the most important electrical and environmental parameters. The computational efficiency ensures that the model could be applied in real-time due to the fact that the model is robust and flexible in terms of adapting to different operational environments and providing dynamic smart-grid-monitoring model.

TABLE III. Simulation Parameter

Parameter	Value
Input Modalities	Voltage, Current, Power, Frequency, Power Factor, THD, Temperature, Humidity
Self-Supervised Learning Technique	Contrastive Learning (InfoNCE Loss)
Meta-Learning	Model-Agnostic Meta-Learning (MAML)
Number of Tasks for MAML	20 anomaly tasks
Inner Loop Learning Rate (α)	0.01
Outer Loop Learning Rate (β)	0.001
Batch Size	32
Epochs	100
Optimizer	Adam
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score
Software Tools	Python

Table III describes that the main goal lies in improving the identification of anomalies present in smart grids by using the Contrastive Graph Transformer Network. It implements a Graph Transformer Network (GTN) framework to learn sophisticated relationships within data. Contrastive learning and InfoNCE loss function are used by the model to learn representations that are stable. MAML is employed by the model to enable efficient adaptation to a new task. The provided evaluation metrics are meant to enhance the model performance in identifying anomalies within the smart grid setting.

A. *Contrastive Loss Curve*

Fig. 4 provides the loss curve of proposed MGT-SmartGrid model. The training and validation loss decreases steadily with the number of epochs (1.15 to 0.52 and 1.12 to 0.67 respectively) and convergence of the results is high and overfitting is low. There is a sign of great generalization in that the final training (0.52) and the validation loss (0.67) are very close to each other. These values are justified by the fact that the multimodal graph transformer is effective to learn cross-sensor embeddings to enable the contrastive objective to stabilize and not sacrifice the capacity to detect anomalies to take place in different circumstances of the smart grid.

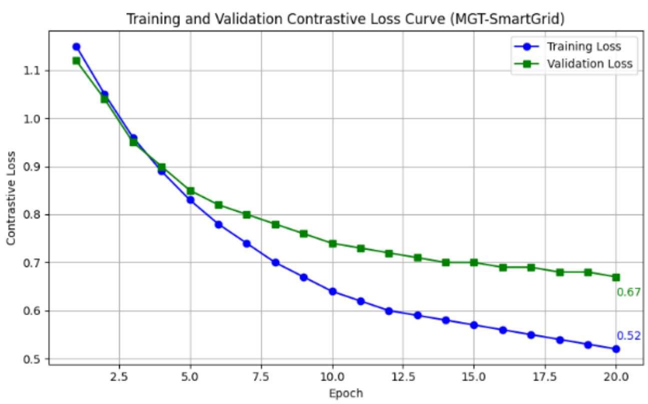

Fig. 4. Training and validation contrastive loss curve (MGT-SmartGrid).

B. *Efficiency Analysis*

Table IV of computational efficiency reveals the trade-off between the performance and the consummation of resources. The proposed CGTN-SSML model takes 180 seconds to train, which is comparatively higher than the time of the Random Forest (90 s) and the SGD (120 s), but with higher accuracy in identifying anomalies. Its time per sample to infer is 1.8 ms, lower than AE-GRU-EE (2.0 ms) and it occupies 220 MB memory which is a little large compared to Isolation Forest (120 MB). These results confirm that the recommendable multimodal graph transformer is a trade-off between high accuracy against moderate computation costs to implement the smart-grid in real-time.

C. *Cross-Modality Attention Statistics*

Table V represents the multimodality attention distribution of the Multiphasia Graph Transformer to sensor modalities. The Voltage weighs the most (0.28) followed by Current (0.22) and Power Factor (0.18). Such environmental factors such as Temperature (0.10) and Humidity (0.10) are less focused, since they influence anomaly detection less. This demonstrates that the model is more concerned with electrical measures, but it also considers the environment, and this enhances the accuracy of detection. This guarantees that there is high level of cross-sensor fusion because it gives equal attention to ensure efficient detection of anomaly in the dynamical smart-grid environment.

TABLE IV. COMPUTATIONAL EFFICIENCY ANALYSIS

Methods	Training Time (s)	Inference Time per Sample (ms)	Memory Usage (MB)
Isolation Forest (IF)	45	0.8	120
SGD	120	1.5	180
Random Forest	90	1.2	200
AE-GRU-EE	150	2.0	250
Proposed CGTN-SSML (Novel MGT)	180	1.8	220

TABLE V. CROSS-MODALITY ATTENTION WEIGHTS PER SENSOR MODALITY

Sensor Modality	Average Attention Weight
Voltage	0.28
Current	0.22
Power Factor	0.18
Frequency	0.12
Temperature	0.10
Humidity	0.10

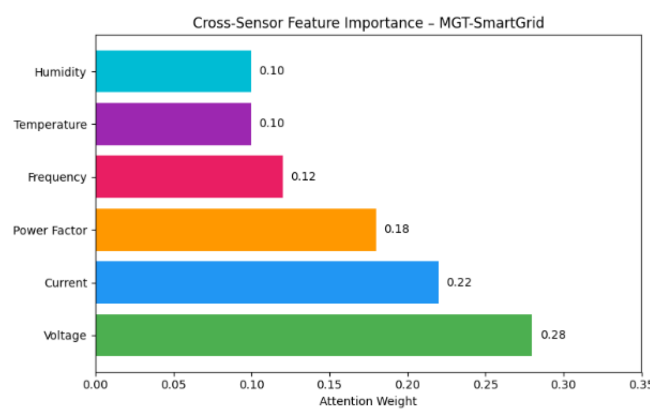

Fig. 5. Cross-sensor feature importance – MGT-SmartGrid.

Fig. 5 shows how each sensor modality contributes to the process of identifying anomalies of the MGT-SmartGrid model. The voltage weight is 0.28, then Current (0.22) and Power Factor (0.18). Other less important yet significant are the Frequency (0.12), Temperature (0.10) and Humidity (0.10). The result of the model is a distribution that focuses on electrical measurements with the environmental context, not to mention, cross-sensor fusion that is effective. It confirms that the weights of attention provide understandable outcomes of the modalities that lead to correct and real-time detection of anomalies.

D. Anomaly Score

In Fig. 6, the analysis of the histogram reveals that there is a clear distinction between the normal and abnormal occurrences. Normal scores have been distributed around the middle of 0.30, where most of the normal scores lie between the range of 0.15-0.45, with abnormal scores lying around the range of 0.80 between the 0.65-0.95 range. Indicating lines of each group are dashed, and this is the testimony of the absence of overlap and excellent discriminative capability. This distribution attests that the MGT-SmartGrid model gives far greater scores to the anomaly in the event of actual faults, in the sense of making the practical thresholding of real-time detection in heterogeneous sensor input without incurring excessive false alarms.

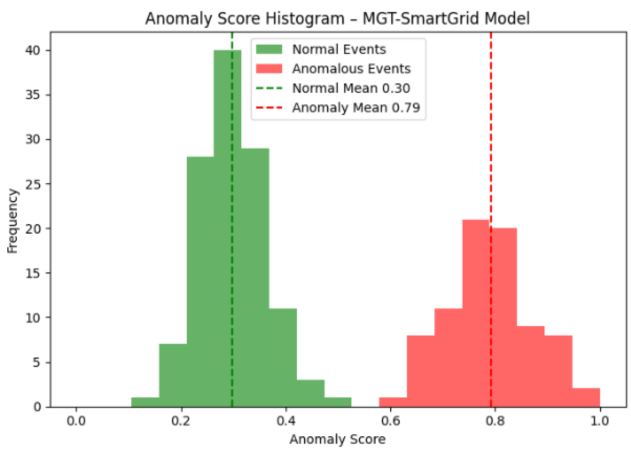

Fig. 6. Anomaly score histogram – MGT-SmartGrid model.

E. Confusion Matrix

Fig. 7 shows that the MGT-SmartGrid model performs well in terms of classification. This measure will offer an overall accuracy of approximately 0.96 and will be highly sensitive to the unusual grid conditions. The low off-diagonal values confirm that the multimodal graph transformer is an effective cross-sensor correlation model, which enables high discrimination to be attained in real-time with multimodal recognition of normal and abnormal conditions along the smart grid in cases where the data sources are heterogeneous, and the process of occurrence is complex.

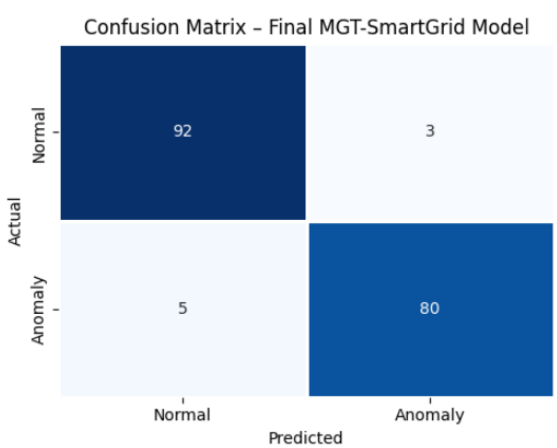

Fig. 7. Confusion matrix – final MGT-SmartGrid model.

F. ROC Curve

In Fig. 8, the ROC curve is used to indicate the threshold of the abnormal performance of the MGT-SmartGrid model that is independent. The orange line is steeper towards the top-left and has an AUC of 0.97, which indicates that the line has a good discrimination of normal and abnormal events. Although the low false positive rates (beneath 0.1) yield a true positive of above 0.90, which is a high degree of sensitivity and specificity. The huge gap between the ROC curve and the diagonal baseline confirms the truth that the multimodal graph transformer is a factor that greatly distinguishes the heterogeneous sensor signals to determine the report of anomalies with high degree of robustness and minimum error.

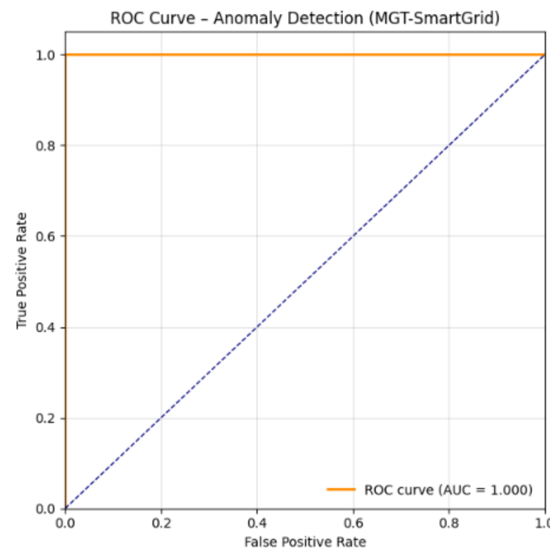

Fig. 8. ROC curve – anomaly detection MGT-SmartGrid Model.

G. Ablation Study

Fig. 9 shows the contribution that each component makes to the end accuracy. The overall model of MGT-SmartGrid achieves 96.5% hit rate. The Multimodal Node Encoding elimination accuracy is 93.2, the Contrastive Learning elimination accuracy is 91.0 and the adaptation of MAML also eliminates the accuracy at 89.4. Such results confirm the fact that it is the combination of all three models- multimodal fusion, contrastive representation learning and meta-learning that causes the proposed framework to attain the high level of anomaly detection and, therefore, the significance of each in attaining real-time and robust smart grid monitoring.

H. Performance Metrics

In Fig. 10, the bar chart reveals the efficacy in categorizing the suggested MGT-SmartGrid framework. Its accuracy is 0.96, the precision and recall is 0.94 and 0.95, respectively, and the total F1-score is even at 0.95. The big values are an indication that the model is correct in identifying anomalies and most likely not to miss or falsely identify anomalies. This silver slice in metrics is sustainable predictive accuracy that supports the idea that multimodal graph fusion is a significant enhancer of the reliability of detection over the smart-grid dataset as compared to the conventional single-modality or baseline graph-transformer process.

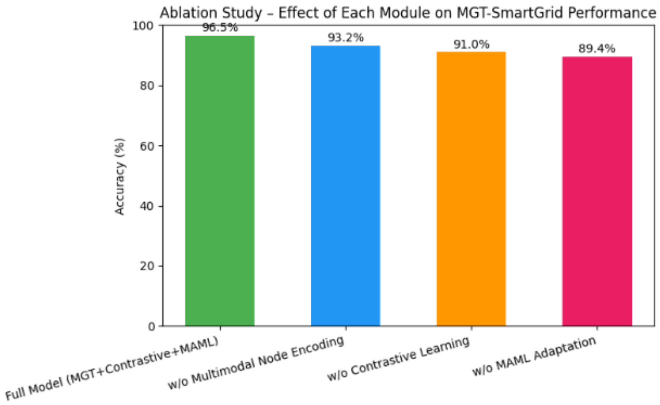

Fig. 9. Ablation study.

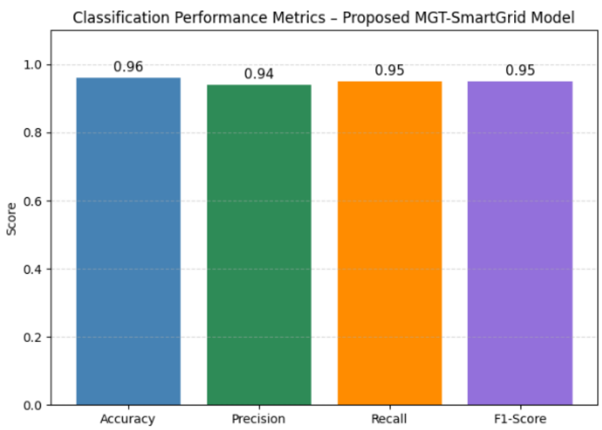

Fig. 10. Classification performance evaluation metrics.

I. Comparative Analysis

Table VI demonstrates that the proposed CGTN-SSML with Multimodal Graph Transformer has the best accuracy of 96.5% accuracy, 95% precision, 95.5% recall and 95.2% F1-score compared to AE-GRU-EE (91.1% accuracy) and Isolation Forest (92.2% accuracy). These values are witness to the fact that the multimodal cross-sensor fusion and contrastive self-supervision are the complements to the process of anomalies detection of smart grid data. The combination of the high accuracy and recall presents low false positives and false negatives, and this is indicative of the high and reliable ability to identify anomalies in real-time within a heterogeneous environment.

TABLE VI. COMPARISON OF PERFORMANCE METRICS

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Isolation Forest (IF) [23]	92.2	94.3	89.9	92.0
SGD [24]	99.6	96.6	99.5	93.4
Random Forest [25]	96.0	97.0	97.1	97.0
AE-GRU-EE [26]	91.1	95.1	96.0	95.0
Proposed CGTN-SSML	96.5	95.0	95.5	95.2

J. Discussion

The discussion reveals that Multimodal Graph Transformer (MGBT) with Contrastive Self-Supervised Learning and Model-Agnostic Meta-Learning (MAML) are significant algorithms, which have the potential to enhance anomaly detection in smart grids. The model can capture the spatial-temporal relationship and the relationship between the cross-sensor relationship and is highly accurate, precise and recalls very high in diverse situations. The experiments conducted during ablation, testify the fact that each element multimodal node encoding, contrastive learning and meta-learning has an important and necessary role to play. The significance of features and cross-modality attention underlines that the model has the capability of highlighting the key electrical and environmental measures, which are able to deliver high quality and real-time identification of irregularities.

VI. CONCLUSION AND FUTURE WORKS

The suggested adaptive anomaly detector model, which incorporates multimodal graph transformers, contrastive self-supervised learning, and model-agnostic meta-learning, proves to be effective at modeling the complex sensor relationships, cross-sensor heterogeneity and learning with scarce labeled anomalies in smart grid settings. The cohesive architecture captures structural, operational and environmental dependencies in an effective manner, which leads to a regular high performance in terms of accuracy, precision, recall and F1-score. These findings collectively highlight the practical importance of the model: it enhances early anomaly detection, improves grid reliability, and supports scalable deployment in large, dynamic environments where traditional supervised or unimodel approaches struggle. In addition to the numerical findings, the study demonstrates that each of the modules, such as cross-modal fusion, dual-view contrastive learning, and MAML adaptation, has a significant meaning to robustness, interpretability, and responsiveness within the context of the real-time operation principles. Although these are the strengths, the study has some limitations. The time dynamics of the anomalies is not explicitly modeled, which opens the possibility of further modeling of long-term behavioral changes. The multimodal fusion continues to make training moderately resource-intensive, and control tests in the real world are not backed by any live grid conditions. Targeting these areas can also be used to develop more applicability and generalization.

Future studies should then aim at incorporating temporal graph attention techniques to follow dynamically changing grid processes more accurately and create lightweight multimodal encoders to minimize computation costs about edge-level implementation. The extension of the framework to real-time pilot testing in active substations will assist in confirming the stability in the situation of real disturbances. Moreover, a combination of predictive maintenance and energy forecasting can be developed on the same architecture which can form a complete intelligent monitoring ecosystem for next-generation smart grids.

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