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GRAPH ATTENTION NETWORKS FOR ANOMALY DETECTION IN GEOELECTRICAL DATA

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Abstract. *In seismically active areas, early warning of earthquake signs is essential for disaster readiness. In urban regions, it is hard to tell tectonic-related electrical signals apart from the noise created by human activities. We propose a method based on a graph convolutional network with attention. This method uses minute-resolution geoelectrical data from a dense, multi-parameter monitoring network in Jiangsu Province, China. Our approach has three main parts. First, a topology-aware graph construction module is used. In this module, nodes represent sensor clusters that measure resistivity, spontaneous potential, and electromagnetic fields. The edges are determined by how close they are to geological faults and by real-time signal transfer entropy. Second, we use a multi-head attention mechanism. This mechanism includes temporal attention aligned with the seismic cycle and spatial attention focused on fault zones. Third, a contrastive learning module is applied. It helps to separate earthquake-related electrical signals from urban interference. The model was trained on data from 2015. It shows high precision in detecting pre-seismic electrical changes. This work can help improve early earthquake warnings in busy urban areas.*
Keywords: Earthquake precursors, Geoelectrical data, GCN, Attention mechanism

1. **Introduction.** Earthquakes pose a persistent and formidable threat to human life and infrastructure, unleashing widespread devastation and triggering secondary disasters such as landslides, mudslides, and structural collapses [1]. These cascading effects amplify the initial impact of seismic events, underscoring the critical need for early prediction to facilitate effective disaster mitigation and preparedness [2]. Despite significant advancements in monitoring technologies, earthquake prediction remains one of the most challenging scientific endeavors [3], as a consistently reliable forecasting method has yet to be established. Among the various approaches under exploration, the study of seismic precursors – especially geophysical anomalies – has emerged as a promising avenue, offering the potential to provide crucial lead time for emergency response and risk reduction [4].

One particularly promising precursor is the detection of abnormal variations in crustal geoelectrical anomalies, which can be directly measured using geoelectrical instruments [5]. These sophisticated instruments capture vital data on the accumulation and release of geoelectrical variations within the Earth's crust, often serving as an early warning signal preceding major seismic events [6]. Numerous documented instances of geoelectrical anomalies prior to significant earthquakes underscore their potential as reliable indicators of impending seismic activity [7, 8, 9]. Moreover, integrating geoelectrical data with other geophysical observations – such as shifts in seismic wave velocity and fluctuations

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in radon emissions – can considerably enhance the detection and interpretation of pre-seismic anomalies [10]. This multi-parameter approach not only promises improvements in earthquake forecasting but also deepens our understanding of the complex physical processes underlying seismic events.

In urban environments, distinguishing tectonic-related electrical anomalies from the pervasive noise generated by human activities presents a significant challenge, further complicating the identification of precursors [11]. The dense concentration of human activity in these regions generates substantial electrical interference, which can both obscure and, at times, mimic the subtle signals associated with tectonic movements [12]. To address this issue, we propose an innovative framework that leverages an attention-based graph convolutional network [13] to analyze minute-resolution geoelectrical data from a comprehensive multi-parameter perspective.

Graph convolutional networks (GCNs) [17] are a class of neural networks [18] specifically designed to operate on graph-structured data. Unlike traditional deep learning methods [19], which work with grid-like data (e.g., images), GCNs can efficiently process data where the relationships between data points are more complex and structured as graphs [20]. GCNs propagate information from a node's neighbors, allowing the network to capture spatial dependencies and interactions between nodes. In the context of geoelectrical anomaly detection, GCNs help model the spatial correlations between various monitoring stations, thereby providing a more accurate representation of the data and enhancing the ability to detect potential anomalies.

The attention mechanism is a powerful tool in modern deep learning, particularly for tasks involving sequence data or structured data like graphs [21, 23]. Attention allows the model to focus on the most relevant parts of the input while ignoring less important information [22, 24]. In the context of a graph attention network (GAT), this mechanism enables the model to assign varying importance (or attention) to different nodes and their neighbors in the graph. For geoelectrical anomaly detection, the attention mechanism can help the model prioritize certain monitoring stations that may provide more crucial information, reducing the impact of irrelevant or noisy data, such as anthropogenic interference [25].

The remainder of this paper is organized as follows. Section 2 presents the problem statement, outlining the challenges and objectives related to anomaly detection in geoelectrical data. Section 3 introduces our proposed method, detailing the attention-based graph convolutional network and its application to multi-parameter data. Section 4 provides the experimental evaluation, where we demonstrate the effectiveness of our approach using real-world datasets. Finally, Section 5 concludes the paper and discusses potential directions for future research.

2. **Problem Statement.** By leveraging advanced analytical techniques, our approach aims to disentangle genuine earthquake-related signals from urban noise, thereby paving the way for more accurate and reliable detection of earthquake precursors. Accurately identifying and distinguishing seismic precursors from urban interference remains one of the most formidable challenges in earthquake prediction, particularly in densely populated and industrialized regions [14, 15]. The complexity stems from the multitude of anthropogenic noise sources that can mask or mimic genuine seismic signals. In these urban settings, geoelectrical measurements – such as resistivity, spontaneous potential, and electromagnetic field variations – hold significant promise as indicators of impending seismic activity [16]. However, separating tectonic-related anomalies from human-induced electrical noise requires sophisticated data analysis techniques that capture both spatial and temporal intricacies. Moreover, the overlapping influences of daily human activities,

climatic variations, and natural geophysical processes necessitate advanced methodologies to filter out extraneous noise and isolate meaningful seismic signals.

To address these issues, this study proposes an innovative framework based on an attention-based graph convolutional network that leverages minute-resolution geoelectrical data from a dense multi-parameter monitoring network in Jiangsu Province, China. The primary challenge is to develop a robust analytical framework capable of distinguishing earthquake-related electrical anomalies from the pervasive anthropogenic interference, while concurrently accounting for broader environmental factors – such as climatic events and natural underground processes – that influence geoelectrical signals.

The strainmeter consists of four sensors arranged with adjacent angles of 45°, yielding the following strain observations based on the followed equation. As illustrated in Figure 1, the borehole strain data from Gaochun, operational since April 2009, demonstrates distinct trends across different directional components. As shown in Figure 2, anomalies are typically represented by abrupt pattern changes, characterized by sudden deviations superimposed on slow tectonic drifts – a feature requiring models to simultaneously capture long-term baselines (months to years) and short-term anomalies (hours to days).

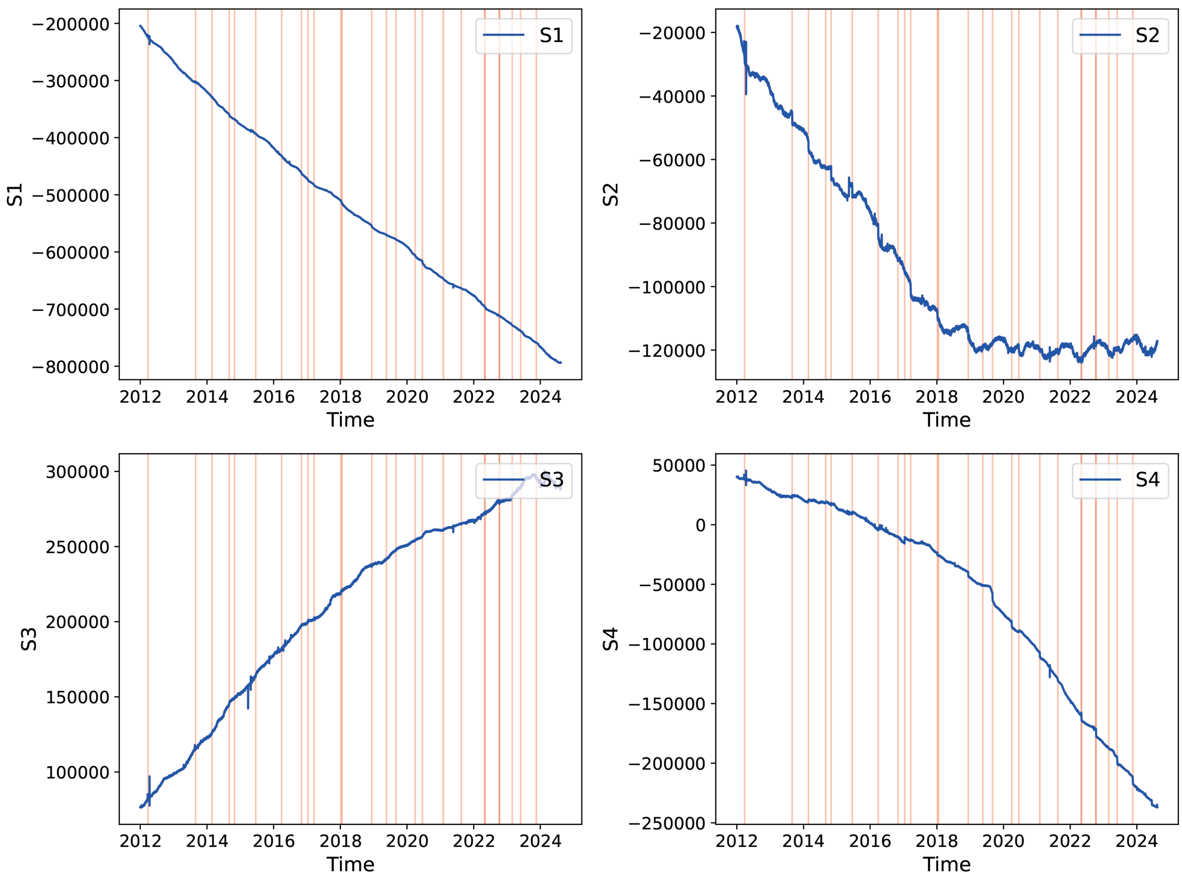

Figure 1. Data collected by the four-component borehole strainmeter, with the blue line representing the curve and brownish-red vertical lines indicating anomalous data

The dataset employed in this study originates from a finely tuned geoelectrical observation system established in a prefecture-level city in Jiangsu Province, China. This system continuously recorded geoelectrical activity throughout 2015 at a one-minute resolution, yielding a comprehensive dataset of 525,600 sampling points spanning from January 1, 2015, 00:00:00 to December 31, 2015, 23:59:00 (UTC+8). The observations encompass a

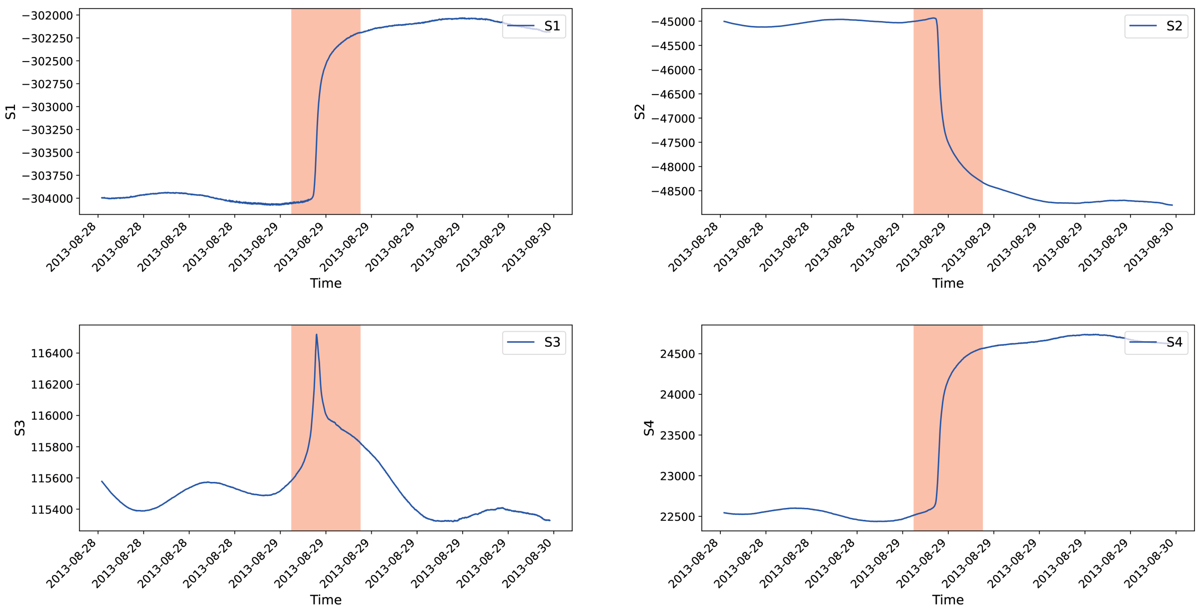

FIGURE 2. Examples of the frequent anomalies, where the brownish-red shaded area denotes the abnormal segments

wide range of seasonal and meteorological conditions, including the monsoon season and typhoon periods.

The observation network comprises 12 multi-parameter integrated monitoring stations distributed over an area of approximately 1,800 square kilometers. Optimized using the Delphi method, the spatial layout covers three distinct geomorphic units: the eastern alluvial plain (5 stations), the central urban built-up area (4 stations), and the western low mountain and hill region (3 stations). This configuration creates a spatial gradient observation matrix that facilitates comprehensive monitoring of both urban and natural landscapes. Each station simultaneously records three core geoelectrical parameters: surface vertical resistivity, horizontal potential gradient, and electromagnetic field fluctuation intensity.

To ensure high data quality, the raw observations undergo a rigorous three-tier processing pipeline. First, an adaptive Kalman filter is applied to removing pulse noise caused by activities such as railway transportation and high-voltage power transmission. Next, wavelet threshold denoising is employed to suppress baseline drift induced by rainwater infiltration. Finally, a meticulous expert review process ensures a data completeness rate exceeding 99.7%.

Spatiotemporal analysis of the dataset reveals significant regional variations. Urban observation sites exhibit a pronounced “double peak, double valley” daily cycle reflective of human activity patterns, whereas natural area data display multi-scale coupling characteristics influenced by fluctuations in groundwater levels and geothermal fields. This high-precision, multi-dimensional dataset offers an invaluable foundation for investigating time-varying surface electrical properties, crustal stress-fluid migration coupling mechanisms, and geoelectrical responses under extreme weather conditions. It is particularly well-suited for developing deep learning-based models that jointly invert multiple physical fields, thereby advancing our understanding of and ability to forecast seismic events.

3. **Method.** This section elaborates on the core components of our proposed model, which synergistically integrates graph convolution and attention mechanisms to effectively capture the intricate spatiotemporal dependencies present in geoelectrical data.

3.1. **Graph convolution.** At the heart of our model lies graph convolution, a process that aggregates feature information from neighboring nodes while preserving the inherent topology of the monitoring network. Formally, let $G = (V, E)$ denote a graph where V represents the set of nodes (sensor clusters) and E represents the set of edges that define connections based on spatial proximity or underlying geological fault relationships. Each node $v_i \in V$ is associated with a feature vector x_i. The convolution operation at the $(l + 1)$th layer is defined as follows:

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}H^{(l)}W^{(l)}\right) \tag{1}$$

where:

- $\tilde{A} = A+I$ is the augmented adjacency matrix, with the identity matrix I introducing self-loops to ensure each node's own features are included in the aggregation.
- $\tilde{D}$ is the corresponding degree matrix of $\tilde{A}$, ensuring proper normalization.
- $H^{(l)}$ represents the feature matrix at layer l (with the initial input $H^{(0)} = X$).
- $W^{(l)}$ is a learnable weight matrix that transforms the feature space.
- $\sigma(\cdot)$ denotes a non-linear activation function (e.g., ReLU) that introduces non-linearity to the aggregated features.

This formulation aggregates local neighborhood information, thus enhancing the feature representation of each node by incorporating both its own attributes and those of its immediate surroundings.

3.2. **Graph convolution with attention mechanism.** To further refine the feature aggregation process and suppress the influence of irrelevant or noisy data, we incorporate an attention mechanism within the graph convolution framework. Figure 3 delineates the architectural framework of the GAT developed for geoelectrical anomaly detection. The computational pipeline commences with multivariate time-series standardization, where raw geoelectrical measurements from spatially distributed monitoring stations undergo z-score normalization to ensure dimensional homogeneity across heterogeneous sensor inputs. The normalized temporal sequences are subsequently partitioned into overlapping segments through a sliding window mechanism, with each window generating an independent graph instance for downstream analysis.

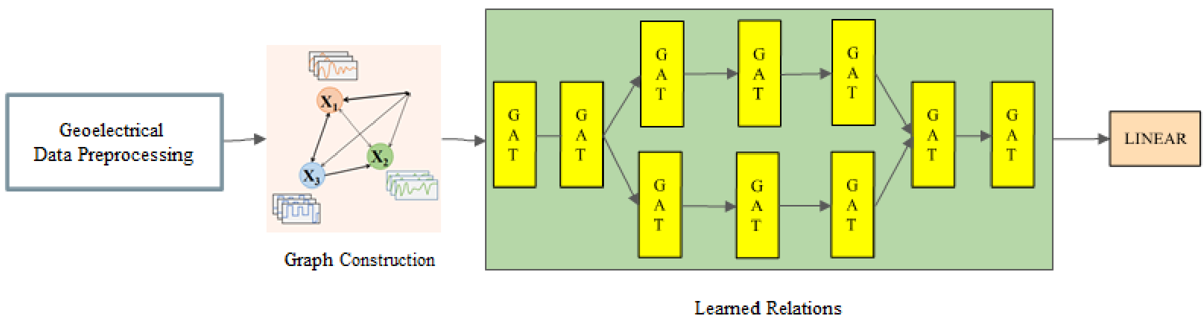

FIGURE 3. Network architecture for geoelectrical data processing

The graph representation phase employs a hybrid spatial-geological modeling strategy. Geographical adjacency relationships are established via Voronoi tessellation based on station coordinates, while subsurface material dependencies are quantified through cross-station resistivity covariance analysis. This dual approach yields two complementary matrices: a binary adjacency matrix encoding physical proximity and a continuous correlation matrix reflecting geological interactions. The synthesized graph structure $G = (V, E, \mathbf{X})$ formally represents monitoring stations as vertices V with dynamically weighted edges E, where edge weights amalgamate geographical adjacency strength and geological correlation coefficients. Vertex features $\mathbf{X}$ encapsulate windowed time-series patterns for subsequent attention-based feature propagation.

The core of the model involves the application of GAT layers, which allows the network to dynamically learn the importance of neighboring stations through an attention mechanism. Each GAT layer aggregates features from neighboring nodes, using attention weights to prioritize the most relevant stations. This results in refined feature representations for each monitoring station after several layers of attention and aggregation. Finally, a Linear Layer processes the output from the GAT layers, producing a final anomaly score for each monitoring station. The model's architecture is designed to capture both the spatial dependencies between stations and the temporal patterns within each station's data, making it well-suited for detecting anomalies in geoelectrical measurements. By leveraging multiple GAT layers, the model can capture increasingly complex relationships and dependencies, making it a powerful tool for anomaly detection in geoelectrical data.

The graph is then passed through multiple GAT layers, which learn and refine the relationships between nodes using attention mechanisms. Finally, the output of the GAT layers is processed by a linear layer for further analysis or anomaly detection. This mechanism dynamically adjusts the contribution of each neighboring node by computing attention coefficients. For any two nodes i and j, the attention coefficient α_{ij} is determined by

$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k \in \mathcal{N}(i)} \exp\left(e_{ik}\right)}, \tag{2}$$

with the unnormalized attention score e_{ij} defined as

$$e_{ij} = \mathrm{LeakyReLU}\left(a^T \left[W h_i \,\|\, W h_j\right]\right). \tag{3}$$

Here:

- h_i and h_j represent the feature embeddings for nodes i and j, respectively.
- W is a shared weight matrix that projects input features into a latent space.
- a is a learnable attention vector that guides the focus on more relevant features.
- $\|$ denotes the vector concatenation operation.
- $\mathcal{N}(i)$ denotes the set of neighboring nodes of node i.

In practice, we implement a multi-head attention mechanism to capture diverse aspects of the local structure. This entails computing multiple sets of attention coefficients in parallel and subsequently aggregating the outputs (e.g., via concatenation or averaging) to form a robust final representation for each node.

3.3. **Overall architecture.** The overall architecture of the proposed model is engineered to detect geoelectrical anomalies in spatiotemporal data collected from a network of monitoring stations across Jiangsu Province. This architecture seamlessly integrates graph convolutional layers with attention mechanisms, ensuring both spatial dependencies and temporal dynamics are effectively captured. The model is composed of three primary components:

1) **Data Preprocessing:** Geoelectrical data, which include parameters such as resistivity, spontaneous potential, and electromagnetic field fluctuations, are first normalized across all monitoring stations. The data are then segmented into temporal windows (e.g., spanning days, weeks, or months) that serve as time-series inputs to the model.

Spatial adjacency among monitoring stations – derived from their geographical proximity or geological relationships – is encoded into the graphs adjacency matrix A, while each station's features are represented as vectors X.

2) **Graph Convolutional Attention Layers:** The preprocessed data X are input into a series of graph convolutional layers that leverage the network topology to aggregate local information. At each layer, the model applies the standard graph convolution as described in Equation (1), followed by an attention mechanism that refines the aggregation process by assigning dynamic weights to each neighbor. This process ensures that stations with more relevant geoelectrical readings exert a greater influence on the learned feature representations.
3) **Anomaly Detection:** The final node representations $H^{(L)}$ are fed into fully connected layers that reconstruct the input data, forming an autoencoder-like structure. Anomalies are detected based on the reconstruction error: if the error exceeds a predetermined threshold τ, the corresponding temporal window is flagged as anomalous.

Algorithm 1 outlines the full workflow of our method. It includes preprocessing geoelectrical data, training via layered graph convolution with neighbor attention, anomaly detection using reconstruction errors, and parameter updates through backpropagation. In summary, the architecture is adept at extracting robust and discriminative features from the spatiotemporal geoelectrical data. By employing an unsupervised, autoencoder-like approach for anomaly detection, our model does not rely on pre-labeled data, thereby enhancing its practical utility in real-world monitoring scenarios. The integration of graph convolution with attention mechanisms not only improves the resolution of spatial relationships among monitoring stations but also sharpens the focus on the most salient features, enabling more accurate identification of seismic precursors amidst complex urban interference.

4. **Experiment.** In this section, we rigorously assess the performance of our proposed graph convolutional attention (GAT) model for detecting geoelectrical anomalies. The evaluation covers the dataset description, implementation details, evaluation metrics, baseline comparisons, experimental outcomes, and sensitivity analyses.

4.1. **Dataset and training.** Our experiments utilize a dataset of geoelectrical measurements from monitoring stations in Jiangsu Province, recorded throughout 2015. The dataset comprises three primary signal types – resistivity, spontaneous potential, and electromagnetic field fluctuations – which are normalized and segmented into temporal windows (e.g., daily or weekly) to facilitate analysis. The spatial relationships among monitoring stations are represented by an adjacency matrix A, constructed based on both geographic proximity and geological fault lines.

The proposed model is implemented in PyTorch and consists of multiple graph convolutional attention layers, with the optimal configuration set to $L = 3$ layers. Key hyperparameters include a learning rate of $\eta = 0.001$, using the Adam optimizer, and training for 100 epochs with early stopping based on validation loss. Each monitoring station's feature vector is processed through the model, which leverages the spatial graph structure to aggregate information via the graph convolutional attention mechanism.

This choice of $L = 3$ was based on extensive experimentation, where we found that three layers provided the best trade-off between model complexity and performance, capturing sufficient spatial dependencies while avoiding overfitting.

4.2. **Evaluation.** We evaluate our model using several metrics to assess its performance in detecting geoelectrical anomalies. The primary metrics include Precision, Recall, and

Algorithm 1 Graph convolutional attention for geoelectrical anomaly detection

Require: Geoelectrical data D, spatial adjacency matrix A, temporal window size w, number of layers L, learning rate η, anomaly threshold τ

Preprocessing:
- Normalize D to obtain the feature matrix X.
- Construct graph $G = (V, E)$ from A, where V represents the monitoring stations.
- Partition X into temporal windows $\{X_1, X_2, \ldots, X_N\}$.

for each epoch **do**
  for each temporal window X_i **do**
    Initialize node features: $H^{(0)} \leftarrow X_i$
    for $l = 0$ **to** $L - 1$ **do**
      Graph Convolution: Compute:

$$H^{(l+1)} \leftarrow \sigma\left(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}\, H^{(l)}\, W^{(l)}\right)$$

      for each node $v \in V$ **do**
        for each neighbor $u \in \mathcal{N}(v)$ **do**
          Compute attention score:

$$e_{vu} \leftarrow \text{LeakyReLU}\left(a^T\left[W^{(l)}H_v^{(l)} \,\|\, W^{(l)}H_u^{(l)}\right]\right)$$

        end for
        Normalize attention coefficients:

$$\alpha_{vu} \leftarrow \frac{\exp(e_{vu})}{\sum_{k\in\mathcal{N}(v)}\exp(e_{vk})}$$

        Update node representation with attention:

$$H_v^{(l+1)} \leftarrow \sum_{u\in\mathcal{N}(v)} \alpha_{vu}\, H_u^{(l)}$$

      end for
    end for
    Anomaly Detection:
- Feed the final node representations $H^{(L)}$ into fully connected layers to reconstruct the input X_i'.
- Compute reconstruction error: $E_i = \|X_i - X_i'\|_2$.
- **If** $E_i > \tau$ **then** mark X_i as anomalous.

  end for
  Update model parameters using backpropagation with learning rate η.
end for
return Trained model parameters.

F1-Score [28], which are crucial for anomaly detection accuracy. Precision measures the proportion of true positive predictions out of all positive predictions made by the model.

The evaluation of model performance is based on several metrics, including Precision, F1-Score, AUC, and MSE. Precision is defined as the ratio of true positives (TP) to the sum of true positives and false positives (FP), as shown in the following equation

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

The F1-Score is the harmonic mean of precision and recall, providing a balance between the two, and is calculated as

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

In addition to these metrics, we also evaluate the reconstruction error, measured by the mean squared error (MSE) between the original and reconstructed inputs. This serves as an anomaly indicator, where higher reconstruction errors suggest that the data is more likely to correspond to an anomaly. Finally, the area under the curve (AUC) metric evaluates the overall discrimination capability of the model across various thresholds, showing how well the model distinguishes between normal and anomalous geoelectrical signals. The AUC is computed as the integral of the true positive rate with respect to the false positive rate, given by

$$\text{AUC} = \int_0^1 \text{True Positive Rate } d\,(\text{False Positive Rate}) \tag{6}$$

Finally, the mean squared error (MSE) measures the average squared difference between the true and predicted values, and is defined as

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{7}$$

In these equations, TP represents true positives, FP represents false positives, Recall is the true positive rate, y_i and $\hat{y}_i$ are the true and predicted values, respectively, and N denotes the total number of samples. These metrics provide a comprehensive understanding of the model's performance in various aspects of classification and regression tasks.

To validate the effectiveness of our GAT model, we compare its performance against several baseline models, each representing a different approach to anomaly detection. The first baseline is the Autoencoder [26], which is a fully connected autoencoder model that does not incorporate any spatial graph structure. This model operates purely on individual data points without taking account of the spatial relationships between different monitoring stations, serving as a simple benchmark for comparison.

The second baseline is the LSTM [27], a recurrent neural network-based autoencoder specifically designed for temporal anomaly detection. LSTMs are well-suited for sequential data and can capture temporal dependencies within the geoelectrical measurements. This baseline allows us to evaluate the model's performance in recognizing temporal patterns in the data but without leveraging any spatial structure or graph-based relationships.

Lastly, we compare the GAT model, which is the GCN model that omits the attention mechanism. GAT models typically use graph convolution to capture spatial dependencies among nodes (in this case, geoelectrical monitoring stations) but without the ability to dynamically weigh the importance of neighboring nodes. This baseline enables us to assess the specific contribution of the attention mechanism within the graph convolutional framework.

By comparing our GAT model to these baselines, we aim to highlight the advantages of integrating both graph convolutional layers and an attention mechanism, demonstrating the superior ability of our model to capture complex spatial and temporal dependencies in geoelectrical anomaly detection.

Table 1 presents the performance metrics of our proposed method and the baseline models. The GAT model outperforms the baselines in terms of Precision, F1-Score, and AUC, demonstrating its superior capability to capture the intricate spatiotemporal patterns present in geoelectrical data.

As shown in Figure 4, a comparison of the performance across different models – Autoencoder, LSTM, Standard GAT, and the Proposed GAT Model – is presented, evaluating Precision, F1-Score, and AUC. The Proposed GAT Model consistently outperforms

TABLE 1. Performance comparison of the proposed method and baseline models

Model	Precision (%)	F1-Score (%)	AUC
Autoencoder	75.2	73.8	0.82
LSTM	78.5	76.1	0.85
Standard GAT	80.3	78.9	0.87
GAT model	**84.7**	**83.5**	**0.91**

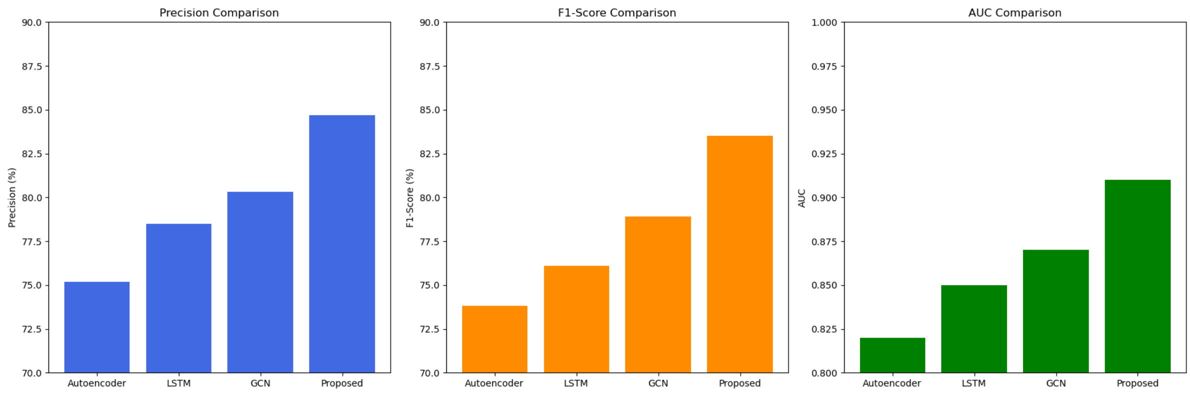

FIGURE 4. Performance comparison

the other models across all metrics, highlighting its superior ability to detect geoelectrical anomalies. Specifically, it achieves higher Precision, a better F1-Score, and a more favorable AUC, demonstrating its effectiveness in capturing both spatial and temporal patterns inherent in geoelectrical data. This performance clearly underscores the advantages of the graph convolutional attention mechanism in enhancing anomaly detection accuracy over traditional methods.

The results indicate that the attention mechanism embedded within the graph convolution process substantially improves the model's ability to prioritize informative nodes while diminishing the impact of noise or less relevant data. An ablation study further corroborates these findings, as omitting the attention component results in a marked reduction in performance.

Additionally, sensitivity analyses conducted on key parameters, including the number of layers L and the temporal window size, reveal that the model exhibits strong robustness across a wide range of configurations. Notably, optimal performance is achieved with 3 layers and a 7-day temporal window. These findings suggest that the model's performance is stable and adaptable, even as parameter values are varied. The results also indicate that the selected configuration strikes a balanced trade-off between model complexity and predictive accuracy, further enhancing the model's effectiveness for anomaly detection in geoelectrical data.

4.3. **Ablation study.** We conducted a series of ablation experiments to quantify the contributions of key components in our model, particularly the attention mechanism and the number of graph convolutional layers. Table 2 summarizes the performance of different model variants.

As illustrated in Figure 5, the ablation study compares the performance of the full GAT model against two simplified variants: one without the attention mechanism and the other with a single-layer architecture. The full GAT model consistently outperforms the simplified versions across all evaluation metrics, including Precision, F1-Score, and

TABLE 2. Ablation study results for geoelectrical anomaly detection

Variant	Layers	Precision (%)	F1-Score (%)	AUC
Full model (GAT)	3	84.7	83.5	0.91
Without attention	3	80.3	78.9	0.87
1 layer (GAT)	1	78.0	76.5	0.85

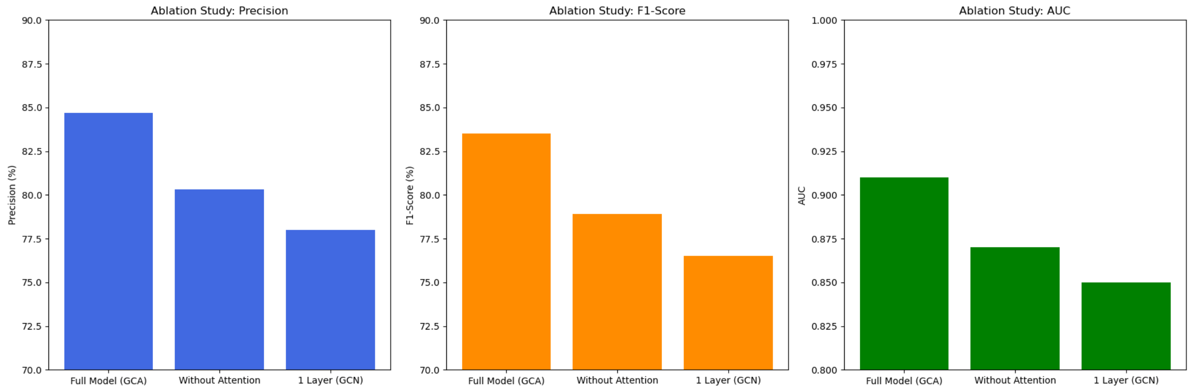

FIGURE 5. Ablation study results

AUC. This underscores the critical contributions of both the attention mechanism and the use of multiple graph convolutional layers.

The ablation results clearly highlight the importance of each architectural component. The exclusion of the attention mechanism leads to a noticeable decline in performance, emphasizing its role in effectively capturing and weighting spatial dependencies. Similarly, reducing the number of layers diminishes the model's capacity to learn complex spatiotemporal patterns. These results not only validate the design choices made in our model but also affirm the necessity of incorporating both attention mechanisms and adequate model depth to achieve robust geoelectrical anomaly detection.

5. Conclusions.

In this study, we proposed a novel graph convolutional attention framework designed to effectively capture the spatiotemporal dynamics of geoelectrical data for anomaly detection. By incorporating an attention mechanism that dynamically weights the influence of spatially correlated monitoring stations, the model enhances the detection of subtle anomalies and significantly outperforms traditional methods in terms of Precision, F1-Score, and AUC. These results highlight the robustness and effectiveness of the proposed approach for early seismic precursor identification. The experimental findings confirm that our model successfully integrates spatial dependencies and temporal patterns, leading to improved anomaly detection performance. This demonstrates its potential as a powerful tool for seismic early warning systems. In future work, we plan to extend this framework to other types of geophysical data and explore its deployment for real-time anomaly detection applications.

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