Learning Topological Consistency in Access Networks Using Graph Neural Networks for Inventory Anomaly Detection

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Abstract. Accurate detection of anomalies within the Physical Network Inventory (PNI) data set is essential in maintaining the integrity and operational efficiency of access networks. The graph-topology nature of typical telecommunications infrastructure makes Graph Neural Networks (GNN) well suited for modelling spatial dependencies within this type of data. Conventional GNN architectures including GCN, GAT and GraphSAGE lack the capacity to capture sequential patterns that arise along ordered cable routes, limiting their effectiveness in anomaly detection tasks. This study proposes a hybrid neural network architecture that integrates GraphSAGE with LSTM-based aggregation mechanism to jointly learn spatial and sequential representations of PNI cable segments. A synthetically-derived dataset mirroring realistic Fibre to the Premises (FTTP) structures and optical signal variations were used to evaluate the hybrid model. Benchmarking against the three baseline GNNs under comparable experimental conditions, the results demonstrate improvements in F1 score, AUC, and embedding separability. Further, these findings highlight superior discriminative performance in identifying anomalous versus non-anomalous segments.

Keywords: Graph neural networks, anomaly detection, physical network inventory, FTTP

1 Introduction

The increasing global demand for high-capacity broadband services has driven widespread deployment of Fibre to the Premises (FTTP) networks [1]. Optical fibre systems are the backbone of modern telecommunications infrastructure, providing the ability to have both high-speed and low-latency communication. The Physical Network Inventory (PNI) is a vital component in service delivery and serves as authoritative system for recording and tracking essential information about network assets and components including cables, splitters, joints, and ducts, along with their location information and interconnections [2, 3]. It is essential in network planning, maintenance, service provisioning, and fault management, cross-checking between alignment and accuracy between physical infrastructure, operational and service-layer activities.

Despite its vitality, the maintenance of accurate and consistent data within PNI raises key challenges, as many existing systems were designed around legacy record-keeping framework that rely on manual updates and static data entries [3, 4]. As the development of fibre networks continually evolves, additional discrepancies also arise, particularly between documented topology and existing physical deployed infrastructure. Such glaring inaccuracies can have significant negative impacts including inefficient resource utilisation, longer service restoration times, and increased operational costs. Most current PNI systems are predominantly static and lack mechanisms for automated validation, data reconciliation, and topology visualization [3]. This work presents a representative *use case* that demonstrates how artificial intelligence can enhance the reliability and correctness of physical network inventories by integrating physical and logical network information [4]. The focus of the research is on FTTP scenarios, where the PNI maintains a record of the physical infrastructure and a separate telemetry system collects real-time optical measurements and connectivity information. While both datasets are valuable independently, their asynchronous management often results in inconsistencies, for example, cable lengths in the PNI may differ from their measured optical distances, or certain network components may appear in telemetry traces but not in the inventory. These inconsistencies impede fault resolution and efficiency of network provision.

To overcome these drawbacks, this study proposes a hybrid deep learning framework comprising Graph Neural Networks (GNNs) to perform automated anomaly detection within FTTP-based PNI systems [4]. The chosen framework uses a combination of static PNI records with telemetry measurements to reflect with real-world network topology including the actual optical signal behaviour. With the hybrid GNN-based learning process, the model identifies inconsistencies with the cable lengths, missing components or inconsistent connectivity. This creates an automated system that is able to validate the data in the real-world conditions and the design. Although the present use case focuses on FTTP infrastructure, the proposed framework is applicable to wider domains where physical and network records intersect.

The main contributions of this study are summarized as follows:

- A hybrid deep learning framework is proposed that integrates GNN and RNN architectures to detect anomalies and inconsistencies within PNI systems.
- A generalized methodology is outlined that can be replicated across other telecommunications or infrastructure domains where physical and logical representations coexist, promoting adaptable and self-validating inventory systems.
- The feasibility and effectiveness of the proposed model are demonstrated through a prototype implementation using simulated FTTP datasets that replicate real-world operating conditions.

Table 1. Comparison of model capabilities and limitations

Criteria	Graph Neural Network (GNN)	Recurrent Neural Network (RNN)	Hybrid (GNN+RNN)	Refs.
Core strength	Captures spatial dependencies and relationships in graph-structured data	Learns temporal patterns in sequential or time-series data	Integrates spatial and temporal learning for comprehensive modeling	[6, 7]
Primary application	Topology mapping and analysis of network components	Monitoring and forecasting temporal changes in network data	Dynamic tracking of topology evolution with improved accuracy	[7, 8]
Key limitation	High computational cost and scalability challenges in large networks	Limited structural awareness of spatial relationships	Integration complexity and limited existing research	[9, 10]
Telecom potential	Infrastructure mapping, optimization, and fault localization	Network monitoring and performance prediction	Inventory validation and automated resource management	[11]

2 Related Work

The advancement of broadband and optical fibre technologies has intensified the complexity of managing physical infrastructure, driving the need for data-driven approaches to manage the PNI and topology information [2]. While ML techniques such as GNNs and RNNs have demonstrated promise in modelling both graph-structured and sequential network data, the specific application to optical PNI systems remains very limited [12, 13]. In addition, GNNs are useful in automating anomaly detection and topology validation because it is able to capture both spatial and relational dependencies. Pairing GNN with the RNN's ability to learn ordered and timestamped structural variations [13–15], it suggests applicability of hybrid approaches to improve the overall accuracy in PNI management. Thus, recent studies have been exploring AI-assisted methods to verify physical inventory records with the operational network behaviour within FTTP environments, commonly where inconsistencies in the infrastructure records can adversely affect operational efficiency and reliability [2, 3, 12, 13].

GNNs and RNNs have been widely used in modeling modern complex network systems because of the complementary strengths of both models. GNNs are effective in capturing spatial dependencies between interconnected nodes but face considerable limitations in scaling complex or dynamic networks [12, 13, 20]. In contrast, RNNs exhibit great adaptability and generally lower computational costs because it able to model temporal and sequential dependencies effectively within time-series data [23, 24]. Although this is RNNs are generally effective in inventory and monitoring applications, it still lacks the structural awareness that is required in graph-based PNI systems [23, 26]. Therefore, the combination of both GNN and RNN architectures provides the ideal framework for modeling both spatial topology and ordered network dynamics, beneficial for improving the accuracy of the PNI system. Table 1 compares the capabilities and limitations of GNN, RNN, and hybrid GNN–RNN models, illustrating the trade-offs between spatial awareness, temporal modeling, and integration complexity in telecommunications network analysis. GNNs excel at capturing spatial dependencies in graph-structured data, RNNs are effective for modeling temporal dynamics, while hybrid GNN–RNN models combine both spatial and temporal learning to support more comprehensive modeling.

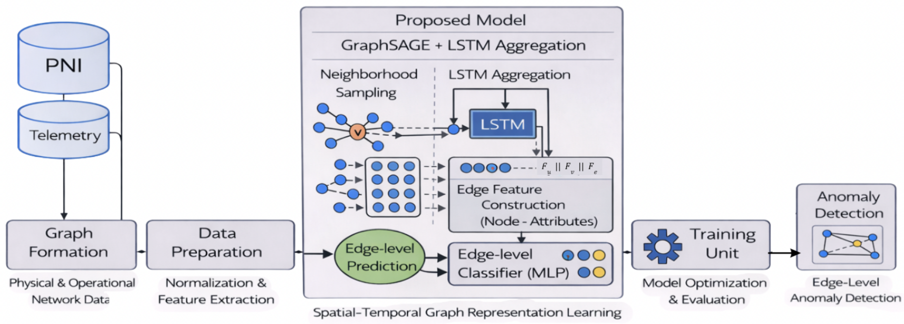

Fig. 1. Overview of proposed hybrid GraphSAGE-LSTM framework.

Research studies analyse the benefits of using hybrid deep learning methods such as the ability to perform both spatial and temporal modeling. Among these studies, the relationship between GNNs and the aggregation of Long Short-Term Memory (LSTM) have shown great potential, specifically in the realm of spatiotemporal anomaly detection tasks [27]. Other types of models and their combinations have also been further researched such as the Graph Convolutional Network-Graph Attention Network (GCN–GAT), which is effective for context-specific anomalies within complex networks [27] and CNN-LSTM which has adequately captured temporal dynamics for anomaly detection [28]. Testing a variety of models confirms the capability of the hybrid frameworks to capture the spatial and temporal features across diverse network types [29, 30]. Although the examples are implemented on traffic and mobility datasets and not specifically within telecommunications networks, it is still highly applicable to the PNI because it reflects similar characteristics. The promising results of previous studies still lack the implementation of the GraphSAGE model and LSTM aggregation in tandem, signifying an important gap in the literature. Through this research, there is potential for advancement within anomaly detection and subsequent performance management in the telecommunications industry.

The most prevalent limitation in the existing implementations of these models is the lack of temporal modeling of GNNs when applied to PNI datasets. Significant examples include Dynamic GNNs and Saptio-Temporal GNNs (STGNNs) which have an improved ability to process continuously changing graph structures but may fail in telecommunications because of its high computation overhead [31]. Because of this, the best results have been received through the use of static GNN formulations. The static model focuses on time-based spatial deficiencies and struggle to detect anomalies with only minor fluctuations or intermittent network behaviour. Another limitation lies in the static aggregation functions (mean, sum, or max-pooling) used by conventional GNNs where the oversimplification of node interactions and reduced sensitivity makes it unable to detect subtle deviations [32]. Both GNNs and RNNs have individually shown success in multiple areas but the application of the combination of the two ML methods have not previously been studied, especially in the case of broadband infrastructure. This research hopes to fill the gap by leveraging strengths of GNNs and RNNs, improving anomaly detection and automate troubleshooting.

3 Proposed Framework

The proposed framework of this research consists of three sequential stages as illustrated in Fig. 1. The first stage integrates the PNI and telemetry datasets into one graph representation which is crucial for data preparation. The second stage describes the ML algorithm (hybrid GNN-RNN model) which learns spatial and ordered-path dependencies through GraphSAGE-based neighbourhood aggregation and LSTM-based sequential processing. The final stage include the training and inference pipeline where the model is optimised and applied to identify anomalous cable segments within the PNI.

3.1 Data Preparation & Feature Extraction

The study utilises two primary datasets: a PNI dataset and a telemetry dataset. The PNI dataset captures the structural attributes of FTTP infrastructure, including cable identifiers, termination points, and segment-level lengths. This dataset adheres to an industry-aligned schema and was developed with support from nbn to ensure alignment with operational PNI practices. The telemetry dataset provides complementary observations derived from active network paths, supplying real-time distance and performance measurements relevant to end-to-end service behaviour. Both datasets were integrated to enable direct comparison between the recorded physical topology and observed operational characteristics. Preprocessing involved normalising key fields, aligning identifiers, and extracting features essential for downstream analysis. While the PNI dataset serves as the primary input for anomaly detection, telemetry records function as an external reference to assess the accuracy of physical inventory data. The resulting unified dataset provides a consistent and structured basis for graph construction and subsequent analytical modelling.

3.2 Graph Structure Representation

The network topology is modelled using a graph based representation, reflecting the inherent structure of access networks composed of interconnected physical elements. In this formulation, each infrastructure component and termination point is represented as a node, while the physical links connecting them are represented as edges. This abstraction enables both structural relationships and segment level attributes to be encoded in a mathematically consistent manner. Formally, each instance is represented as

$$G = (V, E, F_v, F_e) \tag{1}$$

where V denotes the set of nodes corresponding to network elements, E denotes the set of edges representing physical connections, F_v is the node feature matrix containing the attributes of each element, and F_e is the edge feature matrix capturing properties such as segment lengths and route level characteristics. This graph structure provides a suitable foundation for analysing topological behaviour and identifying anomalies within the physical network.

3.3 Proposed Hybrid Model

The proposed *Algorithm 1* adopts a hybrid deep learning architecture that integrates spatial graph-based learning with ordered-sequence modelling. Spatial dependencies within the network topology are captured using a graph convolutional component, while temporal or ordered relationships are modelled through a recurrent aggregation mechanism. Although the input data are not temporally indexed, the LSTM processes the ordered neighbour embeddings to model structural progression among cable paths.

Spatial Aggregation The spatial component uses a GraphSAGE neighbourhood aggregation scheme due to its inductive learning capability, enabling generalisation to previously unseen nodes and local substructures. GraphSAGE generates node embeddings by sampling and aggregating features from neighbouring nodes, thereby preserving the key relational characteristics of underlying PNI topology. This neighbourhood-based aggregation provides a flexible alternative to traditional spectral GNN formulations and supports effective representation learning in heterogeneous network environments.

Temporal Aggregation Long Short-Term Memory (LSTM) units are used to model how aggregate node features continually evolve over sequences. Using LSTM allows for patterns and deviations to be tracked that manifest across ordered observations, including subtle variations in estimated segment lengths within the PNI dataset. Most notably, the LSTM uses ordered topological sequences rather than the classic time-evolving application, modelling the structural progression of cable segments across access paths. Among recurrent neural

Input: Graph $G = (V, E, F_v, F_e)$, edge labels Y_e, learning rate η, number of epochs T

Output: Trained model parameters Θ

1 **for** *epoch* $\leftarrow 1$ **to** T **do**

   `// Node Feature Aggregation`

2   **foreach** $v \in V$ **do**

3   Sample neighborhood $\mathcal{N}(v)$

4   Compute spatial embedding $h_v^{(k)}$

5   **end**

   `// Sequential Modeling`

6   **foreach** $v \in V$ **do**

7   Construct ordered sequence of neighbor embeddings

8   Update node representation $\tilde{h}_v \leftarrow \mathrm{LSTM}(h_v)$

9   **end**

   `// Edge-Level Classification`

10   **foreach** $(u, v) \in E$ **do**

11   Form edge feature vector $z_{uv} \leftarrow [\tilde{h}_u \| \tilde{h}_v \| F_e]$

12   Predict anomaly score $\hat{y}_{uv} \leftarrow \sigma(\mathrm{MLP}(z_{uv}))$

13   **end**

14   Compute binary cross-entropy loss $\mathcal{L}$

15   Update parameters $\Theta \leftarrow \Theta - \eta \nabla_{\Theta} \mathcal{L}$

16 **end**

Algorithm 1: Hybrid GNN–LSTM Training Pipeline for Edge Anomaly Detection

network architectures, LSTM is selected for its ability to retain long-range dependencies while also avoiding vanishing gradient effects, providing a robust mechanism for analysing ordered-path dependencies in FTTP network environments.

In *Algorithm 1*, the training procedure is organised into three sequential phases: Steps 1 to 5 implement node-level spatial aggregation, where each node samples its neighbourhood and computes updated representations, encoding local structural dependencies present in the physical network topology. Steps 6 to 9 introduce ordered-sequence aggregation by processing ordered neighbour embeddings with an LSTM unit. This stage captures sequential dependencies that reflect the ordering of infrastructure elements along access paths, which is critical for interpreting PNI data. Finally, steps 10 to 13 perform edge-level classification by concatenating node embeddings with edge features to determine anomalous segments. The model parameters are optimised in steps 14 and 15 using binary cross-entropy loss. *Algorithm 1* outlines the integrated spatial–temporal learning pipeline used for anomaly detection.

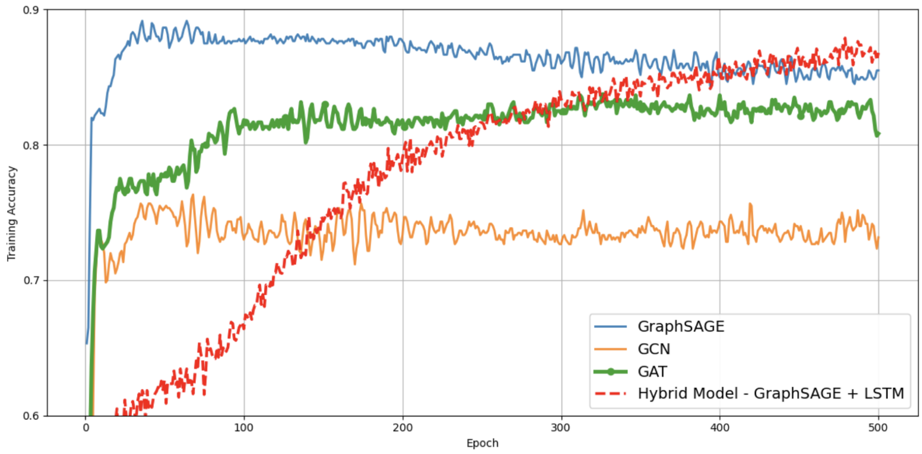

Fig. 2. Training Accuracy across training epochs for baseline and hybrid models.

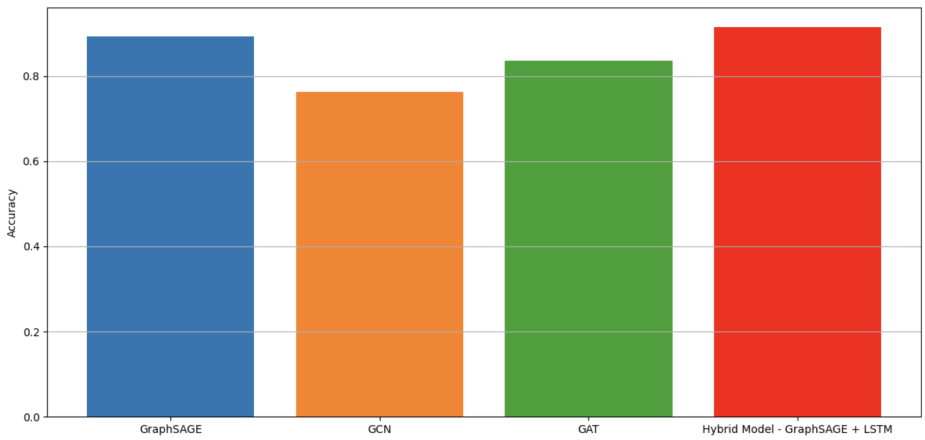

Fig. 3. Final test accuracy for baseline GNN models and proposed hybrid architecture.

4 Experimental Results and Analysis

4.1 Experimental Setup

The experimental framework was designed to evaluate the performance of the proposed hybrid GraphSAGE–LSTM model against three baseline GNN architectures: GCN, GAT and GraphSAGE. The GCN aggregates neighbourhood information through spectral convolution operations, enabling localised feature propagation across graph structures [32]. The GAT extends this approach by applying attention coefficients that weigh the relative importance of neighbouring nodes during aggregation [6]. GraphSAGE, in contrast, adopts an inductive learning framework in which node representations are generated through neighbour sampling and mean aggregation, supporting generalisation to previously unseen substructures [32]. Collectively, these architectures provide a representative baseline for assessing the effectiveness of the hybrid method. The dataset consisted of synthetically generated FTTP cable routes created by combining structural PNI attributes with telemetry-derived distance estimates. The final graph contained 1161 nodes, 2000 edges and 500 cable paths, with anomalous segments comprising approximately 40% of edges. Anomalies were introduced by applying controlled discrepancies between recorded PNI lengths and telemetry measurements. Edges within each path were ordered according to their physical traversal sequence to support LSTM-based aggregation.

Model performance was assessed using accuracy, F1 score, ROC-AUC, confusion matrices and t-SNE visualisations. Accuracy quantifies overall correctness of classified cable lengths while the F1 score describes the harmonic mean of precision and recall. It is particularly important in this study due to its sensitivity to class imbalance between anomalous and non-anomalous segments; high F1 values reflect balanced performance in detecting both classes. ROC-AUC evaluates the model's discriminative capabilities across varying decision thresholds; baseline GNNs exhibit near-chance AUC values due to limited discriminative signal in the synthetic features and the absence of ordered-path modelling. GraphSAGE achieves an overall high ccuracy by exploiting dominant structural cues but lacks ranking robustness across thresholds, leading to low AUC. Confusion matrices and embedding visualisations were used to examine model sensitivity, specificity and latent separability.

Baseline GNN models (GCN, GAT, and GraphSAGE) were trained and evaluated using a stratified 60/20/20 train-validation-test split and optimised for 500 epochs. The proposed GraphSAGE–LSTM model employed the same split ratio but was trained for 1000 epochs to accommodate the additional recurrent parameters introduced by the LSTM-based aggregation mechanism. Prior to training the hybrid model, edge indices were sorted to ensure consistent neighbour ordering, which is required for compatibility with LSTM aggregation. All models were trained using the AdamW optimiser, with learning rates selected per architecture and weight decay set to 1e-6.

Table 2. Performance comparison of baseline GNN models and the proposed hybrid architecture

Model	Accuracy	F1-score	AUC
GCN	0.78	0.41	0.51
GAT	0.81	0.42	0.52
GraphSAGE	0.90	0.45	0.52
GraphSAGE + LSTM (Hybrid)	**0.90**	**0.92**	**0.87**

4.2 Performance Evaluation and Comparative Analysis

This subsection analyses the anomaly detection performance of the proposed GraphSAGE-LSTM hybrid model relative to baseline GNN architectures using complementary quantitative and qualitative evaluation metrics.

The variations and evolution of testing accuracy across training epochs is presented in Fig. 2. The hybrid model exhibits an overall higher accuracy than the GCN, GAT, and GraphSAGE baselines throughout training, which indicates stable optimisation and improved learning dynamics. Although the GraphSAGE model performs comparatively well, the hybrid architecture still demonstrates a clear advantage, suggesting that the incorporation of temporal aggregation improves generalisation. Final test accuracy results shown in Fig. 3 reinforce the stated observations. The hybrid model achieves an accuracy of 0.90, only marginally surpassing the GraphSAGE-only model at 0.892, while significantly outperforming both GCN and GAT. This marginal improvement over GraphSAGE suggests that temporal dependencies in the dataset provide benefit, albeit with limited additional impact on the accuracy metric due to weak temporal variation in the available features.

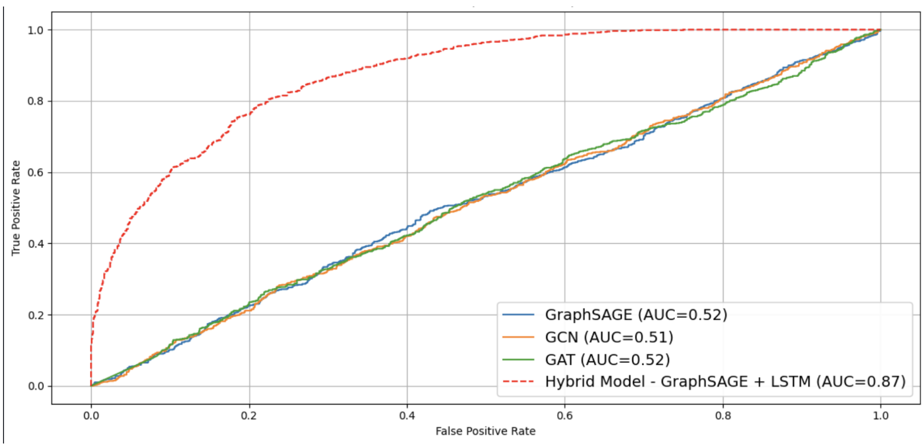

Fig. 4. ROC curves for baseline GNN models and proposed GraphSAGE-LSTM model.

Table 2 summarises and compares the performances between baseline GNN architectures and the proposed hybrid GraphSAGE-LSTM approach. Baseline models struggle to distinguish between anomalous and non-anomalous segments, clearly observed with low F1 scores and AUC values near 0.50. While the GraphSAGE model is able to generalise better than GCN and GAT, it still cannot adequately capture sequential dependencies. This can lead to a limited ability to detect minute changes within the anomaly patterns. By contrast, the hybrid GraphSAGE-LSTM model shows overall better results across all metrics, demonstrating clearer class separation and more reliable anomaly detection. The qualitative differences highlighted in the findings column strengthen the observation that temporal aggregation is essential in capturing the structural-sequential characteristics inherent in PNI cable data. ROC curves in Fig. 4 are used to demon-

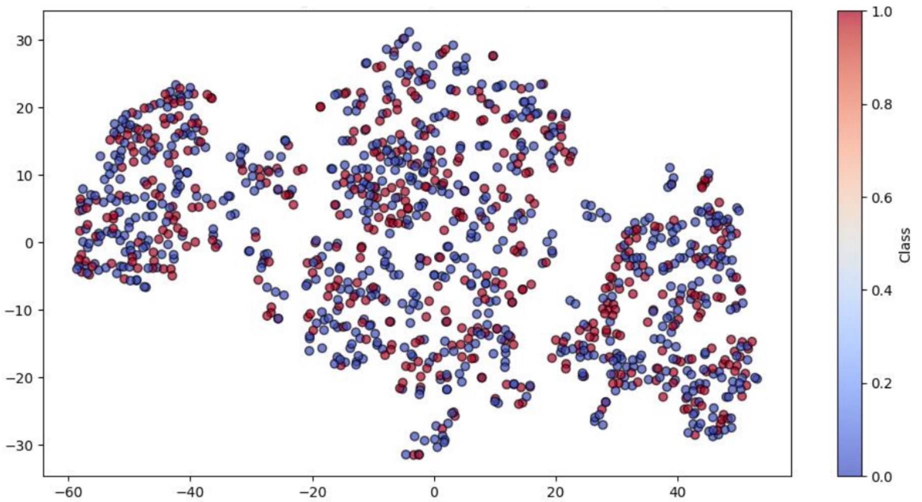

Fig. 5. t-SNE visualisation of node embeddings for the Hybrid Model.

strate discriminative capability in ranking anomalous versus normal edges of the different evaluated models. The hybrid model consistently achieves a higher AUC score at 0.87 compared to traditional baseline models. Strong separation between anomalous and non-anomalous classes across different decision thresholds is suggested by higher AUC values. In contrast, the baseline models all have AUC values near 0.50, reflecting near random behaviour. Although the hybrid model has a relatively smooth curve, there are still minor changes in the slope, likely from sensitivity to minor fluctuations in input patterns.

Although GraphSAGE achieves high accuracy through the exploitation of dominant structural patterns, the low ROC-AUC value indicates limited discriminative ranking capability across decision thresholds. This type of behaviour is expected in scenarios where class imbalance and threshold-sensitive predictions allow strong point-estimate accuracy without robust separation between anomalous and non-anomalous classes. Fig. 5 presents a t=SNE visualisation of the internal feature representation or embeddings produced by the model. There are two dominant clusters in the visualisation, with a partial overlap near the class boundaries representing anomalous and non-anomalous nodes. Distinct clusters demonstrate that the model is successful in encoding meaningful structural and sequential relationships. Misclassified samples generally appear near the cluster boundaries, consistent with the patterns observed in the confusion matrix. The strong cluster separation further supports the enhancements gained through the integration of LSTM-based temporal aggregation.

5 Conclusion

This study has developed a hybrid GraphSAGE-LSTM model and has demonstrated that the proposed model has provided measureable improvements in anomaly detection performance compared to traditional GNN-only architectures. Jointly modelling the spatial structure and sequential dependencies in the hybrid approach addresses the key limitations observed in baseline GCN, GAT, and GraphSAGE models, which often lack the capacity to capture temporal patterns embedded in cable routes. The resulting improvements confirm that incorporating recurrent aggregation enhances class discrimination and strengthens detection reliability. These findings support the viability of hybrid GNN–RNN methods for telecommunications inventory management, where both graph topology and ordered cable sequences play an essential role in anomaly identification.

Future work will focus on extending the evaluation to real-world PNI and telemetry datasets, improving temporal granularity, and addressing overfitting through larger and more diverse training samples. Additional exploration of alternative temporal modules, enhanced regularisation, and deployment in controlled operational settings will further validate generalisability and readiness for real-time network assurance applications.

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