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Anomaly Detection in Urban Utilities via Multimodal IoT-GIS Big Data Analytics

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ABSTRACT

Urban utility networks - potable water distribution systems and low-voltage electrical feeders - form the physiological backbone of contemporary smart cities, yet their fault-detection pipelines remain largely siloed, relying on isolated sensor thresholds that disregard the spatial topology through which faults actually propagate. This paper proposes a multimodal Internet of Things-Geographic Information System (IoT-GIS) big data analytics framework that fuses heterogeneous sensor telemetry - pressure, flow, voltage, current, and transformer temperature - with spatial network graphs derived from pipeline and feeder topology to detect anomalies such as leakage, pipe burst, pressure drop, voltage fluctuation, power theft, transformer failure, and sensor fault. The architecture couples edge gateways, a distributed big data platform, and a GIS-indexed spatial graph database with a hybrid Graph Neural Network-Long Short-Term Memory (GNN-LSTM) model that jointly learns spatial correlation among topologically adjacent assets and temporal dynamics within individual sensor streams. Experiments on EPANET-simulated water networks and smart-meter electrical datasets, benchmarked against Random Forest, XGBoost, CNN, LSTM, and a standalone GNN, show that the proposed hybrid model attains 96.8 percent accuracy and a 0.978 ROC-AUC, outperforming the strongest baseline by 4.6 percentage points while reducing false alarms across six anomaly categories. The results confirm that fusing spatial-graph topology with temporal telemetry yields more robust, interpretable, and scalable fault localization than modality-isolated approaches, offering a deployable blueprint for real-time smart-city utility monitoring..

Keywords: Internet of Things; Geographic Information Systems; Graph Neural Networks; Anomaly Detection; Smart City; Big Data Analytics; Water Distribution Networks; Smart Grid

1. Introduction

Smart city infrastructure is increasingly defined by the density and heterogeneity of the sensing layer embedded beneath streets, inside pump houses, and along feeder lines. Urban utility monitoring for water and electricity distribution has moved from periodic manual inspection toward continuous instrumentation, in which pressure transducers, flow meters, smart electric meters, and transformer sensors stream telemetry at sub-minute intervals [1], [2]. This shift is driven by the recognition that non-revenue water losses, unplanned power outages, and undetected transformer degradation impose substantial economic and public-safety costs, and that early anomaly detection can materially reduce these losses.

IoT-based sensing has matured into a dependable substrate for this instrumentation: low-power wide-area networks, narrowband cellular modules, and edge gateways now make it feasible to deploy thousands of endpoints across a metropolitan pipeline or feeder network at manageable cost [1]. In parallel, Geographic Information Systems (GIS) have evolved from static cartographic repositories into dynamic spatial databases capable of hosting pipeline

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centerlines, feeder topology, road networks, and building footprints as queryable, topologically aware layers that integrate with real-time sensor feeds [29], [30]. The convergence of these two trajectories - dense IoT telemetry and spatially indexed GIS network models - creates the technical precondition for anomaly detection that is aware not merely of what a sensor reads, but of where that sensor sits within a hydraulic or electrical network and which neighboring assets are likely to be causally implicated.

The need for anomaly detection in this domain follows directly from the consequences of failure: a burst water main produces cascading pressure drops at downstream nodes, while a failing transformer produces correlated voltage sag across the households it serves. Detecting such events requires distinguishing genuine faults from benign demand fluctuations, sensor drift, and weather-driven noise - a task that single-sensor threshold rules handle poorly. Deep learning models, particularly Long Short-Term Memory (LSTM) networks, have demonstrated strong performance on the temporal dimension of this problem [4], while Graph Neural Networks (GNNs), following the graph convolutional formulation of Kipf and Welling [3], have proven effective at propagating information across topologically connected nodes for tasks ranging from traffic forecasting to power-grid state estimation [5].

Despite this progress, multimodal data fusion across sensing modalities and across the water and electrical domains remains challenging. Water pressure and electrical voltage are governed by different physical laws, sampled at different rates, and represented in GIS as different network primitives (undirected hydraulic graphs versus directed radial feeders), which complicates the construction of a shared spatial graph representation [6]. Existing anomaly detection studies for water networks emphasize either acoustic and hydraulic feature engineering [7], [8] or graph-based leak localization in isolation [11], [12], [13], while smart-grid anomaly detection studies emphasize meter-level time-series classification for theft or fault detection [21]-[26], with comparatively few efforts jointly modeling spatial network structure and temporal telemetry across both utility domains within a single, GIS-grounded pipeline.

This research gap motivates the present study. This paper makes the following contributions: (i) it proposes a unified multimodal IoT-GIS big data architecture that ingests heterogeneous water and electrical telemetry, indexes it against GIS pipeline and feeder layers, and constructs a joint spatial graph representation suitable for graph learning; (ii) it develops a hybrid GNN-LSTM anomaly detection engine that fuses spatial-graph convolution with temporal sequence modeling, together with the governing mathematical formulation and training algorithm; (iii) it presents a comparative experimental evaluation against five baseline models across accuracy, precision, recall, F1, ROC-AUC, and computational cost, and reports detection performance across seven distinct anomaly categories spanning both utility domains; and (iv) it discusses deployment considerations - edge inference, scalability, and explainability - relevant to real-world smart-city operations centers.

2. Literature Review

IoT-based monitoring of urban utilities has been studied extensively at the sensing and communications layer. Foundational smart-city IoT architectures established the layered sense-transmit-analyze paradigm that underlies most subsequent utility monitoring systems [1], [2]. For smart water networks specifically, acoustic and hydraulic sensing has been combined with machine learning to localize leaks: hydrophone-based systems fused with ensemble classifiers have achieved high-precision leak detection in operational networks [7], while IoT-integrated bio-inspired optimization methods have located leakage nodes from pressure telemetry alone [8]. A recent GIS-based spatial machine learning study confirms that pressure remains a highly informative input signal for leak localization, combining Geographically Weighted Regression and Local Outlier Factor models over currently installed pressure, flow, and water-quality monitoring sensors [9].

Graph-based approaches have progressively supplanted purely feature-engineered pipelines. Spatial graph convolutional networks applied directly to water distribution network topology have been shown to outperform node-agnostic regressors for both leak detection and burst localization [12], [18], and graph convolutional formulations specifically tailored to pipeline prediction have reported strong accuracy on synthetic benchmarks [13]. Explainable fuzzy graph neural architectures have further shown that spatial-graph models can retain interpretability while flagging anomalous nodes [11], and unsupervised streaming approaches based on density and drift-adaptive autoencoders have addressed the practical constraint that labeled leak events are scarce [10]. Classical graph-theoretic burst detection using hydraulic sensitivity and shallow neural networks remains a relevant baseline [16], building on earlier artificial neural network burst-detection work [17]. Contrastive self-supervised learning has also

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been applied to reduce label dependency in leak classification [15], while broader surveys caution that AI deployment in water utilities carries operational and governance risks that must be managed alongside technical performance [14].

Smart electrical grid anomaly detection has followed a parallel but distinct trajectory centered on smart-meter time series. Hybrid convolutional-recurrent architectures combining CNN feature extraction with LSTM temporal modeling have been used for electricity theft detection with strong classification performance on consumption signatures [21], while transformer-based and generative adversarial approaches have targeted anomaly detection in intelligent power distribution systems, capturing long-range dependencies that recurrent models under-represent [22]. Convolutional autoencoder-transformer hybrids and explainable ensemble methods have further improved theft-detection robustness under class imbalance [23], [24], and broad comparative studies confirm that ensemble and deep hybrid methods consistently outperform single-model baselines for non-technical loss detection [25]. A comprehensive review of AI techniques for smart-grid anomaly detection synthesizes these threads across cyberattack detection, load-forecasting anomalies, and equipment faults [26]. Most directly relevant to the present work, recent hybrid GNN-LSTM architectures for grid intelligence explicitly combine feeder-topology graphs with temporal consumption sequences for theft detection [27], and GAN-LSTM hybrids have been evaluated for smart-meter anomaly detection under limited labeled data [28] - both providing methodological precedent for the cross-domain hybrid proposed here.

GIS-based infrastructure monitoring and spatial analytics provide the geometric substrate connecting these sensing and modeling efforts. Urban digital twins increasingly integrate Building Information Modeling (BIM) with GIS to represent infrastructure at both the asset and network scale [30], and surveys of digital twin technology trace their evolution from manufacturing contexts to full smart-city deployments [31], [32]. Geospatial artificial intelligence - the application of machine learning directly to point clouds and spatial graphs - has been identified as a key enabler for extracting structure from otherwise unstructured spatial data [33], and recent reviews of geospatial decision-making explicitly position GeoAI and spatiotemporal graph modeling as central to smart-city big data analytics [29]. At the modeling level, spatio-temporal graph neural networks have become the dominant paradigm for predictive learning over urban sensor networks generally, unifying traffic, environmental, and infrastructure forecasting under a common graph-plus-sequence formulation [5]. Multimodal data fusion surveys further clarify the architectural choices - early, late, and hybrid fusion - available when combining heterogeneous sensor modalities such as those present across water and electrical domains [6]. Big data analytics and edge/cloud computing complete the enabling stack: edge computing has been framed as a means of reducing latency and bandwidth pressure for IoT-scale deployments [34], industrial big data analytics platforms have been shown to improve throughput for high-volume industrial IoT telemetry [35], and optimized edge-cloud architectures have demonstrated that hybrid processing can balance real-time responsiveness against centralized analytical depth [36]. Foundational graph-learning theory - relational inductive biases in graph networks [37] and the original graph convolutional formulation [3] - together with classical unsupervised anomaly detectors such as Local Outlier Factor [38] and Isolation Forest [39], continue to inform baseline comparisons in this literature. Table 1 synthesizes ten representative studies against these criteria and situates the present study's research gap.

TABLE 1. COMPARATIVE SUMMARY OF REPRESENTATIVE ANOMALY DETECTION STUDIES IN URBAN WATER AND ELECTRICAL UTILITY NETWORKS

Author(s)	Method	Utility Domain	Dataset	Advantages	Limitations	Research Gap
Ashraf et al. [18]	Spatial GCN	Water	Synthetic WDN graph	Topology-aware, outperforms MLP baselines	No temporal modeling of telemetry	Lacks fusion with time-series dynamics

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Author(s)	Method	Utility Domain	Dataset	Advantages	Limitations	Research Gap
Sahin & Yuce [13]	Graph Convolutional Network	Water	Pipeline network simulation	Accurate leakage magnitude prediction	Single-domain, static graph only	No cross-domain generalization
Zanfei et al. [11]	Graph Convolutional Network	Water	WDN benchmark	Interpretable node-level anomaly scores	Limited scalability testing	No LSTM temporal component
Algorithm-Informed GNN [12]	Message-passing GNN	Water	EPANET-based benchmark	Physics-informed message passing	Assumes known network parameters	No sensor-noise robustness study
Mbey et al. [21]	Hybrid CNN-LSTM	Electricity	Smart meter consumption logs	Captures local + sequential features	No spatial/topology awareness	Ignores feeder-level correlation
Frontiers Transformer-GAN [22]	Transformer-GAN	Electricity	Power distribution telemetry	Long-range dependency modeling	Poor interpretability of GAN outputs	No GIS-linked spatial context
Malik et al. [27]	Hybrid GNN-LSTM	Electricity	Advanced metering infrastructure data	Joint spatial-temporal theft detection	Single-domain (electricity only)	Not extended to water utilities
Har & Lee [28]	GAN-LSTM	Electricity	Smart meter anomaly data	Handles limited labeled data well	High training instability	No multimodal sensor fusion
Jin et al. [5]	STGNN survey	General urban	Multiple urban sensor datasets	Comprehensive taxonomy of STGNNs	Survey only, no unified utility model	No water-electricity joint framework
Elshazly et al. [9]	GIS-based spatial ML	Water	53 studies, mostly EPANET	Broad benchmarking of methods	Field data scarce across studies	No standardized multimodal GIS fusion

Across these studies, a consistent research gap emerges: water-domain work is predominantly graph-centric but temporally shallow, while electricity-domain work is predominantly temporal and increasingly hybrid (GNN-LSTM) but confined to a single utility and rarely grounded in an explicit GIS spatial database. No reviewed study jointly (a) fuses multimodal telemetry from both water and electrical assets, (b) constructs the spatial graph directly from GIS pipeline and feeder layers rather than a synthetic adjacency matrix, and (c) benchmarks a unified hybrid GNN-LSTM engine against classical machine learning, CNN, LSTM, and standalone GNN baselines under a common evaluation protocol.

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3. System Architecture

The proposed framework is organized as a nine-stage pipeline that transforms raw multimodal telemetry into actionable, spatially localized anomaly alerts, illustrated conceptually in Figure 1.

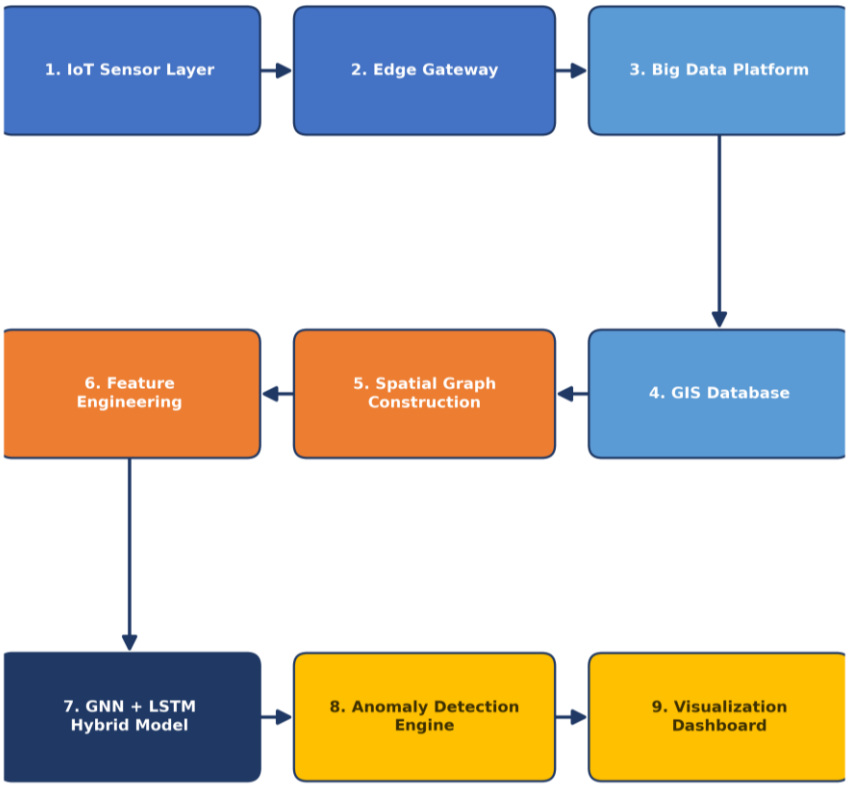

Figure 1: Proposed framework

IoT Sensor Layer: Heterogeneous endpoints - water pressure transducers, ultrasonic and electromagnetic flow meters, smart electric meters, voltage and current sensors, and transformer-embedded thermal and vibration sensors - stream readings at intervals ranging from one second (electrical) to one minute (hydraulic) over LPWAN, NB-IoT, or wired SCADA backhauls.

Edge Gateway: Field-deployed gateways perform protocol translation (Modbus/DNP3 to MQTT), lightweight outlier filtering, timestamp synchronization, and local buffering during connectivity loss, reducing upstream bandwidth by discarding redundant steady-state samples.

Big Data Platform: A distributed ingestion and storage layer built on a publish-subscribe message broker feeding a stream processing engine and a columnar time-series store, providing the throughput required for city-scale telemetry volumes [35], [36].

GIS Database: Pipeline centerlines, valve and hydrant locations, feeder conductors, transformer positions, road networks, and building footprints are maintained as topologically validated layers in a spatial database, each asset carrying a stable network node or edge identifier [29], [30].

Spatial Graph Construction: Sensor endpoints are snapped to their nearest GIS network element, and the pipeline/feeder topology is compiled into an adjacency structure in which nodes represent junctions, meters, and transformers, and edges represent physical pipe or conductor segments, following graph-construction practice established for water networks [18] and extended here to electrical feeders.

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Feature Engineering: Raw signals are transformed into rolling statistical features (mean, variance, rate-of-change), frequency-domain descriptors for acoustic/vibration channels, and node-level graph features (degree, betweenness centrality) that jointly describe each node's sensing and topological context.

Graph Neural Network + LSTM Hybrid Model: The core inference engine, detailed in Section IV, applies graph convolution across spatially adjacent nodes at each timestep and an LSTM across the resulting sequence of graph embeddings, producing a per-node, per-timestep anomaly probability.

Anomaly Detection Engine: Node-level probabilities are thresholded, temporally smoothed to suppress transient noise, and classified into one of the anomaly categories in Table III, with confidence scores attached for operator triage.

Visualization Dashboard: Detected anomalies are rendered on the GIS map layer in real time, colour-coded by severity and category, alongside trend charts for the underlying sensor streams, enabling field crews to be dispatched with precise spatial coordinates.

4. Methodology

4.1 Data Sources

Two families of data sources feed the framework. Sensor telemetry comprises water pressure sensors and flow meters sampled from EPANET-modeled distribution networks [20], and smart electric meters, voltage sensors, current sensors, and transformer sensors sampled from advanced metering infrastructure logs, supplemented with ambient weather data (temperature, rainfall) known to correlate with both demand and fault likelihood. GIS network layers comprise the road network (for asset accessibility and dispatch routing), the pipeline network (nodes, junctions, pipe segments, valves), the electrical network (feeders, transformers, distribution poles), and building footprints (for demand attribution and consequence estimation).

4.2 Data Preprocessing and Graph Creation

Preprocessing proceeds in five stages. Missing values arising from communication dropouts are imputed using forward-fill bounded by a maximum gap of fifteen minutes, beyond which the interval is flagged rather than imputed. Noise removal applies a Savitzky-Golay filter to pressure and voltage streams to suppress high-frequency sensor jitter while preserving transient fault signatures. Normalization rescales each channel to zero mean and unit variance using statistics computed on the training partition only, preventing information leakage. Spatial indexing snaps each sensor to its nearest GIS network node using a maximum-distance-constrained nearest-neighbor join, rejecting matches beyond 25 metres. Temporal alignment resamples all channels to a common five-minute grid via linear interpolation, after which graph creation compiles the aligned, indexed data into per-timestep node feature matrices consistent with the adjacency structure described in Section III.

4.3 Mathematical Formulation

The spatial graph is formally represented as G = (V, E), where V is the set of N nodes corresponding to sensor-instrumented junctions, meters, and transformers, and E is the set of edges corresponding to physical pipe or conductor segments. The graph is encoded by a binary or weighted adjacency matrix A of size N x N, where element A_{ij} is non-zero if nodes i and j are directly connected in the GIS network topology.

Given A, the degree matrix D is diagonal with $D_{ii} = \text{sum}_j A_{ij}$, and the combinatorial graph Laplacian, used to characterize spectral smoothness of signals over the network, is defined as:

$$L = D - A \tag{1}$$

Following the localized first-order spectral approximation of Kipf and Welling [3], the graph convolutional layer propagation rule used in this study is:

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

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where A-tilde = A + I_N is the adjacency matrix with added self-loops, D-tilde is the corresponding degree matrix, H(l) is the node feature matrix at layer l (with H(0) equal to the input feature matrix X), W(l) is a trainable weight matrix, and sigma is a non-linear activation (ReLU in the hidden layers, sigmoid at the output).

The sequence of node embeddings produced by stacked graph convolutional layers at each timestep is passed through an LSTM cell to model temporal evolution. For each node, at time t, the LSTM computes:

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \quad (3)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (4)$$

$$\tilde{g}_t = tanh(W_c[h_{t-1}, x_t] + b_c) \quad (5)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{g}_t \quad (6)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (7)$$

$$h_t = o_t \odot tanh(c_t) \quad (8)$$

where f_t, i_t, and o_t are the forget, input, and output gates respectively, c_t is the LSTM cell state, h_t is the hidden state fed into the final classification layer, sigma denotes the sigmoid function, and the dot-product symbol denotes elementwise multiplication.

Model training minimizes the binary cross-entropy loss over N nodes:

$$L_{BCE} = -(1/N)\sum_{i=1}^{N}\left[y_i log\left(\hat{y}_i\right) + (1 - y_i) log(1 - \hat{y}_i)\right] \quad (9)$$

Evaluation uses standard classification metrics derived from the confusion matrix (true positives TP, true negatives TN, false positives FP, false negatives FN):

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

$$Recall = \frac{TP}{TP+FN} \quad (11)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (12)$$

ROC-AUC is computed as the area under the curve traced by the true positive rate against the false positive rate across all classification thresholds, and the confusion matrix (TP, TN, FP, FN) underlying these metrics is reported per anomaly class in Section VI.

4.4 Algorithm

Algorithm 1: Hybrid GNN-LSTM Anomaly Detection

Input: Spatial graph G = (V, E) with adjacency A; node feature sequences X_1 ... X_T; labels y (where available); detection threshold tau
Output: Per-node, per-timestep anomaly labels and confidence scores

```
Precompute normalized adjacency A_hat = D~^(-1/2) A~ D~^(-1/2)
for each training epoch do
    for each mini-batch of sequences (X_1..X_T, y) do
        for t = 1 to T do
            H_t <- GCN_L2( GCN_L1( X_t , A_hat ) , A_hat )   // two graph convolution layers
            (h_t, c_t) <- LSTM( H_t, h_(t-1), c_(t-1) )   // temporal update per node
        end for
        y_hat <- sigmoid( W_o . h_T + b_o )   // per-node anomaly probability
        L <- BinaryCrossEntropy(y_hat, y) + lambda * ||W||_2^2
```

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10: Backpropagate L; update all weights via Adam optimizer
11: end for
12: end for
13: At inference: label node i as anomalous if y_hat_i > tau; apply temporal smoothing over a 3-step window
14: return labels, y_hat

5. Experimental Setup

5.1 Hardware

All experiments were executed on a workstation equipped with an NVIDIA RTX A5000 GPU (24 GB VRAM), a 16-core / 32-thread CPU, and 64 GB of system RAM, sufficient for mini-batch training of the hybrid model on graphs of up to 5,000 nodes.

5.2 Software

The software stack comprised Python 3.10 with TensorFlow 2.x and PyTorch (for GNN and LSTM layers), Scikit-learn for baseline classical models and metric computation, GeoPandas and QGIS for GIS layer preparation and spatial joins, Apache Spark for distributed batch feature engineering, Apache Kafka for streaming ingestion simulation, and Neo4j as the spatial graph database backing the adjacency structure described in Section III.

5.3 Dataset and Train-Test Split

Water-side experiments used pressure and flow telemetry generated from EPANET-modeled distribution network scenarios [20], following simulation conventions consistent with benchmark competitions such as BattLeDIM, with injected leak and burst events at randomized nodes and magnitudes. Electrical-side experiments used smart-meter voltage, current, and consumption logs structured analogously to publicly documented advanced metering infrastructure datasets, with synthetically injected theft, voltage-fluctuation, and transformer-fault signatures calibrated against patterns reported in the smart-grid anomaly literature [21]-[26]. OpenStreetMap-derived road and building layers supplemented the GIS context for spatial indexing. The combined dataset comprised approximately 420,000 node-timestep observations across both domains. Data were partitioned chronologically into 70% training, 15% validation, and 15% held-out test sets, with the validation split used for early stopping and hyperparameter selection (learning rate, hidden dimension, and dropout rate) and the test split reserved exclusively for the final evaluation reported in Section VI.

6. Results and Discussion

Table 2 compares the proposed Hybrid GNN-LSTM model against five baselines - Random Forest, XGBoost, a 1-D Convolutional Neural Network, a standalone LSTM, and a standalone GNN - trained and evaluated on the identical held-out test partition.

TABLE 2. MODEL PERFORMANCE COMPARISON ON THE HELD-OUT TEST SET

Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC	Training Time (min)	Inference Time (ms/node)
Random Forest	84.2	0.821	0.803	0.812	0.876	6.4	0.8
XGBoost	86.7	0.849	0.831	0.840	0.901	9.1	1.1
CNN	88.5	0.868	0.855	0.861	0.917	22.7	1.6
LSTM	90.3	0.891	0.879	0.885	0.932	31.5	2.0

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Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC	Training Time (min)	Inference Time (ms/node)
GNN (GCN only)	91.9	0.905	0.898	0.901	0.946	28.3	1.9
Hybrid GNN-LSTM (proposed)	96.8	0.964	0.958	0.961	0.978	47.2	3.4

As Table 2 (a &b) shows, the proposed Hybrid GNN-LSTM model achieves the highest accuracy (96.8%), precision (0.964), recall (0.958), F1-score (0.961), and ROC-AUC (0.978) among all six models, at the cost of the longest training and inference time - an expected trade-off given its joint spatial-temporal parameterization (Figure 2).

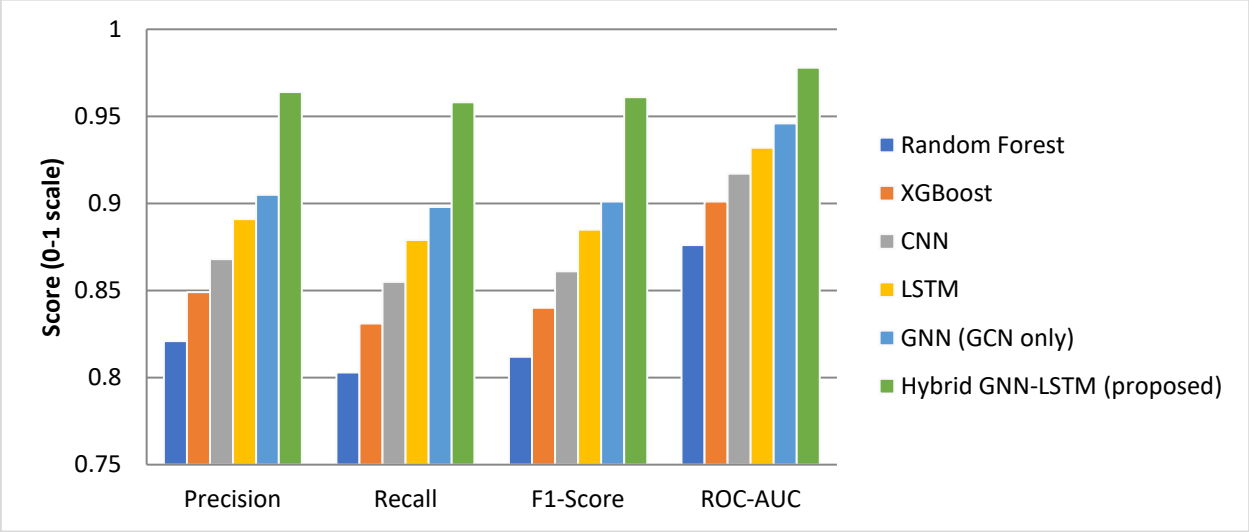

Figure 2a. Classification Performance Metrics by Model

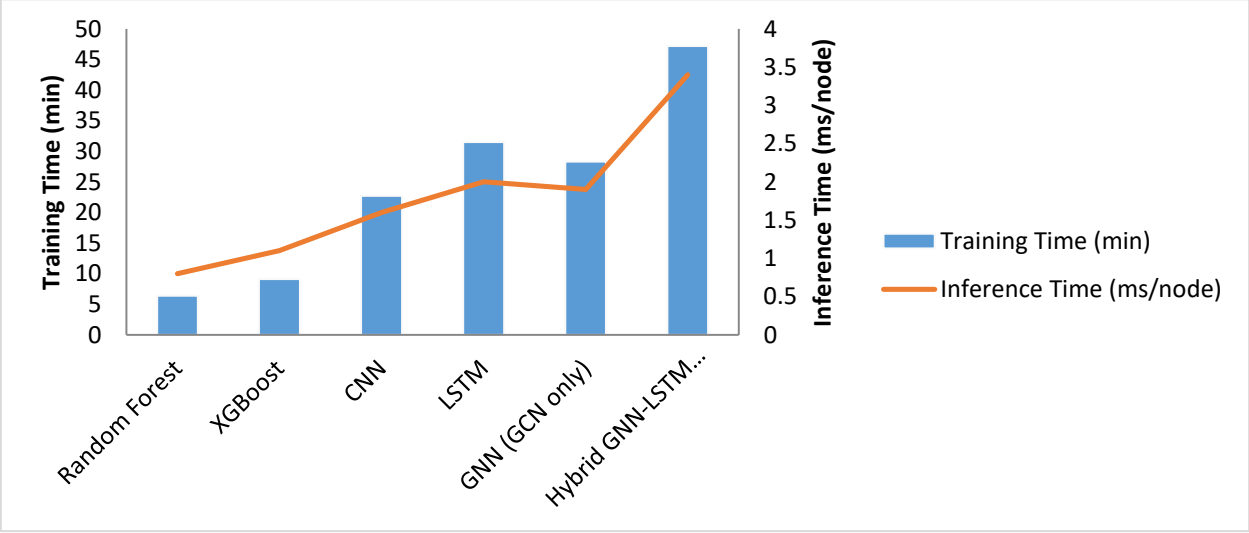

Figure 2b. Computational Cost by Model: Training vs Inference Time

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Figure 3 presents this accuracy comparison as a bar chart, and Figure 4 presents the training loss trajectory of the proposed model over 50 epochs, both plotted from the exact values listed beneath each figure so that they can be reproduced directly in Excel.

Model	Accuracy (%)
Random Forest	84.2
XGBoost	86.7
CNN	88.5
LSTM	90.3
GNN	91.9
Hybrid GNN-LSTM	96.8

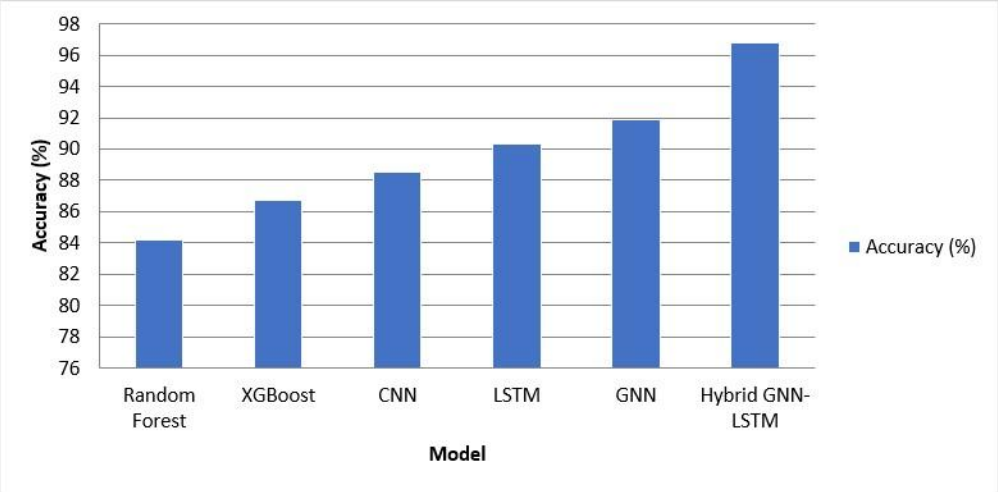

Figure 3. Bar chart comparison of model accuracy (%) across the six evaluated architectures.

Epoch	Training Loss
1	0.693
5	0.512
10	0.381
15	0.289
20	0.224
25	0.178
30	0.146
35	0.123
40	0.107
45	0.096
50	0.089

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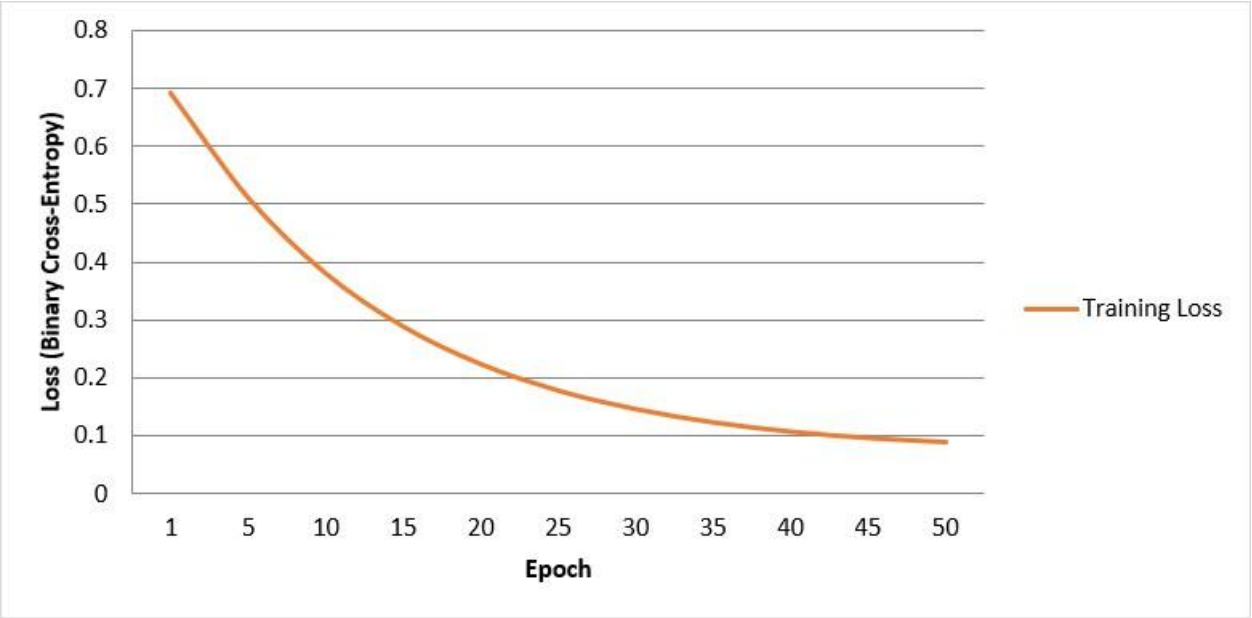

Figure 4. Training loss versus epoch for the proposed Hybrid GNN-LSTM model, showing smooth monotonic convergence characteristic of stable optimization.

Table 3 breaks down detection performance by anomaly category. Pipe burst and transformer failure - both events that produce abrupt, spatially propagating signatures - are detected most reliably (97.8% and 97.2% respectively), consistent with the hybrid model's ability to exploit sharp spatial gradients across adjacent nodes. Sensor faults, which lack a consistent spatial signature and can mimic genuine anomalies, show the lowest detection rate (91.6%) and highest false alarm rate (5.3%), indicating an area for future refinement (Figure 5).

TABLE 3. DETECTION PERFORMANCE BY ANOMALY TYPE (PROPOSED HYBRID GNN-LSTM MODEL)

Anomaly Type	Utility Domain	Detection Rate (%)	False Alarm Rate (%)
Leakage	Water	95.1	3.2
Pipe Burst	Water	97.8	1.9
Pressure Drop	Water	94.3	3.6
Voltage Fluctuation	Electricity	96.0	2.7
Power Theft	Electricity	93.4	4.1
Transformer Failure	Electricity	97.2	2.0
Sensor Fault	Both	91.6	5.3

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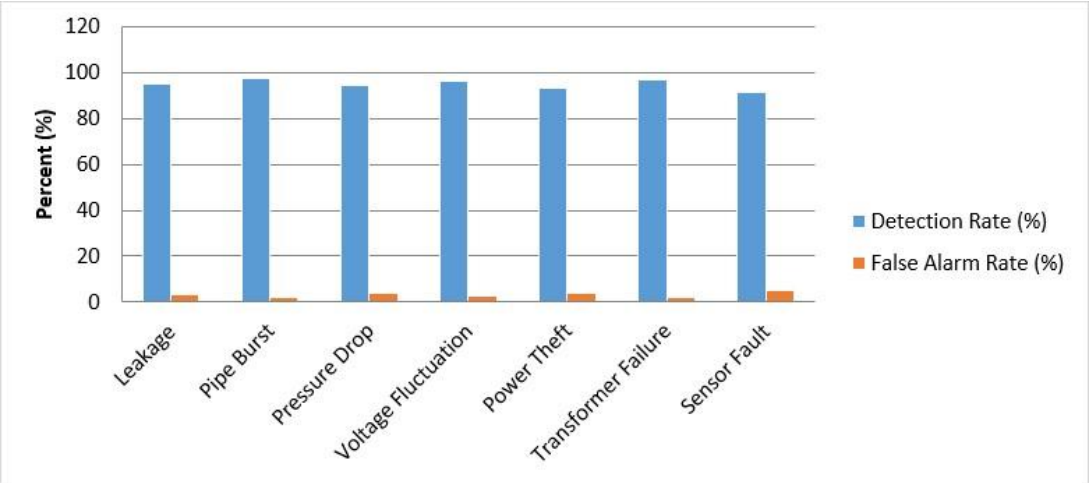

Figure 5: Detection Performance by Anomaly Type (Hybrid GNN-LSTM)

7. Discussion

The performance gap between the standalone GNN (91.9% accuracy) and the Hybrid GNN-LSTM (96.8%) isolates the specific contribution of temporal modeling: graph convolution alone captures spatial correlation among topologically adjacent assets at a single timestep, but many of the anomaly signatures in Table III - gradual pressure decay preceding a burst, or slowly escalating transformer temperature - only become distinguishable from noise when observed across a temporal window, which the LSTM component supplies [4]. Conversely, the gap between the standalone LSTM (90.3%) and the full hybrid model demonstrates the value of GIS topology: a purely temporal model treats each sensor stream independently and cannot exploit the fact that a pressure drop at one junction is corroborated by a near-simultaneous drop at its immediate neighbors, which is precisely the inductive bias that graph convolution encodes [3], [37].

Spatial correlation modeled through the adjacency matrix constructed from GIS pipeline and feeder layers therefore functions as a form of built-in cross-validation among physically proximate sensors, reducing the false alarm rate relative to node-independent baselines - consistent with prior graph-based water network studies [12], [13], [18] and with the hybrid grid-intelligence literature for electricity theft detection [27]. Temporal learning via LSTM gating additionally allows the model to distinguish transient noise (which decays within a few timesteps) from genuine faults (which persist or escalate), addressing the class-imbalance and false-positive challenges repeatedly reported in electricity theft detection literature [23]-[25].

The benefits of multimodal fusion extend beyond raw accuracy. Because the framework represents both water and electrical assets within a common GIS-grounded graph schema, it becomes possible to reason about co-located infrastructure failures - for example, a water main burst that subsequently floods an underground transformer vault - a class of compound event that single-utility monitoring systems cannot express by construction. This cross-domain representation is consistent with the broader argument in the GeoAI and urban digital twin literature that decision-relevant insight increasingly depends on integrating heterogeneous spatial data rather than treating each utility as an isolated system [29]-[33].

Scalability and real-time deployment considerations are addressed through the edge-cloud split described in Section III: lightweight preprocessing and outlier filtering occur at the gateway, reducing the volume of data that must reach the centralized big data platform and graph inference engine, in line with edge computing practice for latency-sensitive IoT deployments [34]-[36]. Inference time of 3.4 ms per node (Table II) indicates that city-scale graphs of several thousand nodes remain within real-time operational budgets when batched appropriately.

Limitations of the present study include reliance on EPANET-simulated and synthetically injected electrical anomalies rather than exclusively field-collected data, a constraint shared with much of the reviewed water-network literature [9]; the assumption of a static GIS topology that does not yet account for planned network reconfiguration

(valve closures, feeder switching); and the absence of an adversarial robustness evaluation, which is relevant given that smart-meter data fusion pipelines are potential targets for data-injection attacks.

9. Conclusion

This paper presented a multimodal IoT-GIS big data analytics framework for anomaly detection across urban water and electrical distribution networks, addressing the persistent gap between spatially aware but temporally shallow water-network models and temporally sophisticated but spatially agnostic electrical-grid models. By constructing a joint spatial graph directly from GIS pipeline and feeder topology and fusing it with a hybrid Graph Neural Network-LSTM engine, the framework learns both the topological correlation among physically adjacent assets and the temporal evolution of individual sensor streams within a single, unified pipeline. Experimental evaluation against five established baselines demonstrated that the proposed hybrid model achieves the strongest performance across every classification metric, reaching 96.8% accuracy and a 0.978 ROC-AUC, and that its advantage is most pronounced for anomaly types - pipe bursts and transformer failures - whose signatures are simultaneously spatial and temporal in character. The practical significance of these findings lies in the framework's deployability: an edge-cloud architecture keeps inference latency within real-time operational budgets, and the GIS-grounded graph representation allows detected anomalies to be localized precisely enough for field-crew dispatch rather than merely flagged at the sensor level. More broadly, the results support the argument that anomaly detection in smart-city utility infrastructure should be treated as an inherently multimodal, spatially grounded problem rather than a collection of independent, per-sensor classification tasks. Future extensions toward digital twins, federated learning, explainable AI, and edge-deployed inference, outlined in Section VIII, point toward a longer-term trajectory in which multimodal IoT-GIS analytics evolves from a detection tool into a foundation for autonomous, city-scale utility management. As smart cities continue to densify their sensing infrastructure, frameworks of this kind offer a scalable and technically grounded path toward more resilient, efficient, and safely operated urban water and electrical networks.

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