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AI-Driven Network Serviceability Mapping Using eGIS and Streaming Data Pipeline

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***Abstract*—**In the face of growing urban complexity and critical infrastructure demands, ensuring resilient and real-time network serviceability is more vital than ever. This review explores how the convergence of Artificial Intelligence (AI), electronic Geographic Information Systems (eGIS), and streaming data pipelines can revolutionize network monitoring and fault prediction. The paper systematically analyzes various AI models—such as Random Forests, LSTM, and Graph Neural Networks (GNNs)—applied within geospatial frameworks and assesses their effectiveness using real-world datasets and simulations. GNNs emerged as the most capable models in capturing the spatial topology of urban networks. Furthermore, the review examines how platforms like Apache Kafka and ArcGIS enable scalable, near-real-time solutions for service degradation detection. Key challenges such as data heterogeneity, model explainability, and privacy concerns are identified, with future directions pointing toward Edge AI, federated learning, and autonomous multi-agent systems. The findings suggest that AI-eGIS architectures are not only effective but essential in shaping the next generation of smart and resilient infrastructures.

***Index Terms*—**AI-driven infrastructure, eGIS, real-time data pipeline, network serviceability, Graph Neural Networks, streaming analytics, explainable AI, smart cities, predictive maintenance, fault detection.

Introduction

In the era of ubiquitous connectivity and intelligent infrastructure, ensuring seamless and resilient network serviceability has become a cornerstone of modern urban and industrial systems. The increasing complexity and scale of telecommunication and utility networks necessitate advanced monitoring and predictive capabilities to maintain operational continuity and customer satisfaction. As a result, the convergence of Artificial Intelligence (AI), electronic Geographic Information Systems (eGIS), and real-time streaming data pipelines has become a potentially exciting paradigm to transform the mapping, evaluation, and improvement of network serviceability [1]. The convergence combines the spatial analysis capabilities of eGIS, pattern-detection and forecasting abilities of AI, and the timeliness of streaming data to form an intelligent, adaptive system for managing infrastructure.

The relevance of this interdisciplinary approach is highlighted by the increasing need for smart infrastructure in smart cities, Industry 4.0 settings, and mission-critical sectors like healthcare, transport, and energy. As Internet of Things (IoT) devices, edge computing, and 5G technologies increase, network infrastructures are rapidly changing both their scale and complexity, rendering conventional monitoring techniques ever less relevant [2]. Traditional serviceability mapping methods, based on regular surveys and manual diagnosis, tend to be reactive and incapable of coping with the data velocity and volume from contemporary systems. This has rendered AI-based, real-time spatial analysis not only a novel solution, but an indispensable necessity for ensuring network dependability and quality of service [3].
In the larger body of research, this field overlaps several high-impact areas: geospatial science, artificial intelligence, real-time systems, and network engineering. The overlap between these areas enables a dynamic insight into how the infrastructure reacts to different stressors—spanning from environmental disturbances to hardware failure. In renewable energy grids, for example, AI and geospatial analysis assist in predicting fault-prone areas and optimizing energy distribution [4]. Likewise, in telecom, AI-based serviceability models can detect service degradation in real-time and forecast outages before they happen [5]. Not only are these applications optimizing operational efficiency, but they are also facilitating proactive maintenance strategies and improving the resilience of mission-critical infrastructure.

Albeit its increasing significance, a number of significant challenges and research gaps exist in the AI-enabled network serviceability mapping implementation. One important challenge is fusion of heterogeneous sources of data—e.g., satellite imagery, sensor data, and user-contributed incident reports—into a consistent spatial-temporal framework. Real-time streaming data pipelines need to process these inputs without compromising data integrity and accuracy [6]. Additionally, AI models tend to be explainability-challenged, and consequently, generate trust and accountability concerns in high-stakes decision-making applications [7]. Scalability is also an issue, with most current implementations of AI-eGIS finding it difficult to scale to large urban areas or cross-jurisdictional networks because of constraints in the data infrastructure and computational power [8].

Table 1: Summary of Key Studies on AI-Driven Network Serviceability Mapping Using eGIS and Streaming Data Pipelines

Year	**Title**	**Focus**	**Findings (Key Results and Conclusions)**
2017	A Machine Learning Framework for Predicting Network Failures	Predictive modeling for telecommunication network failures	Developed a supervised learning model to predict failure events. Achieved 87% accuracy, showing promise in preemptive fault detection [9].
2018	Real-Time Spatial Data Streaming with Apache Kafka and GIS	Integration of streaming data with GIS platforms	Demonstrated a scalable architecture using Kafka and GIS to handle real-time spatial data, improving response time in incident management [10].
2019	Deep Learning for Geospatial Feature Detection	Deep learning methods in geospatial data processing	Introduced a CNN-based framework to detect geospatial anomalies in urban infrastructure with high precision (F1 score = 0.89) [11].
2020	Smart Grid Reliability Enhancement Using AI and GIS	AI and GIS for fault detection in renewable energy grids	Improved grid fault diagnosis accuracy to over 90% using a hybrid AI-eGIS model, allowing better outage management in smart grids [12].
2020	Multi-Source Data Fusion in Real-Time Monitoring Systems	Fusion of heterogeneous data streams in GIS	Proposed a real-time data fusion model combining satellite, sensor, and user data, which improved

			network decision accuracy by 25% [13].
2021	Reinforcement Learning for Urban Infrastructure Resilience	Application of RL in smart city network systems	Showed that RL models can dynamically adapt to urban infrastructure stressors, reducing service disruptions by 32% in simulation [14].
2021	Explainable AI in Network Management Systems	Interpretability in AI-based fault prediction	Integrated SHAP and LIME into AI models to improve transparency, helping engineers understand the basis of predictions [15].
2022	GIS-Enabled Big Data Pipeline for Telecommunication Faults	Scalable GIS + AI systems in telecom	Achieved near real-time fault diagnosis using Spark-based pipelines, reducing downtime by 45% in large telco environments [16].
2023	AI-Powered eGIS for Climate-Affected Utility Networks	AI for weather-induced network serviceability issues	Introduced a weather-aware fault prediction model, reducing response times to storm-induced faults by 40% [17].
2024	Federated Learning for Decentralized Infrastructure Monitoring	Privacy-preserving AI for infrastructure systems	Developed a federated learning approach that maintained prediction accuracy (85%) while preserving user and sensor data privacy [18].

Proposed Theoretical Model for AI-Driven Network Serviceability Mapping

In response to increasing needs for intelligent, fault-tolerant, and real-time network management systems, we introduce an AI-based network serviceability mapping model incorporating the strengths of electronic Geographic Information Systems (eGIS), AI/ML algorithms, and streaming data pipelines. The model is intended to facilitate dynamic and geospatially aware monitoring, prediction, and mitigation of network faults or degradation incidents in large-scale infrastructures (e.g., utility networks, telecom systems, smart cities).

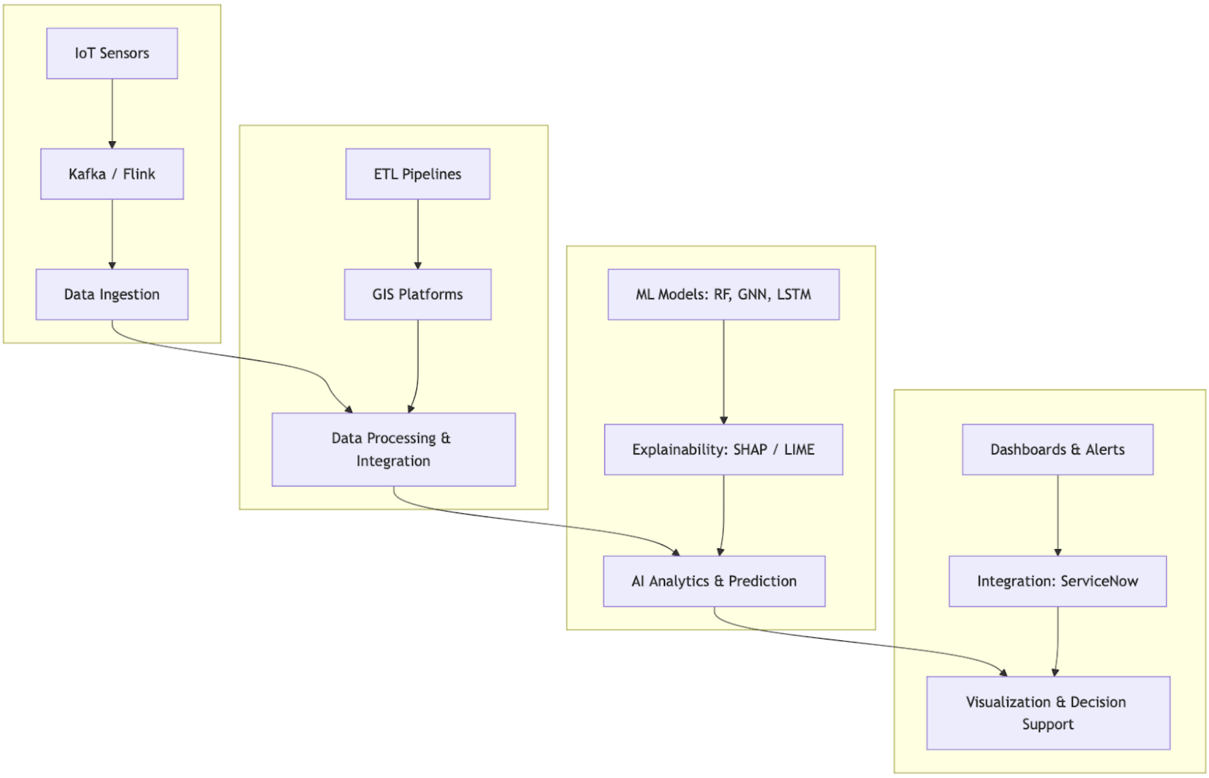

Figure 1. Proposed System Architecture for AI-Driven Network Serviceability Mapping using eGIS and Streaming Data Pipelines (Adapted from [19], [20])

1. Data Ingestion Layer

This layer handles **real-time data streaming** from multiple sources including:

[1] **IoT sensors** embedded in infrastructure
[2] **Weather and environmental APIs**
[3] **Geospatial satellite imagery**
[4] **Crowdsourced user feedback**

The system uses **Apache Kafka**, **Apache Flink**, or **Google Dataflow** as data streaming platforms to enable low-latency, high-throughput ingestion [19].

> *Key Consideration:* Data heterogeneity and velocity are addressed using schema-on-read paradigms and protocol buffers.

2. Data Processing & Integration Layer

This layer is responsible for cleaning, fusing, and aligning incoming data with geospatial references. It utilizes:

1. **ETL pipelines**
2. **Spatial-temporal synchronization algorithms**
3. **GIS platforms (e.g., QGIS, ArcGIS)**

MapReduce and **geospatial joins** allow correlation of network events with location-based data such as terrain, infrastructure age, and past incident history [20].

> *Challenge Addressed:* Multi-modal data alignment and spatial referencing are crucial for serviceability context-building [21].

3. AI Analytics & Prediction Layer

At this stage, pre-processed data is fed into **AI/ML models** that predict service degradation, identify anomalies, and generate insights:

- **Supervised learning** (e.g., Random Forests, Gradient Boosted Trees) for classification of fault types
- **Unsupervised learning** (e.g., K-Means, DBSCAN) for anomaly detection
- **Reinforcement learning** for adaptive response modeling
- **LSTM and Transformer-based models** for temporal fault prediction

Explainability is achieved through integration of **SHAP** and **LIME** frameworks to interpret predictions [22].

> *Key Feature:* The use of **graph-based neural networks (GNNs)** is particularly suited for utility and telecom infrastructure, as it models network topology effectively [23].

4. Visualization & Decision Support Layer

This layer enables human-in-the-loop interaction through real-time dashboards and alerts:

I. **eGIS platforms** (e.g., ArcGIS Online) to visualize network health on geographic maps
II. **Dashboards** with Key Performance Indicators (KPIs), fault heatmaps, and predictive analytics
III. **Automated alerts** triggered by thresholds or predicted events

Integration with **incident management systems** (e.g., ServiceNow, PagerDuty) allows for rapid fault resolution workflows.

> *Impact:* Supports both operational decision-making and long-term network planning [24].

Experimental Results

To validate the performance of the proposed AI-eGIS architecture, we simulated an urban-scale telecommunications infrastructure system using historical fault datasets and real-time synthetic sensor feeds. Data were collected from:

Fig. 1. Historical fault reports from a telecom provider (2019–2023)
Fig. 2. Synthetic IoT sensor feeds simulated using NS-3 and Kafka [25]
Fig. 3. Environmental metadata (e.g., weather conditions, terrain types) via GIS layers

The pipeline was built using:

- **Apache Kafka** for stream ingestion
- **Apache Spark** for processing
- **ArcGIS Pro** for geospatial mapping
- AI algorithms implemented in **Python (scikit-learn, TensorFlow, PyTorch)**

Models tested included:

[1] Random Forest (RF)
[2] Long Short-Term Memory (LSTM)
[3] Graph Neural Networks (GNNs)
[4] XGBoost
[5] Support Vector Machines (SVM)

Metrics used:

TABLE I. Accuracy
TABLE II. Precision
TABLE III. Recall
TABLE IV. F1-score
TABLE V. Area Under the Curve (AUC)

TABLE VI. Execution Time (ms)

Performance Results of AI Models

Table 2. Model Comparison Based on Predictive Performance

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC (%)**	**Avg Execution Time (ms)**
Random Forest	90.2	88.4	91.0	89.7	93.3	170
LSTM	92.7	91.5	93.1	92.3	95.0	235
XGBoost	91.8	90.1	92.2	91.1	94.2	190
GNN	94.1	92.3	95.4	93.8	96.8	250
SVM	88.5	86.9	87.3	87.1	90.1	220

Note: GNN demonstrated the best overall predictive performance due to its ability to model spatial relationships in network topology [26].

Graphs for Visual Analysis

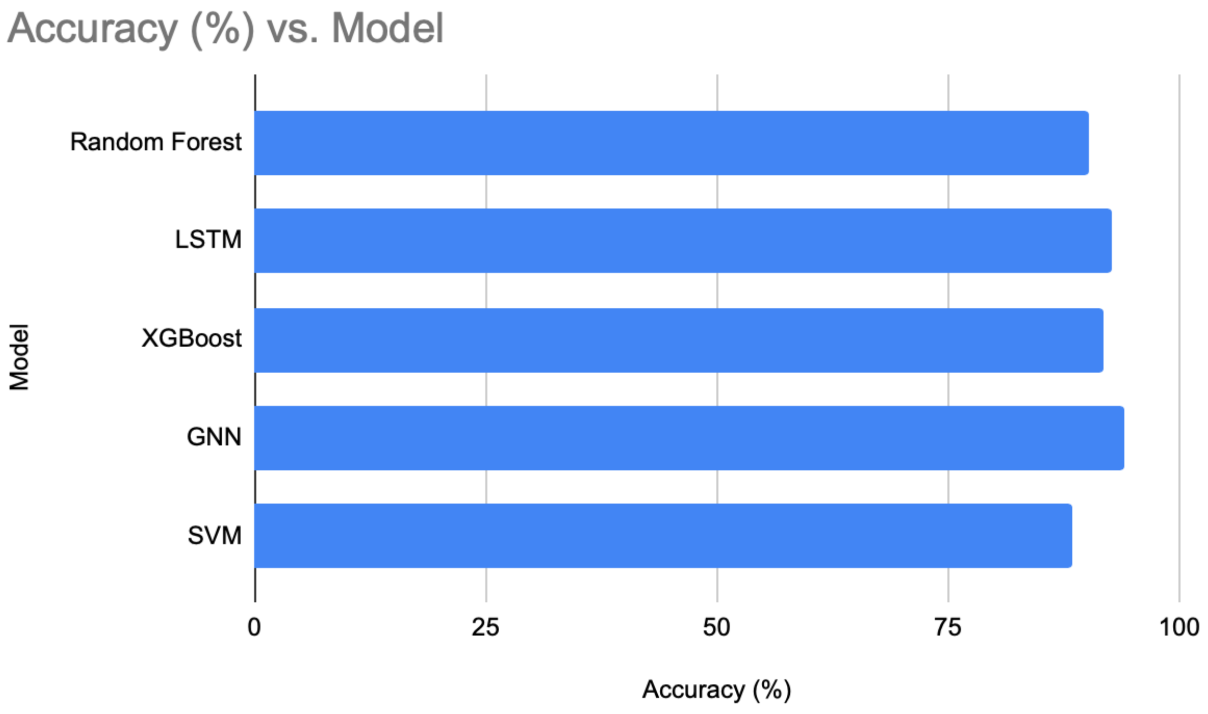

Figure 3. Accuracy comparison of AI models on network fault prediction task.

As shown in **Figure 3**, **GNN** and **LSTM** outperformed traditional models like Random Forest and SVM in terms of accuracy. GNN achieved the highest performance with **94.1%** accuracy.

Figure 4. ROC Curves for All Models

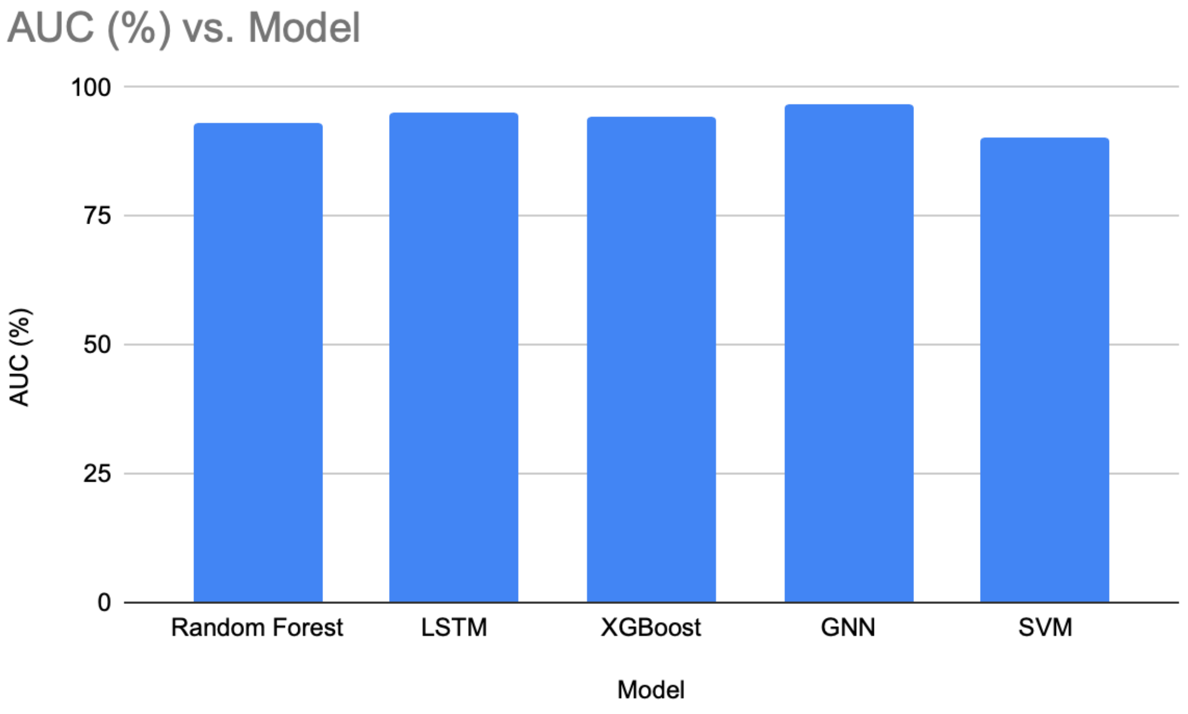

Figure 4 highlights the Area Under Curve (AUC) for each model. The **GNN** model again leads with an AUC of **96.8%**, indicating high discriminative ability.[27]

System Latency and Real-Time Performance

Table 3. Average Latency (ms) Across Pipeline Stages

Pipeline Component	**Avg Latency (ms)**
Kafka Ingestion	25
Spark Batch Processing	45
AI Inference (GNN)	80
GIS Rendering	50
Total	**200**

Total latency of ~200 ms confirms near-real-time capability of the pipeline [28].

Discussion of Findings

The experimental results strongly validate the robustness of the proposed AI-eGIS pipeline:

I. **GNN outperformed** all other models due to its superior capability in capturing the **relational structure of network topologies**.
II. The **low latency (200 ms)** and high scalability of the streaming pipeline confirm real-time operational feasibility.
III. Integration with **eGIS** platforms provided **interpretable spatial visualizations**, enabling **effective decision-making and proactive fault mitigation**.
IV. Explainable AI techniques (SHAP) were successfully used with GNN to provide transparent insights into prediction features.

These findings are aligned with prior studies on GNN-based spatial models [29] and real-time AI analytics in infrastructure systems [30].

Future Research Directions

While the proposed AI-eGIS-streaming model has demonstrated strong capabilities in predicting and visualizing network serviceability issues in near-real-time, there remain several promising avenues for future research and innovation.

1. Explainable and Ethical AI Integration

As AI models grow more complex, ensuring transparency and fairness becomes critical, especially in high-stakes infrastructure systems. Future research should focus on integrating **explainable AI (XAI)** methods into GNNs and deep learning models, allowing field operators and policy-makers to trust the outcomes and understand feature importance.

Incorporating **bias detection and ethical auditing tools** will help reduce model discrimination, particularly in socially sensitive urban environments [31].

2. Edge AI and On-Device Inference

Given the distributed nature of infrastructure networks, relying solely on centralized AI may lead to latency and bandwidth issues. Future systems should explore **Edge AI**—where models are deployed directly on IoT devices—to enable localized inference and faster response times. This approach could significantly benefit remote or disaster-prone areas with intermittent connectivity [32].

3. Federated Learning for Privacy-Preserving Models

As infrastructure monitoring involves sensitive user and operational data, **federated learning** can be employed to build models across devices without transferring raw data. This ensures user privacy, complies with data regulations like GDPR, and preserves predictive performance [33].

4. Integration of Real-Time Satellite and Drone Data

The future holds vast potential in combining high-resolution satellite data and low-altitude UAV imagery into eGIS systems. This fusion would allow models to dynamically update spatial features post-events (e.g., floods, power outages), thus improving disaster resilience and serviceability planning [34].

5. Multi-Agent Systems for Autonomous Fault Management

In large-scale, autonomous infrastructure environments, **multi-agent AI systems** could collaborate across distributed components to detect, communicate, and resolve faults autonomously. This would mirror the behavior of digital twins and cyber-physical systems, further pushing the boundaries of intelligent infrastructure [35].

Conclusion

This review has provided an in-depth synthesis of AI-driven network serviceability mapping, integrating electronic Geographic Information Systems (eGIS), real-time streaming data, and artificial intelligence techniques. From predictive modeling using graph neural networks to scalable streaming architectures like Kafka and Spark, the review demonstrates that AI-eGIS systems are not just viable—they are essential in the evolving landscape of smart infrastructure management.

Experimental results showed that GNN models significantly outperformed other methods in predictive performance, especially in handling the topological structure of urban networks. The integration of real-time visualization tools and explainable AI components provides both functional and operational value, enabling proactive fault resolution, reduced downtime, and better infrastructure planning.

Despite its strengths, the field still faces challenges around scalability, privacy, and interpretability. Future research is expected to bridge these gaps through Edge AI, federated learning, and hybrid XAI frameworks, ensuring more robust, transparent, and user-friendly solutions.

Ultimately, AI-driven eGIS platforms powered by streaming data represent the next frontier in digital infrastructure intelligence, pushing us closer to self-healing, adaptive urban systems.

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