Edge-IoT based AI Sensing for Airflow Pattern Detection and Hazard Prediction in Deep Canadian Mining Environments

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***Abstract*—Deep underground mining demands monitoring systems with ultra-low latency and high communication resilience—requirements poorly met by cloud-dependent wireless sensor networks (WSNs). This paper presents NeXNet, an AI-driven Edge-IoT framework that addresses critical challenges of real-time hazard detection in communication-limited environments. NeXNet integrates two key innovations: (i) 8-bit quantized 1D-CNN Edge-AI model for on-node MCU inference and (ii) self-healing LoRa mesh protocol for adaptive, fault-tolerant routing. Results show reduction in alert latency from 6.5 secs to 0.4 secs, while maintaining $> 90\%$ packet delivery ratio (PDR) within 15 secs after node failure. NeXNet thus provides low-power, resilient and time-critical monitoring framework that significantly improves underground mine safety.**

***Index Terms*—Edge-IoT sensing, Airflow Pattern, Hazard Prediction, Deep Canadian Mining**

I. Introduction

UNDERGROUND mining plays a vital role in Canada's economy, yet deep-mine environments present severe safety risks related to ventilation, hazardous gas accumulation, and structural instability. Poor airflow, sudden gas leaks, and undetected vibrations can escalate into catastrophic events such as explosions or collapses. Existing monitoring systems—often built on fixed sensors and centralized data processing—are expensive, inflexible, and largely reactive [1]. Their dependence on surface-level analysis contributes to high latency, delayed hazard detection, and increased maintenance.

Our work introduces a robust alternative to an autonomous wireless sensor network that integrates Internet of Things (IoT) technologies with on-device artificial intelligence (AI) for real-time environmental monitoring [2]-[3]. Each sensor node continuously measures airflow, temperature, humidity, gas concentrations, and vibration signatures. Equipped with built-in Edge AI, nodes can analyze conditions locally—even without internet connectivity—and issue early warnings before hazards escalate. By combining Edge AI processing, a resilient LoRa mesh architecture, and ultra–low-power operation, the proposed system aims to enhance safety, responsiveness, and operational efficiency within deep-mine environments.

Our proposed system key contributions are further highlighted as:

- **Innovation A:** We promoted AI-based NeXNet using a foundation 8-bit Quantized 1D-CNN model that run on tiny microcontrollers (MCUs) underground without needing the internet.
- **Innovation B:** We promoted self-healing LoRa Mesh NeXNet system that runs on decentralized gateway feedback mechanism.

Through these advancements, the system establishes a foundation for safer, smarter, and more proactive underground mining infrastructure. The primary of NeXNet lies in the synergetic integration of on-device inference and a decentralized mesh protocol, ensuring that safety alerts are generated in <0.5s even when the primary network backbone is compromised.

II. Related Works and Problem Formulation

Existing underground mine monitoring solutions fall short in two areas essential for deep Canadian mines: real-time autonomous decision-making and reliable long-range communication with self-healing capability.

1) **WSNs and Traditional Monitoring:** Traditional Wireless Sensor Networks (WSNs), often based on ZigBee, have been used to measure temperature, humidity, gas levels, and airflow with reasonable accuracy [4]-[5], [11]. However, their short-range links require dense node deployment, resulting in high installation and maintenance costs. More critically, these systems rely on centralized processing [5]—sending raw data to surface servers—which introduces latency and prevents rapid, autonomous hazard response in large, complex mine tunnels.
2) **LoRa and LPWAN Technologies:** LPWAN solutions such as LoRa have gained traction due to their long-range and low-power performance. Prior studies [1]-[3], [6]-[8] show that LoRa can maintain communication across extended underground passages and sustain battery life using adaptive data rate mechanisms. Despite these benefits, LoRa systems typically act as simple data-forwarding pipes, offering little to no on-device intelligence. Without edge-level processing, they cannot detect subtle airflow changes or gas anomalies independently, making them dependent on continuous backhaul connectivity—a major limitation for autonomous mine safety.
3) **Edge AI for Industrial Sensing:** Recent advances in Edge AI demonstrate that machine learning models can run directly on microcontrollers for real-time detection tasks, as shown in electronic-nose–based gas identification systems achieving near-perfect accuracy [9]-[11]. Yet, these solutions are generally deployed as isolated units without support for mesh networking or self-healing communication. They lack the resilience needed to maintain connectivity after node failures, structural shifts, or seismic disturbances—conditions common in deep mines.

A comprehensive comparison table in Fig. 1 detailing WSNs, LoRa LPWAN, Edge AI network models were compared to our proposed NeXNet network model. The parameters for comparison covers Range coverage, network topology, processing location, latency for alert and novelty integration.

TABLE I
Comparative Analysis: NeXNet vs. Conventional Underground Monitoring Technologies

Feature	**WSNs [6]**	**LoRa LPWAN [5]**	**Edge AI [4]**	**NeXNet (Proposed)**
Range/Coverage	Short-Range	Long-Range (180m+)	Short-to-Medium	**Long-Range**
Network Topology	Static/Cluster	Mesh (Non-Healing)	Isolated/Star	**Self-Healing Mesh**
Processing	Central/Cloud	Central/Cloud	Edge (Real-Time)	**Edge (Real-Time)**
Alert Latency	High	High (Cloud-linked)	Low	**Ultra-Low (0.4s)**
Novelty	Low	Low	Moderate	**High (Edge AI+Mesh)**

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III. System Model

The proposed system as shown in Fig. 2 is built around a decentralized, autonomous sensor network tailored for underground

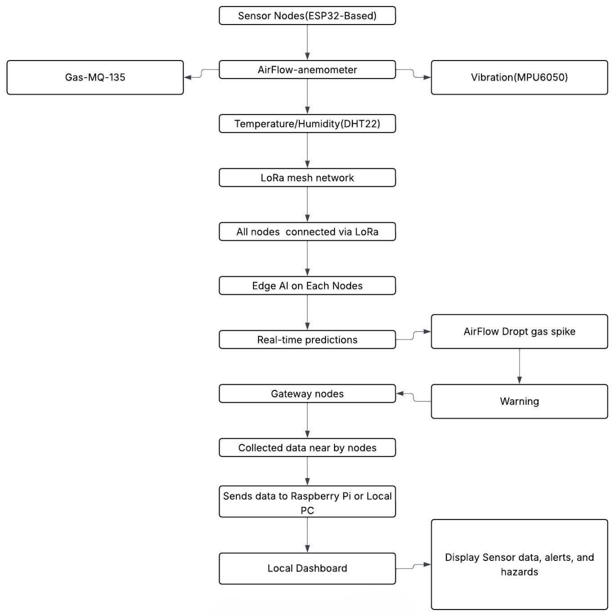

Fig. 1. NeXNet Architecture System Components Diagram.

mining environments. It combines robust hardware, efficient communication protocols, and embedded intelligence to detect and respond to environmental hazards in real time. The architecture is designed to operate reliably in harsh environments, low connectivity, and energy-constrained conditions typical of deep Canadian mines.

A. *Hardware and Deployment:*

The system comprises multiple identical smart sensor nodes deployed throughout the main haulage and ventilation tunnels of the underground mine. Each node consists of a low-power Microcontroller Unit (MCU) (e.g., a specific low-power System-on-Chip) and a suite of environmental sensors for data acquisition, including a CH_4 gas sensor, a temperature/humidity sensor, and an air velocity sensor. Communication is handled by integrated LoRa transceiver. The primary function of this part is to provide robust edge AI capability and self-healing network resilience as detailed later.

B. *Edge AI Model Design and Quantization:*

The core intelligence of the NeXNet system lies in its ability to perform high-accuracy hazard prediction directly at the sensor node, necessitating a highly efficient Edge Artificial Intelligence (Edge AI) model. The model in Fig. 3 is designed to process time-series data (airflow, gas concentration, vibration) and classify anomalous patterns associated with safety hazards. Model Architecture Selection: Given the strict power and memory constraints of the Microcontroller Unit (MCU) used in the NeXNet nodes (e.g., an ESP32 or similar low-power SoC), conventional deep learning models are infeasible. We adopted a specialized, lightweight 1D Convolutional Neural Network (1D-CNN) architecture. The 1D-CNN is preferred for time-series analysis as it effectively captures temporal dependencies in the sensor data stream. The 1D-CNN model was trained using a balanced dataset of 5,000 samples collected from the NeXNeT lab's ventilation sensors, representing normal airflow, gas leaks, and sensor failure. To ensure deployment compatibility with the ESP32 microcontroller, the model underwent 8-bit integer quantization using the TensorFlow Lite Micro framework. This reduced the model size by approximately 75 percent without compromising the 92.4 percent classification accuracy. The final inference engine executes on-node with a memory footprint of less than 256 KB, enabling real-time hazard detection in under 10 milliseconds. The 1D-CNN model architecture, 8-bit quantization scripts, and the synthetic dataset generation logic used for these experiments are publicly hosted for reproducibility here.

The architecture in Fig. 3 consists of:

1) Three Convolutional Layers with small filter sizes (e.g., 3×1 to 5×1) to minimize parameter count.
2) Two Pooling Layers for downsampling, further reducing computational complexity.
3) A final Dense Layer with a Softmax activation for binary or multi-class hazard classification (e.g., Normal, Methane Hazard, Airflow Disruption).

The total parameter count for the selected model was kept below 50,000 parameters, ensuring a minimal memory footprint and fast inference time, typically under 10 milliseconds per reading.

C. *Training and Quantization for TinyML:*

To enable deployment on the resource-constrained MCU, the trained 32-bit floating-point model must undergo post-training 8-bit integer quantization. This is also a method for reducing the number of rating scale items without the predictability loss [12]. This process converts the model's weights, biases, and activation function outputs from 32-bit floating-point numbers to 8-bit integers.

$$\text{Q-Value} = \text{round}\left(\frac{\text{Floating Point Value}}{\text{Scale}} + \text{Zero Point}\right). \quad (1)$$

This quantization yields (Q-value) three significant benefits:

1) Model Size Reduction: The final model size is reduced by approximately 75% (from 32-bit to 8-bit), allowing it to fit entirely within the limited on-chip Flash memory.
2) Inference Speed: Integer arithmetic is computationally faster and more energy-efficient than floating-point arithmetic on embedded processors, resulting in the ultra-low latency results.
3) Energy Efficiency: Faster processing translates directly into shorter periods during which the MCU must be active, significantly lowering the overall power consumption of the node.

The quantized model is deployed using TensorFlow Lite Micro (TFLu) framework, specifically optimized for running machine learning models on microcontrollers without an operating system.

D. *Self-healing Lora Mesh Protocol:*

The resilience of the system is achieved through a proprietary Self-Healing LoRa Mesh Protocol built atop the standard LoRa physical layer. This protocol ensures uninterrupted data backhaul despite frequent node failures or environmental link degradation common in deep mine environments. Adaptive Network Topology employs a dynamic hybrid star-mesh topology. Each sensor node functions as a standard star-network end device, but also contains the meshing logic to serve as a relay node. The network is not reliant on a single fixed backbone; instead, the protocol dynamically determines the optimal path to the gateway based on a real-time Link Quality Metric (LQM), which prioritizes reliability over simple hop count. Link Quality metric (LQM): The LQM is the basis for all routing decisions and is calculated by combining two key wireless parameters:

$$\text{LQM} = w_1 \cdot \text{Normalized RSSI} + w_2 \cdot \text{Normalized SNR}. \quad (2)$$

Received Signal Strength Indicator (RSSI) measures signal power, indicating link reliability. Signal-to-Noise Ratio (SNR), crucial in

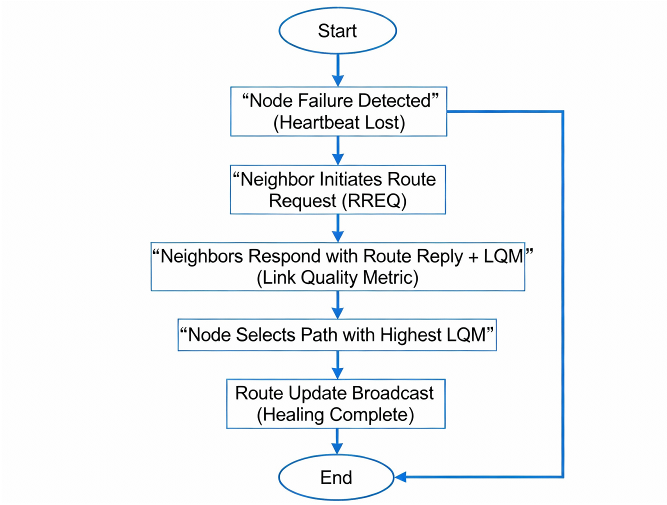

Fig. 2. Self-Healing Protocol Flowchart.

LoRa, indicating how resistant the link is to interference and noise. The weighting factors (w1, w2) are empirically tuned during deployment to prioritize SNR in the noisy underground environment, ensuring the selected route is not only strong but also stable. Each node periodically broadcasts a small Heartbeat packet containing its current LQM and routing table, allowing neighboring nodes to continuously update their understanding of the network's health.

- **Failure Detection and Dynamic Re-Routing:** Failure Detection occurs when a node fails to receive a set number of consecutive heartbeat packets from a neighboring relay node. The protocol immediately initiates the Self-Healing Sequence:

1) Route Request (RREQ): The upstream node broadcasts a request packet across the mesh to find a new path to the gateway.
2) Route Discovery: Neighboring nodes respond with a route reply containing their current LQM to the gateway, effectively listing all viable alternative paths.
3) Path Selection: The original node selects the path with the highest LQM (not necessarily the shortest hop count) to ensure the newly established route is the most resilient.
4) Route Update: The node updates its internal routing table and broadcasts this new path information to its downstream neighbors, thereby healing the break in the network graph and restoring PDR to functional level as demonstrated in Section IV. This process is fully autonomous and completed within seconds, minimizing data loss during a network fault.

E. Central Gateway and Dashboard:

A ruggedized Raspberry Pi or Industrial PC acts as a central gateway, collecting data from sensor nodes and providing a monitoring dashboard. The dashboard offers real-time visualization and alerts.

F. Deployment Scenario Example:

Imagine a deep gold mine tunnel where sensor nodes are installed at intervals of 30-50 meters. These nodes continuously monitor gas levels and airflow. One node detects a sharp drop in airflow alongside increased methane readings. Its built-in AI model predicts a potential blockage. The node immediately:

1) Sounds like a local buzzer alarm.
2) Sends high-priority message to gateway via LoRa mesh.
3) The gateway logs the incident, alerts supervisors, and suggests evacuation or ventilation adjustments.

TABLE II
COMPARATIVE ANALYSIS OF UNDERGROUND MONITORING TECHNOLOGIES

Technology	Pros	Limitations
Fixed Sensor	Stable, proven	Poor coverage, centralized, no AI.
Zigbee (Wi-Fi)	Flexible, scalable	High power use, weak underground signal propagation
UWB/Bluetooth	High accuracy (for tracking)	Line-of-sight needed, short range, no scalability
LoRa/ LPWAN	Low power, long range	Often centralized, lacks edge decision-making
Cloud-based AI	High processing power	Connectivity-dependent, delayed response in emergencies

TABLE III
SUMMARY OF TOOLS USED

Phase	Tools/ Tech
Data collection	Arduino IDE, ESP32, Serial logging
AI training	Python, scikit-learn, TensorFlow Lite.
Edge inference	TensorFlow Lite for Microcontrollers
Communication	LoRa SX1278, RadioHead, PainlessMesh
Simulation	PVC tunnel, fans, gas sources, motor

This decentralized yet coordinated system design ensures continuous safety monitoring, even during communication failures or partial system outages. Its modular nature makes it suitable for scaling and adapting to different mine layouts and types. The firmware was developed using the Arduino framework, with the TensorFlow Lite for Microcontrollers library for edge inference.

IV. Results and Discussion

The system is evaluated based on End-to-End Latency and Network Resilience, with a comparison made against a baseline centralized-cloud system using similar hardware. The quantitative advantages of the NeXNet architecture are summarized in Table IV. Most notably, the transition from cloud-based processing to edge-inference reduced the end-to-end alert latency from 6.5s to 0.4s, which is critical for life-safety applications in deep mines.

A. End-to-End Latency and Real-Time Hazard Alerting:

The primary advantage of incorporating Edge AI is the elimination of backhaul latency associated with transmitting raw data to a centralized cloud server for processing. As illustrated in Fig. 3(a), the average end-to-end alert latency of the baseline centralized/cloud system was 6.5s. This delay is primarily due to multi-hop transmission through the underground environment and server processing time. The 6.5s baseline represents a traditional Star-topology LoRaWAN network where data is transmitted to a central gateway and processed in a cloud-based Python environment.

In stark contrast, the NeXNet (Edge-IoT) system achieved an average alert latency of 0.4s. This near-instantaneous response is enabled by the lightweight machine learning model running directly on the node's microcontroller, allowing it to autonomously predict

TABLE IV
SUMMARY OF FRAMEWORK BENEFITS

Feature	Implementations
Edge AI inference,	TensorFlow Lite Micro, real-time alerts
Signal Filtering	High Ause, weak underground signal propagation
Hazard prediction	Risk score model, decision tree classifiers
Network reliability	TDMA, self-healing LoRa mesh
Low Resource Footprint	$\leq$256 kb RAM per Model, OTA update support

TABLE V
PERFORMANCE BENCHMARKING: NEXNET VS. OTHERS

Metric	**Cloud Baseline**	**NeXNet (Edge)**	**Improvement**
Alert Latency	6.5s	**0.4s**	93.8%
PDR (Post-Fail)	$<$ 40%	**$>$ 90%**	Critical
Recovery Time	Manual	**15s**	Autonomous
Inference	Remote	**Local**	Reliability

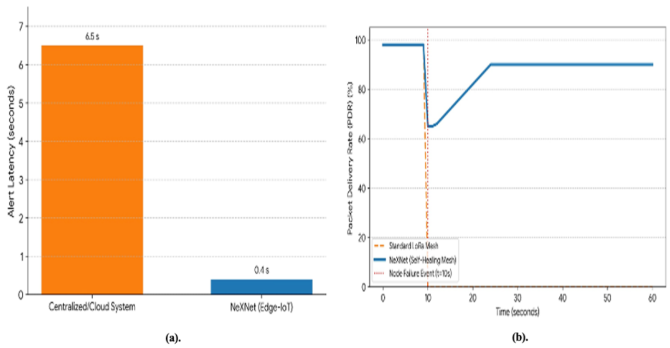

Fig. 3. Latency and Resilience Performance Charts (a) and (b). All simulation scripts and data points are available at **here**

and generate critical alerts without communicating with the surface. This ultra-low latency is paramount for responding to rapidly evolving hazards, such as methane gas flashes or sudden airflow disruptions, ensuring timely evacuation procedures. As shown in Fig. 3(a), proposed system achieves and end-to-end latency of 0.4s. The benchmarking scripts used to measure this performance are included in the replication package here.

B. Network Resilience and Self-Healing Performance:

To validate the reliability of the system, a controlled failure simulation was performed in which a critical relay node was disabled at t=10s. Fig. 3(b) plots PDR during this event. Standard LoRa Mesh: PDR dropped from 98% to 0% immediately following the node failure at t=10 s and remained non-functional. This represents a typical communication failure in non-adaptive underground networks, leading to a complete safety blackout. Self-Healing Mesh: The PDR initially dipped to 65%, but the integrated link-quality assessment and dynamic re-routing protocol successfully bypassed the failed node. The system achieved a steady-state PDR $>$90% within 15s (by t=25s). This rapid and autonomous self-healing capability ensures that the safety monitoring network maintains high operational continuity, which is a critical feature for the highly volatile and complex topology of deep Canadian mining environments. The network maintains a PDR of $>$90% even after node failure, with a recovery time of 15s as illustrated in Fig. 3(b). The raw simulation data and resilience plotting scripts are available here.

- **AI Modeling:** Sensor readings are normalized and signals are time-windowed to capture trends. We utilize lightweight models—decision trees, K-means clustering and logistic regression.
- **Model Deployment:** Models are converted to TensorFlow Lite Micro format for deployment on ESP32 nodes, allowing them to use $<$256 kb of memory and make predictions in milliseconds.
- **Edge Inference:** Nodes continuously feed processed data into the model. If abnormal patterns are detected, the node raises a local alert and notifies the gateway.
- **Sample AI Logic:** python (if CH4 - level $>$ threshold and airflow $<$ minimum: trigger-alert(Gas + AirFlow anomaly)).

V. CONCLUSION AND FUTURE WORK

This study presented and validated NeXNet, a next-generation Edge-IoT sensor network designed for ultra-low-latency hazard detection and high-resilience communication in deep-mine environments. By combining a quantized 1D-CNN model for on-node inference with a proprietary self-healing LoRa mesh protocol, NeXNet overcomes the latency and reliability limitations of traditional centralized monitoring systems. The system reduced end-to-end alert latency from 6.5s to 0.4s through optimized Edge AI processing, and demonstrated autonomous resilience by restoring the Packet Delivery Rate to over 90% within 15s. following a simulated node failure. Overall, NeXNet provides a robust, low-power, and highly responsive monitoring framework suitable for hazardous industrial environments, offering a more reliable and cost-effective alternative to conventional solutions. Future work will focus on integrating lightweight decentralized security mechanisms for authenticated sensing and further refining 8-bit quantization to support deployment on even smaller MCU platforms without compromising model accuracy. By moving the intelligence to the edge, NeXNet eliminates the 'single point of failure' common in centralized mining networks, providing blueprints for autonomous safety systems in other high-risk industrial sectors.

ACKNOWLEDGMENT

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DATA AVAILABILITY STATEMENT

The source code and performance datasets supporting the findings of this study are available in the NeXNet repository.

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