LoRa-Enabled Edge-IoT with Attentional Bi-LSTM for Predictive Gas, Environmental, and Health Monitoring

1st Mona Saghafi Binabaj
Department of Computer Engineering
Ferdowsi University of Mashhad
mona.saghafibinabaj@alumani.um.ac.ir

2nd Seyed Amirhossein Farjadi
Department of Computer Engineering
Ferdowsi University of Mashhad
farjadi@alumani.um.ac.ir

3rd Sara Ershadi-Nasab
Department of Computer Engineering
Ferdowsi University of Mashhad
ershadinasab@um.ac.ir

***Abstract*—This paper presents a low-cost and intelligent Internet of Things (IoT) system for gas, environmental, and health monitoring in hazardous industrial environments. The proposed system integrates low-power sensing modules with LoRa communication and an Attentional Bi-LSTM model deployed at the edge. Distributed sensor nodes, built on Arduino microcontrollers, collect temperature, humidity, and gas concentration data using DHT and MQ-series sensors. These readings are transmitted via LoRa to a NanoPi Neo Plus2 gateway, where the Attentional Bi-LSTM model performs multivariate time-series forecasting for early hazard prediction by capturing temporal dependencies and dynamically focusing on critical features. Local edge processing eliminates cloud dependency, reduces latency, and enables immediate visual and auditory alerts through reverse LoRa communication in case of potential risks. Experimental evaluation demonstrates stable LoRa transmission exceeding 1 km in obstructed environments at a baud rate of 9600 bps, along with high predictive accuracy and robust system performance. By combining LoRa-based wireless sensing with edge-deployed deep learning, the proposed system provides a scalable, energy- efficient, and practical solution for proactive gas detection and environmental and health monitoring in safety-critical industrial applications.**

***Index Terms*—Attentional Bi-LSTM, environmental monitoring, gas detection, Internet of Things, LoRa.**

I. Introduction

Industrial workplaces such as mines, chemical plants, and large manufacturing sites expose workers to severe hazards, including toxic gases, high temperatures, and oxygen depletion. Preventing accidents requires continuous monitoring and predictive insight into environmental conditions. Failures in early detection of hazardous gases such as methane, carbon, or hydrogen sulfide can lead to catastrophic explosions or health risks. Recent advances in the Internet of Things (IoT) and low-power wide-area networks (LPWANs) have made large-scale, real-time monitoring feasible at low cost. Among LPWAN technologies, LoRa and LoRaWAN stand out for their long-range coverage, low power consumption, and suitability for obstructed industrial environments [1], [2]. Leveraging these capabilities, researchers have proposed connected safety systems that merge physiological and environmental data, wide-area health monitoring frameworks for remote locations, and wearable devices with emergency alerting. LoRaWAN has also been applied to low-latency environmental and health monitoring in high-risk factories [3], gas detection and classification in industrial plants, and underground coal mining, where IoT-enabled methane monitoring combined with LSTM forecasting demonstrated predictive capabilities for hazard prevention [4].

Despite these advances, most existing solutions address either environmental hazards or physiological monitoring in isolation, limiting their ability to provide comprehensive risk assessments. Moreover, many LoRaWAN deployments rely on centralized gateways [3], introducing latency and reducing flexibility in small- to medium-scale industrial sites. Only a few studies integrate both environmental and health monitoring within a single architecture capable of on-gateway processing [5], [6].

Predictive monitoring introduces further challenges. State-of-the-art machine learning and deep learning methods—such as VMD-CNN-LSTM with self-attention [7], BiLSTM with local attention [8], and attention-based dilated CNN-BiLSTM [9]—achieve impressive forecasting results, but their computational demands make them unsuitable for embedded industrial devices. Consequently, existing LoRa-based safety systems rarely unify environmental and physiological monitoring in a predictive, resource-efficient manner. When prediction is included, the models are often too heavy for real-time execution on constrained gateways [2].

To address these limitations, this paper proposes a fully distributed IoT system for proactive gas detection, environmental and health monitoring in hazardous industrial environments. Low-cost Arduino-based sensor nodes equipped with MQ2, temperature, and humidity sensors transmit data via LoRa to a receiver site, which is a LoRa gateway powered by the NanoPi Neo Plus 2 single-board PC running Debian 12. On this gateway, a lightweight attentional Bi-LSTM model performs multivariate time-series forecasting for accurate, low-latency hazard prediction. Unlike cloud-dependent designs, inference is executed locally, ensuring robustness in connectivity-limited sites, while immediate alerts are issued through reverse LoRa communication to activate visual and auditory warnings at worker locations. The main contributions of this work are:

(1) a scalable, low-cost IoT framework for distributed environmental sensing, (2) integration of LoRa communication with edge-deployed attentional BiLSTM forecasting, and (3) elimination of cloud reliance through real-time local inference validated in obstructed environments over distances exceeding 10 km.

II. RELATED WORK

The integration of the Internet of Things (IoT), wireless communication technologies, and artificial intelligence (AI) has significantly transformed environmental and health monitoring and hazard detection in industrial settings, particularly in mining and safety-critical environments. Recent studies highlight that IoT-enabled systems equipped with low-cost sensors can collect, analyze, and transmit environmental data in real time, providing early warnings for hazardous conditions [10], [11]. LoRaWAN has emerged as a prominent communication protocol due to its low power consumption, long- range connectivity, and scalability, making it suitable for large, obstructed environments such as underground mines [12], [13], [14]. Research demonstrates that LoRa networks maintain stable performance under challenging conditions, including non-line-of-sight (NLoS) scenarios, extreme temperatures, and high interference, which are common in industrial facilities [15].

Gas detection systems have been widely explored in industrial IoT applications, emphasizing accuracy, low cost, and resilience. Field evaluations of electrochemical and metal-oxide gas sensors confirm their reliability under extreme temperature and humidity, enabling their deployment in harsh environments [16]. Moreover, integrating wireless underground sensor networks (WUSNs) with LoRa has enhanced system robustness and reduced deployment costs compared to wired solutions [17]. These systems enable predictive maintenance by leveraging real-time monitoring data and machine learning (ML) models to identify early signs of equipment failure or hazardous events, leading to safer and more efficient operations [11], [17].

Complementing these efforts, a recent study [18] presented an IoT-based infrastructure for industrial air quality monitoring that combines LoRaWAN communication, multi-sensor pollutant detection, and machine learning–driven data analysis, demonstrating how IoT platforms can provide predictive insights and real-time alerting in industrial environments.

Recently, Wiese et al. [19] proposed a multi-modal IoT node that integrates 11 environmental sensors with an ultra-low- power GAP9 SoC, enabling energy-efficient edge AI processing for environmental monitoring. Their work illustrates the potential of combining multi-modal sensing with embedded AI to overcome computational and energy constraints in long-term industrial deployments.

Artificial intelligence techniques, including convolutional neural networks (CNN), long short-term memory (LSTM) networks, and hybrid deep learning models, have been increasingly applied to IoT systems for predictive analytics [20], [21]. For example, hybrid CNN-LSTM architectures have been implemented to forecast methane gas concentrations in underground mines, providing accurate predictions and proactive alerts [21]. Similarly, AI-driven approaches enhance intrusion detection in industrial IoT networks, ensuring system security and reliability in mission-critical environments [20]. Similarly, Marzouk and Atef [22] developed an IoT-based framework for indoor air quality monitoring in academic buildings, integrating deep learning models to predict multiple air parameters with high accuracy. Their work highlights the effectiveness of combining IoT sensing with AI for real-time environmental forecasting, even outside industrial domains.

The adoption of LoRaWAN and AI-driven IoT frameworks has also expanded into smart city and industrial automation domains, offering scalable solutions for monitoring environmental conditions, energy systems, and worker safety [23], [24], [25]. Large-scale reviews emphasize that IoT and LoRa- based monitoring systems have evolved beyond data acquisition, incorporating edge and cloud computing to enable real-time decision-making and multi-site management [23]. Additionally, studies underscore the need for adaptive power control mechanisms in LoRa networks to maintain quality of service in environments with significant signal-to-noise variations [10], highlighting future directions for optimizing network performance in industrial IoT deployments.

Collectively, these studies demonstrate that combining IoT sensors, LoRaWAN, and AI/ML models provides a scalable, low-cost, and reliable solution for real-time hazard detection and environmental monitoring. The literature underscores a clear trend toward integrating edge intelligence and robust wireless communication technologies, setting the stage for advanced predictive safety systems in industrial applications [23], [17], [26]. A recent study [30] demonstrated that attention-based Bi-LSTM architectures can effectively support edge-level time series forecasting for environmental monitoring applications.

III. PROPOSED METHOD

In this section, we present the proposed IoT-based system architecture for proactive gas detection, environmental and health monitoring. The methodology is organized into six parts, starting with an overview of the system architecture, followed by data acquisition, forecasting model design, edge deployment, alerting mechanism, and validation.

A. System overview

The proposed system adopts a four-layer IoT architecture for proactive gas detection, environmental and health monitoring (Fig. 1).

1) Sensor Layer: Arduino-based nodes integrate an MQ-2 gas sensor and a DHT11/22 temperature–humidity sensor. The microcontroller performs basic preprocessing and transmits feature frames including sensor values and metadata.

2) Communication Layer: LoRa provides long-range, low-power wireless connectivity between distributed nodes and the central gateway, supporting reliable uplink reporting and reverse downlink alerts.

3) Edge Computing Layer: A NanoPi Neo Plus2 serves as the gateway, hosting an Attentional Bi-LSTM model to forecast hazardous trends in multivariate time series. Based on predictions, the gateway triggers reverse-LoRa alerts to activate

visual and auditory warnings locally, eliminating cloud dependency. Compared with prior LoRa-based monitoring systems, this design integrates edge-level forecasting and a closed feedback loop, offering a low-cost yet scalable solution for safety-critical industrial sites.

4) Alert Layer: Upon hazard prediction, the gateway sends reverse-LoRa commands to the originating node(s). The nodes trigger local actuators—LED beacon and buzzer—providing immediate on-site alerts independent of cloud connectivity.

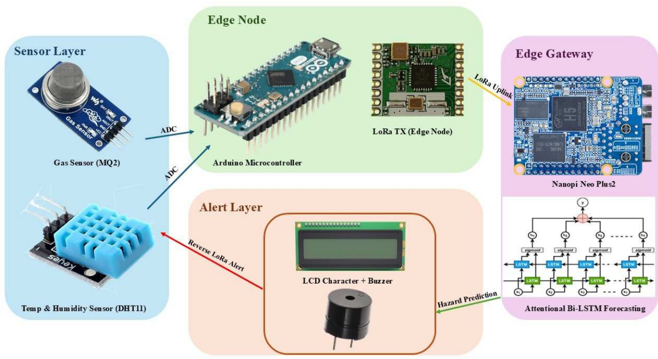

Fig. 1. Four-layer system architecture: Sensor Layer (Arduino + MQ2 + DHT), Communication Layer (LoRa), and Edge Computing Layer (NanoPi Neo Plus2 with Attentional Bi-LSTM), Alert Layer.

B. Forecasting Model (Attentional Bi-LSTM)

The forecasting module adopts a sequence-to-vector design (Fig. 2) tailored to multivariate sensor data. A Bidirectional LSTM (Bi-LSTM) encodes each input step from both forward ($\vec{h}_t$) and backward ($\overleftarrow{h}_t$) directions; the hidden states are concatenated as

$$h_t = [\vec{h}_t, \overleftarrow{h}_t],$$

forming a dual-context representation.

To emphasize the most informative time steps, we integrate a Bahdanau-style attention mechanism. Alignment scores are computed as

$$e_t = v^T \tanh(W_h h_t + W_s S), \quad (1)$$

and normalized via softmax to obtain attention weights which is fed to a dense head to produce the multivariate next step prediction $\hat{y}_{t+1}$. Training is end-to-end with Mean Squared Error (MSE) loss and the Adam optimizer ($lr = 10^{-3}$).

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{L} \exp(e_k)}. \quad (2)$$

The context vector is then

$$c = \sum_{t=1}^{L} \alpha_t h_t \quad (3)$$

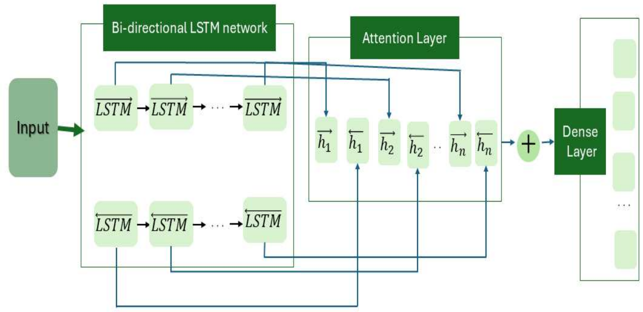

Fig. 2. Attentional Bi-LSTM architecture used for hazard prediction.

C. Edge Deployment on NanoPi Neo Plus2

The choice of NanoPi Neo Plus2 as the gateway is motivated by its superior compute and memory over boards used in prior works (Table I). With a quad-core ARM Cortex-A53 (1.5 GHz), 1 GB DDR3, and Debian 12 delivers edge capacity unattainable on Arduino/ESP32 while remaining compact and low power (<5 W). These resources enable real time Attentional Bi-LSTM inference via PyTorch Lite / TensorFlow Lite, supporting predictive hazard monitoring without cloud dependence.

The overall system architecture, including Arduino-based sensor nodes with LoRa and the NanoPi Neo Plus2 gateway, is shown on Fig. 3. Section 1 shows the NanoPi Neo Plus2, Section 2 shows the Arduino board, Section 3 highlights the LoRa module, Section 4 shows the LCD display, and Section 5 illustrates the router and network connectivity.

D. Alerting Mechanism

Upon detecting a potential hazard, the NanoPi gateway riggers reverse-LoRa communication to the corresponding sensor nodes. These nodes activate local actuators, including visual (LED beacon) and auditory (buzzer) alarms, ensuring immediate on-site alerts and real-time hazard awareness without cloud reliance.

IV. RESULT AND EVALUATION

A. Data Acquisition and Preprocessing

We used meteorological data from World Weather Online (WWO) and, from the full schema, retained only variables most relevant to gas concentration and dispersion: temperature (tempC), humidity, and pressure. Data was collected for two cities, California (USA) and Singapore, over the period from September 1, 2021, to September 1, 2025, with hourly resolution (35,089 samples). These data were then time-aligned with node measurements, cleaned for outliers, normalized (min–max), and organized into sliding windows for multivariate Attentional Bi-LSTM forecasting.

TABLE I
COMPARISON OF PROCESSING BOARDS IN RELATED WORKS

Study / Board	Processor & Memory	Edge ML	Remarks
Reddy & Naik (2023) [27]	Arduino UNO/Nano + LoRa	None	Focus on sensing; cannot host deep models locally
R. Prabu et al. (2024) [28]	Arduino-class MCU (8-bit, low RAM)	Very limited	Threshold-based tasks; low cost but not scalable
O'Brien et al. (2025) [29]	ESP32 LoRa Dev Board (dual-core MCU)	Moderate	Good for tiny ML, but limited RAM/compute for deep models
This work	NanoPi Neo Plus2 (ARM Cortex-A53, 1 GB RAM)	High	Runs Attentional Bi-LSTM locally; balances cost, power, compute

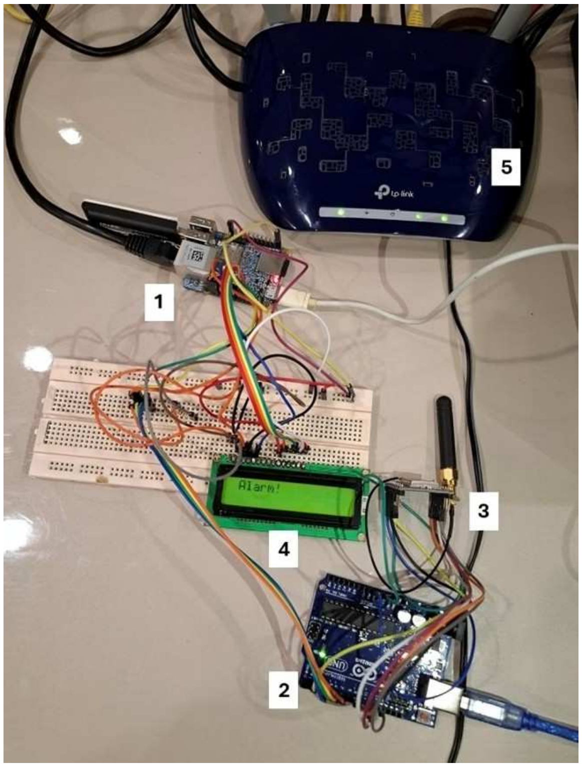

Fig. 3. Overall system setup, including Arduino sensor nodes, LoRa communication, and the NanoPi Neo Plus2 gateway.

B. Prediction Accuracy and Model Performance

To evaluate the proposed system, two experiments were conducted focusing on wireless communication stability and predictive accuracy. For communication testing, an indoor experiment was carried out in the Department of Computer Engineering at Ferdowsi University of Mashhad. The transmitter and receiver nodes, each equipped with small LoRa antennas, were positioned at different locations on the same floor with several obstacles simulating non-line-of-sight (NLoS) conditions. Sensor data were continuously transmitted at a baud rate of 9600 bps, and packets were received reliably without noticeable delay or loss, confirming stable short-range communication under moderate obstructions.

For model evaluation, the Attentional Bi-LSTM network was tested for predicting hazardous events such as gas leaks and abnormal environmental conditions. Data from the MQ2 gas and DHT temperature-humidity sensors served as multivariate time-series inputs. The model provided accurate and timely hazard predictions, demonstrating effective edge-level inference. Fig. 4 shows real-time readings of gas concentration, temperature, and humidity. Future work will involve outdoor field tests with high-gain antennas and additional sensing modalities to enhance long-range performance and predictive accuracy.

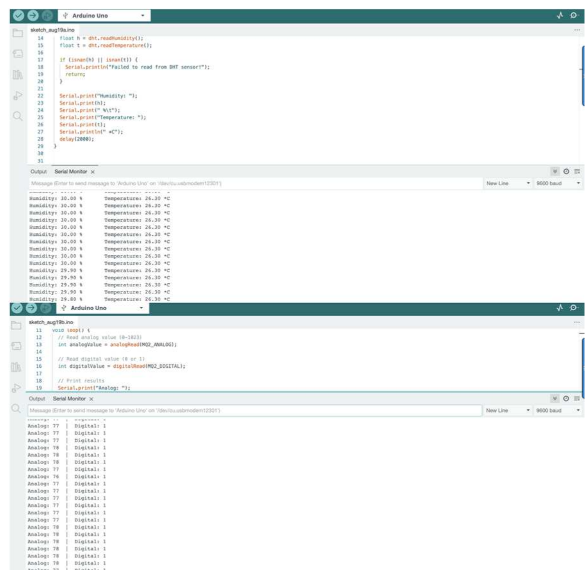

Fig. 4. Real-time sensor readings from the DHT (temperature-humidity) and MQ2 (gas) sensors transmitted via LoRa at a baud rate of 9600 bps. The data were collected indoors under obstructed conditions and used for hazard prediction.

TABLE II
PERFORMANCE COMPARISON OF THE PROPOSED ATTENTIONAL BI-LSTM MODEL WITH BASELINE LSTM VARIANTS ON THE WWO DATASET

Model	MSE	RMSE	MAE	R2
Attentional Bi-LSTM	**0.001913**	**0.043736**	**0.018867**	**0.9284**
Bi-LSTM	0.001952	0.044185	0.020738	0.9229
Vanilla LSTM	0.002128	0.046132	0.022769	0.9117
Attentional LSTM	0.004252	0.065204	0.039729	0.7827

To evaluate the effectiveness of the proposed Attentional Bi-LSTM, we compared its performance with baseline LSTM variants. The comparison, based on WWO dataset, is shown in Table II. As shown, the proposed model outperforms both Bi-LSTM and Vanilla LSTM in terms of MSE, RMSE, MAE, and R2, achieving a high R2 score of 0.9284.

IV. Conclusion

This study presented an intelligent and low-cost IoT framework that integrates LoRa-based wireless sensing with an edge-deployed Attentional Bi-LSTM model for predictive gas and environmental monitoring in hazardous industrial settings. The proposed system enables real-time forecasting and immediate on-site alerting without relying on cloud infrastructure, ensuring rapid response to potential hazards. Experimental results demonstrated stable LoRa communication at 9600 bps and high predictive accuracy in obstructed environments.

Future work will focus on extending the communication range using high-gain antennas and integrating wearable sensing devices for continuous worker health monitoring, leveraging the existing LoRa-based architecture to enhance safety and predictive capabilities in industrial environments.

References

[1] A. Sharma, V. Khullar, I. Kansal, G. Chhabra, P. Arora, R. Popli, and R. Kumar, "Gas detection and classification using multimodal data based on federated learning," *Sensors*, vol. 24, no. 18, p. 5904, 2024.

[2] S. Barsude, B. Bachewar, S. Antad, A. Gadiya, and H. Badagandi, "Real-time gas monitoring and anomaly detection in petroleum industry using iot and machine learning," *International Journal of Computing and Digital Systems*, vol. 16, no. 1, pp. 1–11, 2024.

[3] D. Tamang, A. Pozzebon, L. Parri, A. Fort, and A. Abrardo, "Designing a reliable and low-latency lorawan solution for environmental monitoring in factories at major accident risk," *Sensors*, vol. 22, no. 6, p. 2372, 2022.

[4] S. Paty, A. Biswas, S. Djebali, G. Guerard, and S. Kamilya, "Iot-enabled methane monitoring and lstm-based forecasting system for enhanced safety in underground coal mining," *ACM Transactions on Internet of Things*, vol. 6, no. 1, pp. 1–29, 2025.

[5] F. Wu, T. Wu, and M. R. Yuce, "An internet-of-things (iot) network system for connected safety and health monitoring applications," *Sensors*, vol. 19, no. 1, p. 21, 2018.

[6] Y.-W. Chan, E. Kristiani, H. Fathoni, C.-Y. Chen, and C.-T. Yang, "A smart edge computing infrastructure for air quality monitoring using lpwan and mqtt technologies." *Journal of Supercomputing*, vol. 80, no. 7, 2024.

[7] W. Zhao, B. Shao, N. Tian, W. Zhang, X. Zhao, and S. Wu, "Early warning study of field station process safety based on vmd-cnn-lstm-self-attention for natural gas load prediction," *Scientific reports*, vol. 15, no. 1, p. 6360, 2025.

[8] Y. Fan, Q. Tang, Y. Guo, and Y. Wei, "Bilstm-mlam: a multi-scale time series prediction model for sensor data based on bi-lstm and local attention mechanisms," *Sensors*, vol. 24, no. 12, p. 3962, 2024.

[9] U. Saleem, W. Liu, S. Riaz, M. M. Aslam, W. Li, and K. Wang, "Enernet: Attention-based dilated cnn-bilstm for state of health prediction of cs2 prismatic cells in energy systems," *Electrochimica Acta*, vol. 512, p. 145454, 2025.

[10] M. Gonza´lez-Palacio, D. Tobo´n-Vallejo, L. M. Sepu´lveda-Cano, M. MAURICIO, C. Ro¨ehrig, and L. Bao Le, "Machine-learning-assisted transmission power control for lorawan considering environments with high signal- to -noise variation," *IEEE Access*, vol. 12, pp. 54 449–54 470, 2024.

[11] R. Hajovsky, M. Pies, J. Velicka, V. Slany, R. Rous, L. Danys, and R. Martinek, "Design of an iot-based monitoring system as a part of prevention of thermal events in mining and landfill waste disposal sites: A pilot case study," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1–14, 2023.

[12] O. Elijah, S. K. A. Rahim, V. Sittakul, A. M. Al-Samman, M. Cheffena, J. B. Din, and A. R. Tharek, "Effect of weather condition on lora iot communication technology in a tropical region: Malaysia," *IEEE Access*, vol. 9, pp. 72 835–72 843, 2021.

[13] K. Lin and T. Hao, "Experimental link quality analysis for lora-based wireless underground sensor networks," *IEEE Internet of Things Journal*, vol. 8, no. 8, pp. 6565–6577, 2021.

[14] Q. Guo, F. Yang, and J. Wei, "Experimental evaluation of the packet reception performance of lora," *Sensors*, vol. 21, no. 4, 2021. [Online]. Available: https://www.mdpi.com/1424-8220/21/4/1071

[15] B. Abdallah, S. Khriji, R. Che´our, C. Lahoud, K. Moessner, and O. Kanoun, "Improving the reliability of long-range communication against interference for non-line-of-sight conditions in industrial internet of things applications," *Applied Sciences*, vol. 14, no. 2, 2024. [Online]. Available: https://www.mdpi.com/2076-3417/14/2/868

[16] R. Papaconstantinou, M. Demosthenous, S. Bezantakos, N. Hadjigeorgiou, M. Costi, M. Stylianou, E. Symeou, C. Savvides, and G. Biskos, "Field evaluation of low-cost electrochemical air quality gas sensors under extreme temperature and relative humidity conditions," *Atmospheric Measurement Techniques*, vol. 16, no. 12, pp. 3313–3329, 2023. [Online]. Available: https://amt.copernicus.org/articles/16/3313/2023/

[17] S. Suganthi, G. Valarmathi, V. Subashini, R. Janaki, and R. Prabha, "Coal mine safety system for mining workers using lora and wusn," *Materials Today: Proceedings*, vol. 46, pp. 3803–3808, 2021, international Conference on Materials, Manufacturing and Mechanical Engineering for Sustainable Developments-2020 (ICMSD 2020). [Online]. Available: https://www.sciencedirect.com/science/article/pii/S221478532101097X

[18] L. Garc´ıa, A.-J. Garcia-Sanchez, R. Asorey-Cacheda, J. Garcia-Haro, and C.-L. Zu´n˜iga-Can˜o´n, "Smart air quality monitoring iot-based infrastructure for industrial environments," *Sensors*, vol. 22, no. 23, 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/23/9221

[19] P. Wiese, V. Kartsch, M. Guermandi, and L. Benini, " A Multi-Modal IoT Node for Energy-Efficient Environmental Monitoring with Edge AI Processing ," in *2025 IEEE International Conference on Omni-layer Intelligent Systems (COINS)*. Los Alamitos, CA, USA: IEEE Computer Society, Aug. 2025, pp. 1–7. [Online]. Available: https://doi.ieeecomputersociety.org/10.1109/COINS65080.2025.11125738

[20] N. Nikolakis, G. Kantaris, K. Bourmpouchakis, and K. Alexopoulos, "A cyber-physical system approach for enabling ventilation on-demand in an underground mining site," *Procedia CIRP*, vol. 97, pp. 487–490, 2021, 8th CIRP Conference of Assembly Technology and Systems. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2212827120314955

[21] P. Dey, S. Chaulya, and S. Kumar, "Hybrid cnn-lstm and iot-based coal mine hazards monitoring and prediction system," *Process Safety and Environmental Protection*, vol. 152, pp. 249–263, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957582021002950

[22] M. Marzouk and M. Atef, "Assessment of indoor air quality in academic buildings using iot and deep learning," *Sustainability*, vol. 14, no. 12, 2022. [Online]. Available: https://www.mdpi.com/2071-1050/14/12/7015

[23] H. Zhang, B. Li, M. Karimi, S. Saydam, and M. Hassan, "Recent advancements in iot implementation for environmental, safety, and production monitoring in underground mines," *IEEE Internet of Things Journal*, vol. 10, no. 16, pp. 14 507–14 526, 2023.

[24] I. K. Enriko, F. Gustiyana, K. Kurnianingsih, and E. Sari, "Lorawan for smart street lighting solution in pangandaran regency," *JOIV : International Journal on Informatics Visualization*, vol. 7, 12 2023.

[25] J. M. Marais, A. M. Abu-Mahfouz, and G. P. Hancke, "A survey on the viability of confirmed traffic in a lorawan," *IEEE Access*, vol. 8, pp. 9296–9311, 2020.

[26] B. Abdallah, S. Khriji, R. Che´our, C. Lahoud, K. Moessner, and O. Kanoun, "Improving the reliability of long-range communication against interference for non-line-of-sight conditions in industrial internet of things applications," *Applied Sciences*, vol. 14, no. 2, p. 868, 2024.

[27] S. K. Reddy and A. S. Naik, "An enhanced iot and lora-based communication system for underground mines," in *Signals, Machines and Automation*, A. Rani, B. Kumar, V. Shrivastava, and R. C. Bansal, Eds. Singapore: Springer Nature Singapore, 2023, pp. 513–521.

[28] R. J and N. D, "Lora wan based smart system for unsafe event detection in mining industry using ml," in *2024 9th International Conference on Communication and Electronics Systems (ICCES)*, 2024, pp. 684–691.

[29] C. W. O'Brien, H. Salamy, and C.-H. Min, "Design of a wireless cyber–physical system for gas leak detection with lora," *IEEE Internet of Things Journal*, vol. 12, no. 14, pp. 27 998–28 010, 2025.

[30] N. Hajizadeh, S. Yazdani, S. Ershadi-Nasab, "Attentional Bi-LSTM for Multivariate Time Series Forecasting on Edge Devices: A Case Study on NanoPi Neo Plus2," in *2025 15th International Conference on Computer and Knowledge Engineering (ICCKE)*, 2025, pp. 2025364448.