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Design of a portable IoT robot with azure machine learning for monitoring mine workers' health

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ABSTRACT

The mining environment exposes workers to physical, environmental, and health risks. The lack of effective real-time health monitoring systems leads to delayed medical responses. Hence, this paper discusses developing a portable Internet of Things (IoT) robot with advanced machine learning and cloud computing to monitor mine workers' health and send out alerts. The system is equipped with IoT sensors that monitor parameters continuously, such as heart rate, body temperature, blood pressure, and environmental factors (gas concentrations, air quality). Data collected in real-time is transmitted to a cloud-based platform for analysis using advanced machine learning algorithms. MQ-135 detects harmful gases, and DHT11 measures humidity and transmits data to the Arduino UNO. The HC-SR04 sensor measures object distances by emitting ultrasonic waves and detecting their echoes, aiding in obstacle detection. The NEO-6M GPS with GSM SIM900 modules transmits location data and emergency alerts via the GSM network, enabling responses to potential dangers. Simulation via Proteus validates the robot's transceiver connectivity, mobility, and sensing functions. To enhance monitoring precision, the system adopts XGBoost, which classifies mine conditions, and the training model achieves 96.77% accuracy with high precision and recall. The system with Azure Machine Learning improves detection accuracy, raising temperature, CO, NH_4, and NO_2 precision by 7.25%, 15%, 17%, and 18%, respectively. Thus, the system features an intelligent alert mechanism to notify users of emergencies, enhancing worker safety and minimizing health-related risks in mining operations.

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1. INTRODUCTION

Efforts to monitor mines are essential for improving safety, maintenance, and surveillance. The systems [1] implement efficient monitoring and alert mechanisms for workers in underground environments. This study focuses on the design and development of a smart alert system for miners. To alert the control center and warn miners of potential dangers, a protection helmet is proposed. The STM32 module employs multiple sensors to continuously monitor the surrounding environment and the health of workers [2]. Another system involves the creation and application of a continuous monitoring device to assess miners' physiological parameters at elevations above 2,000 meters above sea level [3]. One study uses coal seam, rock stratum, and coal-rock mixed-layer images from a coal mining area as research objects. Here the neural network is utilized to categorize and identify whether the shearer's current mining target is a coal seam, rock stratum, or coal-rock mixed layer [4]. Another system incorporates a digital device equipped with an accelerometer, dust sensor, and ZigBee communication technologies to exchange collected data [5], [6] shows text mining method using artificial intelligence (AI) to extract safety insights and patterns from mining accident reports automatically for improved risk analysis. A wearable resonator employs a dual-resonator mass sensor composed of a quartz crystal microbalance and a film bulk acoustic resonator is proposed [7]. Smart clothing for coal mine workers combines wearable clothing with sensors, microcontrollers, and communication modules to enhance worker safety, health monitoring, and efficiency [8]. Another system aims to create a safety monitoring solution for coal mines using a real-time operating system (RTOS) robot module to improve safety and reduce accidents [9]. The study focuses on autonomous robots, capable of detecting and predicting dangerous gases (methane and carbon monoxide) [10]. The inference of various advanced technologies for coal mine safety that includes wearable alert systems, Internet of Things (IoT)-enabled devices, AI-based helmets and physiological monitors are discussed in Table 1. The inventions were focused on improving monitoring, communication and safety of the worker with few challenges like power limitations, harsh environments and cost.

Table 1. Comparison of advanced technologies for safety and monitoring in coal mines

References	Work description	Trends	Challenges
[1]–[3], [7], [8]	Wearable-based miner safety and health monitoring using IoT sensors, embedded systems and smart personal protective equipment (PPE).	Integration of smart wearables, real-time physiological and environmental monitoring, embedded sensing in clothing and helmets.	Harsh environmental conditions, battery limitations, calibration issues, high cost and maintenance.
[11] [12]	AI/ML-based analysis including natural language processing (NLP), artificial neural network (ANN) and deep learning for classification, detection and safety insights.	Adoption of AI for automation, real-time objects detection, predictive analytics and intelligent decision-making.	Data variability, need for large datasets, computational complexity, low-light, privacy concerns.
[5], [13]	Wireless sensor networks (WSN) and communication systems for underground monitoring and data transmission.	ZigBee and optimized WSNs, self-healing networks, energy-efficient communication.	Limited communication range, energy imbalance, unstable connectivity, real-time repair complexity.
[9], [10], [14], [15]	Robotics and autonomous systems for surveillance, rescue and hazardous environment exploration.	Autonomous and semi-autonomous robots, IoT-enabled rescue systems, robotic exploration in extreme conditions.	Navigation in GPS-denied environments, reliability, worker adoption, underwater condition constraints.
[16], [17], [18]	Simultaneous localization and mapping (SLAM) and localization techniques for underground navigation using LiDAR and sensor fusion.	Advanced SLAM algorithms, multi-sensor fusion, improved mapping accuracy.	Dust, poor visibility, scene degeneration, high computational requirements.
[19]	Environmental and electromagnetic safety modeling in mining structures.	EM wave analysis for safety in underground energy systems.	Complex modeling, ensuring safety compliance, accurate predictions.

A strong localization framework was established based on hybrid 3D light detection and ranging (LiDAR) and simultaneous localization and mapping (SLAM) methods to improve vehicle positioning in room-and-pillar underground mines, solving the problem of 2D LiDAR in irregular terrains [20]. A patrol robot for underground mine safety was designed with LiDAR, inertial measurement unit (IMU), and environmental sensors for accurate navigation, gas and dust detection, and autonomous hazard mapping in real mine tunnels [21], [22] shows modern target localization technologies in underground mines which focuses on positioning accuracy, signal processing methods for accurate tracking. A systematic review of autonomous mobile inspection robots in deep mining found few developments [23]. A variable wheel diameter coal-mine robot was also proposed, enhancing the ability to cross obstacles by more than 60% and enhancing adaptability to uneven underground ground surfaces [24]. A method of 3D point cloud registration was developed for mine rampways tunnel [25].

From all the references [1]–[25], the study talks about the various types of various safety devices, mining robots which focuses on the safety of the mine workers. Present coal mine monitoring systems include wearable control, smart helmets, physiological sensors, ZigBee devices, resonators, AI-based image analysis, robotic platforms and smart clothing. Taking these advances in the field, still few limitations persist in power constraints, communication stability, autonomous navigation, sensor accuracy, harsh environmental effects and network reliability in complex global navigation satellite systems (GNSS) denied underground conditions for improved safety. Also, the limitation of the works leads to further research in this area. Therefore, below contributions are performed in this article to support for the further research: i) The proposed portable mine monitoring system integrates advanced sensors (MQ-135, DHT11, HC-SR04) with

IoT technology to continuously monitor critical environmental parameters such as harmful gases (CO, NH_4, NO_2), temperature, and humidity, ensuring real-time detection and prevention of hazards in mining environments. ii) The presence of GPS, GSM modules, high-intensity alarms, and visual indicators in the portable monitoring system ensures rapid communication of hazardous conditions to rescue teams. iii) The portable IoT robot incorporates Azure machine learning (AML) that improves the accuracy and reliability of environmental monitoring systems. iv) The implementation of the XGBoost algorithm provides robust classification and forecasting of mine safety conditions based on historical data available. v) Also, the proteus simulation validated the system's functionality, including transceiver connectivity, obstacle detection, and mobility controls. vi) Finally, the comparative analysis of environmental parameters with and without AML integration from the real time development of portable robot highlights AML's effectiveness in reducing measurement errors and improving monitoring accuracy by 7.25% to 18% across different parameters.

In this article, section 2 describes the modelling of secure device for mine workers. Section 3 demonstrates the prediction of mine safety conditions using XGBoost, prediction of mine safety conditions using XGBoost is illustrated in section 4, real time implementation of environmental monitoring and hazard detection in mines are discussed in section 5 and finally the conclusion of the work is presented.

2. METHODOLGY AND MODELLING OF SECURE DEVICE FOR MINE WORKERS

In this section the modelling of secure device for mine workers are discussed. Additionally, the data analysis and transmission network with simulation work of the portable IoT mine safety robot are discussed here. The proposed mine workers' rescue system is shown in Figure 1. The power supply is provided to the Arduino UNO, which acts as the controller. The MQ-135 sensor detects harmful gases such as ammonia, sulfur, benzene, carbon dioxide, and smoke, and transmits the data to the Arduino UNO. The DHT11 sensor measures humidity in the range of 20%–80% with 5% accuracy, and its operating temperature range is -40 °C to 120 °C with a ± 2 °C margin of error. It operates between 3.3–5 V with a maximum current consumption of 2.5 mA. In a functioning coal mine, the typical temperature range is 15 °C to 45 °C. The HC-SR04 sensor measures the distance to objects by emitting ultrasonic waves and detecting their echoes, making it useful for obstacle detection.

The Arduino UNO receives input data from the sensors and executes logic to control outputs based on programmed conditions. A motor driver circuit and DC motor are used for powering ventilation systems that ensures adequate airflow which supports mechanized safety interventions. The NEO-6M GPS, GSM SIM900 module plays a vital role in transmitting location data, emergency alerts via the GSM network, enabling swift responses to potential hazards. An alarm provides loud, high-intensity notifications to warn miners and control centers of serious dangers, the buzzer offers lower-intensity audible warnings for early-stage detections, less critical issues. Further an LED serves as a visual indicator that displays system's operational status which alert the workers based on real-time sensor data. This enhances the overall safety in the hazardous underground environment. Table 2 shows the parameters (Temperature, CO, NH4 and NO2 as °C and ppm) measured from the mine environment monitoring system. The normal temperature is 0 – 29 °C, CO is 0 – 14, NH_4 is 0 – 15, NO_2 is 0 – 13. Figure 2 illustrates a safety mechanism in a mining environment where the health of the workers is continuously monitored using a smart device. Initially, the worker is engaged in routine mining activities; however, upon experiencing discomfort, the smart device detects a drop in oxygen levels which alerts the robotic system. The robot equipped with sensors (passive infrared (PIR)) which identifies human presence and sends an emergency signal to the rescue team. The rescue team responds instantly which ensures the worker is treated, retrieved and eventually prepared to resume work. The proposed systems with integrated wearable technology and robotics enhance safety, improve response time in hazardous mining conditions.

The proposed device with the mentioned sensors regularly extracts the data from the mine environments. The values extracted are transmitted to Arduino UNO, which do the initial preprocessing and validating the sensor values based on the parameters outlined in Table 2. The GSM and GPS communication protocols for long-range and the data transfer in underground environments are performed by Wi-Fi and ZigBee network.

The GSM ensures reliable transfer of sensor data to the cloud; therefore, GPS provides real-time worker and robot localization. After the extracted data reaches AML cloud module, the prediction engine based on XGBoost analyzes the patterns, filters noise and corrects sensor drifts. The AML model regularly identifies from incoming data and thus enables adaptive thresholds which reduce false alerts during fluctuating mine conditions. Further, the cloud transfers the hazard predictions to the IoT robot via GSM which enables the real-time alerts, path planning instantly for rescue initiation. This 2-way communication loop—sensor → Arduino → GSM/GPS → AML cloud → IoT robot, ensures continuous monitoring and instant response. Thus, allowing AML to dynamically enhance the decision accuracy, where the IoT device executes timely onsite actions.

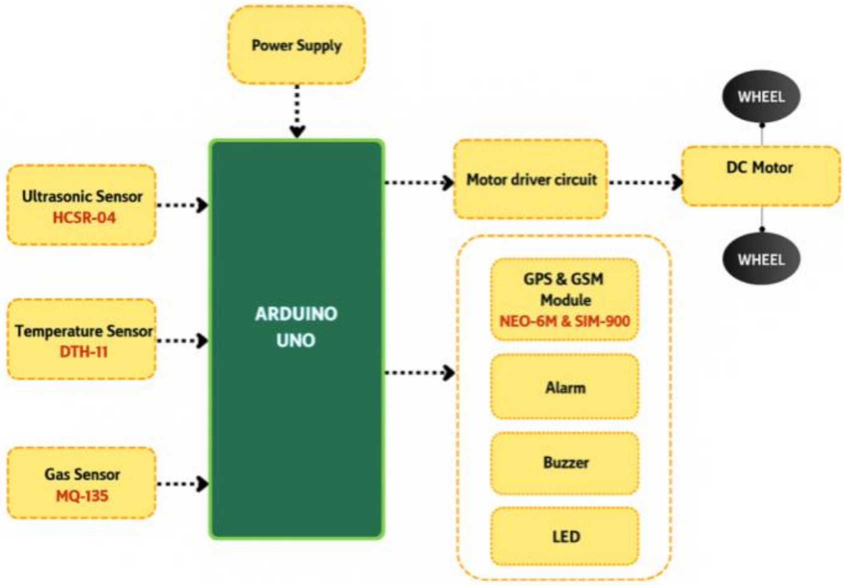


Figure 1. Layout of mine environment monitoring system

Table 2. Measure of various environmental parameters

Measurement Parameters	Unit	Normal	Abnormal
Temperature	Celsius	0 °c – 29 °c	Above 29 °c
CO	ppm	0 - 14	above 14
NH_4	ppm	0 - 15	Above 15
NO_2	ppm	0-13	Above 13

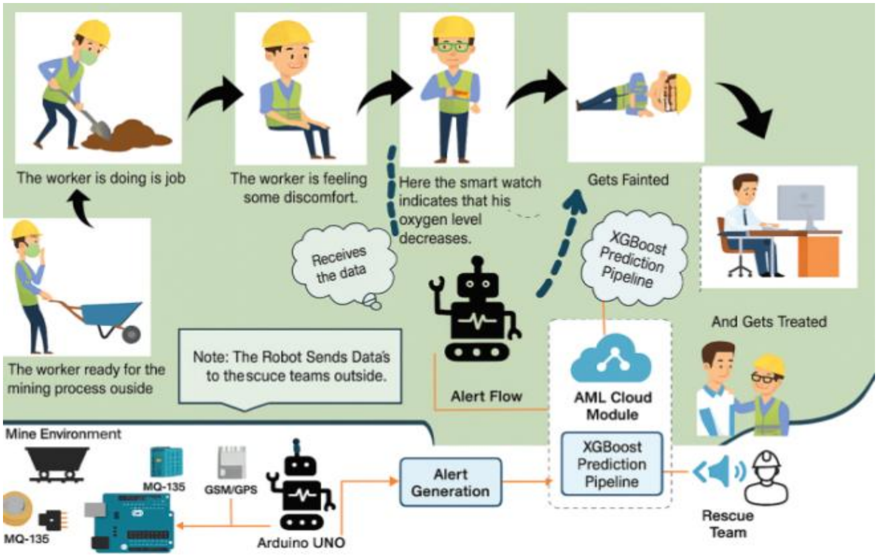


Figure 2. Workflow of the proposed mining system

2.1. Simulation work of the portable IoT mine safety robot

As shown in Figure 3, the proteus simulation for the portable IoT robot with AML cloud computing to monitor mine workers health and send out alerts confirmed flawless functionality. It validated transceiver connectivity, precise mobility controls, obstacle detection, and efficient monitoring. The simulation assures that the robot is operative, showcasing its potential for real-world applications. The simulation of the proposed mine safety robot is shown in Figure 1. The mine safety robot provides the required alert in the form of buzzer and LED, is shown in Figure 4.

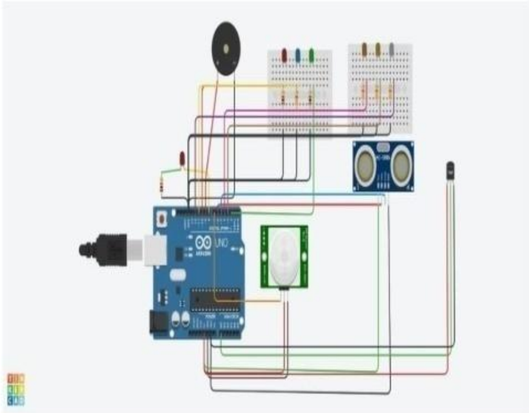


Figure 3. Simulation of portable IoT mine safety robot

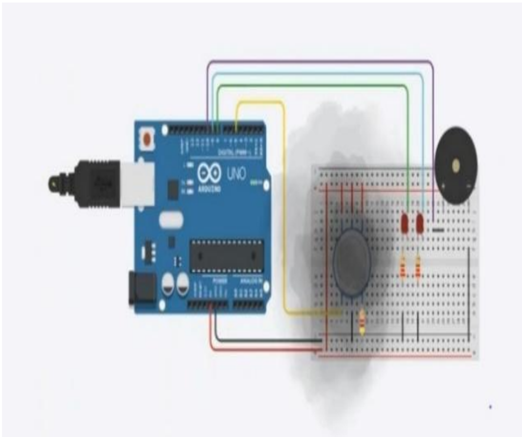
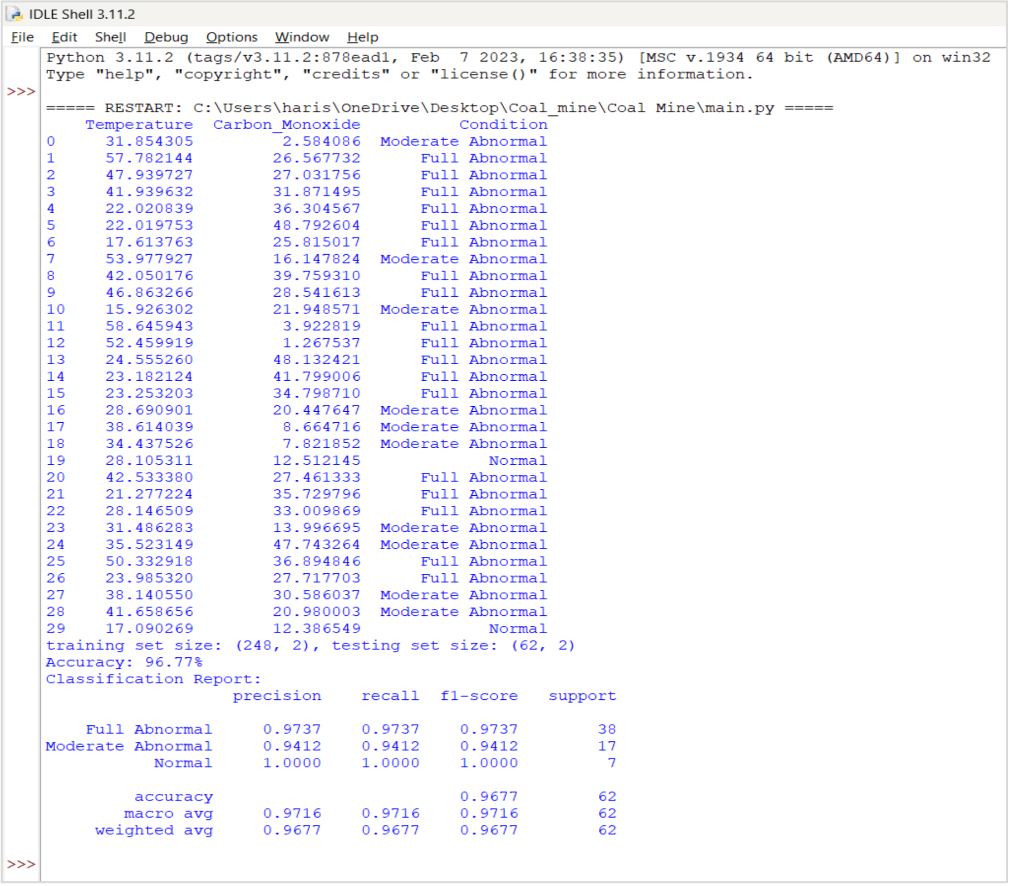


Figure 4. Result from portable IoT mine safety robot

2.2. Mine safety conditions using XGBoost

The proposed system uses XGBoost (advanced machine learning algorithm) which classify and forecast environmental conditions in mines based on temperature and carbon monoxide levels. The dataset contains historical data related to these variables which undergoes preprocessing to address missing values and is divided into input features (temperature and carbon monoxide) and target labels (normal, moderate abnormal and full abnormal). The target labels are converted into numerical values using label encoder which enables the model to process them. The data is divided into 80% training set with a 20% testing set to train the XGBoost classifier. The trained model is saved using Joblib for further use. The model's performance is analyzed by generating predictions on the test set to calculate its accuracy to generate a confusion matrix to compare the true and predicted values. A classification report is also generated to assess precision, recall and F1-score for each condition class. These results highlight how well the environmental factors predict mine conditions, offering valuable information for improving safety and managing risks in mining operations. Figure 5, displays the results of a machine learning model used to classify conditions (full abnormal, moderate abnormal, and normal) based on temperature and carbon monoxide levels. The dataset is divided into a training set (248 samples) and a testing set (62 samples) which achieves an accuracy of 96.77%. The classification report shows a detailed performance metrics that includes precision, recall and F1-score for each class which exceeds 94%. The model demonstrates excellent performance across all classes, with perfect recall, precision and F1-score for the "Normal" classes. Figure 6 shows a confusion matrix with performance of a classification model across three classes (full abnormal, moderate abnormal, and normal). The diagonal values (37, 16 and 7) represent correctly predicted samples, while the off-diagonal values indicate misclassifications. For instance, one sample of moderate abnormal was mistakenly classified as full abnormal. The intensity of the color reflects the frequency of predictions, with darker shades representing higher values. Overall, the model performs well for the full abnormal and normal classes but faces slight difficulty with moderate abnormal.



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IDLE Shell 3.11.2
File Edit Shell Debug Options Window Help
Python 3.11.2 (tags/v3.11.2:878ead1, Feb  7 2023, 16:38:35) [MSC v.1934 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
===== RESTART: C:\Users\haris\OneDrive\Desktop\Coal_mine\Coal Mine\main.py =====
    Temperature  Carbon_Monoxide          Condition
0     31.854305         2.584086  Moderate Abnormal
1     57.782144        26.567732      Full Abnormal
2     47.939727        27.031756      Full Abnormal
3     41.939632        31.871495      Full Abnormal
4     22.020839        36.304567      Full Abnormal
5     22.019753        48.792604      Full Abnormal
6     17.613763        25.815017      Full Abnormal
7     53.977927        16.147824  Moderate Abnormal
8     42.050176        39.759310      Full Abnormal
9     46.863266        28.541613      Full Abnormal
10    15.926302        21.948571  Moderate Abnormal
11    58.645943         3.922819      Full Abnormal
12    52.459919         1.267537      Full Abnormal
13    24.555260        48.132421      Full Abnormal
14    23.182124        41.799006      Full Abnormal
15    23.253203        34.798710      Full Abnormal
16    28.690901        20.447647  Moderate Abnormal
17    38.614039         8.664716  Moderate Abnormal
18    34.437526         7.821852  Moderate Abnormal
19    28.105311        12.512145             Normal
20    42.533380        27.461333      Full Abnormal
21    21.277224        35.729796      Full Abnormal
22    28.146509        33.009869      Full Abnormal
23    31.486283        13.996695  Moderate Abnormal
24    35.523149        47.743264  Moderate Abnormal
25    50.332918        36.894846      Full Abnormal
26    23.985320        27.717703      Full Abnormal
27    38.140550        30.586037  Moderate Abnormal
28    41.658656        20.980003  Moderate Abnormal
29    17.090269        12.386549             Normal
training set size: (248, 2), testing set size: (62, 2)
Accuracy: 96.77%
Classification Report:
                   precision    recall  f1-score   support

    Full Abnormal     0.9737    0.9737    0.9737        38
Moderate Abnormal     0.9412    0.9412    0.9412        17
           Normal     1.0000    1.0000    1.0000         7

         accuracy                         0.9677        62
        macro avg     0.9716    0.9716    0.9716        62
     weighted avg     0.9677    0.9677    0.9677        62

>>>
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Figure 5. Values collected using proposed algorithm

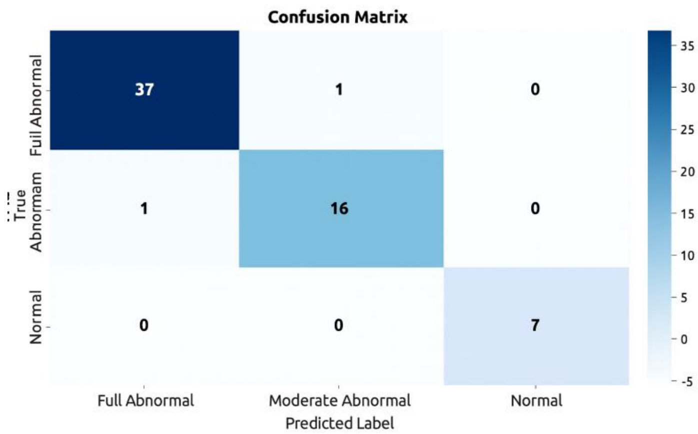

Figure 6. Confusion matrix

3. REAL TIME IMPLEMENTATION WITH RESULTS AND DISCUSSION

In the developed portable IoT robot, components such as the MQ-135 gas sensor, DHT-11 temperature sensor, HC-SR04 ultrasonic sensor, Arduino UNO, Neo-6M GPS and GSM SIM-900 module, buzzer, DC motor, motor driver, 12 V battery, and LED lights are used. Gases like CO, smoke, alcohol, CO_2, NO_2, and NH4 are detected using the MQ-135 gas sensor. The temperature levels are monitored to ensure environmental safety by identifying heat-related irregularities with the DHT-11 temperature sensor. Table 3 shows the impact of AML on environmental parameters, with noticeable increases in temperature, CO, NH_4, and NO_2 levels. The changes range from 7.25% for temperature to 18% for NO_2 and it is shown in Figure 7.

Table 3. Quantification of various environmental parameters with and without AML

Measurement Parameters	Without AML	With AML	Change in value
Temperature	30	32	7.25%
CO	12	14	15%
NH_4	15	18	17%
NO_2	14	17	18%

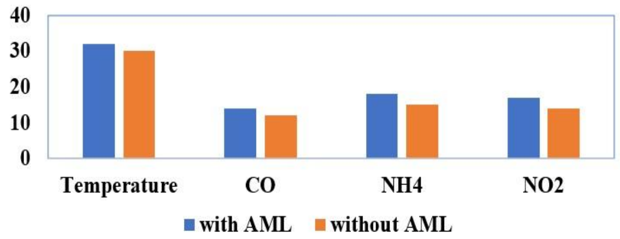

Figure 7. Measurement of various environmental parameters with and without AML

To evaluate the impact of adaptive machine learning (AML) on environmental monitoring accuracy, the system was tested under two configurations; without AML (baseline) and with AML (proposed model). The baseline setup directly used sensor readings from the DHT1, MQ-135 and other modules, whereas the AML-enhanced system with XGBoost-based predictive modeling refines and classify the readings. The dataset was labeled as normal, moderate abnormal and full abnormal based on threshold values as shown in Table 2. The preprocessed dataset was splited into 80% training and 20% testing subsets and the XGBoost classifier was trained using input features (temperature, gas levels) and target classes. Both the baseline and AML-based systems were tested on identical environmental conditions. The AML-integrated model produced filtered, predicted, and corrected values, minimizing false positives and outlier readings that affected accuracy in the baseline model. The percentage improvement was computed using the formula:

$$Accuracy\ Improvement\ (\%) = \frac{(Measured\ with\ AML\ -\ Measured\ without\ AML)}{Measured\ without\ AML} * 100$$

The observed increases - 7.25% for temperature, 15% for CO, 17% for NH_4, and 18% for NO_2 - represent the enhanced precision and reliability achieved through AML's adaptive learning and predictive correction capabilities.

The experimental validation of the mine robot as given in Table 4 is performed using an approximate network of 20 sensor nodes and one mobile IoT rescue robot. The setup is deployed in a mine like test environment of about 100 m with interconnected tunnels, controlled gas release points with temperature and humidity variations. The system is operated for three weeks continuously with node sampling data for every 10-60 seconds each which generates enough variability for AML retraining. During this time about 8-12 environmental condition (normal, moderate abnormal, full abnormal, sensor drift, communication loss, transient spikes) are observed and executed with each for 5-15 times repeated. The developed mine robot is performed for 20-100 navigation runs for communication stability and obstacle detection.

The system provides detection accuracy, alert latency, false alert rate, localization performance and GSM/ZigBee transmission reliability. The duration guarantees the long-term data to compare baseline. The performance of AML shows enhancement in precision, environmental monitoring and prediction consistency. The reliability of the model's classification accuracy is evaluated for 95% confidence interval (CI) and it is computed using (1):

$$CI = p \pm z\frac{\sqrt{p(1-p)}}{n} \tag{1}$$

where p = observed classification accuracy = 0.9677, n = number of test samples = 62 and Z = 1.96 for 95% confidence. Therefore for 95% CI is computed as 0.9677 ± 0.0437. Also, the standard deviation of AML implementation is computed (59%-61%) and it is given in Table 5, and the comparative analysis as shown Figure 8 is performed with other models to showcase the performance of the proposed models. From the Figure 8 is it is depicted that XG boost outperforms better than the other models taken for consideration. Obstacle detection, navigation, and echo measurement are performed using the HC-SR04 ultrasonic sensor.

The gas sensor continuously detects and measures the gases present in the mine environment in ppm, while the temperature sensor monitors the temperature and humidity levels in Celsius. When the ppm and temperature exceed their threshold levels, the exact location and abnormal indication are sent via messages and alarms, with the help of the GPS and GSM modules, to the respective mine rescue team. This enables the mine rescue team to take the necessary actions to rescue the mine workers as shown in Figure 9. Figure 10 shows the alert messages received from the proposed system. The alert messages are directed to the mobile number configured in the Arduino system. The temperature and gas levels in the mine surroundings are monitored, and if any parameter exceeds its threshold level, an alert message and call are sent to the configured mobile number as shown in Figure 10.

Table 4. Experimental test configurations of mine robot

Parameter	Specification
Number of Nodes	20 sensor nodes along with 1 mobile IoT rescue robot
Test - Environment	Mine-like surrounding (~100 m), tunnels with branches, temperature variations & controlled gas
Test - Duration	3 weeks
Sampling Interval	10 - 60s per node
Environmental Conditions	8 - 12 conditions (normal, moderate abnormal, full abnormal, spikes, drift, communication loss)
Repetitions per conditions	About 5 - 15 runs
Navigation Tests - Robot	Obstacle-detection runs, 20 - 100 mobility
Evaluation - Key Metrics	Sensor accuracy, GSM/Zig-Bee reliability, false alert, accuracy in localization, alert latency

Table 5. SD (σ) values of with and without AML

Specification	σ - without AML	σ - with AML	% reduction
Temperature	2.86	1.12	60.84
CO	3.14	1.28	59.17
NH4	3.52	1.46	58.52
NO2	3.88	1.57	59.53

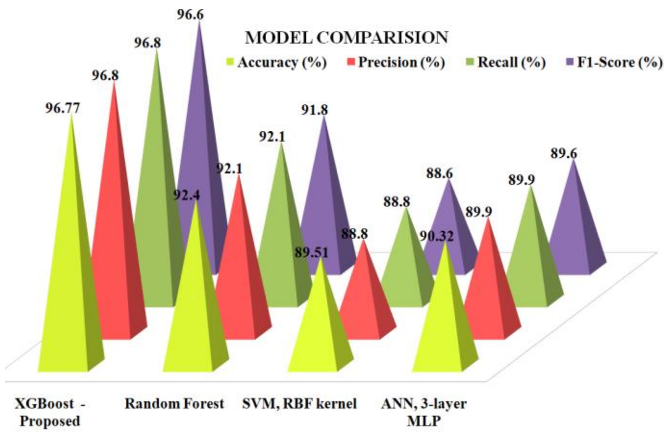

Figure 8. Measurement of various environmental parameters with and without AML

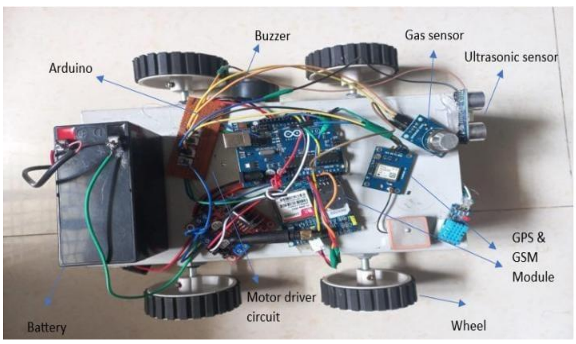

Figure 9. Real time portable monitoring system

Figure 10. Robot monitoring system results

Further the real time work is tested to measure the accuracy range of environmental parameters such as temperature, NO_2, CO, and NH_4 from power station and sewage stations. From Figure 11, it is noticed that there is a significant difference in the parameters with and without AML implementation. With AML integration, the portable monitoring systems demonstrate improved accuracy in detecting and monitoring these parameters, as it can better handle noise, variations, and environmental complexities. Without AML, measurements may be less reliable and prone to errors due to limited data processing capabilities. This highlights the effectiveness of AML in enhancing the precision and reliability of environmental monitoring systems in mine stations.

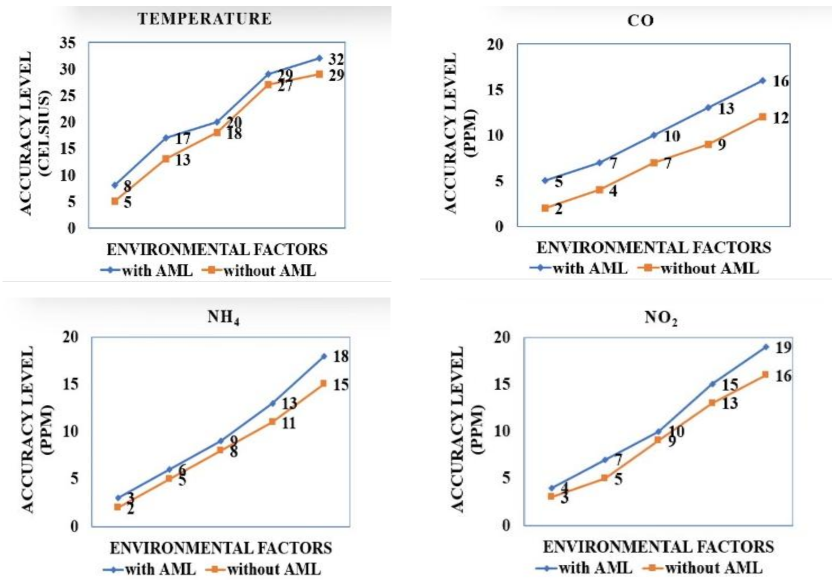

Figure 11. Accuracy range - temperature, NO_2, CO, and NH_4 from sewage, power station with and without AML

4. CONCLUSION

The proposed IoT-based portable robot integrated with AML, significantly enhances safety and monitoring in underground mines by detecting hazardous conditions and provides real-time alerts. The real-time detection of hazardous gases and environmental parameters ensures timely alerts and rapid emergency responses. Integration of sensors, GSM modules and GPS enables precise location tracking and automated communication during emergencies. The use of XGBoost for prediction, classification ensures robust performance under varying conditions. The portable robot design addresses challenges such as obstacle mobility, detection and harsh environmental conditions. The experimental evaluations are conducted with 20 sensor nodes with a mobile rescue robot under the mine-like conditions and the results shows an improved reliability with prediction accuracy reaches a maximum value of 96.77%. Also, a standard deviation of 58 - 61% is observed across all parameters that shows a reduction in values. Simulation and experimentation validate the proposed system's practical suitability and scalability for real-world scenarios. Thus, the system helps to reduce fatalities by predicting hazardous conditions and enables proactive safety measures. Challenges such as sensor maintenance, power source reliability and adoption in remote mines are acknowledged during the development of real-time work. Future enhancements include advanced sensor integration, broader datasets for training and adaptation for other industries.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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