# Smart Helmet with LoRaWAN and Relay Node for Monitoring Underground Mine Worker Health in Hazardous Environment.

Dr. Manigandan M
*Dept. of Electronics and Communication Engg.*
*Vellore Institute of Technology - Chennai, India*
Email: sir@email.com

Sanskriti Singh
*Dept. of Electronics and Communication Engg.*
*Vellore Institute of Technology - Chennai, India*
Email: sanskriti.21.03@gmail.com

Srishti
*Dept. of Electronics and Communication Engg.*
*Vellore Institute of Technology - Chennai, India*
Email: bhardwajsrishti3120@gmail.com

Vinodkumar Sanjiv
*Dept. of Electronics and Communication Engg.*
*Vellore Institute of Technology - Chennai, India*
Email: sanjivvinod107@gmail.com

*Abstract*—This invention relates to a LoRa-based smart health predictor system designed for real-time monitoring and predictive analysis of underground mine workers' health conditions in hazardous environments. The system comprises wearable Helmet-LoRa transmitter modules, each integrated with multiple sensors, including an Ear Pulse Sensor for heart rate (BPM) monitoring, a BMP280 sensor for temperature, atmospheric pressure, and altitude measurement, an Accelerometer for step count and distance tracking, and an MQ135 Gas Sensor for air quality index (AQI) assessment. Each Helmet-LoRa transmitter module is assigned a unique DEVICE ID for precise worker identification and seamless data logging. The system employs a multi-node LoRa wireless network, utilizing relay nodes (1 to N-1) for extended-range data transmission from the wearable transmitters to an Nth relay receiver node, which continuously forwards the collected physiological and environmental data to a centralized monitoring server. The server hosts an AI-based predictive health analytics module, which processes real-time sensor data using a gradient boosting machine learning model to predict future BPM values based on past AQI, altitude, pressure, temperature, and movement patterns. The system enables early warning alerts for potential health risks, including abnormal heartrate variations, deteriorating air quality, altitude-related fatigue, and excessive exertion. By applying time-series analysis and multi-epoch training, the AI model detects deviations in worker health parameters and movement behaviour, triggering proactive alerts for timely intervention. The invention ensures continuous worker health surveillance, proactive risk assessment, and enhanced occupational safety in deep underground mining operations, offering a scalable and cost-effective solution for real-time health monitoring and predictive analytics.

*Index Terms*— LoRa, Underground mine Workers, Health Monitoring, IoT, Deep Learning, Air Quality, Real-Time Data Transmission, Predictive Analytics.

## I. Introduction

The mining industry, while crucial for economic development and resource extraction, is inherently hazardous, posing significant risks to workers' safety and well-being. Traditional safety measures often prove inadequate in addressing the dynamic and challenging environments of underground mines. Recent advancements in intelligent technology for underground hard rock mining have concentrated on six critical processes: rock drilling, blasting, transportation, hoisting, ventilation, and support and filling. These developments aim to enhance efficiency and safety in mining operations through the integration of cutting-edge technologies, including machine learning and artificial intelligence. These innovations, highlighted in [1], emphasize intelligent sensing, fault diagnosis, and control technologies to address operational challenges. In the forestry sector, particularly in New Zealand, IoT solutions have garnered attention for their potential to improve workplace safety in one of the most hazardous industries. Despite advancements in other high-risk sectors, there remains a lack of human-centred IoT safety systems in forestry. The study in [2], explores the feasibility of using IoT as assistive safety technology, presenting a proof-of-concept deployment and evaluating its application in two forestry scenarios. The risks associated with gas explosions in underground mines have been comprehensively examined in [3], with a focus on hazard analysis and specific case studies in India. The research underscores the critical need for continuous real-time monitoring of environmental parameters to enhance safety and optimize production. Furthermore, [3] reviews the adoption of IoT technologies, such as ZigBee and LoRa, for efficient wireless communication in underground mining environments. A smart coal mining helmet equipped with a comprehensive sensor system to monitor environmental parameters, such as temperature, humidity, and gas levels, is detailed in [4]. This innovation addresses the pressing need for improved safety measures in the mining sector. The system continuously collects data and communicates alerts through IoT, enhancing safety for miners and supervisors. The evolution of wearable technology, including its architectures, data processing, and communication methods, is thoroughly explored in [5]. The study highlights the rapid growth of interconnected devices driven by IoT proliferation and user demand. With advancements in smart devices, the wearable market is expected to experience substantial growth, offering opportunities for enhanced safety and functionality in various sectors, including mining. The integration of advanced digital technologies is transforming various industries, including construction, sports, healthcare, and extreme environments, through the adoption of wearable sensing technologies (WSTs). WSTs have demonstrated significant potential in monitoring worker behaviour and physiological conditions, enhancing safety performance, and supporting digital transformation efforts in construction by enabling continuous monitoring of workers' physical and psychological states [6]. The emergence of Safety 4.0, which incorporates cutting-edge technologies such as artificial intelligence (AI), the Internet of Things (IoT), and robotics, has played a pivotal role in enhancing workplace safety and productivity. This approach aligns with the United Nations Sustainable Development Goals (SDGs) by emphasizing sustainability and innovation in industrial settings [7]. Advances in computer vision (CV) methods have introduced non-invasive, cost-effective solutions for personal protective equipment (PPE) detection. These systems, driven by IoT and machine learning (ML), automate PPE compliance monitoring, reducing reliance on human inspection. The introduction of datasets like SH17 has further enhanced detection capabilities, addressing limitations and improving system generalizability across diverse industrial environments [8]. IoT has also made significant contributions to occupational safety and health (OSH), particularly within the framework of Industry 4.0. Research highlights its impact on occupational well-being, focusing on human-cantered approaches that address physiological and psychological aspects of worker health. The role of Occupational Health and Safety (OHS) programs in mitigating workplace injuries and illnesses is increasingly critical in this context [9]. In underground mining, the application of wireless sensor networks (WSNs) has been pivotal in overcoming the limitations of traditional safety systems. WSNs facilitate real-time monitoring of environmental parameters, worker location, physiological conditions, and body kinematics, addressing the challenges of managing dynamic and hazardous mining environments [10]. The incorporation of state-of-the-art technologies, including advanced sensors, artificial intelligence (AI), and the Internet of Things (IoT), has become a crucial area of research and development in order to reduce these risks and improve worker safety. The wireless IoT integration and AI/ML capabilities of smart helmet technology are subject to a number of restrictions. Implementing hybrid communication networks like LoRa, ZigBee, and 5G in a mesh architecture for redundancy can help overcome the significant connectivity issues in underground mining caused by signal attenuation and interference. Energy-efficient designs and energy harvesting systems are necessary to prolong battery life due to the high power consumption of sensors and processing units. Using industrial-grade, self-calibrating sensors can help reduce the effects of environmental factors like dust and temperature extremes that can affect sensor accuracy in mines. Real-time processing of massive volumes of data can cause latency; delays can be minimized by incorporating edge computing for local data processing. Smart helmets' high price prevents many people from using them, but modular designs with optional cutting-edge features can make them more affordable. The sensitive nature of worker health and safety data raises additional concerns about data security; blockchain-based solutions and encryption can improve security.

## II. Related Works

Due to the inherent risks associated with the mining industry, creative safety solutions leveraging smart technologies have been developed. It has been suggested to use ZigBee communication in a smart helmet-based monitoring system to guarantee dependable long-range communication. In order to detect hazardous conditions, this system uses a variety of sensors, such as gas and atmospheric pressure sensors. It highlights the importance of the Internet of Things in real-time data transmission and monitoring to improve miner safety [11]. Temperature, gas, and pressure sensors are integrated into the smart safety helmet to reduce accidents by providing real-time alerts for environmental hazards and toxic gases [11]. The development of intelligent headgear that addresses fire hazards, air quality, helmet removal, and mercury detection emphasize the significance of keeping an eye on harmful gases like CO, CH4, and particulate matter. Monitoring hazardous gases in mining environments is crucial, and the system uses LoRa WAN technology to provide air quality alerts [12]. Similarly, to provide complete safety, a smart helmet made for coal miners incorporates sensors like temperature, humidity, and heartbeat monitors. Using RF circuitry for real-time miner tracking, this system focuses on using Industrial Internet of Things (IoT) and Artificial Intelligence (AI) technologies to reduce the risks posed by gases such as carbon monoxide and methane [13]. Smart helmets and wearable IoT-based jackets for early disaster prediction are examples of further developments. By sending data over Wi-Fi, these systems keep an eye on hazardous gases, environmental conditions, vital signs, and GPS location.

With real-time data acquisition made possible by the IEEE 1451 protocol, a ZigBee-based safety system was also suggested that would sound alarms when sensor thresholds are surpassed [14]. It has been investigated to combine visible light communication (VLC) and LoRa technology to overcome difficulties with data transmission and miner localization. In order to improve safety and operational effectiveness, these technologies seek to address pathloss and signal attenuation problems in underground mines [15]. The development of resistive-type IoT-based methane sensors that use SnO2 as a sensing medium has been a focus of methane detection technologies. With different methane concentrations, these sensors measure variations in electrical resistance and use the Internet of Things to transmit data. A Wheatstone bridge is used to improve accuracy and sensitivity and overcome the limitations of commercial SnO2-based sensors, including temperature sensitivity, to ensure efficient monitoring in hazardous environments [16]. The importance of cutting-edge sensing and communication technologies in enhancing miners' safety procedures is highlighted by these developments. The mining industry is inherently hazardous, with frequent accidents caused by roof collapses, gas explosions, and toxic gas leaks, necessitating advanced safety measures. Several researchers have highlighted the potential of IoT and AI technologies in improving miner safety by enabling effective monitoring and swift data transmission. Smart helmets equipped with various sensors have been proposed to monitor environmental hazards and provide real-time alerts, thereby reducing risks and improving safety in dangerous underground environments [17]. Existing systems for mining safety often rely on communication technologies such as ZigBee and Wi-Fi, which face limitations in underground environments due to short range and high power consumption. LoRa WAN technology has emerged as a superior alternative, offering long-range communication and power efficiency. Helmets employing LoRa WAN not only monitor hazardous conditions like temperature, humidity, and harmful gases but also incorporate vibration-based alerts to overcome the challenges of noisy environments. Additionally, wear detection features ensure compliance with safety protocols, and data is transmitted to control rooms for remote monitoring [18]. The integration of IoT into smart helmets has enabled real-time monitoring of both environmental conditions and miners' physiological health. These systems, designed to predict and prevent mining hazards, emphasize features such as location tracking, GPS integration, and health monitoring, which facilitate swift emergency responses and improve safety standards. Studies also underscore the importance of detecting undetectable gases such as methane and carbon monoxide, which are major contributors to mining accidents [19] and[20]. Several advancements in smart helmet technologies have been documented. For instance, Karna et al. introduced an IoT-based helmet utilizing the LoRa WAN protocol for real-time communication with control rooms, enhancing situational awareness. Banik et al. developed systems for real-time hazard detection and proactive safety management, while Paul et al. proposed a sensor-based model for gas detection and GPS enabled emergency coordination. Sagare et al. emphasized the integration of health monitoring and location tracking to bolster industrial safety practices [21]. Innovative helmets have also incorporated HEPA-filtered respiratory masks to protect miners from airborne particles, such as those causing Black Lung disease. These helmets, featuring advanced sensors for monitoring air quality, pressure, and radiation, transmit data to management via LoRa technology. This integration allows for proactive safety measures aimed at significantly reducing accidents and health issues in the mining industry [21]. The collective efforts in research demonstrate the transformative potential of IoT and AI technologies in mining safety. By addressing critical challenges such as communication reliability, battery life, and real-time hazard detection, these studies provide a strong foundation for the development of advanced safety solutions for hazardous mining environments [17–21]. The mining industry is critical for economic development but is fraught with risks, including hazardous working environments and frequent life-threatening incidents. Numerous studies have proposed advanced safety solutions to mitigate these risks, particularly through the integration of IoT, AI, and wearable technologies. These innovations aim to improve real-time monitoring, enhance communication, and reduce accidents through predictive safety measures and rapid responses [22]. The use of IoT-enabled smart helmets equipped with sensors such as LM35, MQ-6, MQ-7, and MQ135 has been extensively explored for monitoring gas levels, temperature, and other environmental parameters. These systems, typically integrated with microcontrollers like Arduino Uno R3 or ESP32, transmit data to the cloud for real-time alerts via SMS or other communication methods. The multisensory approach also incorporates electrochemical sensors for gas detection and accelerometers for assessing potential brain injuries due to impacts. These advancements represent significant progress in personal protective equipment (PPE) for miners [23]. Wireless sensor networks and IoT technologies have been emphasized for their ability to facilitate real-time monitoring and communication in mining environments. LoRaWAN protocols are particularly noted for their long-range communication and power efficiency compared to ZigBee or Wi-Fi technologies, which face limitations in underground settings. These systems enhance miner safety by providing timely alerts and enabling data transmission to control rooms for remote monitoring and swift emergency responses [23]. The integration of AI and computer vision technologies has transformed mining safety, particularly through human pose estimation, PPE compliance monitoring, and rescue operations. These advancements enable precise safety monitoring, predictive analytics, and effective response strategies, even in harsh conditions. The combination of AI and deep learning models has been pivotal in developing comprehensive datasets for body situation classification and refining PPE detection to enhance operational safety [24]. Several studies have focused on the development of smart helmets designed to address the unique challenges of mining environments. Karna et al. introduced an IoT-based helmet employing LoRa WAN for real-time communication and hazard detection, while Banik et al. and Sagare et al. emphasized the incorporation of health monitoring and location tracking. Additional innovations include HEPA-filtered respiratory masks to protect against airborne particles, such as those causing Black Lung disease, and automatic oxygen supplies for use during emergencies [21, 24]. Despite these advancements, challenges such as network reliability, battery life, and the integration of real-time health analysis in existing systems persist. Studies underscore the need for further research into ambient intelligence techniques and comprehensive safety protocols to bridge these gaps. Future designs should focus on enhancing ventilation systems, integrating mobile app solutions, and leveraging advanced analytics for predictive safety measures [23, 26]. By synthesizing the findings from these studies, this research proposes an innovative IoT-enabled helmet that incorporates advanced sensors, AI-driven analytics, and robust communication protocols. This prototype aims to address existing limitations, enhance real-time monitoring, and improve rescue operations, thereby setting a new standard for safety in the mining industry [25].

Table I: Innovative IoT-enabled helmet incorporating advanced sensors, AI-driven analytics, and reliable communication protocols to enhance safety and operational efficiency in hazardous mining environments.

| Ref. | Technology | Challenges | Applications |
|---|---|---|---|
| [11], [14] | ZigBee | Limited range and high power consumption. | Smart helmet monitoring, real-time data transmission. |
| [12], [18] | LoRaWAN | Signal attenuation in underground environments. | Long-range, low-power monitoring of hazardous conditions. |
| [11], [13], [17], [23] | IoT Helmets | Battery life, network reliability. | Sensor integration, GPS tracking, predictive hazard detection. |
| [13] | RF Circuitry | High interference susceptibility. | Real-time miner tracking and safety monitoring. |
| [14] | IEEE 1451 | Needs IoT framework integration. | Real-time alerts when safety thresholds exceed limits. |
| [14], [18] | Wearable IoT | Battery life issues, network dependency. | Vital signs monitoring, GPS tracking, early disaster prediction. |
| [16] | Methane Sensors | Temperature sensitivity. | Real-time methane detection using IoT. |
| [15] | VLC | Signal interference issues. | Data transmission and miner localization in underground mines. |
| [21], [24] | HEPA Helmets | Needs better integration with automation. | Respiratory protection, air quality monitoring. |
| [23] | Microcontrollers | Limited AI processing power. | IoT-enabled real-time alerts and cloud transmission. |
| [24] | AI & Vision | High computational demands. | PPE compliance, miner safety analytics, hazard response. |

Summary: The collective efforts in research demonstrate the transformative potential of IoT, AI, and wearable technologies in mining safety. By addressing critical challenges and leveraging advanced communication and sensing technologies, these studies provide a solid foundation for developing robust safety solutions. This research builds on these advancements, proposing an innovative IoT-enabled helmet incorporating advanced sensors, AI-driven analytics, and reliable communication protocols to enhance safety and operational efficiency in hazardous mining environments as mentioned in Table.

## III. System Architecture

### *A. Overview*

The proposed invention is a LoRa-based health monitoring system designed for landmine workers to continuously track their physiological and environmental conditions in real-time. The system consists of multiple LoRa transmitter modules, relay nodes, and a LoRa receiver module connected to a central server. Each worker wears a helmet-mounted transmitter module, which is equipped with multiple sensors to collect vital health parameters, including heart rate (BPM), air quality index (AQI), temperature, pressure, altitude, step count, and distance travelled.

The collected data is transmitted via LoRa to a base station, which is responsible for storing, analysing, and predicting worker health status using a deep learning model. To extend the communication range and ensure seamless connectivity in underground environments, $N$ relay nodes are deployed between the transmitter modules and the base station. These relay nodes optimize and forward sensor data packets from multiple workers, ensuring efficient and real-time monitoring.

A centralized server processes the incoming data, stores it in a database, and displays real-time worker health parameters on a web dashboard. Additionally, a deep learning-based AI model is used to analyse time-series sensor data and predict potential health risks, allowing for proactive health interventions.

### *B. System Components*

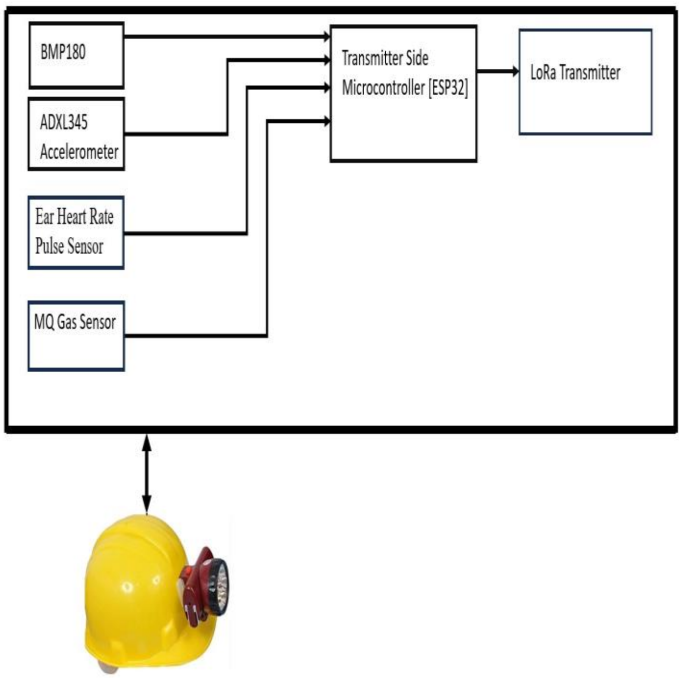



*Figure 1: Transmitter Block Diagram*

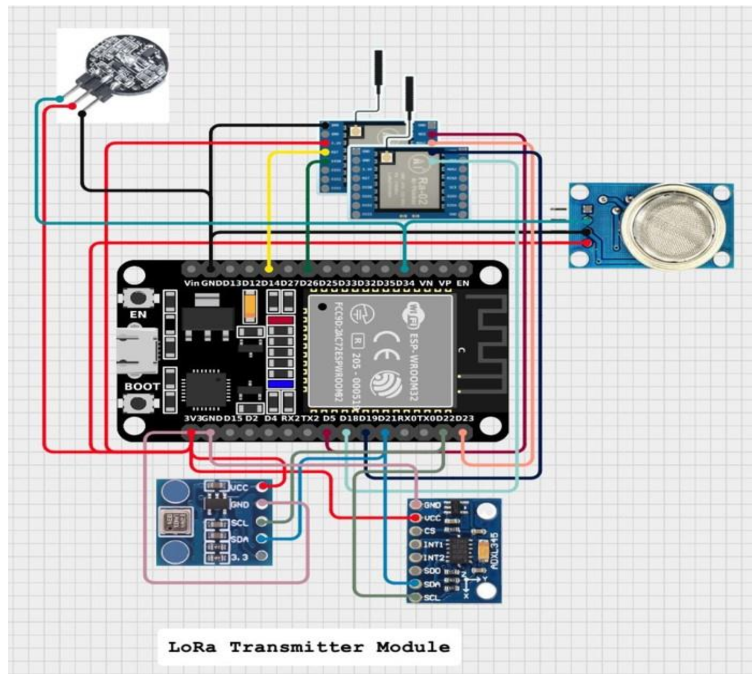



*Figure 2: Transmitter Circuit Diagram*

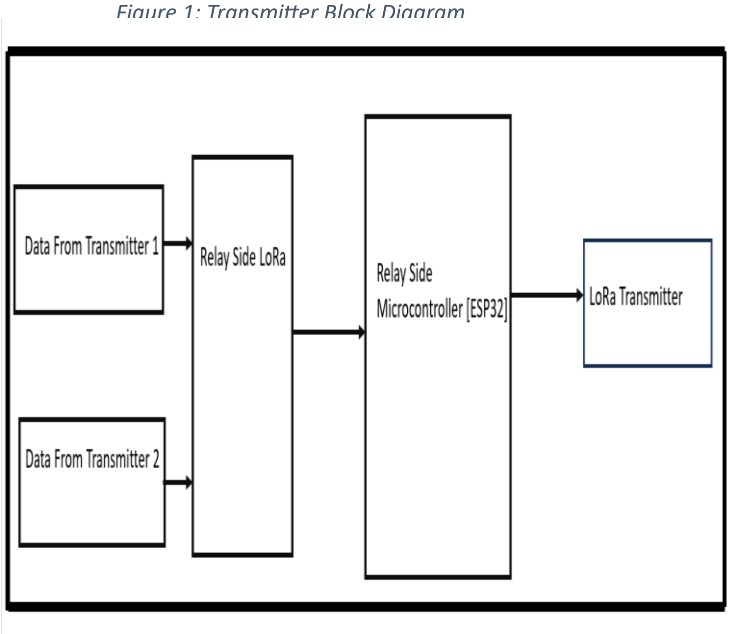



*Figure 3: Relay Block Diagram*

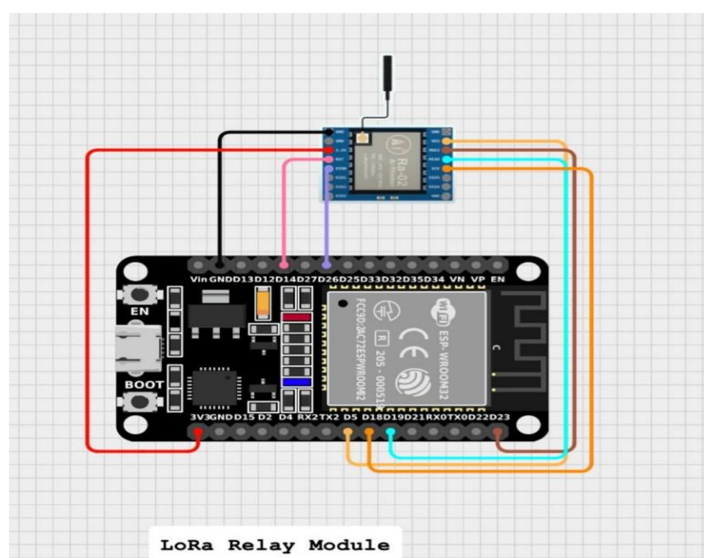



*Figure 4: Relay Circuit Diagram*

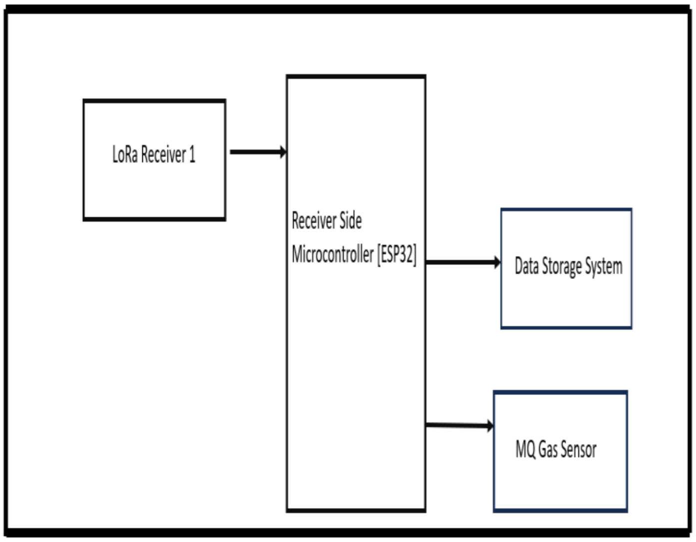



*Figure 5: Receiver Block Diagram*

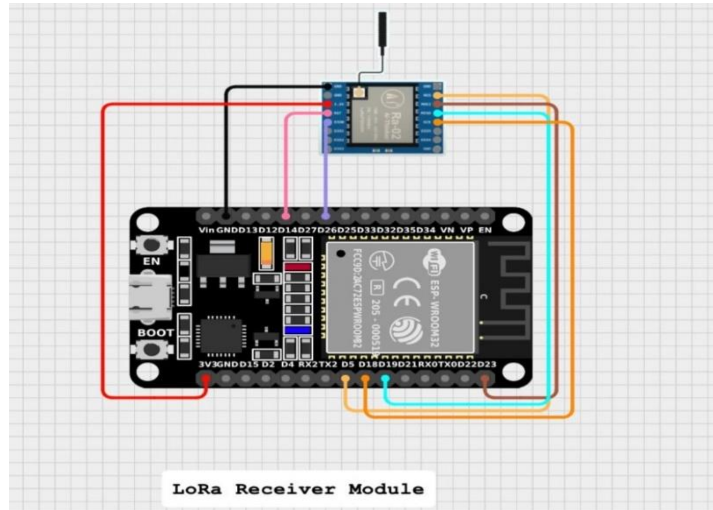



*Figure 6: Receiver Circuit Diagram*

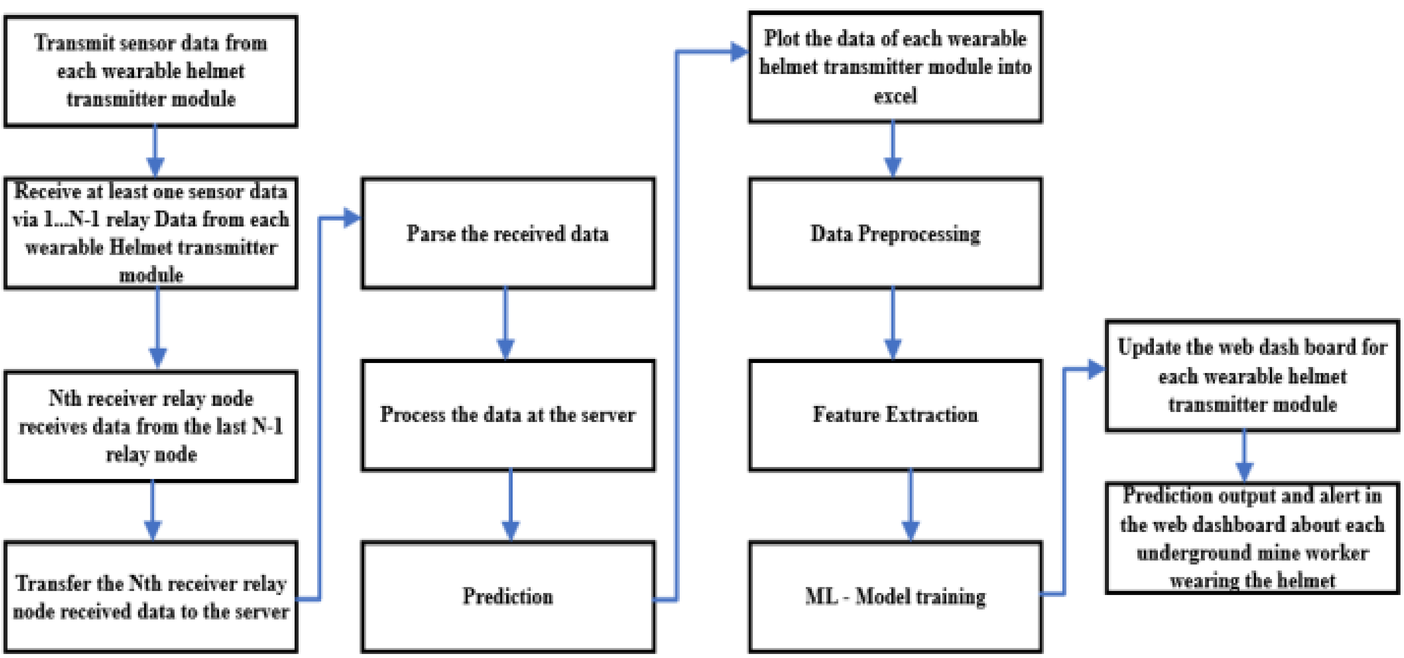



*Figure 7: Proposed Framework for Dashboard and ML Analysis*

### C. Hardware Components

The system has integrated a number of physical components to ensure seamless data acquisition, transmission, and analysis.

| Component | Function | Range | Parameters Measured |
|---|---|---|---|
| LoRa Transceiver (SX1276/SX1278) | Transmits sensor data to relay nodes or base station | 5–10 km (open area), 1–2 km (underground) | Sensor Data Transmission |
| Ear Pulse Sensor | Measures heart rate (BPM) to monitor fatigue and stress levels | Attached to the ear | Heart Rate (BPM) |
| BMP280 Sensor | Monitors temperature, pressure, and altitude to detect environmental hazards | ±1 hPa (pressure), ±0.5°C (temperature), ±1m (altitude) | Temperature, Pressure, Altitude |
| Accelerometer | Tracks movement, counts steps, and estimates distance traveled | Based on worker movement and calibration | Step Count, Distance Traveled |
| MQ135 Gas Sensor | Measures air quality by detecting harmful gases | 0–500 AQI scale | Air Quality Index (AQI), $CO_2$, $NH_3$, $NO_2$ levels |
| Microcontroller (ESP32/Arduino) | Controls sensor data collection and manages LoRa transmission | Low-power optimized | Sensor Data Processing, Transmission Control |
| Power Source (Li-ion Battery 3.7V, 2000mAh) | Supplies power to the entire transmitter module | Varies based on power consumption | Power Supply, Battery Life Management |

*Tabular Analysis of the Components*

### D. BPM Calculation from Ear Lobe Pulse Sensor (Graylogix)

The Graylogix ear lobe pulse sensor detects blood flow variations through infrared light absorption. The pulse rate is extracted using a peak detection algorithm:

$$BPM = \frac{60}{T} \tag{1}$$

where $T$ is the time interval between successive peaks in the pulse waveform.

A moving average filter is applied to smooth noise, improving accuracy:

$$BPM_{avg} = \frac{1}{N}\sum_{i=1}^{N} BPM_i \tag{2}$$

where $N$ is the number of recent BPM readings used in averaging.

### E. BMP180 Sensor for Environmental Monitoring

The BMP180 sensor is embedded inside the helmet module to measure ambient temperature, pressure, and altitude. This sensor detects high temperatures, sudden pressure variations, and changes in altitude, indicating dangerous environmental conditions. It features:

- Pressure accuracy:
  - ±1 hPa
- Temperature accuracy:
  - $\pm 0.5^\circ C$
- Altitude accuracy:
  - ±1 meter

### F. Step Count Calculation from Accelerometer Data

The accelerometer measures acceleration along three axes: X, Y, and Z. The total acceleration magnitude is given by:

$$A_{total} = \sqrt{A_x^2 + A_y^2 + A_z^2} \tag{3}$$

A step is detected when the acceleration crosses a predefined threshold $A_{th}$:

$$A_{total} > A_{th} \Rightarrow \text{Step detected} \tag{4}$$

The distance traveled is then calculated as:

$$D = S \times L \tag{5}$$

where:

- $D$ = Distance traveled (meters)
- $S$ = Number of steps
- $L$ = Average step length (typically 0.65m for adults)

### G. Air Quality Index (AQI) Calculation using MQ135 Sensor

The MQ135 gas sensor monitors air quality by measuring resistance changes due to gas concentration. The sensor resistance $R_s$ is given by:

$$R_s = \frac{V_{RL}}{I_{RL}} \tag{6}$$

The ratio of sensor resistance to clean air resistance is:

$$R_{ratio} = \frac{R_s}{R_0} \tag{7}$$

Gas concentration (PPM) is then estimated using:

$$PPM = a \times (R_{ratio})^b \tag{8}$$

The AQI is categorized into:

- 0–50: Good
- 51–100: Moderate
- 101–150: Unhealthy for Sensitive Groups
- 151–200: Unhealthy
- 201–300: Very Unhealthy

- 301–500: Hazardous

*H. Temperature Calculation*

The true temperature $T$ in Celsius is computed as:

$$X1 = (UT - AC6) \times \frac{AC5}{2^{15}} \quad (9)$$

$$X2 = \frac{MC \times 2^{11}}{X1 + MD} \quad (10)$$

$$B5 = X1 + X2 \quad (11)$$

$$T = \frac{B5 + 8}{2^4} \quad (12)$$

where:

- $UT$ = Raw temperature value
- $AC6, AC5, MC, MD$ = Calibration parameters

*I. Pressure Calculation*

The true pressure $P$ in Pascals is computed as:

$$X1 = \frac{B6^2}{2^{12}} \quad (13)$$

$$X2 = B2 \times X1 \quad (14)$$

$$X3 = \frac{B1 \times X2}{2^{10}} \quad (15)$$

$$B3 = B1 + X3 \quad (16)$$

$$P = \frac{B3 \times 2^{12}}{X3 + X2 + 2^{16}} \quad (17)$$

where:

- $UP$ = Raw pressure value
- $B1, B2, B6$ = Calibration parameters

## IV. Data Transmission Mechanism

The data transmission mechanism involves multiple stages, ensuring reliable communication between the helmet-mounted transmitter module and the base station. The process utilizes LoRa technology to transmit sensor data efficiently over long distances. Below is a breakdown of the transmission process from the helmet module.

*A. Data Transmission Process from the Helmet-Mounted Transmitter Module*

The helmet module collects sensor data from BPM, AQI, temperature, pressure, altitude, steps, and distance.
The data is formatted into a structured packet with a unique DEVICE ID.
The module transmits the packet via LoRa to either a relay node or the base station at regular intervals (every 30 seconds to 1 minute).

*B. Relay Node Functionality*

*Purpose of Relay Nodes:* Since underground mine environments have low signal penetration and high interference, relay nodes are deployed to extend the transmission range and ensure seamless communication between transmitter modules and the base station.

*Relay Node Working Mechanism:*

The relay node listens for incoming LoRa packets from worker transmitter modules.
It checks signal strength (RSSI) and determines whether to forward the packet to the next relay node or the base station.
If the base station is within range, the relay node sends data directly; otherwise, it forwards it to the next closest relay node using an adaptive multi-hop algorithm.
The relay nodes optimize data transmission by removing duplicate packets and ensuring minimal delay.

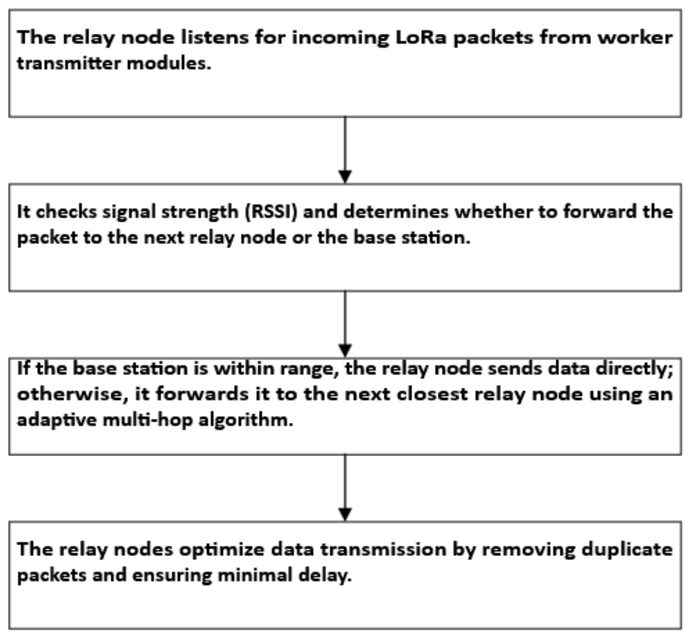



*Figure 8: Steps Involved in Relay Node Working Mechanism*

*C. Base Station LoRa Receiver Module*

*1) Base Station LoRa Receiver Module:* The Base Station LoRa Receiver Module is the central hub of the underground mine worker health monitoring system, responsible for collecting, processing, and forwarding sensor data received from the helmet-mounted LoRa transmitter modules and relay nodes deployed in the underground environment. The receiver ensures real-time data transmission to a centralized server, where the data is stored, analysed, and displayed on a web-based monitoring dashboard.

*2) Structure and Functionality of the Base Station Receiver:* The LoRa receiver module at the base station is strategically positioned at a secure and accessible location within or near the underground mine area. It features a high-gain LoRa antenna to maximize signal reception and ensure uninterrupted communication with multiple worker transmitter modules and relay nodes.

Upon receiving sensor data packets from the workers' helmet-mounted LoRa transmitters, the receiver performs packet validation and error correction to ensure that only accurate and complete data is processed. Each transmitted data packet consists of:

- DEVICE ID (unique to each worker)
- Heart Rate (BPM) from the Ear Pulse Sensor
- Air Quality Index (AQI) from the MQ135 Gas Sensor
- Temperature, Pressure, and Altitude from the BMP280 Sensor
- Step Count and Distance Travelled from the Accelerometer

The LoRa receiver module is designed to operate in a low-power, long-range communication mode, ensuring stable data collection even in deep underground environments where traditional communication methods (such as Wi-Fi, Bluetooth, or GPS) are unreliable.

Once the receiver successfully decodes a sensor data packet, it checks for packet integrity and then forwards the processed data to a centralized server using Wi-Fi or Ethernet connectivity. This transmission enables real-time data logging and health monitoring, allowing supervisors and safety personnel to track worker conditions continuously.

*3) Data Transmission from the Base Station to the Centralized Server:* Once the LoRa receiver module collects and processes the sensor data, it is transmitted to a centralized server using one of the following methods:

- Wi-Fi Connectivity
- Wired Ethernet Connection
- Cellular (4G/5G) Network (Optional Backup System)

The Base Station LoRa Receiver Module plays a crucial role in ensuring real-time health monitoring for underground mine workers. By collecting, validating, and forwarding sensor data to a centralized server, it enables continuous tracking of worker safety conditions. The integration of Wi-Fi, Ethernet, and cellular communication ensures seamless data transmission to the web-based dashboard, where supervisors can analyse trends, receive alerts, and make informed safety decisions.

This system significantly enhances occupational health and safety in hazardous underground mining environments.

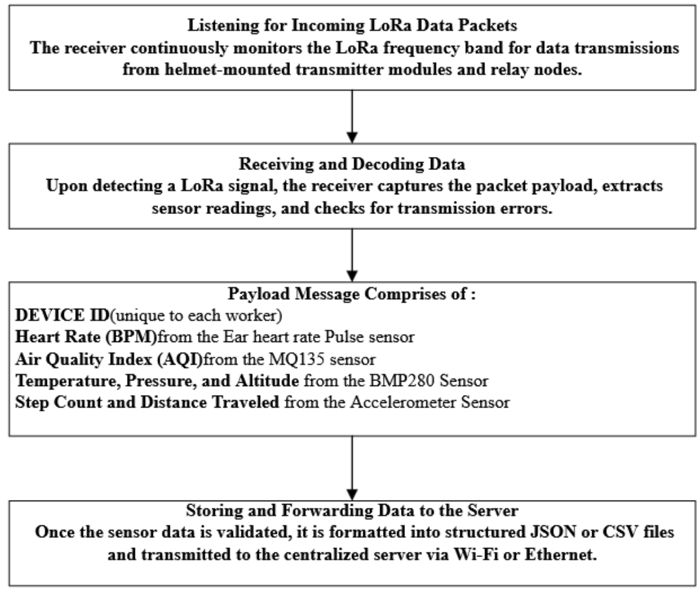



*Figure 9: Steps involved the Base Station LoRa Receiver or LoRa Relay Node N connected to server*

## V. Web Dashboard Analysis

### *A. Web Dashboard for Real-Time Monitoring*

The Web Dashboard for Real-Time Monitoring is a crucial component of the underground mine worker health monitoring system. It provides supervisors and safety personnel with a comprehensive and real-time visualization of each worker's health parameters, ensuring that potential hazards or health risks are detected early and mitigated effectively. The dashboard is accessible via web browsers on computers, tablets, and mobile devices, allowing seamless remote monitoring from anywhere.

### *B. Data Processing at the Centralized Server*

The centralized server is responsible for:

- Storing real-time sensor data in a secure database (SQL, Firebase, or Influx DB).
- Analysing trends and detecting anomalies in worker health and environmental conditions.
- Displaying live monitoring data on a web-based dashboard for supervisors.
- Triggering automated alerts if dangerous conditions are detected.
- Feeding sensor data into a deep learning AI model for health risk predictions.

The web-based dashboard provides a graphical user interface (GUI) where supervisors can:

View real-time sensor data from all workers, Analyse historical trends in BPM, AQI, temperature, pressure, and movement, Receive alerts for abnormal conditions affecting worker safety and Generate reports for occupational health and safety compliance.

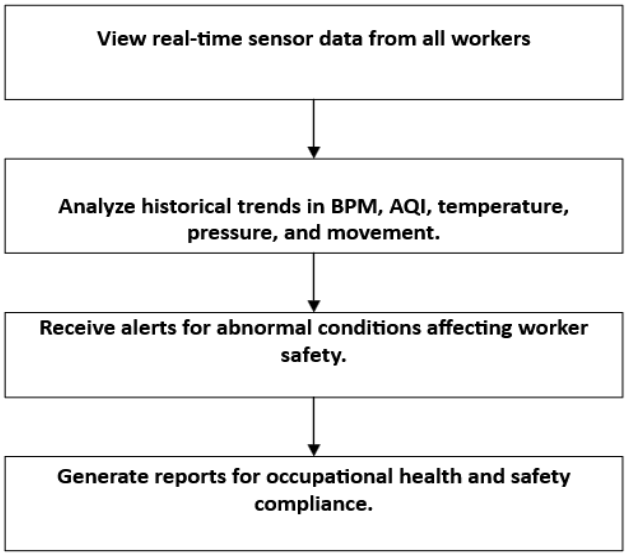



*Figure 10: Steps involved in Data Processing at the Centralized Servers*

*C. Real-Time Display of Worker Health Data*

The web dashboard is designed to display live data received from the helmet-mounted LoRa transmitter modules worn by the workers. The system collects sensor readings from each worker at regular intervals and updates the dashboard in real-time. The following vital health and environmental parameters are monitored:

Heart Rate (BPM) Monitoring:

Displays each worker's current heart rate as measured by the ear pulse sensor.

Plots a graphical trend of heart rate over time to track fatigue, stress, or cardiovascular anomalies.

If BPM exceeds normal thresholds (e.g., above 120 BPM for prolonged periods), an automatic alert is triggered.

Air Quality Index (AQI) Monitoring:

Displays the real-time AQI values from the MQ135 gas sensor.

Categorizes air quality into Good, Moderate, Unhealthy, Very Unhealthy, or Hazardous.

Generates alerts if AQI exceeds dangerous levels (e.g., above 200).

Temperature, Pressure, and Altitude Tracking:

Continuously updates readings from the BMP280 sensor.

Detects rapid temperature changes indicating hazardous underground conditions.

Tracks altitude variations to monitor workers moving between mine levels.

Step Count and Distance Traveled:

Uses accelerometer data to count worker steps and estimate distance traveled.

Helps detect exhaustion or inactivity due to injuries or unconsciousness.

*D. Mapping Worker Location Based on Distance-Traveled Estimation*

Since GPS signals are unreliable underground, the dashboard uses step-count-based distance tracking to estimate each worker's location. The dashboard visualizes worker movement using a map-based interface displaying movement relative to mine entrance points, tunnels, and work zones. If a worker remains inactive for an extended period in an unsafe zone, an alert is triggered.

*E. Automated Alerts for Critical Health Conditions*

The dashboard is programmed with an automated alert system that continuously analyzes incoming data and triggers real-time notifications for potential health risks and hazardous conditions. Alerts are displayed on the dashboard and sent via email, SMS, or mobile notifications to relevant personnel.

High BPM Alerts:

If a worker's heart rate exceeds safe levels (e.g., above 120 BPM), an alert is generated.

Alerts are color-coded for severity (yellow = warning, red = critical).

Poor Air Quality Alerts:

If AQI levels exceed 150 (Unhealthy), a warning is displayed.

If AQI rises above 300 (Hazardous), the system triggers an evacuation alert.

Abnormal Movement Alerts:

If a worker stops moving for an extended period, the system flags a possible emergency.

*F. Admin Panel for Worker Health Status Tracking and Historical Data Analysis*

The dashboard includes an admin panel for tracking worker health history, analyzing trends, and generating reports for occupational safety compliance.

Worker Health History and Trends:

Displays past sensor data for each worker to track longterm health trends.

Enables comparison of BPM, AQI, and step count over days/weeks/months.

Customizable Alerts and Safety Thresholds

Allows custom configuration of alert thresholds for BPM, AQI, temperature, and step count.

Enables adjustments based on mine conditions and worker health profiles.

Exportable Reports for Occupational Safety Compliance

Allows data exports in CSV/PDF format for audits.

Generates automatic compliance reports.

Real-Time and Predictive Analysis Using AI

Integrates with deep learning for predictive analytics.

Forecasts potential health risks based on historical worker health data.

### *G. User Access and Security Features*

The web dashboard includes secure authentication and multi-user role management.

Administrator Access

Full control over system features, including sensor configurations and alerts.

Supervisor Access

Ability to monitor real-time data, receive alerts, and access worker health trends.

### *H. Technology Stack for the Web Dashboard*

The dashboard is developed using modern web technologies:

- Frontend: React.js / Angular.js
- Backend: Python (Flask/Django) or Node.js
- Database: SQL / NoSQL (MongoDB or Firebase)
- LoRa Data Processing: MQTT, WebSockets
- AI Model: TensorFlow/PyTorch

The Web Dashboard for Real-Time Monitoring provides comprehensive health tracking, real-time alerts, worker movement visualization, and predictive safety analytics. It enhances worker safety in underground environments by identifying potential hazards and health risks, ensuring continuous monitoring, analysis, and proactive intervention.

## VI. Introduction to Machine Learning Models

In sophisticated settings like underground mines, where there are several environmental parameters such as air, temperature, and pressure that interact dynamically, conventional threshold-based solutions tend to miss subtle or non-linear relationships that indicate potential health risks. Machine Learning (ML) provides the answer in the form of learning from past data continuously and reacting to new data by delivering early warnings of anomalies before the situation

becomes critical. Our Smart Health Predictor System takes advantage of the strength of Temporal Convol- tional Networks (TCN) with Rectified Linear Unit (ReLU) activation to conduct predictive

analysis on time-series sensor data gathered from underground mine workers. Where health parameters in such high-risk surroundings like mines can change randomly because of changes in air quality, movement, pressure, and altitude, an effective model is needed to identify early warning signs of worsening health. TCNs are specifically suited to address sequential data, and therefore this is the right application for them.

## VII. Why temporal convolution networks [TCN]

Temporal Convolutional Networks are a specific form of convolutional neural network for time-series data. Relative to standard Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks, TCNs do have certain advantages:

• Parallel Processing: TCNs handle information with convolutional filters, enabling parallel computation, which is more efficient compared to RNN's sequential computation.

• Long-Term Dependency: Due to an enormous receptive field, TCNs can manage long-term its dependencies accurately, which are required for gradual health deteriorations to be recognized.

• No Vanishing Gradient Problem: TCNs do not have the vanishing and exploding gradient problem, which makes training efficient and stable.

In our system, TCNs process inputs from various sensors like MQ135 for air quality, ADXL345 for movement, BMP180 for pressure and altitude, and a heart rate ear sensor. Through analyzing time-series patterns, the model is able to identify slight anomalies that may suggest looming health hazards.

## VIII. Role of ReLU activation

The Temporal Convolutional Network (TCN) model uses the Rectified Linear Unit (ReLU)

activation function because it performs well and is simple. The ReLU function can be

represented mathematically as:

$$f(x) = \max(0, x) \tag{18}$$

This operation returns to zero for negative arguments and does not touch positive values, which inturn enables smooth flow of the gradients and training convergence at a faster rate.

• Effective Gradient Flow: Since positive values cannot loose Gradients , ReLU does not have the vanishing gradient problem which results in faster convergence.

• Computational Simplicity: Since it adds non-linearity at a low computational expense, it’s suitable for real-time processing of data.

• Improved Generalization: ReLU does not allow overfitting, thereby making the model better at generalizing new data.

Thereby, we can say that the use of ReLU and TCN, our model effectively captures non-linear patterns among health variables and weather parameters for early diagnosis of health abnormalities.

## IX. Advantages of the Model

The use of TCN and ReLU has numerous important advantages in health monitoring for underground mine workers:

- Real-Time Monitoring: Continuous data collection and processing help in real-time identification of potential health risks.
- Early Anomaly Detection: Variations in sensor readings can be precisely predicted in advance, allowing us to remain vigilant for any possible risks
- Resistant to Environmental Fluctuations: It's resilient and reliable to fluctuations in environmental conditions, thus providing reliability in unstable situations.
- Scalability: The efficient training and deployment of TCN with ReLU makes the system deployable to large scale mining sites.

## X. Mathematical Formulation of TCN with ReLU

The Temporal Convolutional Network (TCN) combined with the Rectified Linear Unit (ReLU) activation function is highly effective for time-series analysis in health prediction systems. The following mathematical formulations illustrate how this model operates.

### *A. 1D Causal Convolution*

The 1D causal convolution operation in TCN ensures that the output at time t is convolved only with elements from time 't' and earlier. The mathematical expression is given by:

$$y(t) = \sum_{i=0}^{k-1} x(t-i) \cdot w(i) \tag{19}$$

Where:

- y(t) is the output at time t,
- x is the input sequence,
- w represents the convolutional filter weights,
- k is the filter size.

### *B. B. Dilated Convolution*

Dilated convolution introduces a dilation factor 'd' to expand the receptive field without increasing the number of parameters. It is defined as:

$$y(t) = \sum_{i=0}^{k-1} x(t-d \cdot i) \cdot w(i) \tag{20}$$

Where:

- 'd' is the dilation factor controlling the spacing between filter elements.

### *C. Residual Connection*

Residual connections in TCN mitigate the problem of gradient vanishing by allowing the model to learn identity functions when needed. The formulation is:

$$y = F(x) + x \tag{21}$$

Where:

- F (x) is the output of the convolutional block,
- x is the input.

### *D. ReLU Activation Function*

The Rectified Linear Unit (ReLU) activation function is defined by:

$$f(x) = \max(0, x) \tag{22}$$

Properties of ReLU in the context of TCN include:

- Effective Gradient Flow: No vanishing gradient for positive values.
- Computational Simplicity: Efficient and fast convergence.
- Improved Generalization: Reduces overfitting.

### *E. Loss Function*

For health prediction, Mean Squared Error (MSE) is commonly used to minimize the difference between predicted and actual values:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{23}$$

Where:

- $y_i$ is the actual value,
- $\hat{y}_i$ is the predicted value,
- n is the number of samples.

### *F. Model Optimization*

Optimization is performed using gradient descent, where weights are updated iteratively:

$$w = w - \eta \cdot \frac{\partial L}{\partial w} \tag{24}$$

Where:

• η is the learning rate,

• L is the loss function.

## XI. CONCLUTION OF THE MODEL USED

The application of the Temporal Convolutional Network (TCN) with Rectified Linear Unit (ReLU) activation demonstrates a strong approach to predictive health monitoring in hazardous settings such as underground mines. Efficient processing of time-series data from multiple sensors — air quality, movement, pressure, altitude, and heart rate — the model can detect subtle patterns and early warnings of deteriorating health. Dilated and causal convolutions have a broad receptive field without losing temporal order of things, and residual connections give enhanced gradient flow with fast convergence.

ReLU activation not only minimizes computation but also fixes the vanishing gradient issue and enables generalization to new data. Employing Mean Squared Error (MSE) as the loss function and parameter optimization via gradient descent keeps the model at an equilibrium of prediction accuracy and computational efficiency.

Overall, this system provides an active approach towards enhancing worker safety through the provision of timely warnings before the development of life-threatening health conditions. In its learning with dynamic environments, the TCN with ReLU model provides a point of departure for further research on real-time health predicting systems across various industries

## XII. RESULTS AND DISCUSSION

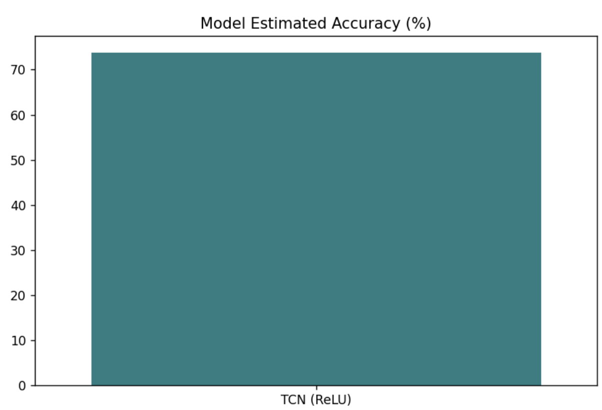



*Figure 11: TCN Estimated Accuracy*

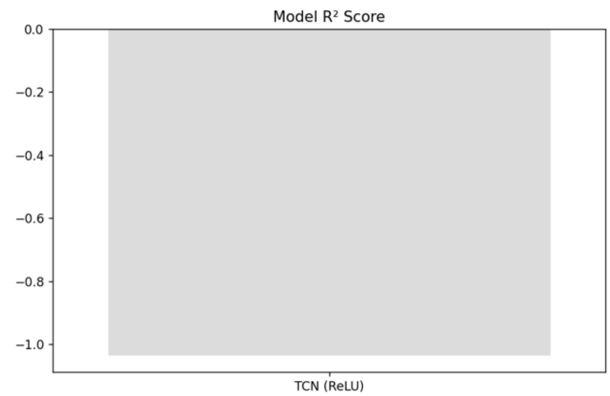



*Figure 12: TCN Model $R^2$ Score*

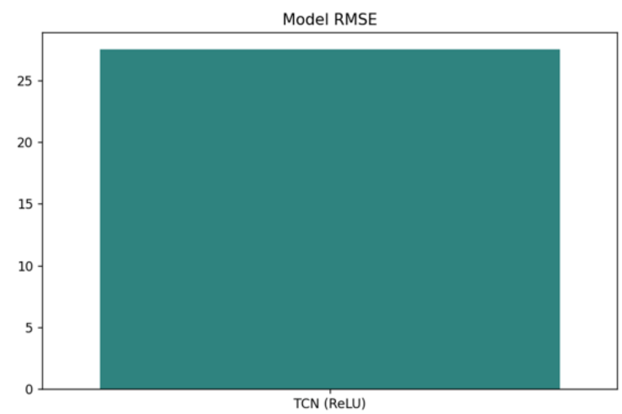
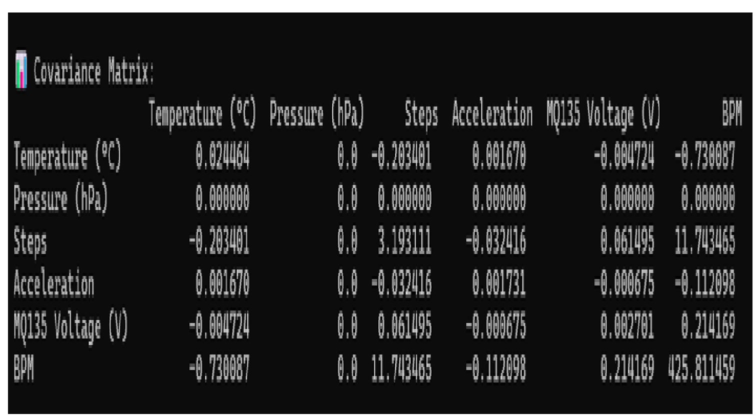



*Figure 13: Root Mean Square Error [RMSE] Analysis*



Covariance Matrix:

| | Temperature (°C) | Pressure (hPa) | Steps | Acceleration | MQ135 Voltage (V) | BPM |
|---|---|---|---|---|---|---|
| Temperature (°C) | 0.024464 | 0.0 | -0.203401 | 0.001670 | -0.004724 | -0.730087 |
| Pressure (hPa) | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| Steps | -0.203401 | 0.0 | 3.193111 | -0.032416 | 0.061495 | 11.743465 |
| Acceleration | 0.001670 | 0.0 | -0.032416 | 0.001731 | -0.000675 | -0.112098 |
| MQ135 Voltage (V) | -0.004724 | 0.0 | 0.061495 | -0.000675 | 0.002701 | 0.214169 |
| BPM | -0.730087 | 0.0 | 11.743465 | -0.112098 | 0.214169 | 425.811459 |

*Figure 14: Co-variance Matrix*

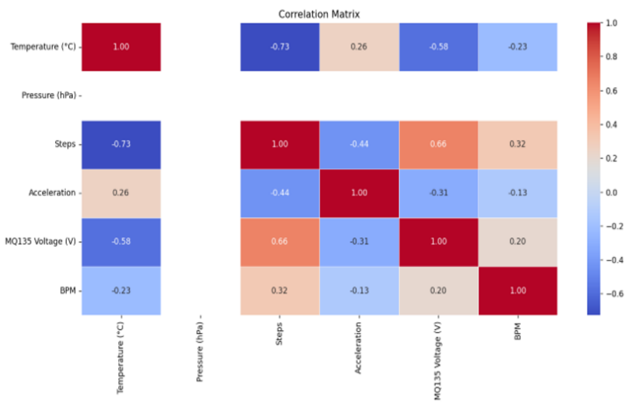



Figure 15: Correlation Matrix

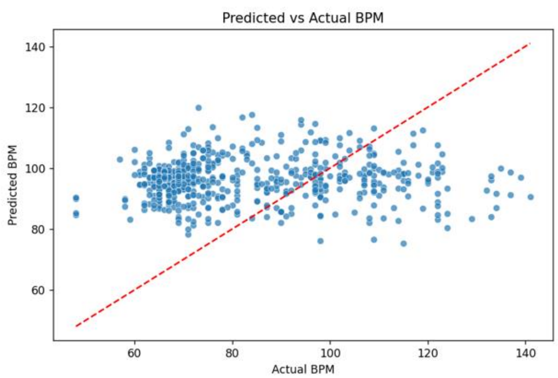



Figure 16 : Predicted vs Actual BPM

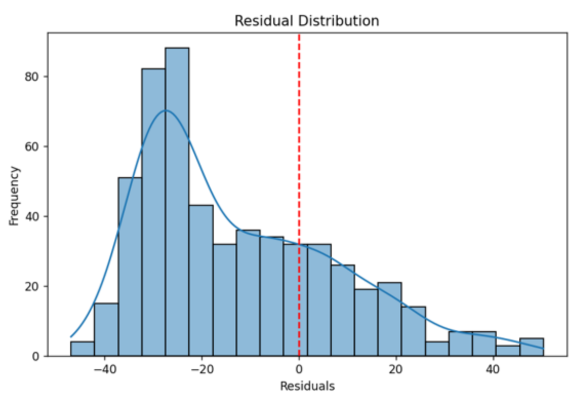



Figure 17 : Analysis of Residual Distribution

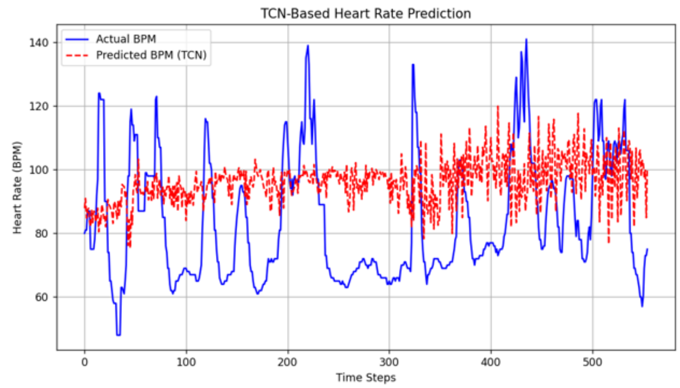



Figure 18 : TCN Based Heartrate Prediction


Figure 19: Dashboard Temperature and Pressure Display

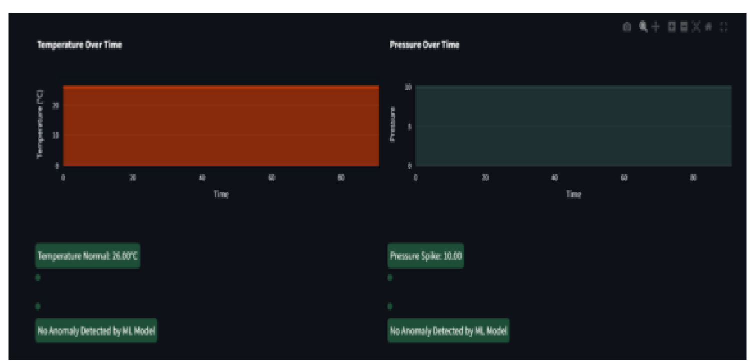



Figure 20: Dashboard Temperature and Pressure Display

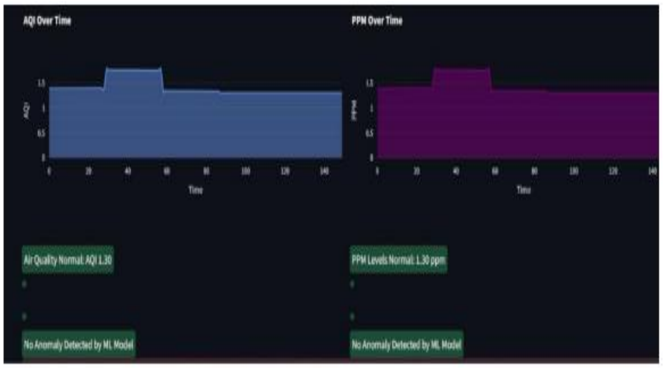



*Figure 21 : AQI and PPM Display*

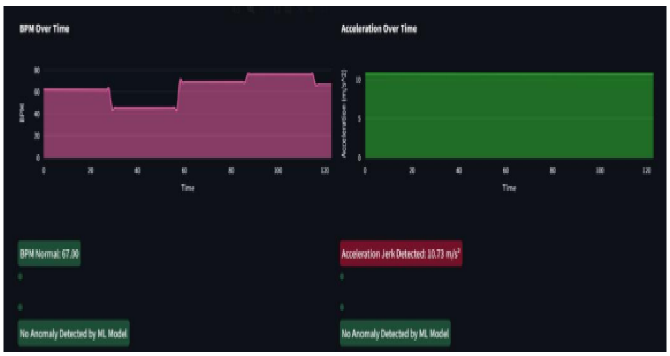



*Figure 22: BPM and Acceleration*

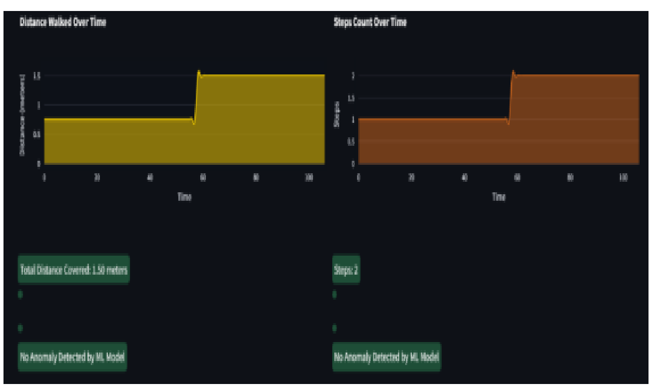



*Figure 23: Distance and Step Count*

## XIII. Conclusion

The developed project is an all-inclusive IoT-based monitoring system with multi-sensor data acquisition and efficient data transmission using LoRa communication and data analysis based on machine learning. In the integrated project, there are BMP180, ADXL345, MQ Gas Sensor, and a pulse rate sensor providing measurements of environmental and health parameters including temperature, pressure, acceleration, gas levels, and pulse rates in real-time. The processed data is forwarded through a LoRa network. The relay node in this topology stretches the distance and ensures proper communication to the receiver node. Such a design is an efficient one for applications requiring long-range low-power network capabilities to overcome the traditional communication hurdles in remote settings.

Further offline analysis becomes possible with sensor readings stored in Excel. An app-based dashboard realizes real-time data visualization, thereby giving meaning to the project as it allows one to detect anomalies, predict trends, and make decisions from data. It is a very good example of how the practical application of IoT is implemented in real-life challenges, such as health monitoring and environmental safety, having integrated both the hardware and software components of the system. It is an open, scalable, cost-effective, and reliable project, making it a good framework in which advanced monitoring solutions can be rolled out across different fields.

In short, the project achieved its objective through a strong real-time monitoring system, which successfully enables data acquisition, transmission, and analysis. The platform laid down great foundations for further and critical spreading of IoT systems into the mainstream of critical industries, marking a very important step toward smarter, data-driven solutions.

## XIV. Future Scope

This project has quite a lot of room for further development and scaling. Other types of sensors to be integrated into these health monitoring devices include GPS sensors to track their real-time location, humidity sensors, and other related devices that can help improve the environment being monitored. Further, the LoRa communication architecture can be extended into a mesh network. It would allow not only increased range and scalability of the system but also seamless communication between multiple nodes in large or complex deployments.

Further enhancements to the system with the added capability of data analysis would be by implementing AI-based predictive models. Such integration will provide warnings for hazardous conditions or abnormal health parameters. It may even provide predictions over anomalies of temperature or dangerous levels of gas. Some of the advanced visualization features to be provided by dashboards would include customizable graphs of data, more explicit analytics, and alert systems for breaches in threshold levels. Much capability in the areas of scalability, storage, and analytics would be much better through robust cloud platforms like AWS IoT and Google Cloud IoT, with support going beyond Thing Speak.

It will make sustainability possible and remove all dependence on some external power source to allow nodes to work untamed at remote sites. The encryption can be made in an end-to-end way along with authentication mechanisms making the data safe, hence there will not be any issue of privacy. This might also extend the system to new applications such as precision farming in agriculture, safety for mine workers, or even disaster management monitoring hazardous conditions in real time.

These future developments will enable the system to scale robustly, adaptively, and opportunistically as an IoT solution in a broader range of applications, all while maintaining the efficiencies and promises of reliability.

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