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# Continuous monitoring of coal mine dangers with an automated internet of things system

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## Abstract

The safety of mine workers is a major concern in the modern world. The life and health of miners are vulnerable against a few fundamental problems, such as their workplace and its adverse effects. A novel and inventive approach is needed to increase profitability and reduce mining costs while keeping worker safety in mind. For tracking the level of concentration of hazardous gases, semiconductor gas sensors are used. In the mine worker area, air contamination is primarily caused by outflows from particulate matter and gases, such as sulfur dioxide (SO 2), nitrogen dioxide (NO 2), carbon monoxide (CO) furthermore, the goal of this project is to design a real time IOT system that can monitor temperature, humidity, dangerous gasses, and smoke status in an underground mine utilizing sensors with an ODROID-N2+controller and designed a base station to receive data from all coal mines via the ODROID-N2+module. We also built a web-based interface accessible through computers and Android/iOS devices. The suggested system seamlessly integrates surveillance, analysis, and localization strategies using cloud computing, application gateways, real-time operational databases, Internet of Things (IoT), and application program interfaces to enhance the management of safety and prevent injuries in underground coal mines.

**Keywords:** Internet of Things; Underground mines; Event detection; Warning index; Miner's algorithm

## 1. Introduction

Because of the presence of hazardous gasses like coal dust and methane, working in an underground coal mine has always been extremely harmful and unsafe [1]. It's been estimated that blasts involving carbon monoxide or methane gases account for 33.8% of casualties in the mining industry. There were 1601 recognized mine incidents of fire in the U.S.A simply from 1990 and 2007 [2]. The latest study conducted by the Directorate of Mines, Punjab, Pakistan [3] revealed that gas recuperation under the coal mines of the salt-range region held responsibility for a significant number of underground mining accidents (38%). Despite methane gas has a flammable range of 5-15%, even low amounts can cause serious harm to the health of people [4]. Underground coal mines can also include other hazardous gases, such as (H2S), (CO2), and (CO). Although initial exposure to these gases may be harmless, sustained exposure almost always results in substantial bodily effects [5]. For the protection of mine workers and property, careful observation of the underground mining environment is therefore important. The creation of electronic control interfaces for the Internet of Things (IoT) in a variety of industries over the past ten years is changing how the internet interacts with ordinary things through wireless sensor networks (WSNs) that can be distinctively identified [6]. Observing the environment is a potential use case for IoT [7]. In order to follow a mining tailing dam in real time, the authors in [8] recently incorporated cloud computing and IoT. Corresponding to this, IoT-based cloud computing has been applied to event detection, real-time knowledge sharing, and spatial and temporal information processing; all of which are encouraging first steps toward welcoming in the next phase of protection in mines. Adopting these strategies will help to improve

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worker and ecological security, as they have not often been tracked down for underground mining. In order to create a thorough supervision and safety system suited for underground mines, the goal of this research is to examine the distinct security attributes of underground mines, analyze how they are interconnected, and effortlessly combine IoT-based, unique systems. To make the Internet of Things better, we want to find cheap ways to combine technologies like exchanging information in real time, recognizing and authenticating intelligent events, standardizing monitoring, and mining localization. Our all-inclusive objectives are to increase entire safety within mines and get more aware of the challenging and real underground application environment. Pakistan's underground mine safety will significantly increase with the implementation of such a system.

## 2. Related Work

A minimal understanding of the interaction and the need for an operator formed the basis of the first concept of digital underground mining. At present, this concept can be divided into three distinct parts: systems for databases, wireless networking, and skilled systems for relief and safety in deep mines. [9] provides a summary of a large body of research on current wireless communication and monitoring techniques in underground mines. Research on WSN application in beneath the ground mines is new [10]. In recent years, Shangwan Coal Mine in Erdos, China, installed a very reliable smart system [11]. They replaced the outdated cables environmental monitoring network with a WSN. Additionally, to being able to periodically examine and interrupt, this system also monitors the environment. In a bord-and-pillar mine, an alarm-based early fire detection method was implemented as a WSN [12, 13]. Finding a fire in the deep mine and detecting it early are two of this system's greatest potential aspects. In order to improve protection and efficiency, WSNs have been applied in numerous previous studies [14, 15] with an emphasis on low energy consumption and low operating costs in actual subterranean circumstances. In underground coal mines, MDML is an economical, efficient, and secure routing algorithm that supports essential and non-emergency transmission [16]. According to Jin-ling et al. [17] suggested using orthogonal multiplexing of frequencies in conjunction with digital multiple-input multiple-output (V-MIMO) to address the issues of diffusion, extinction, and dispersion in wireless sensor networks (WSNs) in mining environments. The computational data revealed that the utilization of SISO (single input, single output) in deep tunnels resulted in decreased bit error rates and enhanced wireless transmission efficiency. To locate miners, on top of fixed mesh nodes, Li and Liu [18] constructed a Structure-Aware Self-Adaptive (SASA) WSN to find miners. In underground coal mines, this system may do limited evaluations of environmental factors and use a traditional signaling mechanism to identify the movement of roofs that have fallen. RSS, ToA, TDoA, and AoA are among the numerous indoor navigation systems that have been implemented in wireless sensor networks [19],[20]. Due to its ease of use and ability to precisely determine the location of the mobile node (MN) without the need for extra hardware, RSS-based indoor localization has gained popularity lately [21]. An RSSI technique with a lower accuracy error was presented by Akeila et al. [22] for Bluetooth node indoor localization. A detecting system built on the Wasmote and Meshlium entrance was introduced by Qandour et al. [23]. By using the data-forwarding technique, this system made it possible for the detecting system and routing nodes (RNs) to communicate more effectively over wireless (ZigBee/802.15.4). Furthermore, the cloud services for information management and mine informatics were built by Bychkov et al. [24]. Molaei et al., [25] evaluated how well the mining sector has adapted to Internet of Things (IoT) systems and how it is currently developing. It also looked into the major issues facing the sector and offered suggestions for creating an effective model that can be used for different mining sectors, including exploration, operation, and safety, by utilizing cutting-edge technologies like IoT and wireless sensor networks. Hussain Arif et al., [26] A wireless sensor network (WSN) with ZigBee support is being suggested to facilitate connectivity among sensor and the coal mine's security monitoring systems. It was suggested to use the I Beacons to identify workers. To build the system, a service-oriented architecture, or SOA, was used. Using artificial neural network (ANN) technology, the proposed system was able to forecast the presence of methane. Various modern technologies were contrasted with the suggested system. The suggested system proved to be more effective than any other approach used for comparison. [27] Sathishkumar et al. developed a lightweight services mashup technique and suggested a consistent message space and data distribution strategy. Visualization Technology was used to build a graphical user interface for several subsurface physical sensor tools. Furthermore, the performance was assessed and examined for four distinct categories of coal mine safety monitoring and control automation situations. It has been proven that the automation applications were successfully managed and costs were drastically lowered by the lightweight mashup middleware. Dheeraj et al.,[28] A structure was suggested in order to maintain the safety of workers in coal mines. All monitored parameter values would be recorded, displayed, and controllable via a phone within the cloud. One of the main factors transforming our surroundings is the digital changes. Mining is another sector where digitalization will be important because of how important connectivity is. In order to enable communication and data exchange between devices in areas without internet access, more electrical sensors and software are intended to be implanted. Saranya, G. et al., [29] suggested the setting up a wireless sensor network (WSN) that could be used to monitor an underground mine's temperature, humidity, gas, vibration, and smoke condition with the use of an ARM controller. The device also regulates airflow required by mine workers based on the current environmental situation in the mining area. The system used a gas sensor, smoke detector, low-cost ARM, DHT11 sensor, and smoke detector to sense the ambient temperature parameters of the mine. Wi-Fi was utilized for remote data logging at a central location, allowing the environment to be controlled by the assistance of a computer. Coal mining security operations benefits significantly from the use of traditional wired network solutions for monitoring coal mines. The complications with the coal mine safety monitoring system based on wireless sensor networks have been overcome to a point where output security is monitored and coal mine accidents are decreased. An architecture for coal mine safety monitoring that utilizes GPRS and Zigbee wireless communication was created by M. Shakunthala et al.,[30] according to GPRS innovation, he was able to transmit information virtually and receive updates via a short text message sent to his mobile phone. This enhances the detection of real incidents and ongoing medical treatment, so improving the safety of coal mines. [31] The use of WSN and IoT-based systems for monitoring coal mine safety can be a promising approach to improve the working conditions of coal miners and reduce the risks of accidents and illnesses associated with coal mining. In summary, the safety of underground coal mines can be significantly enhanced through the integration of online cloud service-based miner location, tracking, gas monitoring, and event detection capabilities onto a unified platform. But the amount of basic monitoring and event reporting that has been carried out in the past in relation to mine safety is low. There is a lack of comprehensive system-level integration of multiple safety components, such as data on underground mine employees and operations. The mine's dynamic underground environment won't be entirely secure with just these measures. Since it needs to be adjustable for huge underground mines, the solution needs to include flawless integration at the global as well as local levels. It additionally becomes crucial for the system to be economical and capable of monitoring unusual activities. A primary server is also required in the solution in order to keep an eye on the mine's overall condition in the case that something goes wrong in a particular area. This study's primary objective is to develop a method for tracking air quality indicators in underground mines by means of an IoT platform that relies on widely distributed Arduino sensor modules. Using the Bluetooth low energy (BLE) protocol, this system tracks the precise location of miners and keeps an eye on the air quality in the mines. Our system approach is designed for supporting real-time event identification.

## 3. Methodology

### 3.1. Our system Design Architecture

It is well known that the Internet of Things (IoT) is dynamic, that its networks have spread out, and that multiple devices can connect with each other at the same time to collect, analyze, and share information [29]. These features allow for the creation of early-warning systems that rely on the Internet of Things (IoT), which distinguishes it from and elevates it above prior smart systems. If the system is to successfully reduce the occurrence of mine accidents and increase safety, The system needs to (i) track the miner's job under the coal mine, (ii) provide valuable tracking data, and (iii) deliver data in real time in order to successfully avoid mining incidents and improve safety. Using IoT, mine safety solutions based on gas sensor monitoring, miner tracking, and cloud computing effectively integrate analytics-based intelligent safety cycles. In this research, data from sensors that are connected to an Odroid N2+module is transmitted over BLE in IoT. Checking out the mine's current status of service and exchanging data are made easier via the Internet of Things. Minimizing mine accidents can therefore be achieved by smooth integration. In order to effectively gather and analyze data, detect unusual occurrences automatically, and share information, connectivity based on the Internet of Things idea is required. Figure 1 shows how different technologies can be integrated into an IoT-driven quick alert system for coal mines.

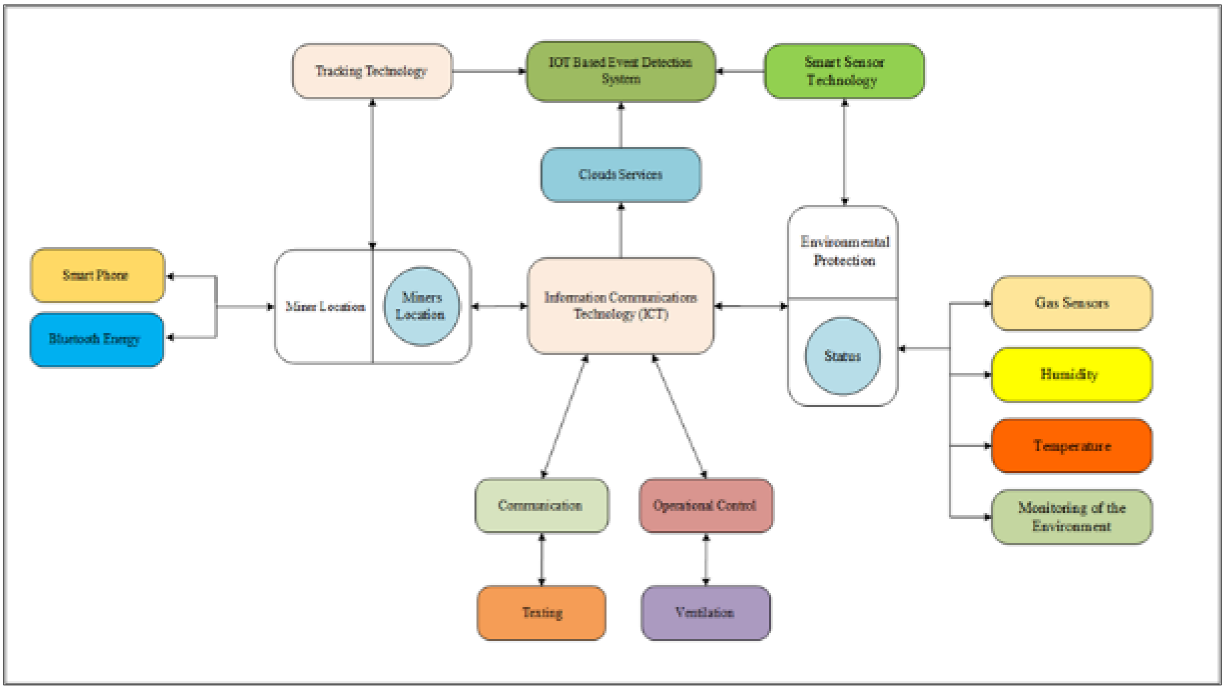


**Figure 1** Presented IOT utilized quick alert safety system for coal mines

The IoT mainframe features four layers: a network layer, an application layer, a perception layer, and a middleware layer. Within the IoT system as a whole, each layer has its job to do. Figure 2, which illustrates the stratified structure of IoT-based event recognition and early warning systems for underground coal mines, renders the functions of each layer of IoT readily apparent.

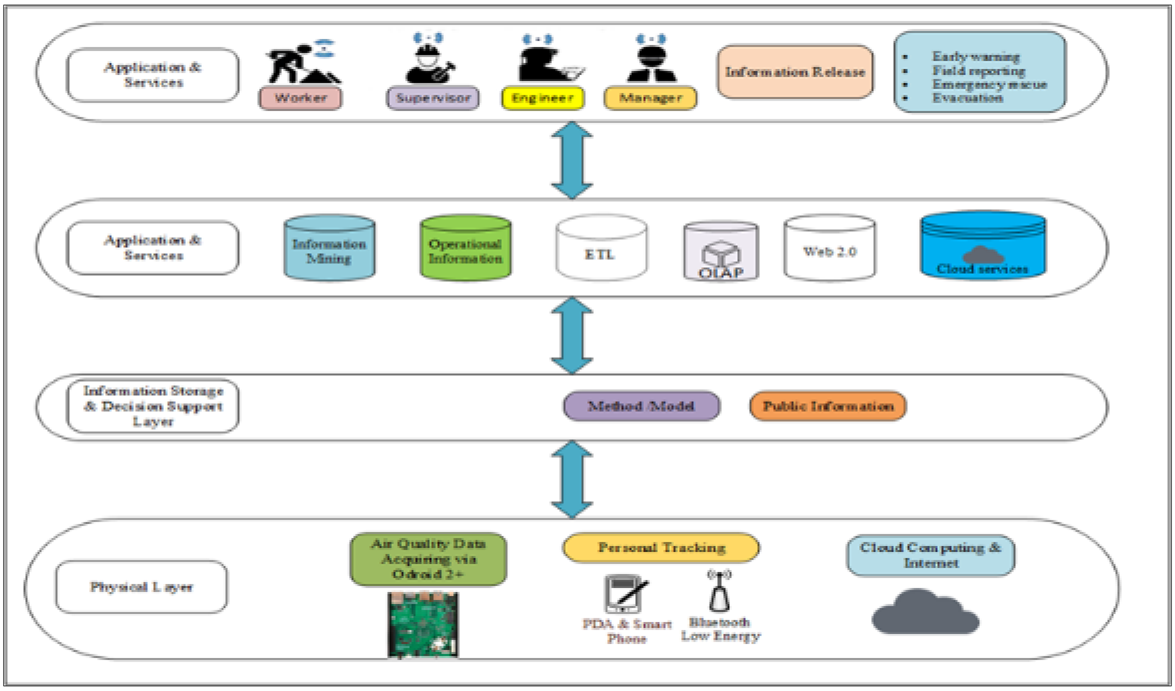


**Figure 2** Illustrates the layered framework of the internet of things early warning mechanism in coal mines

The design of the underground coal mines' IoT-based event detection system is shown in Figure 3. The entire mine is covered by the ODROID-N2+ module's use of the Bluetooth-based communication protocol. Based on how they are used, the nodes in this network are classified. The central nodes for monitoring mine air characteristics are stationary nodes (SNs), while router nodes (RNs) are the principal nodes of a subordinate cluster consisting of several SNs. Lastly, a gateway is used by both SNs and RNs to send data via the Bluetooth communication protocol to the base station (BS). The central station offers information analysis for the sensory data by having a direct connection to cloud computing and the worldwide internet.

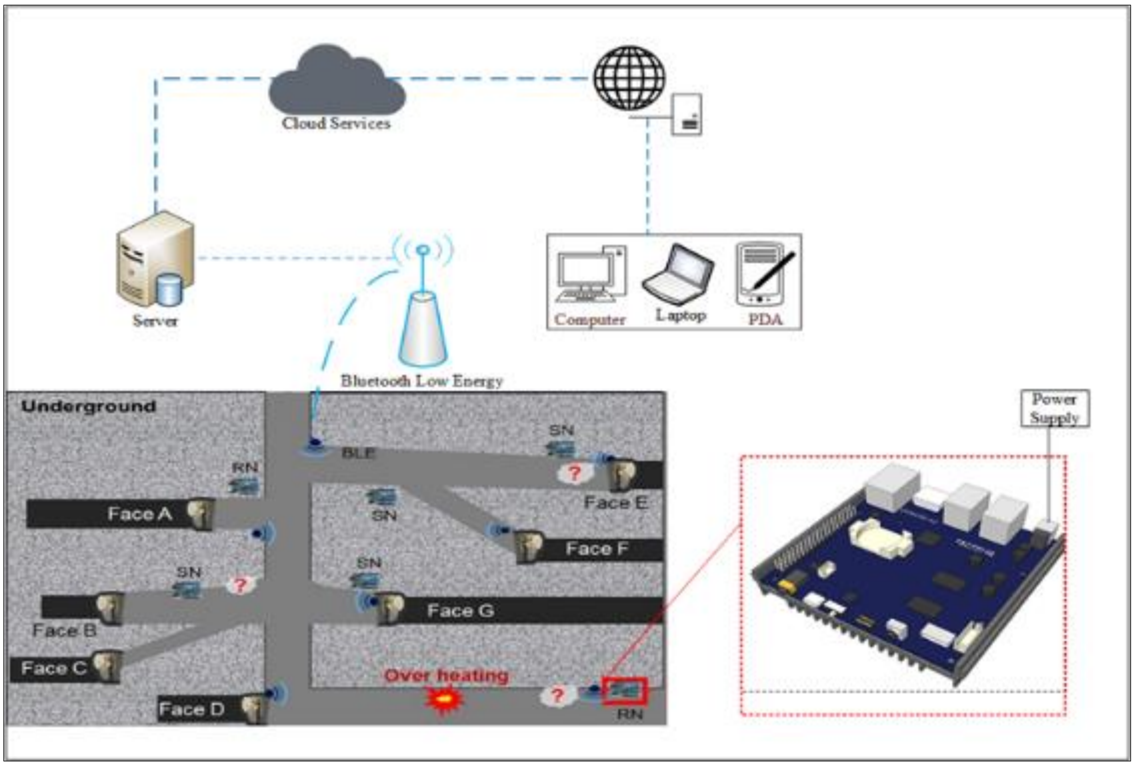


**Figure 3** Shows the general design of the suggested Internet of Things system for underground mines

### 3.2. Stationary Node Design (Environment Parameter Monitoring)

The basic sensing unit of the proposed IoT platform is Odroid N2+ 4GB ram variant, a microcontroller for GPIO (I/O) output. The Figure (4a) with Odroid N2+, (4b) MQ9, SHT71, Figure (4c) sensor modules were used for monitoring the underground environment. Figure 4d shows the circuit diagram of sensors attached to the different pins of the Odroid N2+ (Amlogic S922X). Additionally, Table 1 represented technical specifications of the sensors.

**Table 1** Technical Specifications of the Sensors

| **Specification** | | |
|---|---|---|
| **Sensor Model** | **MQ9** | **SHT71** |
| Operating Voltage | +5V | 2.4 V to 5.5 V |
| Detection | Methane, Propane, and CO | Humidity & Temperature Sensors |
| Measurement & Range | 1000/10000/10000ppm | 0%RH to 100 %RH |
| Accuracy | ±5%RH | ±3%RH |
| Sensitivity | 0 to 5 parts per million | 11% RH |
| Configuration | 4 Pins | 4 Pins |
| Digital / Analog | Digital / Analog | Digital /Analog |

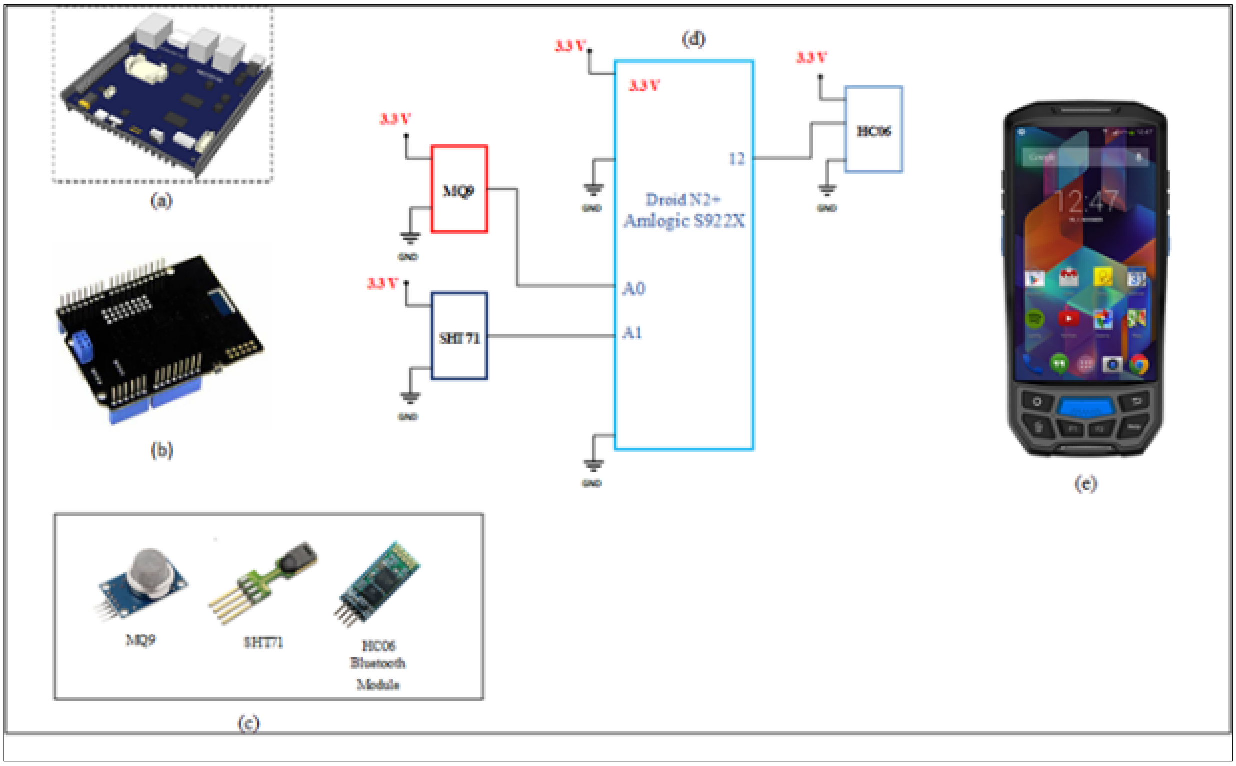


**Figure 4** (a) Odroid N2+ (b) BLE (c) Sensors (c)Circuit layout design

### 3.3. Tracking the Location of Miners Using Mobile and Other Nodes

In Figure 4e, we see a smartphone that measures (136.6 69.8 7.9mm) and weighs 145 grams. Miners carry this portable device with them. The operating system of these devices is Android v14 (Upside Down Cake) and they are powered by a Qualcomm Snapdragon 8 Gen 3. As outlined in Section 4.2, they established Bluetooth communication with SNs and RNs. They have an easy recharge process and use Li-ion batteries (3000 mAh). MNs can communicate with the closest SN to share information. The miner can perform a location algorithm and issue emergency signals based on his health by using an MN. As a result, these MNs can be used to track miners' movements and health. The BLE base system in the mine, however, is offered by stationary RNs. SNs differ from RNs in that they also have sensor modules attached. The RN's primary duty is to offer access and collect data from the sub SNs. A total of four SNs may be held by RNs under this framework. The devices establishing the connection between the RN and SN and the base platform are known as gateway networks. The primary interface for network communication is Bluetooth. Global event detection and declaration fall under the responsibility of the BS.

### 3.4. Protocol for Communication at the Network Layer

The underground mine safety research has made utilization of BLE, a widely accessible to mobile phone capability with a 2.4 GHz bandwidth. In comparison to Bluetooth classic, BLE discovers devices around it faster. Furthermore, comparing BLE to WiFi and Bluetooth traditional, a smaller amount of energy is used for detecting [32]. The capability to send data without the need for extra data transmission operations is one benefit of Bluetooth's receive signal strength index [33]. A serially linked Odroid N2+ 4GB ram variant, a microcontroller for GPIO (I/O) output. which is the main part of both SN and RNs. In order to be compatible with 3.3 V, it contains 4GB RAM and Use a microSD card with a capacity of at least 16GB can be used to store programmed. the BLE can accommodate 40 connections. At a performance level of 15.5 dbi, the level of effectiveness was 98% and the margin of error drop-down communication was ±25. To simplify communication between the MN, SN, and RNs, a Bluetooth link is maintained and is provided to every worker as they enter the mine.

### 3.5. Application Layer, Decision Support System, and Information Storage

In our suggested approach, the user obtains information via an internet-based webpage featuring two modes of triggered incidents and periodical evaluation. The computer's BS algorithms are always searching for worldwide incidents. Utilizing the Representational State Transfer (REST) programming interface, connection across programs, sections, regulations, and gateways was established in our real-time information sharing platform. The real-time operational database (RODB) effectively handles huge amounts of information that comes from sensor networks. In order to gather and analyze information obtained by users, such databases are used together with extract-transform-load (ETL). Initially, an intended subset of data is extracted via the extract function by reading data from many sources. Subsequently, the function known as transform manipulates the gathered data to achieve its intended state. Lastly, the data that results is written to a target database using the load function. By establishing a username, addresses, and profile server (NAPS) via the IPv6 protocol Low-Power Wireless Personal Area Networks (6LoWPAN) as the link layer protocol, each sensor node was assigned an IP address. Application software and application gateways (AGs) for various platforms and jobs were implemented using a constrained application protocol (CoAP). The (SOA) Service-oriented Architecture in our system is divided into large systems to simple, well-organized applications and parts. It does this by using standard protocols and general interfaces. In addition, cloud-based services are connected to external information storage platforms like Google Cloud Storage, Amazon S3, and Amazon EBS. These platforms offer analytical languages like SQL, Hadoop, and MapReduce, and they can enable load, refresh, and combine operation platforms. They additionally offer analytics for big data frameworks such as Google Data Mobility, Spark, Storm, and Flink. There is also an e-science tool in this study for analyzing data, doing computing online, and processing information in real-time. Applications such as Infrastructure as a Service (IaaS), Software as a Service (SaaS), Platform as a Service (PaaS), and Data as a Service (DaaS) are supported by the e-Science platform.

### 3.6. Index for Mine Warning

Equation (1) [34] is a common representation of the Heat Index (HI), which is the sum of the effects of both heat and humidity on individual’s body.

$$
\begin{aligned}
HI = & -42.379 + (2.04901523 \times T + \left(10.14333127 \ \times \ rh\right) \\
& - \left(0.22475541 \ \times \ T \ \times \ rh\right) - (6.83783 \times 10^{-3} \times T^{2}) - \\
& (5.481717 \times 10^{-2} \times rh^{2}) + (1.22874 \times 10^{-3} \times T^{2} \times rh) \\
& + (8.5282 \times 10^{-4} \times T \times rh^{2}) - (1.99 \times 10^{-6} \times T^{2} rh^{2})
\end{aligned}
\quad \ldots\ldots\ldots\ldots\ldots (1)
$$

Where T stands for temperature in degrees Fahrenheit and rh for relative humidity.

The four levels of HI are as follows: "caution," "extreme caution," "danger," and "extreme danger," with values ranging from ~90 to 143. In our haste to reconcile the three phases of HI with the three phases of the suggested system, we overlooked to account for the extremely dangerous finding in the research. We made the assumption that workers would leave the mine before the system reached the second threshold limit. This is because the amount of comfort that workers perceive is primarily connected with the health index (HI).

Furthermore, an individual MWI parameter was introduced based on the combined effect of gas concentration and HI on the human body. The MWI facilitates the initial assessment of mine environments and facilitates a quick exchange of information. This MWI determination system employs data gathered from every sensor location. MWI can be described as:

$$
\text{MWI} = \frac{n\sqrt{(G_2 \times G_2 \ldots G_n) \times HI}}{1000} \quad \ldots\ldots\ldots\ldots\ldots\ldots (2)
$$

Variables G1, G2, and Gn, where "n" denotes the total number of gases being monitored, reflect the concentrations of harmful gases being monitored by a specific system. Depending on the amount of gases that need to be monitored by the system, the nominator can change from case to case to determine the MWI scale. Because they give threshold limiting levels, standardization, prior study, and work are valuable resources when developing systems that are intelligent. In Table 2, for warning (yellow) and alerting (red) conditions, the MWI's normal and threshold requirements for gases and HI are summarized.

**Table 2** Presents the threshold limit values for temperature, humidity, and dangerous combustible gases, taking into account their impact on human beings

| MWI | Serving State | HI | Temperature | Humidity | $CH_4$ | Co | $Co_2$ |
|---|---|---|---|---|---|---|---|
| 0–3.5 | Normal | <90 | $T_i \leq 28$ | $H_i \leq 70$ | $G_{ia} \leq 2000$ | $G_{ib} \leq 15$ | $G_{ic} \leq 2000$ |
| 3.5–7.9 | Warning | $90<H_i<103$ | $28 < T_i < 40$ | $70<H_i<80$ | $2000<G_{ia}<4000$ | $15<G_{ib}< 25$ | $2000<G_{ic}<5000$ |
| 8–10 | Alarming | $103<H_i<124$ | $T_i \geq 40$ | $H_i \geq 80$ | $G_{ia} \geq 4000$ | $G_{ib} \geq 25$ | $G_{ic} \geq 5000$ |

The skewness, standard deviation, average, mode, and median statistical models make it possible to easily scale multidimensional data and to identify suspicious data. Additionally, the correlations and dependencies of the various parameters are determined by comparing these models at various locations within the mine. Equations (3)–(4) provide the statistical models that are employed in the approach we use.

$$Average(\overline{x}_t) = (1/n)\sum_{i=1}^{n} xi$$

$$SD_t = \sqrt{(1/n-1)} \times \sum_{i=1}^{n} (x-\overline{x})^2$$

$$S_t = (\sum_{i=1}^{n} (x-\overline{x})s^3 / (n-1)s^3 \quad \text{………………(3)}$$

The normal distribution's generalized form can be expressed as

$$f\left(x \mid u, \sigma^2\right) = \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right) e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad \text{……………(4)}$$

The statistical model values are influenced by the change in gas concentration while monitoring is underway. The interrupted symmetry surrounding the mean value (normal distribution) becomes immediately obvious when the value of a statistical model is changed [35]. The skewness of the model is correlated with a disturbance in its uniformity. The distribution of values is uniform around its mean when the skewness is zero, and it is on both sides if the skewness is greater than or less than 0. Skewedness readings that are not zero are a certain sign of an occurrence in that area.

### 3.7. Method for Identifying Outliers

The suggested system's BS performs global event detection and each SN uses a distributed approach for local events. A fundamental component of any method for detecting events is outlier detection, which comprises the identification of values that deviate significantly from the norm in a dataset [36]. Noise or sensor errors could be the cause of outliers. Consequently, every SN's event identification algorithm is programmed to detect an event if it receives four outlier readings in a row. Despite the abundance of outlier identification methods, clustering was deemed the best fit due to its ease of use, high dependability, low false positive rate, and high outlier detection rate. Because it may be applied without supervision and incorporates various variables, K-means has been popular among partitioning clustering techniques [37]. To divide up the data, we employed the K-means algorithm's time series equation. Assuming $k$ is less than or equal to $n$, where $k \leq n$ is the count of observations, it adheres to the rule. The following relationship was used to remove track duplication of *dist* (a, b) from the Malinowski space using the Euclidean

$$(d_{ab})^2 = (\sum_{a=1}^{n} (x_{ia} - c_{ka}))^2 \quad \text{…………… (5)}$$

In this context, " $d_{ab}$ " represents the distance between the *i-th* data point and the center of cluster *k*. "($\zeta i$) " refers to the *i-th* data point, whereas " $k, xi$ " represents the centroid of the cluster. The Silhouette value "(ζi) " [38] is a reliable measure used for verifying cluster analysis. It falls within the range of $-1 \leq \zeta i \leq$ and can be easily represented graphically. The silhouette coefficient values are calculated for n clusters.

$$\zeta_i = (1/n)\sum_{i=1}^{n}((\beta_i - \alpha_i, \beta_i)) \quad \ldots\ldots\ldots\ldots(6)$$

The average distance of the *i-th* object in a certain group within the same cluster is denoted as αi in this context. If the value of αi is not known, the smallest distance (βi) is selected from a neighboring cluster. In a mining setting, this makes it simple to spot an anomaly in the data. Here are the procedures to determine the contribution of each weight using the cumulative Euclidean distance derived from K-means: (1) First, we find the contribution of each attribute by analyzing their mean and covariance. (2) Next, we calculate the Euclidean distance again for each attribute using the remaining attributes' means and variances. (3) Then, we subtract the newly calculated distance from the cumulative distance $D_m$. (4) Finally, we divide the results of step two by $D_m$ to get the role of attributes.

### 3.8. Events Monitoring and Universal Event Detection

The effectiveness of transmission is significantly enhanced by data aggregation. For local events, this is done at the SN level; for global events, it is done at the BS level. In Table 5, the frameworks of local events are summarized. Due to a parameters excess, a frame including data regarding the environment has been given a value of 0x0a, with a limited value of 0x01. It can also be set to 0 to indicate the parameter type in the Type field. The monitored variables have been configured with specific values in PaRm. Additionally, SN implements an algorithm for geographic positioning and localization, which includes the updating of 32 bits for the coordinates of x and y.

**Table 3** Structure of SN frames

| **1 Byte** | **1 Byte** | **1 Byte** | **Variable** |
|---|---|---|---|
| *RFD (0_0a)* | *Limit* | *Type* | *PaRm* |

Once gathered data from SNs is received, the RN is set to 0X0b to preserve the identity of the environment-related data. Additionally, the SN's identity is added before transmission from RNs. You can find the total number of SNs in the Num field, and each SN's IP address is represented by *Addr*. Since data collision is a major consideration in wireless sensor networks routing at all times, Num and *Addr* are useful for preventing data collision. Table 3 shows monitoring frame doesn't need changing. In addition, in order to identify these transmissions as critical emergency data, the data is delivered immediately to RNs without any aggregate for delays. You may see the RN frame layout in Table 4.

**Table 4** The frame layout for RNs is presented

| **8 Bits** | **8 Bits** | **8 Bits** | **8 Bits** | **Variable** | **…………** | **16 Bits** | **8 bits** | **Variable** |
|---|---|---|---|---|---|---|---|---|
| *RN(0x0b)* | *NUM* | *Addr1* | *Type1* | *PaRm1* | *…………* | *Addr n* | *Type n* | *PaRm n* |

When a *SeqF* sequence number is added to {LGTI}, the BS for SNs changes the (LGTI). The BS adds new information to the *LocalizInfo* of *{LGTIi}* and *SeqF*, as shown in Table 5, and also sends more packets into the information flows. The transmitted packets provide a list of items. Any time an RN i gets a *LocalizInfo,* it checks its records against those it has already received. It also checks the *SeqF* against the one before it. The presence of new information for this node *(LGTIi)* is indicated by a greater *SeqF*. In this way, it revises *SeqF* and updates the relevant data. Afterwards, the RN verifies data pertaining to succeeding SNs. SN is updated if it's not empty, otherwise it's ignored.

**Table 5** With column names and sizes for each *LocalizInfo* packet

| Pt_ID | *SeqF* | Pt_Num | Node_ID | Next | -------- | Node_ID | Next |
|---|---|---|---|---|---|---|---|
| *1* | *1* | *1* | *2* | *2* | -------- | *2* | *2* |

### 3.9. Algorithm for Tracking Miners

Since RSS is the backbone of most tracking methods now in use, tracking in underground mines remains an open question. Due to the rough terrain and unpredictable conditions inside the mine, RSS readings are prone to inaccuracies. By striking a balance between precision and computing complexity, this effect was reduced in our study utilizing a weighted centroid technique based on RSS range. Using the logarithmic distances from SNs as input, this algorithm calculates the RSS values of mobile nodes. We assume that the RSSI and logarithmic distance are linearly related in our model, as shown by

$$RSSI(dbm) = A - 10n\log_{10}(d) \quad \text{............(7)}$$

This approach utilizes power measurements from three or more reference SNs to get the approximate value for MN, which improves estimation accuracy. One method of refinement is the triangulation of centroid localization. It is essential to establish SNs across the entire system with established coordinates to estimate the position of MN within the coverage range of SNs $N_k = N_l(x, y)$.

$$Pk(xk, yk) = (1/n)\sum_{l=1}^{n} N_1(xk, yk) \quad \text{.............(8)}$$

This localization ignores the RSS values of MN and just takes into account the SN coverage range. All reference nodes have equal distances used in the calculation of these results. Since each SN provides something by providing the RSS a weight factor, we looked at more complex methods based on weighted centroids. To figure out where MN is within the range of coverage of each SN,

$$P_i(x, y) = \frac{\Sigma_{j=1}^{n\ \ AP}\left(w_{ij}.AP_j(x, y)\right)}{\Sigma_{j=1}^{n\ \ AP} w_{ij}} \quad \text{............. (9)}$$

The weight of the object is determined by utilizing the following;

$$w_i = 1/d_{ij}^{\ g}$$

This is where g stands for the degree to which each anchor node contributes, often set to 1, and dij denotes the RSSI-determined distance between MN and SN. We can find wi's normalized weight using;

$$w_i = \frac{w_i}{\Sigma_{j=1}^{m} W_j} = \frac{\sqrt{(10^{RSSIi/10})^8}}{\Sigma_{j=1}^{m}\sqrt{\left(10^{RSSI_J/10}\right)^8}} \quad \text{..........(10)}$$

The target node's estimated positions are as follows:

$$X_{est} = \sum_{i=1}^{m}(w_i \times x_i) Y_{est} = \sum_{i=1}^{m}(w_i \times y_i) \quad \text{............... (11)}$$

Equation (9) denotes the hypothetical location of a target node. This technique has the advantage of not requiring any parameter or loss of path component calculations. This results in the advantages of minimal complexity and high accuracy.

### 3.10. Evaluation and Performance of the System

#### *3.10.1. Calibration*

In Figure 5, we can see that there is a straight path connecting the mine face 1 and halfway sensor readings from our OS to those from commercially available alternatives. Figure 5a-d shows that there are strong relationships between the humidity and temperature readings from commercially available sensors and those from Arduino-based sensors. There was a continuous over-0.96 regression constant for humidity and temperature at both of these sites. The root mean square error was consistently less than 0.762 and the mean square error was consistently less than 0.581 in Figure 5a-d. Figure 5e shows that, throughout the range of 750–1850 ppm, the Gas Central CH4C 100 and CH4, which were tracked by OS, exhibited a linear correlation constant (R2) of 0.9715 and a slope of 1.018. At the halfway point of the mine, Figure 5f also shows an R2 of CH4 (0.9962). With relation to the level of carbon dioxide (CO2) as determined by Telaire 7000 and OS, a correlation constant R2 = 0.9857 was computed, exhibiting a slope of 1.01. Similarly, Figure 5h illustrates the slope and R2 values of CO2 for the midway mine. The mean square error for examples 5e-h was relatively substantial due to the abrupt changes and large swings in CH4 and CO2 levels. For these instances, the minimum root square error was found to be higher than 4.33. Regression studies indicate that the OS is a viable substitute for costly and ineffective mine monitoring systems for these particular features.

### *3.10.2. Efficient Decision-Making*

Table 6 provides the real-time readings of all the gases at the mine face 1 from t0 to t1440 together with the statistical model's values as shown the temperature, humidity, and CO readings are exact (standard error <5%). All other monitored parameters, with the exception of the temperature, demonstrated values in the normal state from t0 to t1440, as they fluctuated within the permissible limit values in Table 6. In Table 7, you can see the statistical model results for the monitored parameters at the midpoint of the mine. The operational status of the mine was quickly assessed by contrasting the normal distribution of the parameters being examined at mine face 1 and the midpoint. The skewness values of both tables are either >0 or <0, which shows that the air is less dense at the midpoint of the mine after leaving the wall of the mine.

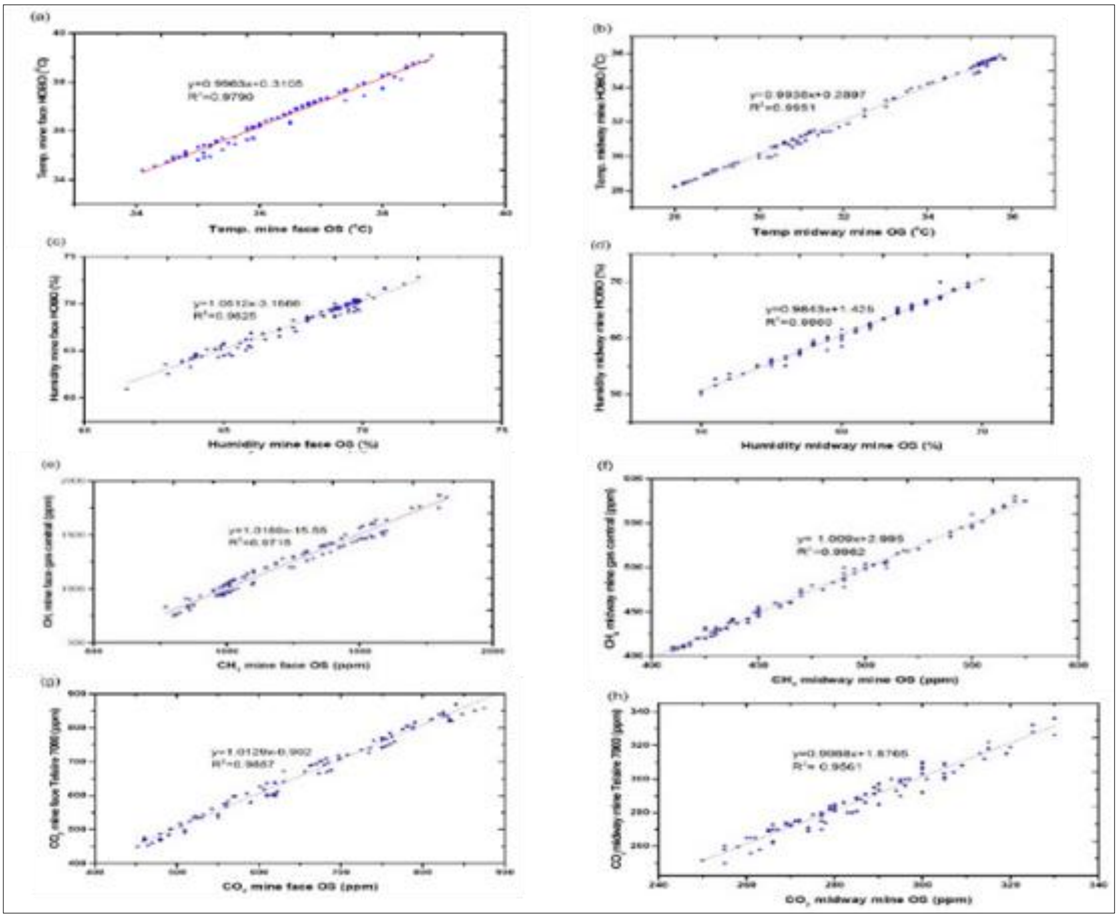

**Figure 5** Fluke CO-220, midway mines, and temperature readings along with their associations, with CH4 concentrations and CO2 levels

**Table 6** Mine face parameters

| $T_0$………$T_{11440}$ | Temperature | (RH) Humidity | $CH_4$ | $Co_2$ | CO |
|---|---|---|---|---|---|
| Avg. | 36.35567 | 67.57835 | 12224.175 | 651.6824 | 2.536082 |
| Std. error | 0.124595 | 0.24012 | 28.06941 | 12.36075 | 0.1185 |
| Median | 36 | 68 | 1185 | 656 | 3 |
| Mode | 35.9 | 69.7 | 985 | 460 | 3 |
| Std.Deviation | 1.227 | 2.364917 | 276.4516 | 121.73932 | 1.16709 |
| Skewness | 0.221967 | -0.50707 | 0.317597 | 0.0118 | -0.128 |
| Var $\sigma^2$ | 1.5058 | 5.6510 | 76176 | 351.6563 | 1.3621 |

**Table 7** Midway mine parameter monitoring results

| $T_0$………$T_{11440}$ | Temperature | Humidity | $CH_4$ | $Co_2$ | CO |
|---|---|---|---|---|---|
| Avg. | 32.06907 | 61.26804 | 465.3711 | 285.7732 | 2.5154 |
| Std. error | 0.258292 | 0.5165 | 6.68 | 1.9040 | 0.119 |
| Median | 36 | 68 | 1185 | 656 | 3 |
| Mode | 35.2 | 64 | 450 | 300 | 3 |
| Std.Deviation | 2.54388 | 5.087 | 65.8494 | 18.75 | 1.17736 |
| Skewness | 0.1108 | -0.37651 | -2.3288 | 0.366078 | -0.11685 |
| Var $\sigma^2$ | 6.4713 | 25.857 | 4336.152 | 351.6563 | 0.5262 |

Utilizing a comparison of the results of mathematical models at mine face 1 and the point in the mine where the mine is at its midpoint. Temperature and CH4 are the two parameters in this study that are most crucial in an emergency. These were taken into account in order to create a correlation. In the event of a normal distribution inside two of the chosen locations, the degree of independence was found to be 0.05 or lower during the examination of a normal distribution with a confidence interval of 0.95. This demonstrates unequivocally that CH4 is temperature-dependent, with a higher temperature corresponding to a higher concentration of CH4. Conversely, CO is temperature independent since rising temperatures have no effect on CO's statistical model values. Therefore, intelligent decision-making is governed by temporal statistical models, which are effective under the challenging conditions of an underground mine.

### *3.10.3. Event Identification and Outlier Detection*

The raw temperature data clusters are shown in Figure 6b. Cluster 2 and 3 are less clearly defined than cluster 1, which stands out due to its lower silhouette values. The data obtained is more variable when the cluster value is larger. Figure 6c shows the three groups of raw humidity data, with cluster 2 exhibiting the most fluctuation. Cluster 1's relatively consistent CH4 measurements at the mine face and halfway point are shown in Figure 6d. Similarly, cluster 8e has reduced fluctuation in CO2 raw data compared to cluster 1. Figure 6f again highlights CO clustering, which exhibited strong consistency in both groups.

K-means clustering is a method that splits data into a preset number of clusters through the use of the degree of separation and compactness. The cohesion of these clusters is shown on the x-axis, while the y-axis represents the breadth of the cluster, which is estimated from $\zeta i$. When finding the Euclidean distance, larger numbers on the x-axis are more useful. A cluster is considered more compact when its silhouette value is closer to 1, and the Euclidean distance defines a new cluster when its value decreases. Values that lie on the negative x-axis represent extreme values or clusters of values that deviate greatly from the usual range. Predicting the underground mine's air quality is another area where K-means clustering shines. In order to guarantee precision, the experimental clusters were compared to four sets of training-session clusters. The fundamental components of clustering include time, accuracy percentage, and average values. The system was evaluated for outlier detection under various conditions and consistently achieved efficiencies of above 90%.

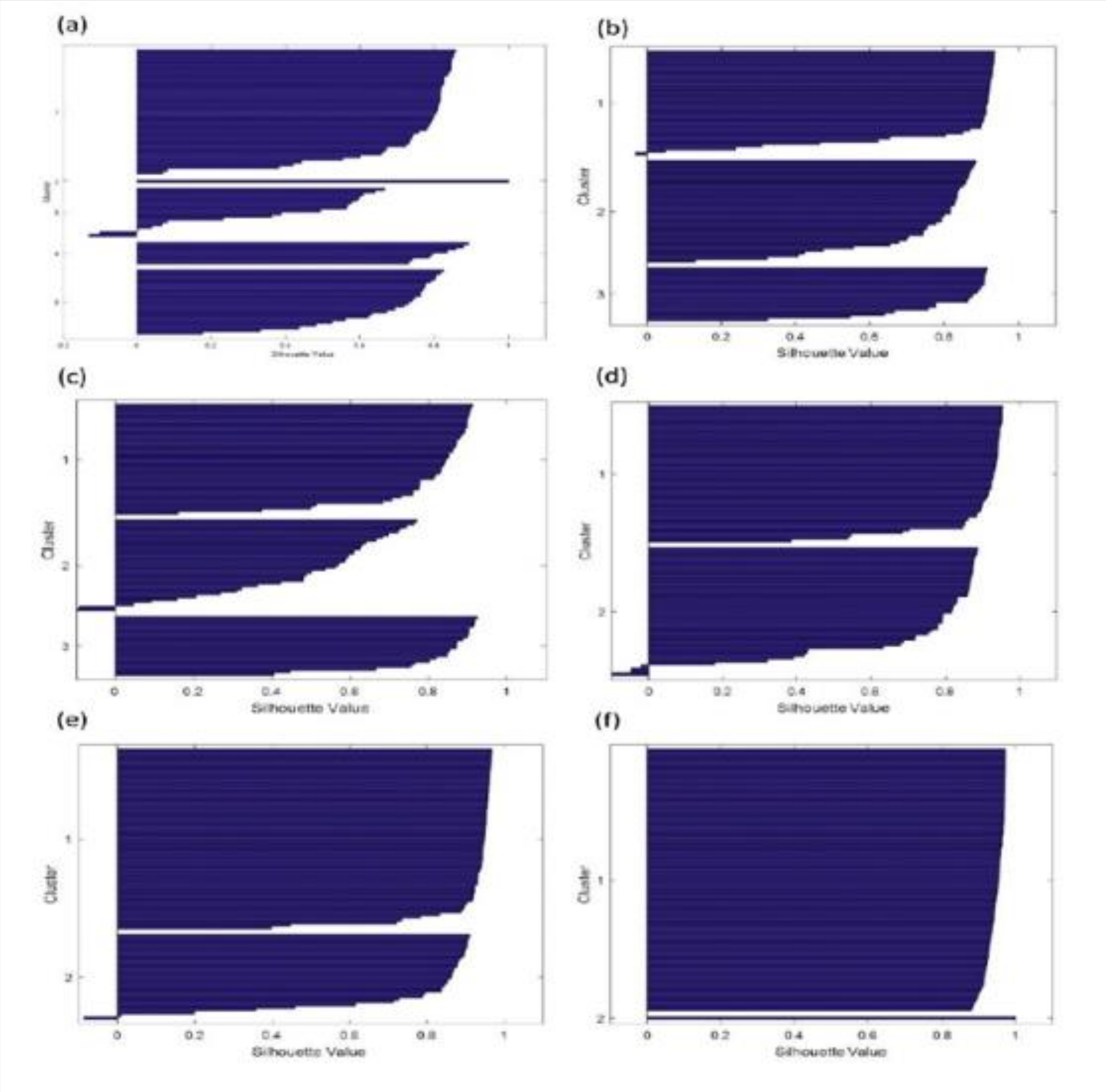


**Figure 6** During a two-month period, a K-means clustering experiment was conducted in a mine to monitor temperature, humidity, CH4, CO2, and CO. The parameters were analyzed to form five clusters

### *3.10.4. Results of Localization*

Figure 7a depicts the plotting of the RSS values of a moving MN against its distance from SN.The RSS that is estimated theoretically is shown in the same picture by the symbol ANCi-the, and the RSS values that were obtained by testing are displayed by the symbol ANCi-act, which is determined for the j-th to i-th anchor. However, MN was positioned at the similar height, the RSS values of the various anchor nodes were quite distinct from one another. This was ascribed to obstructions, uneven mine wall surfaces, and wavelength changes. As the distance increased, the RSS value dropped. Once more, the identical graphic displays a progressive shift in the theoretically computed RSS values. The RSS measurements level on at 17 m, which is another evidence that our system's spatial structure is ideal for the Bluetooth RSS measurements. The computed inaccuracy between source anchor nodes and MNs is displayed in Figure 9b, where the distance is varied between 1 and 30 m with a 2 m step interval. For a node located 30 meters away from the source anchor node, the system's standard deviation in the mine's main roadway was less than 1.8 meters. Alternatively, when the same MN was located thirty meters away from the source node, it was discovered that the basic RSS had an error that was higher than two and a half meters. As a result, accuracy was increased by 30% using the suggested RSS range-based weighted centroid localization approach. Since it just considers the weights of anchor nodes without knowing their state, the degree of error is unjustified, according to one of the primary principles of this experiment.

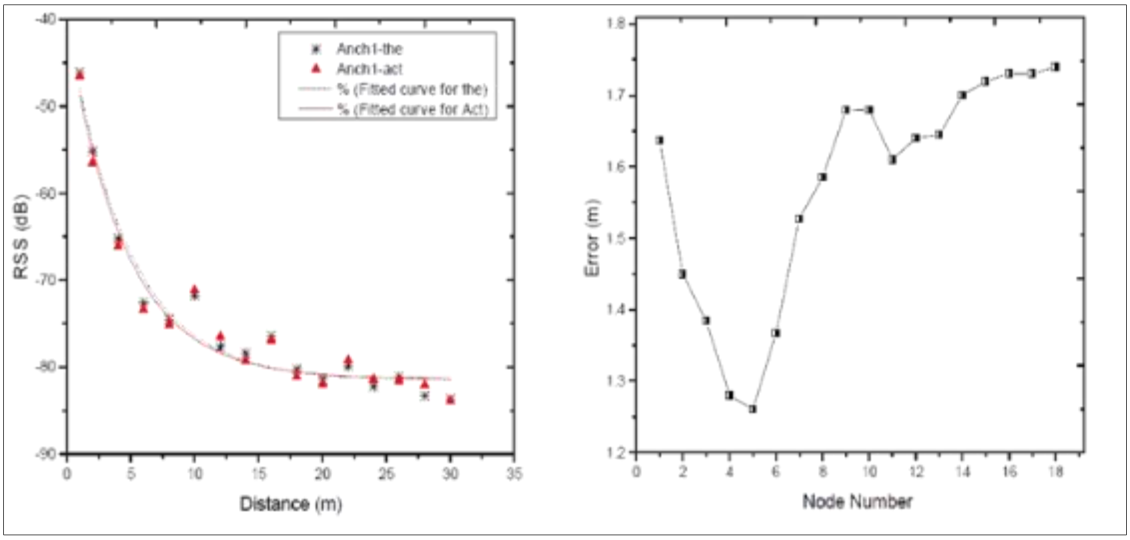


**Figure 7** Distance error for different nodes as well as changes in the receive signal intensity index (a) as a function of distance (b)

*3.10.5. Accessible Information Website*

Web 2.0 apps, e-Science platforms, support application platforms, and Java 2 Enterprise Edition (J2EE) were used in the implementation of the system interface (detailed in Section 4.3). Additionally, the I/O data was processed using Java Database Connectivity (JDBC). A screenshot of standard monitoring at various SNs is depicted in Figure 8, Figure 9 demonstrates how to use a computer's Web interface to remotely control or deactivate two ventilation fan actuators. The central server swiftly determines the surroundings through the comparison of existing data to threshold limit values during the initial assessment of the mine are serving state. On some nodes, you can find alarms and warning lights that serve as alerts during emergencies.

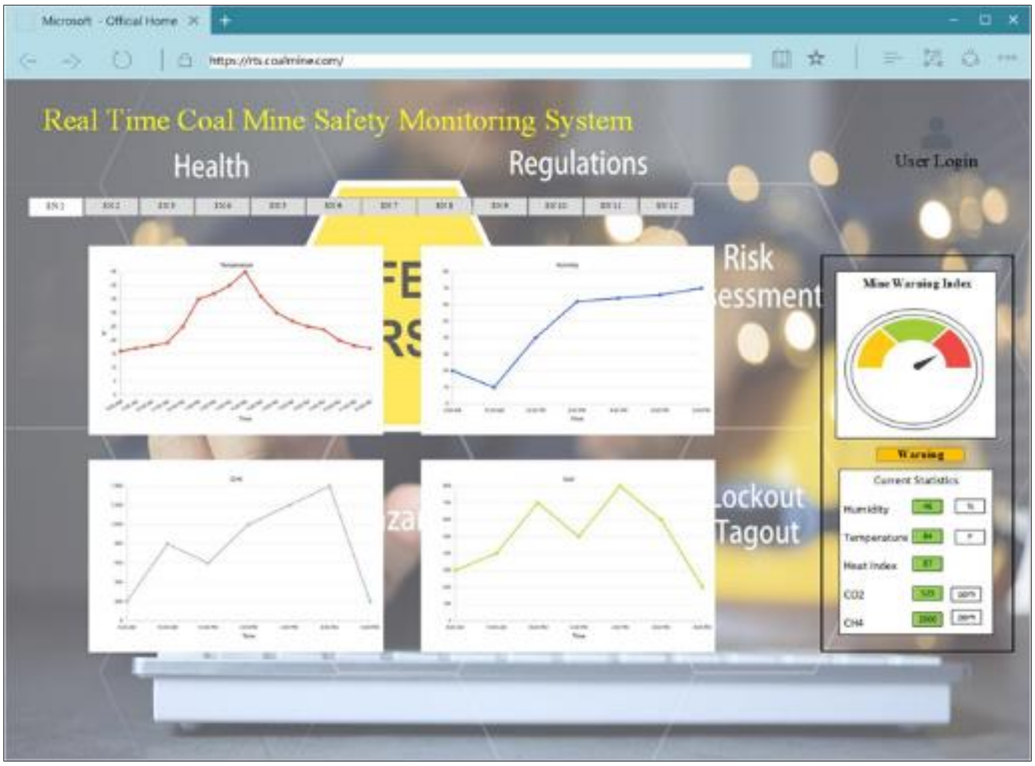


**Figure 8** Displays a screenshot of the sharing of information and sensing data through the Internet of Things


**Figure 9** A computer screen view of the interface that was built for turning auxiliary fans on and off

*3.10.6. Web Page Performance*

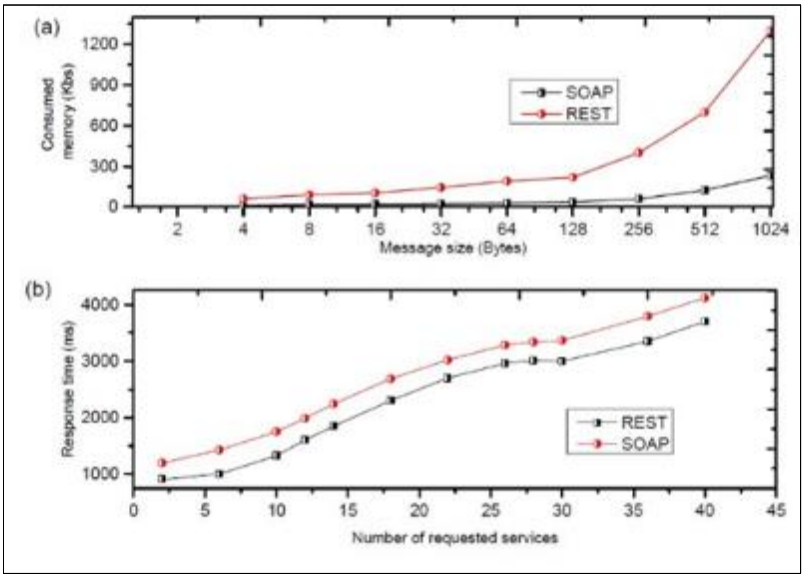


**Figure 10 A** comparison of the memory use and response time of the REST and SOAP protocols

In order to facilitate the efficient exchange of information in real time, the website must be both scalable and lightweight. To evaluate the efficacy of our website, we created a remote web-monitoring framework that was based on the equivalent simple object access protocol (SOAP) to evaluate its scalability, overhead, and flexibility. A client might submit many queries at once to make comparisons easier, and multi-threading was used to handle all of those inquiries. Figure 10(a) depicts the amount of memory that is consumed by web pages that are based on REST and SOAP over more than fifty queries. The message capacity increases in proportion to the number of requests. Differentiation in figure 10(b) presented web-based service framework SOAP and web service application Interface for the program. For the same number of queries, the REST-based application interface takes a far shorter time than the SOAP-based website. Request completion time and response time were two areas where REST performed better than SOAP-based web services. As a consequence of this, the online interface that is based on the REST protocol is both lightweight and effective. A further point to consider is that the SOAP-based web server uses a bigger quantity of RAM than the REST-based webpage.

## 4. Discussions

Aside from the rudimentary telephone connections between the surface and subterranean stations, the mine lacked any kind of safety management system prior to the installation of this system. It was very difficult to establish a quantitative comparison between the accident rates prior to and following the implementation of the integrated system due to the unreliability of the old approach of manually entering accident data. Four people were contacted after this procedure was implemented. These individuals included the mine manager, a technical advisor, and two miners who were employed by the mine. To educate miners about the system's capabilities and the benefits it offers, training sessions were planned to take place after the system had been installed. Two miners' representatives were questioned following that. For reasons including its portability, security, and amusement value, they were enthusiastic about bringing MN along. Mine accidents decreased dramatically as well. Therefore, this system is an excellent substitute for the prior mine management system and has shown to be quite suited. Mine managers benefit from this method since it allows them to constantly track the whereabouts of the mine crew. Therefore, this approach allows for better management performance, particularly in confined spaces. Constant monitoring of miners aids in avoiding unapproved access to hazardous gas-rich restricted zones. In addition, the system's ability to share information in real-time with all managers and employees is a key feature. In the event of an accident or other unforeseen threat, this technology allows for rapid rescue operations. Also, the technique was useful for showing how the coal mine's gas emissions were trending overall. In Table 8, we can see how our suggested system differs from the few that have come before it in relation to certain key qualities.

**Table 8** Compares with other studies by showing our suggested system's unique features

| **Characteristics** | **Our System** | **[25]** | **[15]** |
|---|---|---|---|
| Open-Source | Yes | Yes | x |
| Efficient and affordable | Yes | X | N/A |
| Computing in the cloud | Yes | X | X |
| Several safety-related factors and parameters | Yes | Partial | certain parts of security |
| User-friendly interface | Yes | Yes | X |
| Practical applicability | Yes | X | X |
| Saves energy | N/A | X | N/A |

Actually, thinking about things like energy management can improve the utilization of WSNs in mines even more [39, 40]. Furthermore, the utilization of both hard and soft thresholds could greatly enhance the operational efficiency of the proposed WSN based platform. In accordance with the recommendation in [41], the sensor nodes should notify the user whenever a predetermined difference exists between the current and previous values of the measured parameters.

## 5. Conclusion

Our suggested method showed the first steps toward creating an internet of Things (IoT)-based tool for sharing information, finding events, and getting alerts in advance. This platform could offer better services and more comprehensive safety in underground coal mines. Our system includes cloud services, application programming interfaces for data processing, and the capability to observe the coal mining environment. By employing sensor in coal, mine which is connected to ODROID-N2+ module, the five parameters—temperature, humidity, CO2, CO, and CH4—were measured at various locations. These modules achieved an efficiency of over 99% and a correctness of over 95%, respectively. Gas, temperature, and humidity limit values form the basis of MWI's contingency table. Implementation of a simple ambient intelligence system based on temporal statistics outperformed traditional qualitative decision-making, supporting a claim made in a recent literature review on hazardous gases, seamless integration, and event detection. When it comes to spotting suspicious occurrences in a subterranean coal mine, K-means clustering with silhouette values and Euclidean distance measures works well. With the examination of sensor data, attributed and systematically linked event detection algorithms provide preliminary warnings for disaster mitigation. For mining monitoring, the Centroid technique using RSS range is a good option, despite its lack of accuracy. An effective and memory-efficient underground sensors can be accessed with ease using a web-based, lightweight REST-style remote monitoring and control system. The approach was tested in several actual underground coal mining scenarios and a variety of computer-generated events were produced in order to gauge the efficiency of the proposed integrated system. The system's robustness was demonstrated by these experiments. However, before completely implementing this approach in deep coal mines, there are some certain problems that need to be carefully assessed. The following obstacles exist: processing requirements, the mine's harsh surroundings, data from multiple sources operation, confidentiality of data, the complexity of IoT-based systems, and autonomous sensing. Before employing the K-means method to identify outliers, it is necessary to establish the cluster centers. In general, this system was beneficial in addressing the challenges of availability, ability to serve, connectivity and adaptability in the development of an "Internet of Things" for coal mines.

## Compliance with ethical standards

### *Disclosure of conflict of interest*

As the corresponding author, I would like to declare that none of my co-authors nor I have any conflicts of interest that might affect the findings presented in this paper.

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