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Predictive safety helmet for miners using internet of things and artificial intelligence

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ABSTRACT

Mining is still responsible for many deaths since mines have dangerous environmental conditions including mine collapses, gas emissions, and high temperatures. However, traditional helmets do not provide adequate protection; besides, they cannot analyze miners' health as well as the environmental hazards. In order to solve this issue, this work presents a predictive safety helmet equipped with several sensors and means of communication. Specifically, the helmet comprises a micro-electro-mechanical systems (MEMS) accelerometer for vibration monitoring, a gas sensor for detecting the presence of harmful gases, a heartbeat sensor for assessing workers' well-being, and a temperature sensor for monitoring the environmental parameters. Additionally, the device is provided with a global positioning system (GPS) module for location determination and a global system for mobile (GSM) module for transmitting alert notifications in case of emergency situations. The collected data is analyzed on an internet of things (IoT)-based system; any signs of danger cause alerts to be sent immediately.

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1. INTRODUCTION

Mining has long been recognized as one of the most dangerous industries in the world, where workers are constantly exposed to harsh and unpredictable environments. There are serious difficulties in underground performances [1]. These are poor ground conditions, unsafe air, dust and heat, and lack of ventilation. The International Labor Organization (ILO) estimates that mining employs an average of 1% of the world population but almost 8% of the annual occupational deaths. This is regardless of the safety measures that have been adopted and the fact that modern equipments are used with miners still subjected to life threatening conditions daily. The conventional safety control methods including the hard hats and simple protective equipment only offer a partial control against external risks like falling debris and head injury, and the minor impact. Nevertheless, they cannot be used to fight more complicated threats like toxic or explosive gases (e.g., methane and carbon monoxide), health crises, or unexpected alterations in the underground surroundings. These risks are usually invisible and odorless; this is the reason why an accident can happen any time. To overcome such dangers, real-time observation of both the environmental and the physiological situation has been critical. New opportunities have emerged due to recent technological advances in the field of safety improvement in hazardous industries, especially regarding the internet of things (IoT), wearable devices, and sensor integration. As an example, smart helmets fitted with sensors might be seen as a wearable device that will continuously scan the environment and the health condition of miners, sending the necessary alarms, which will enhance the safety in the workplace. One of the most tragic incidents that prove the necessity of advanced safety systems is a mining accident in Copiapo in Chile that occurred in 2010. In this accident, 33 underground miners spent 69 days underground after a cave collapse that occurred due to the unstable formations of rocks.

There were no early warning systems and the delay in real-time communication was severe, which made rescuing activities extremely difficult. Even though the miners were all eventually rescued, the accident cast some serious doubts as to whether the current safety measures put in place in such risky workplaces were sufficient. Helmets with gas sensors and IoT-enabled communication devices would have given a real time alert to the surface, therefore would have acted promptly to intervene and probably avert the calamity altogether. Regulatory control and investment in mine safety [2] is still limited in most of the developing countries, and predictive safety systems are becoming even more urgent in these nations. Many of the mines have not yet had sophisticated tracking and monitoring systems installed hence the occurrence and severity of accidents. The application of IoT and sensor-based technologies to smart helmets will not only help minimize the number of accidents but also enhance the time taken to respond to the accident emergency, which will save lives. These helmets may be fitted with various in-built sensors such as micro-electro-mechanical systems (MEMS) accelerators in the case of sudden jolts or falls and gas sensors to detect dangerous gases like methane and carbon monoxide. The current literature review is shown in Table 1.

Table 1. Current literature review

Author	Method	Objective	Layer	Weakness	Year
Mahjoob *et al.* [3]	Green multi-period inventory routing with pickup and split delivery	Optimizes inventory routing and reduces environmental impact in the flour industry	Supply chain and green computing layer	Focuses on logistics optimization and does not address worker safety or health monitoring	2021
Wan *et al.* [4]	Wearable IoT-enabled health monitoring	Monitors real-time health parameters using wearable IoT devices	Wearable IoT Layer	Lacks integration with mining environmental hazard detection	2018
Proposed work	IoT-integrated predictive safety helmet	Real-time prediction of danger health alerts	IoT + sensors + AI	Needs underground communication infrastructure	2025

2. METHOD

Based on the surveys drawn using different sources, we have discovered the challenges that are encountered in the current system at hand, and we are therefore in a position to state the problem statement: Mining operators experience a lot of safety challenges. This is because the environment in which they work is dangerous. Workers are routinely exposed to life-threatening situations such as landslides, gas leaks, and dangerous temperatures, structural collapse, and traditional security systems. It tends to be more reactive than proactive [5]. This means threats are only approached when they tend to become critical. This slows down the response times of employees and creates more risk. The other major concern in mining is the health of the workers themselves. Mining is very labor-intensive. And exposure to harsh conditions for a long period of time may lead to chronic health problems or even sudden infliction of physical harm. Many mining operations currently do not have real-time health monitoring of the workers. This means issues like fatigue, heat exhaustion, or exposure to toxic gases cannot be noticed until the situation is critical. The lack of effective data management system [6] also adds further to the problem of environmental and health data being collected on dispersed and unsecured systems consequently leading to the potential of tempering with or loss of the information, or unavailability due to the incompleteness of the data as well as the impossibility of the security mechanisms to perform properly if there is no central and secure way of reporting of health reports and/or accurate monitoring of environmental data. As a resolution of the issue, these difficulties must be faced.

2.1. System architecture

2.1.1. Sensor

The intelligence helmet is fitted with a series of sensors which keep track of the health of the miner and the environment at the mining location [7]. All the sensors are selected due to their accuracy, reliability, and ease of integration. The sensors are pre-calibrated as given in Table 2 to allow them to give the right readings. Calibration checks were advised frequently to make sure that there is reliability in the data. Sensor selection criteria: the sensors were selected on precision, strength to operate in harsh mining conditions, low power usage, affordability and their integration with wearable IoT. The sensors target keysafety parameters independently, which are the gas detection, environment, motion detection, and physiological health sensors.

Table 2. Sensor calibration details

Sensor type	Placement on helmet	Make / model	Parameter measured	Sampling rate	Calibration method
Body temperature	Forehead near heart rate (HR) sensor	MLX90614	Core body temperature	0.5 Hz	Infrared calibration standard
Humidity and temperature	Top/side of helmet	DHT22	Ambient humidity, temperature	1 Hz	Standard environmental chamber
Gas sensor	Side of the helmet	MQ-2	Methane, CO, LPG	1 Hz	Standard gas mixture
MEMS accelerometer	Top-center of the helmet	ADXL345	Motion, vibration	100 Hz	Motion calibration routine
Radar sensor	Front/rear of helmet	HB100 or similar	Terrain displacement / landslide prediction	Continuous	Reference terrain scan
Heart rate and SpO_2	Front forehead region	MAX30102	Heart rate, blood oxygen	1 Hz	Factory-calibrated, verified weekly

2.1.2. Microcontroller unit (MCU) and the IoT communication

MCU is the core processing unit of the smart helmet. It is responsible:

a. Data acquisition: it receives real-time data of all the sensors [8], MEMS accelerator, gas sensors, heart rate sensor, temperature sensors, pulse oximeter, and radar.
b. Preprocessing: it removes sensor noise with the help of digital filters, converts the units, and computes derived values, e.g., the moving average of heart rate and gas concentration trends.
c. Error handling: information technology (IT) checks sensor connectivity and retries or issue local alerts in case sensor data is lost or abnormal. Redundant sensors are used to assure reliability of the system in case it fails.
d. Communication management: it provides support to different communication protocols such as mobile network sending of critical alerts via global system for mobile (GSM) / general packet radio service (GPRS), wireless fidelity (Wi-Fi) and cellular fourth generation (4G) / fifth generation (5G) to sustain high-frequency data stream, global positioning system (GPS) module to track the real time location, data buffering it is used to store data during network failure and forwards it once network connectivity is reinstated to avoid data loss.

2.1.3. Blockchain

The blockchain module provides integrity of data [9], secure storage and access control:

a. Secure ledger: every sensor reading is assigned a timestamp and a hash, and then it is chained to the blockchain, which helps to check against any coins.
b. Access control: data can only be accessed by authorized individuals, i.e., safety officers and mine management.
c. Redundancy: the distributed ledger is replicated in a variety of nodes [10], meaning it would still be available in the event of failure in one of the nodes.

2.1.4. Feature extraction

It takes significant features out of sensor data, like how fast gas concentration is changing [11], or the heart rate changing, or the sudden change in terrain as noticed by radar. The block diagram is shown by Figure 1.

a. Model choice: the reason behind using the random forest (RF) classifier is that it is reliable in handling noisy data and mixed type features (continuous and categorical).
b. Training and validation: historical mining data are separated into 70 percent of training, 15 percent of validation, and 15 percent of testing in order to optimise model parameters.
c. Hyper-parameter tuning: it entails the tuning of tree depth, estimators' number, and minimum samples per leaf.
d. Real-time prediction and integration with iot: real time incoming data are evaluated to determine possible hazard like health risk threshold that alerts when the probability 6 is 30 or above, landslide risk threshold that immediate notify when the probability stands at 80 and above, alert mechanism. Once thresholds are surpassed, the system will activate audio-visual warnings to the miner, notify central control and record the occasion on the blockchain. The AI predictions are transmitted through the IoT to the central monitoring system [12] to be visualized, trend analyzed, and decisions made.
e. Feedback: models are retrained with feedback from previous alerts, as the predictive accuracy increases over time. Benefits [13]. By doing this, predictive and proactive safety is encouraged as opposed to mere reaction to incidents and this greatly reduces the response times as well as the possibility of accidents.

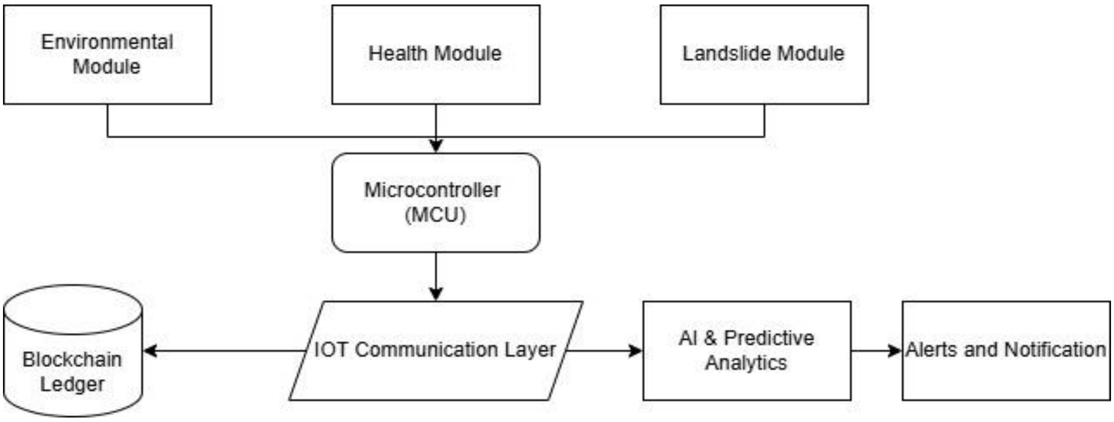

Figure 1. Block diagram

2.2. Workflow of the IoT-based predictive safety helmet

The following outlines the main stages of the preventive safety helmet as Figure 2 provides the flow diagram.

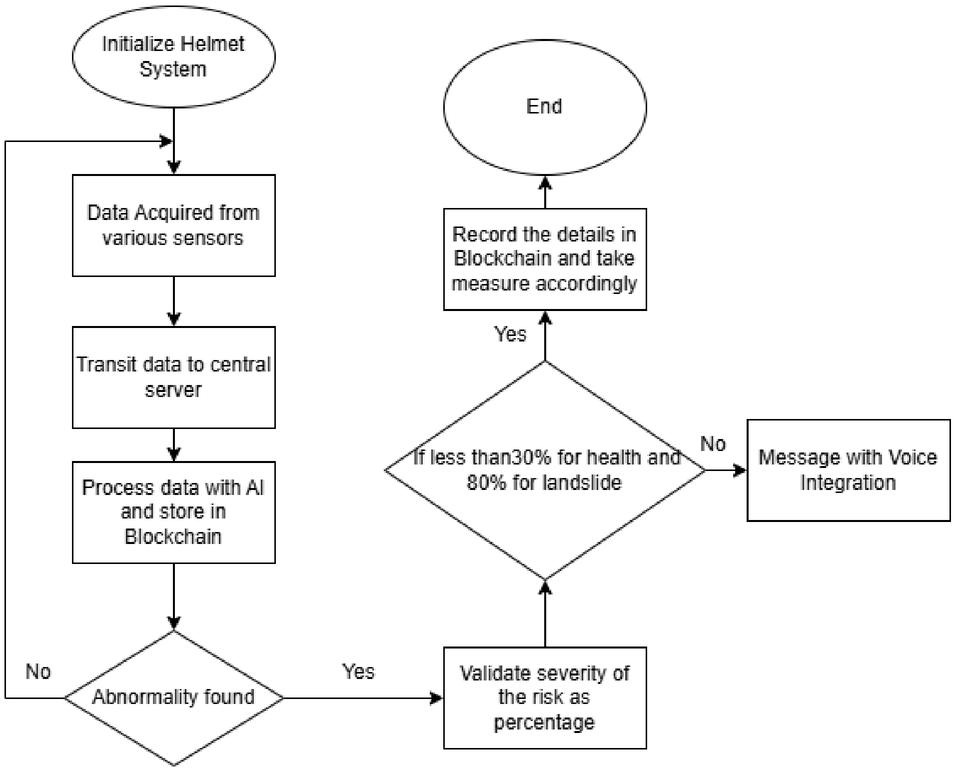

Figure 2. Workflow of predictive smart helmet

a. System startup: the helmet system is started and all the parts of the system, such as sensors, Microcontroller, communication modules [14], and AI analytics are initialized. Calibration checks are done to check whether the results are correct.
b. Data transmission of data through IoT layer: the sensor data is transmitted over the IoT algorithms will be able to work with the large data volume performed by numerous helmets simultaneously.
c. AI and predictive analysis: the AI engine of the server processes the incoming information to point out the deviations and the existence of possible risks, such as landslides, structural instability, or threatening areas of gas. Machine learning models are continuously updated with predictions depending on the new data.

d. Data recording and blockchain archiving: all sensor readings, risk evaluations, and actions taken are securely stored in a blockchain ledger. This provides tamper-proof storage, traceability, and audibility of safety events, which is essential for regulatory compliance and post-incident analysis.
e. Feedback loop: the system is improved by learning through the events recorded and enhancing AI prediction models and alerts threshold.
f. Generation of alerts and respond: trigger automated safety measures (e.g., stop machine and evacuate human) in case of thresholds exceeding alert to the blockchain, store data on record and enable the use of previous data to create more accurate predictions over time.

3. RESULTS AND DISCUSSION

The proposed system consists of three main modules: environmental prediction, health prediction, and landslide prediction [15]. Each module independently assesses whether the mining workers are working in safe or unsafe conditions as described in Table 3. The results shown in this section are generated by using synthetic data that simulates a realistic mining scenario.

Table 3. Overall system performance evaluation

Category	Parameter	Normal / benchmark	Status	Observed value
Health monitoring	Oxygen level	≥95% (World Health Organization (WHO) / Occupational Safety and Health Administration (OSHA))	Alert	91%
	Heart rate	60–100 bpm	Normal	76 bpm
	Body temperature	36.1–37.2 °C	Abnormal	30.2 °C
Hazard detection	Gas level	>300 ppm = emergency	Emergency	450 ppm
	Alert time	<2 sec (smart helmet benchmark)	Fast response	1.26 sec
Sensor performance	Temperature accuracy	>95%	High	98.12%
	Gas sensor accuracy	90–95%	High	96.51%
	Vibration accuracy	90–95%	Reliable	94.73%
Communication performance	Signal delay	<200 ms (emergency IoT)	Optimal	170 ms
	Success rate	>95%	Excellent	97.51%
	Battery drain	~100 mAh/hr	Efficient	92 mAh/hr

3.1. Environmental prediction module

The environmental prediction module is constantly tracking the critical environmental factors such as temperature and air quality, which are major risk factors in underground mining conditions. The system, based on a RF classification algorithm [16], determines if the measured parameters are beyond the defined safety limits and classifies the conditions into either safe or dangerous categories. Figure 3 shows the mean-based trend analysis for smoothing the environmental data and obtaining a consistent risk assessment. On detecting the dangerous levels, the system produces real-time voice notifications using a text-to-speech engine, as shown in Figure 4. The notifications allow miners and supervisors to take corrective action immediately [17]. Environmental monitoring is an automated process that provides full validity of the safety with no human involvement. The testing was done on the experimental basis with the dataset of university mental health iot dataset.csv on Kaggle.The experiment confirms that monitoring the environment with the help of AI is more responsive and eliminates the risk of hazardous exposure remaining unnoticed.

3.2. Health prediction module

The module of the health prediction is also related to the real-time monitoring of the physiological parameters of the workers, including heart rate, oxygen saturation, blood pressure levels, glucose intake, and breathing rate anomalies. The module aims at detecting the initial signs of physical stress and health degeneration under dangerous mining conditions [18]. The experiments were applied to the gym members exercise tracking.csv data in the Kaggle. The predicted results are presented and the alert generation procedure is presented in Figure 5 under the circumstances when the health parameters exceed the safe values. The system can recognize normal physiological states as opposed to abnormal conditions hence only alarming when a need arises.

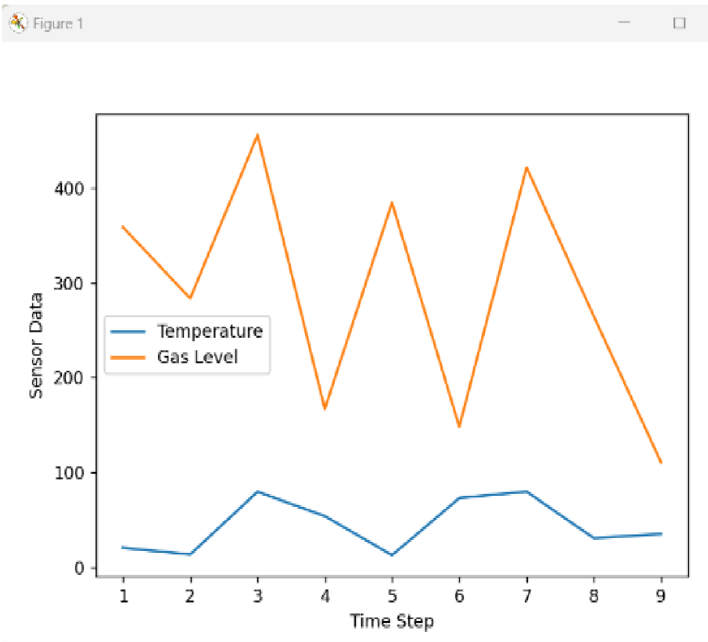

Figure 3. Graph of environment prediction

```
D:\Documents\Python\Smart_helmet_mining>C:/Users/Ronisha/AppData/Local/Programs/Python/Python312/python.exe
d:/Documents/Python/Smart_helmet_mining/Integrate.py
Press 'E' to run the Environmental Module
Press 'H' to run the Health Module
Press 'L' to run the Radar Module
Press 'Q' to quit
Running Environmental Module...
Environmental Module is now running. Press 'Q' to stop.
Stopping Environmental Module...
Environmental Module Report:
Total Time Steps: 27
Alerts Triggered: Timestep 3: Carbon monoxide detected, Timestep 7: Carbon monoxide detected
Module complete. Press 'n' to proceed to the next module or 't' to terminate.
```

Figure 4. Environment prediction accuracy

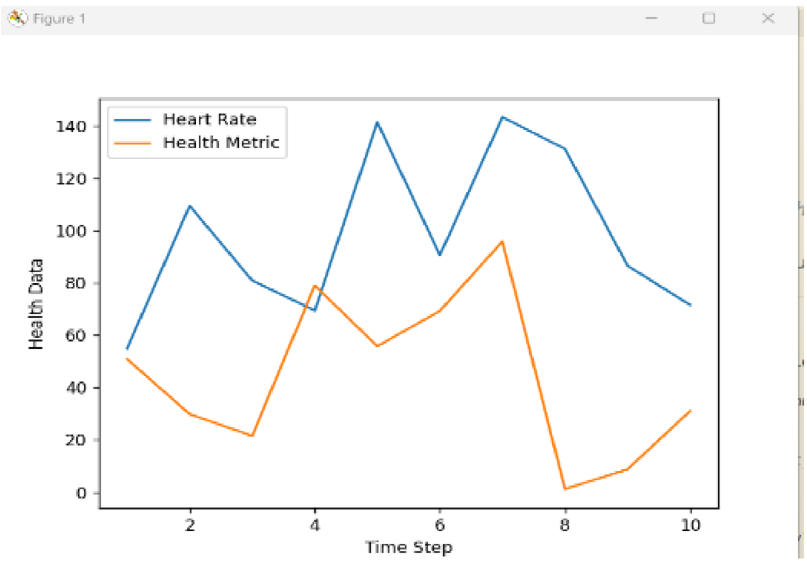

Figure 5. Graph of health prediction

The module will reduce the use of manual health checks (the use of AI-based continuous monitoring will relieve the health checkers of their tasks). The module will ensure that the workers are constantly safe. The system is responsive to the health anomalies and responsive to them in an appropriate fashion. The predictive analysis and real-time monitoring [19] can assist to provide timely medical care, avoid serious health incidents and enhance the safety of workers in risky environments. This system is a crucial tool in the work environment as it allows a toddler to receive the necessary care at the very moment as shown in Figure 6, avoiding health degradation, and save lives in dangerous workplaces due to the integration of predictive systems, combined with real-time analytics [20].

```
D:\Documents\Python\Smart_helmet_mining>C:/Users/Ronisha/AppData/Local/Programs/Python/Python312/python.exe
d:/Documents/Python/Smart_helmet_mining/Integrate.py
Press 'E' to run the Environmental Module
Press 'H' to run the Health Module
Press 'L' to run the Radar Module
Press 'Q' to quit
Running Health Module...
Health Module is now running. Press 'Q' to stop.
Stopping Health Module...
Health Module Report:
Total Time Steps: 25
Alerts Triggered: Timestep 1: Pulse is low, Timestep 7: Critical health metric
Module complete. Press 'n' to proceed to the next module or 't' to terminate.
```

Figure 6. Alert based on the prediction of health metrics

3.3. Landslide prediction module

The landslide prediction module is intended to evaluate geological risks by processing parameters such as the angle of slope, rainfall intensity, erosion factors, and vibration patterns. Machine learning (ML) algorithms [21] are used to predict dangerous situations such as landslides or seismic instability. The experiments used the Landslides_Factors_IRAN.csv dataset, which was supplemented with artificial data to simulate different mining sites and conditions. Threshold levels were established according to Bureau of Mines safety standards and WHO/OSHA permissible exposure limits. As shown in Figure 7, the system detects landslide risk when critical levels, such as slopes greater than 30° or rainfall intensity greater than 50 mm/h, are exceeded. One of the main advantages of this module is the development of a non-sequential alerting system [22], in which alerts are produced only when dangerous conditions are maintained for non-sequential time intervals.

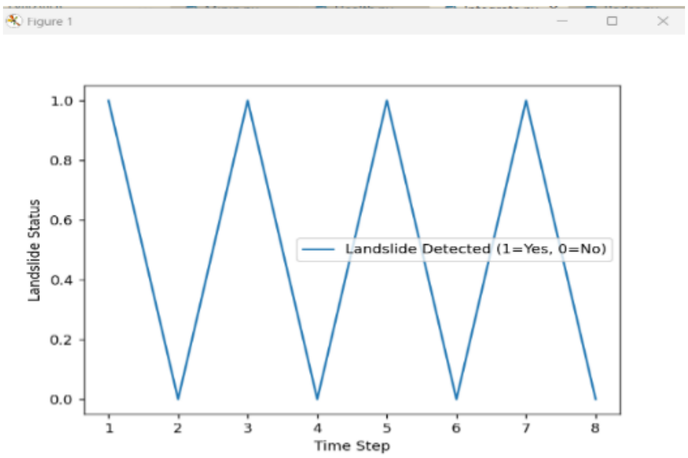

Figure 7. Graph of the prediction of the landslide

This approach has been shown to greatly decrease false alarms due to temporary environmental changes, a common problem in seismic alerting systems. The experimental findings showed that the false alarms [23] would be reduced by approximately 15-20 percent compared to the old system of sequential alerting and without the rate of false-negative increased beyond 5 percent as shown in Figure 8.

```
D:\Documents\Python\Smart_helmet_mining>C:/Users/Ronisha/AppData/Local/Programs/Python/Python312/python.exe
d:/Documents/Python/Smart_helmet_mining/Integrate.py
Press 'E' to run the Environmental Module
Press 'H' to run the Health Module
Press 'L' to run the Radar Module
Press 'Q' to quit
Radar Module is now running. Press 'Q' to stop.
Stopping Radar Module...
Radar Module Report:
Total Time Steps: 21
Alerts Triggered: Timestep 1: Landslide detected, Timestep 3: Landslide detected
Module complete. Press 'n' to proceed to the next module or 't' to terminate.
```

Figure 8. Alert based on the prediction of a landslide

The system is also enhancing the credibility of the results since the AI predictions are combined with voice notifications and visualization of the data [24]. Although we might have cases of undetected cases due to sensor noise or loss of data, the next research will involve solving this problem by using multi sensor fusion of radar and vibration sensors. The Landslide Prediction module is therefore effective in issuing early warning to effective management [25] of the risk of disasters in the mining activities.

4. CONCLUSION

This study has developed and experimented on a smart helmet system using IoT technology to enhance safety in the mining industry. The results of this research have clearly indicated that environmental and physiological factors can be monitored in real time and can significantly aid in the reduction of the time of warning and response towards possible danger as opposed to traditional safety systems. Future research directions are also mentioned in the study including applying machine learning algorithms to predictive risk analysis, blockchain technology to securely store data, and edge computing to minimize latency. Drift of sensors, degradation of hardware, environmental noise and power consumption are some practical problems that should be considered in these systems. To sum up, the IoT-based wearables can be used as an efficient, proactive, and scalable method of enhancing mining safety.

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Janani Vigneswaran	✓		✓	✓			✓		✓		✓		✓	✓
Pooja Senthamarai Kannan		✓			✓	✓		✓		✓	✓	✓	✓	

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

CONFLICT OF INTEREST STATEMENT

The authors of this paper would like to state that there are no financial, personal, professional, or institutional conflicts of interest that could have affected the outcome of this study. This study was done independently, and all results are based solely on the analysis of the data.

DATA AVAILABILITY

The data provided includes sensor performance data, system response times, and environmental data collected during prototype testing. Due to storage and security reasons, the data is not publicly available but can be requested.

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