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AI based Safety Helmet for Mining workers using IoT Technology and ARM Cortex-M

Lalitha K, Ramya G and Shunmugathammal M

***Abstract*— Coal mining is one of the most hazardous activities in the world. They frequently encountered unexpected emergencies. The use of the IoT and AI in mining helps improve worker health management and prevent injuries. In this study, a Personal Protective Equipment (helmet) is proposed, which can provide alert signals to the control center to inform the miner about the risk. With the use of several sensors integrated into the STM32 module, it continuously analyzes ambient conditions (toxic gases, temperature, and humidity), as well as the worker's health conditions, such as heart rate and vibration generated by excavation and blasting, which are subsequently relayed to the control center using a low-energy Bluetooth module. This system also has a panic button that may alert the control unit if there are any dangers to the workers. The DHT11 (Digital Temperature humidity Sensor) can measure the temperature and humidity levels with a degree of accuracy that falls within a range of ± 5%. The MQ135 Sensor, on the other hand, can sense gas concentrations with 85% accuracy. In coal mines, high gas concentrations can cause miners to feel dizzy and disoriented. To address this issue, miners can press a panic button located on their helmets, which alerts the control center staff and speeds up the rescue operations. In addition, a heart rate sensor was integrated with the STM module using the I2C protocol. If the heart rate reading falls below 60 or exceeds 100, it is considered an abnormal condition that requires attention. Furthermore, a machine learning algorithm with a convolutional neural network helps to train the artificial intelligence model to recognize the worker's gestures. Here, four types of gestures were fixed, which helped the workers communicate. These gestures have been labeled GOOD, NOT GOOD, DOING FINE, and EMERGENCY EVACUATION. A receiver API is proposed to visualize the results from various sensors and take appropriate action to safeguard miners.**

Index Terms—Internet of Things, coal mine, Personal protective equipment, ARM cortex-M, Remote Monitoring, Machine learning algorithm

I INTRODUCTION

The mining industry is one of the most important, influential, and economically significant sectors in the modern world [1]. The growth of other businesses, such as those that produce power, cement, and commercial and residential buildings, is necessary for the expansion of the mining sector. According to the National Foundation of India, the coal economy directly or indirectly affects millions of Indians. The coal mining, transportation, electricity, sponge iron, steel, and brick industries collectively employ more than 1.3 crore Indians. The working conditions in the mining sector are notoriously dangerous [2][3]. The safety and security of miners pose a significant challenge globally owing to the frequent release of toxic gases from underground mines. The manual monitoring of environmental conditions in a coal mine is a challenging task. However, this task can be made much easier using cost-effective wireless communication devices installed at strategic locations within the mine. The proposed system uses low-power sensors that are highly efficient in detecting the worker's pulse, respiratory rate, and any harmful gases that may be released into the environment. Hazardous gas levels are constantly analyzed and communicated in real-time to prevent any risky situations that may pose a threat to the safety of mining laborers. Miners are particularly susceptible to the adverse health effects of these gases, which often puts their lives at risk. Notably, it is difficult for humans to detect these gases based on their sensory abilities. The traditional communication approach for monitoring systems involves burying communication cables underground, which can be challenging in certain locations, such as coal working faces. These faces underwent constant changes during the digging process. However, with the emergence of Wireless Sensor Networks (WSN), their applicability in the industry has been demonstrated owing to their ease of use. Monitoring the mining environment and ensuring worker health are critical aspects of mining operations. However, workers often avoid wearing safety equipment because of their weight, heat, and discomfort. Although safety helmets are currently used to protect workers from head injuries caused by falling objects or collisions with protrusions in tunnels, they can be cumbersome and inconvenient to wear.

Mine flooding, gas explosions, ceiling collapses, mine haulage, abrupt inrushes, mine inundations, spontaneous combustion, and inadequate escape routes are just a few dangers that afflict miners. There is no precise answer that can predict these risks and prevent them even before they materialize. When operating below underpasses, these mining workers are vulnerable to sudden temperature variations, oxygen shortages, hazardous gases (Carbon Dioxide, Sulphur Dioxide, Ammonia, and Methane) variable humidity, and other adverse and unforeseen dangers [4]. Several warning generation devices have been installed in mines. However, they are unable to recognize sudden health symptoms, including breathing and changes in heart rate. Various researchers have focused on Zigbee, IEEE 803.15.4, and wireless sensor networks [5]. These researchers have not yet presented a workable architecture or system functioning, and their study is limited to the simulation environment [6]. To track and analyze important dangerous

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data in real time, an efficient system can be mounted on coal miners' helmets. This paper proposes a novel idea that includes a temperature and humidity sensor, gas sensor, MEMs accelerometer sensor, and pulse sensor that can identify these parameters, analyze them, and promptly alert personnel on the ground via a proper signal, such as a buzzer and gesture recognition. For simplicity, tiny sensors and low-energy Bluetooth radio signals from the modules are used. An embedded camera module is used to monitor the miner's gesture [7-9]. The TensorFlow Lite Micro framework was used to run Python code with the ARM Cortex-M platform for recognizing the gestures given by the worker. The proposed study will concentrate on developing a real-time monitoring helmet equipped with Internet of Things sensors that can deliver early warning data regarding the presence of fire, dust particles, temperature, toxic gases, and other situations that reduce worker health risks [10]– [14]. Ensuring the health and safety of miners is a critical aspect of mining operations and the proposed smart helmet system can play a significant role in achieving this goal. Although some workers may avoid wearing certain safety equipment owing to discomfort, the smart helmet is a lightweight and convenient option, as it is already used to protect workers from head injuries caused by falling objects or collisions with protrusions in the tunnel. The combination of AI and IoT is utilized to collect data from multiple sensors and integrate it with data from the camera module to predict the conditions prevailing in the mining area [15]. Recent research in mining has focused on improving the safety of workers by introducing various techniques, as discussed below.

The mining industry is attempting to implement several emerging technologies to transform mining into digital automation. Narrow tunnels, complicated geological structures, and extreme atmospheric conditions are challenging factors limiting the performance of a mine. Alok Ranjan et al. have performed a survey about health sensing and monitoring for mining workers. Development of a theoretical prototype with wearable sensors that can be added to personal protective equipment (PPE) such as clothes, caps, and glasses. The possible methods of occurrence of accidents are analyzed, and rescue operations may start quickly if the information about the miner is known a priori [16]. John J.Sammarco et al. focused about integrated lighting system with LED technologies to improve the visibility in dark environment[17]. Justin et al. proposed a wearable measurement unit for data collection regarding the performance of miners under various lighting conditions [18]. However, they are unsuitable for mines with variable roof heights. A position estimation method based on an acoustic system was proposed by Pfeil et al. to avoid accidents by estimating the position of the miner. It uses the received signal strength indicator to estimate the position. However, it suffers from signal degradation owing to multipath reflection [19]. Cheng proposed a method to improve mining safety using middleware technology [20]. A review of underground mine positioning has been conducted by Fabian et al. The challenges encountered in realizing localization technologies are also discussed [21]. A Zigbee network was deployed to monitor safety in the coal mine area. The details of the sensing systems are not included. The location of the miner was determined using a known coordinate system and depth analysis in underground mines. Internet of things and Mine internet of things (MIoT) architectures for wireless communication technology in underground mines are discussed for establishing secured wireless communication [22] [23] [24].

wireless video systems with sensors are recommended to speed up rescue operations; however, the complexity of the reconstruction algorithm is high, which requires more computing resources [25] [26]. Rescue Robots with Binocular Vision have been suggested, and the challenges involved in the mining field have been discussed [27]. S. Vadrevu et al. implemented health monitoring system using IoT and unsupervised learning algorithm. This initiates a new approach to health monitoring system [28]. The exchange of information between the worker and the control room is a way to convey information with the available bandwidth [29]. This can be implemented through gesture recognition using mediapipes [30]. This prototype can be made simple by executing machine learning algorithm in Microcontroller using TinyML [31][32].

II PROPOSED ARCHITECTURE

The risks associated with underground mining include suffocation, gas injury, roof collapse, and gas burst. The Internet of Things (IoT) and communication technologies have made it feasible to create PPE models and equipment wit h cuttingedge capabilities, such as environmental sensing, mon itoring, and risk identification. In the proposed model, a framework is designed using STM32 technology that consists of one transmitter module embedded into the helmet and receiver module kept outside the mining area called the control module. The helmet transmitter comprises five sensors namely, temperature, humidity, gas pressure, MEMS accelerometer, and heart rate sensor, to monitor the circumstances in the coal mine and miners' health conditions. There is also a built-in camera module to communicate the gesture conditions of mining workers to the control unit (outside the mining area). This unique wearable helmet with smart technology is illustrated in Fig 1. The heart of the system is STM32L4R5 microcontroller. First, data from the surroundings are collected by a digital temperature sensor (DHT 11) and a gas sensor (MQ135) and transmitted to the microcontroller module. The second part involves the collection of health conditions of mining workers using heart rate sensor, and motion MEMS and microphone sensor(X-NUCLEO-IKS02A1). X-NUCLEO-IKS02A1 is placed above STM32L4R5 microcontroller through R3 connector. Information exchange between the X-NUCLEO-IKS02A1and ST microcontroller is performed using the I2C protocol. All this information is communicated to the control module with the help of a Bluetooth module (X-NUCELO IDBO5A1 and the control module depicted in fig 2. has a receiver API to analyze and monitor these quantities in real time. The Control module generates warning signals when a hazardous working environment is detected. This will help to lower the number of unpredictable accidents, serious workplace illnesses (such as black lung disease), and even the early mortality rate. Fig.3. illustrates the various steps involved in acquiring the sensor data and wireless transmission.

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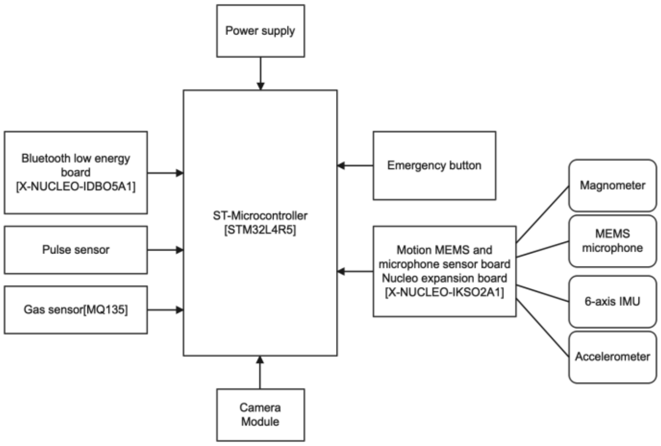

Fig. 1. Proposed framework for helmet unit

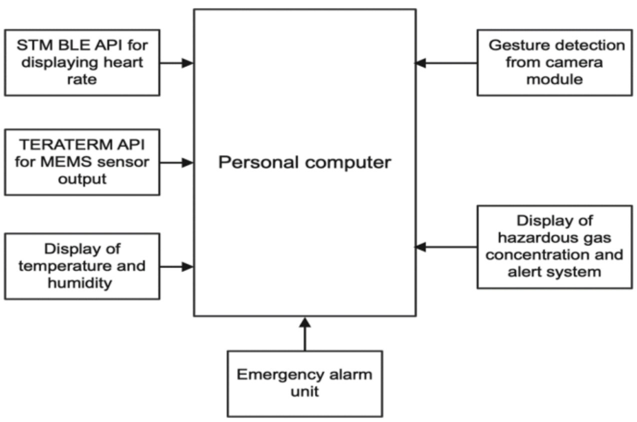

Fig. 2. Proposed framework for control Module

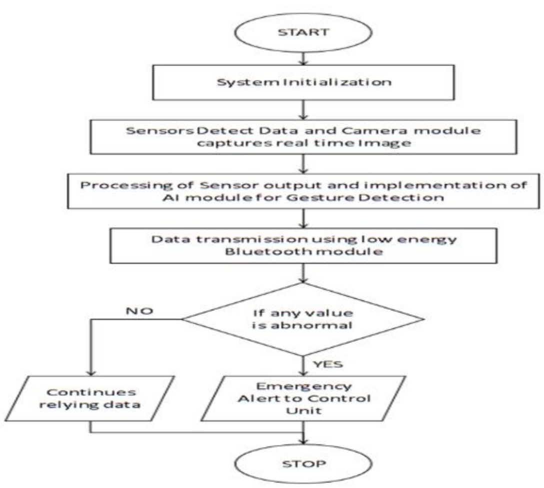

Fig. 3. Flowchart for multiple sensor integration

A. IoT sensor module

The physical conditions of the mining area and workers' health conditions are continuously monitored by several sensors and analyzed with the help of IoT node (STM32L4R5). The Microcontroller STM32L4R5 collects the temperature and humidity levels from the DHT11 sensor. The hazardous gas level is monitored by the MQ135 sensor. workers' health conditions are monitored by heart rate sensor and a MEMS accelerometer sensor. All these parameters are analyzed and transmitted to control module with the help of Bluetooth board for further action.

B. Gesture Detection Unit using Machine learning Algorithm

Hand gesture recognition is a tool which can recognize fingers motion in real time recording. The images collected from the video is studied using a mediapipes to find finger's position before any operation is performed. Region of interest (ROI) theory and Micro Python programming are used to identify the presence of a hand. A safety helmet for mining workers with a machine learning algorithm implemented using the Micro Python programming language was used to identify the gestures given by the worker and help them according to the gestures. A Camera module is interfaced into the safety helmet, which is used to capture and send the images of the hand gestures given by the worker, which is then sent to the control unit, where the machine learning algorithm is used to detect those gestures based on the training data already given to the program. Machine learning is based on neural networking, where a convolutional neural networking model is used for the better detection and identification of gestures. This machine learning algorithm consists of three neural networks. The first is the input layer, where the images received by the camera module are used as inputs to the model. The second layer is the processing layer, where the images are processed, that is, the hand gesture is detected using the node positions. The final layer was the output layer. Here, the detected gesture is identified based on the training data already provided to the program and is given as an output to the user. In this machine learning algorithm, libraries such as open cv2, numpy, mediapipe, and TensorFlow are used. Open cv2 is an open algorithm that can be used in machine learning to detect images and crop only the required parts from a given input image. Live video capture can also be used as input with the help of an open CV. Here, the gestures or node positions are stored as arrays and matrices, and calculations are performed on these matrices to identify the coordinates of each node in the given input image. Numpy is used so that both complex and basic matrix calculations can be performed using Python. Mediapipe is a pre-trained algorithm provided by Google Corporation. In the mediapipe, the algorithm is trained with more than 10000 images to detect the gestures and positions of the nodes in both hands and faces. Mediapipes can be used to detect hand and facial gestures. In this algorithm, a mediapipe is used to detect the hand gestures of a worker.

The gestures were detected using 21 nodes placed on the hands of the worker, as shown in fig.4a. The architecture for gesture detection is illustrated in fig.4b.The first node was present at the end of the palm and at the beginning of the wrist. This node is the most important node because the main location of the hand is detected using this node. The remaining nodes were placed such that each finger had three nodes connected to a node at the end of the finger and inside the palm. All these nodes are

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connected to each other so that the position of each node can be detected when a gesture is being made. The Mediapipe consists of many gestures, from which only the gestures that are required are selected and used in this algorithm.

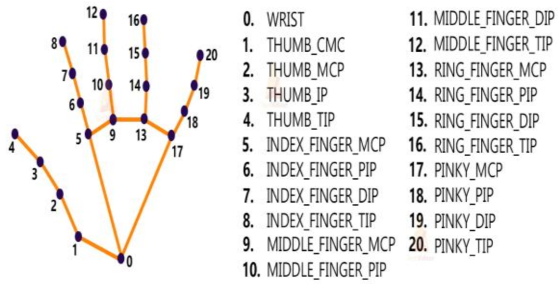

Fig. 4.a Guesture detection with node representtion

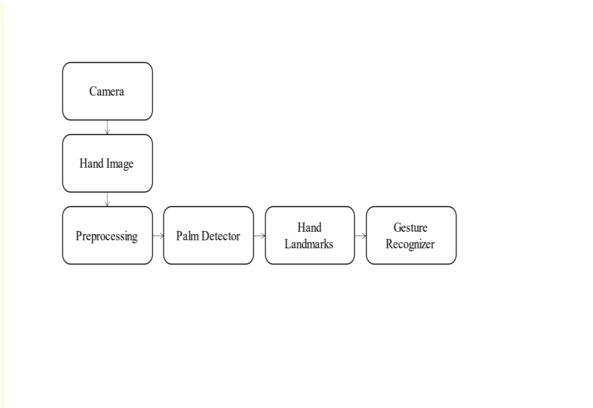

Fig. 4.b Guesture detection Architecture

In this algorithm, TensorFlow is used to process the matrices, determine the frame shape, and match it to the correct gestures among the four gestures. These results are then printed as outputs for the user. The coordinates of each node are detected in each frame, which in turn sent to the program that will match the frame shape to its gesture name. The landmarks, that is, the nodes, are connected to each other using media pipe giving each frame their shape. These are then checked if they match any of the gesture coordinates after which the output is displayed. If the obtained coordinates do not match any of the gesture coordinates, then 'nil' is given as the output to the user.

III EXPERIMENTAL RESULTS & DISCUSSION

This section presents the experimental verification of the proposed architecture. The temperature and humidity of the environment were measured using the DHT11. Temperature sensors can provide early warning of overheating or potentially hazardous conditions. A circuit diagram of the sensor and camera modules are shown in Fig.5. and Fig.6.The DHT11 consists of three pins: VCC, ground, and data. It uses single wire serial communication. The temperature and humidity values were displayed as digital data in an organic light-emitting Diodes) display, as shown in Fig.7, and transmitted to the control room. The output of the DHT11 sensor is a 40-bit data stream. The first eight bits depict the humidity value, the next eight bits show the decimal equivalent of humidity, the third group of eight bits show the integral value of temperature, and the fourth group of eight bits illustrates the decimal equivalent of temperature. The last group of eight bits are used for error verification, and the data signal from the sensor is in the form of a time-varying pulse. The microcontroller measures the durations of the high and low pulses to determine the bit value. The microcontroller can extract the required parameter values by decoding the pulse sequence. The temperature is specified in degrees centigrade and in Fahrenheit. DHT11 was used to indicate temperature values of 0^o C– $+50^o$C with an accuracy equivalent to ±2 °C and digital humidity from 20 to 95% with an accuracy equivalent to ±5%. Here, if the temperature is increased above 35 °C, it is considered as high temperature, and a humidity level above 86% is represented as high humidity. The air quality of the environment was verified using the MQ135 sensor and threshold value is set by potentiometer. The MQ135 gas sensor is useful for a range of applications, including air quality, gas leakage, and environmental monitoring. The output of the MQ135 gas sensor typically includes an analog voltage signal corresponding to the gas concentration. This signal was then processed by a microcontroller to determine the concentration of the gas in parts per million (ppm). The heart rate sensor output was transmitted using a low-energy Bluetooth board, as shown in Fig.8. as mobile application. The value of heart beats per minute is shown on the Y-axis, and the time of recording is denoted on X-axis. The graph shows a sudden spike or drop owing to an irregular heart rate. A MEMS accelerometer sensor was used to indicate the vibration level along the three axes, as depicted in fig.9. The MEMS accelerometer sensor(X-NUCLEO-IKS01A2) with STM32L4R5 is a specialized device that uses microelectromechanical technology to measure acceleration or changes in motion in three dimensions (X, Y, and Z). This sensor interfaces with the STM32L4R5 microcontroller from STMicroelectronics to process the electrical signal generated by three sensors: MEMS accelerometer, gyroscope, and magnetometer. The output of the MEMS accelerometer sensor typically includes measurements of the acceleration in three dimensions as well as additional information such as orientation. This information is provided as raw digital values that can be analyzed and further processed using software. If the miner moves, the output value depicts the magnitude and direction of acceleration. The gyroscope measures the rate of rotational motion of the miner or the angular velocity of the three axes. The output value was zero for each axis, which corresponds to the absence of rotational motion. Table 1 lists the values of the sensors at different instants in time. Table 2 shows the various sources available in the mining areas for production of hazardous gases. Microcontroller compares those values with threshold and act accordingly. A Magnetometer senses the orientation of the miner. The values were displayed in the TERATERM application environment. Finally, the camera output, along with the machine learning algorithm, is utilized to detect the gestures of a mining worker, as shown in fig.10., fig.11. and fig.12.The prototype verified was experimentally using a hardware unit, as shown in fig.13. The placement of various modules is shown in fig.14. Table 3 lists the different gestures used to communicate with the control module.

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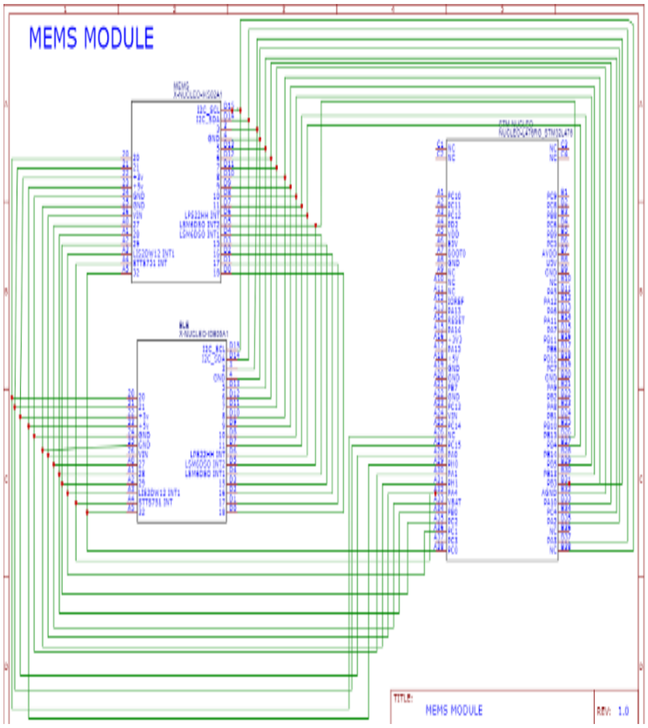

Fig. 5. Circuit diagram of Sensor unit

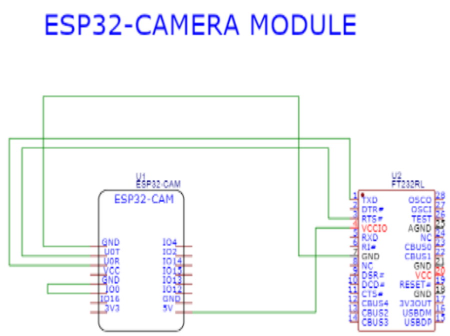

Fig. 6. Circuit diagram of Camera module

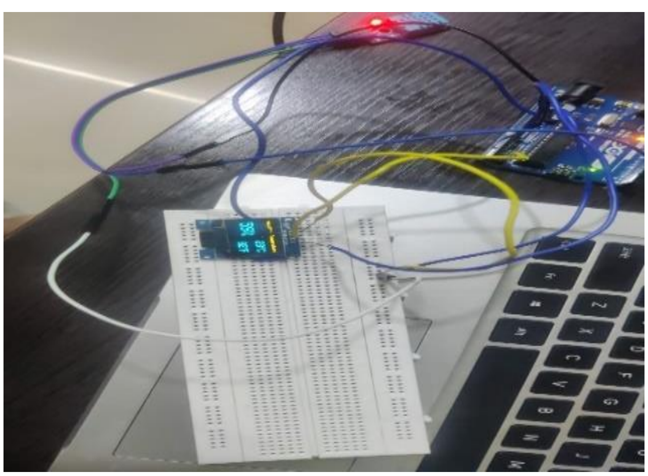

Fig. 7. Temperature and humidity value in OLED Display

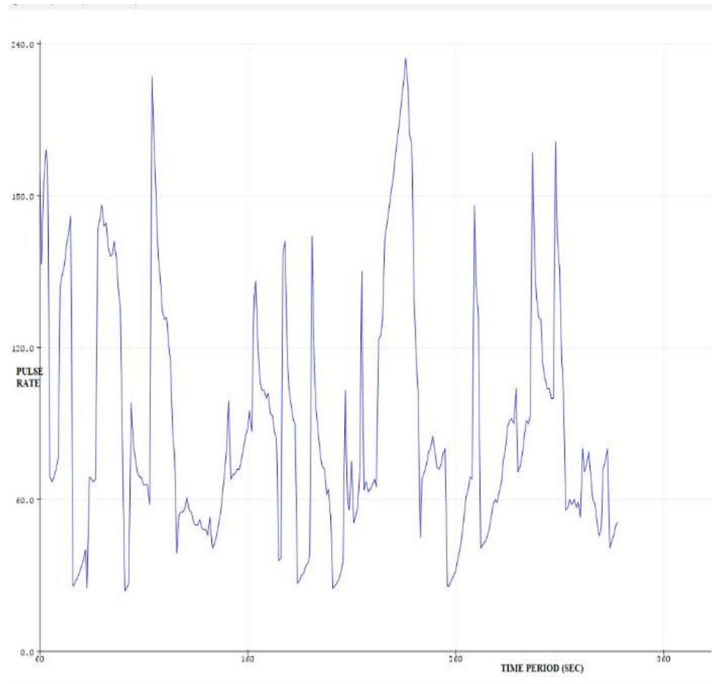

Fig. 8. output of heart rate sensor in mobile application

TABLE I Sensor outputs at different conditions

Gas	Symbol	Toxic	Sources	Threshold limit
Carbon Dioxide	CO_2	Yes	Diesel engine, Coal oxidation, blasting	2000 PPM
Sulphur Dioxide	SO_2	Yes	Sulphide dust explosions	6 PPM
Ammonia	NH_3	Yes	Blasting, cooling plants	50 PPM
Methane	CH_4	No	Coal seam, sewage	4000 PPM
Water vapor	H_2o	No	Humidity, hot weather	-
Mine dust	-	Yes	Drilling, blasting, loading, crushing, transportation	Inhalable dust (< 100 µm) respirable dust 10 µm)

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TABLE II pollution in coal mines and its sources

S.No	Name of the sensor	Parameter	Threshold value	Measured value at T=T1	Remark	Measured value at T=T2	Remark
1	DHT 11	temperature	25	31.05	Unsafe condition	25	safe condition
2		Humidity	45	33	Safe condition	32	Safe condition
4	MQ135	CO_2	1000 PPM	518.6 PPM	Safe condition	530 PPM	Safe condition
4		SO_2	6 PPM	5PPM	Safe condition	5 PPM	Safe condition
5		NH_3	50 PPM	42.9 PPM	Unsafe condition	43 PPM	Unsafe condition
		CH_4	4000 PPM	2500 PPM	Safe condition	2480 PPM	Safe condition
6	Heart rate sensor		60-100 BPM	86	Safe condition	79	Safe condition

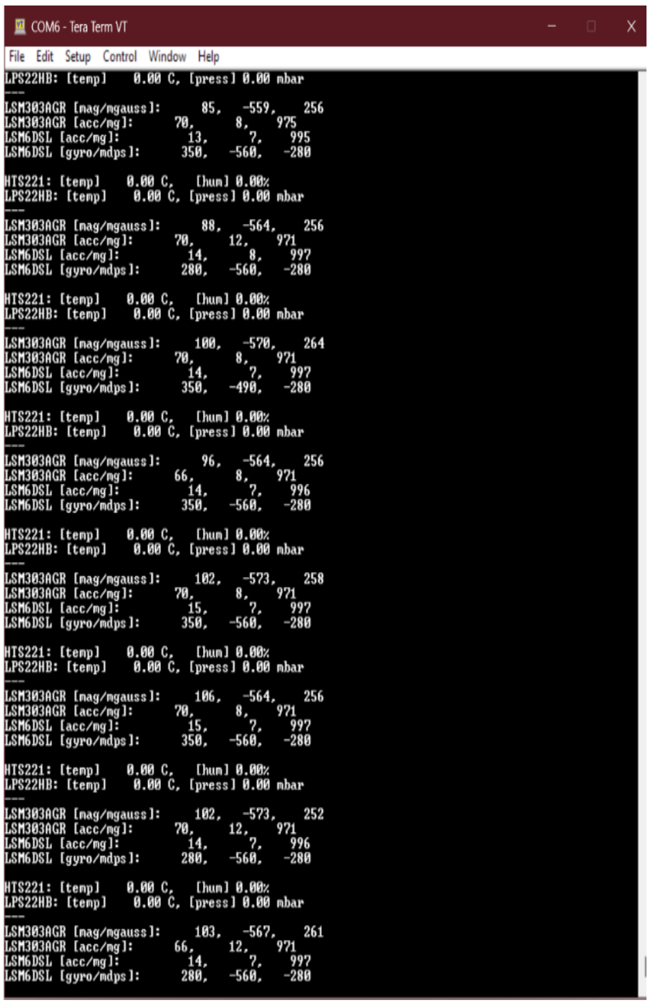

Fig. 9. output of MEMS accelerometer sensor in tera term application window

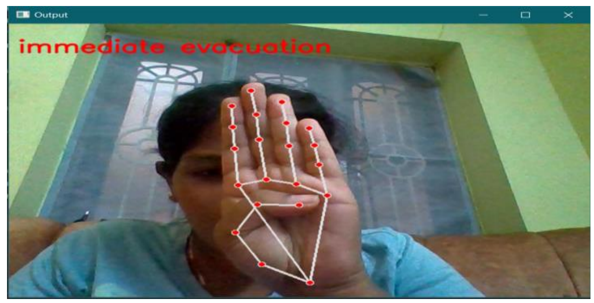

Fig. 10. Immediate evacuation gesture

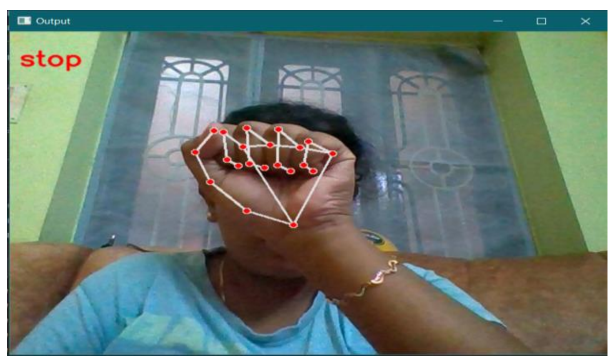

Fig. 11. Gesture to stop ongoing work

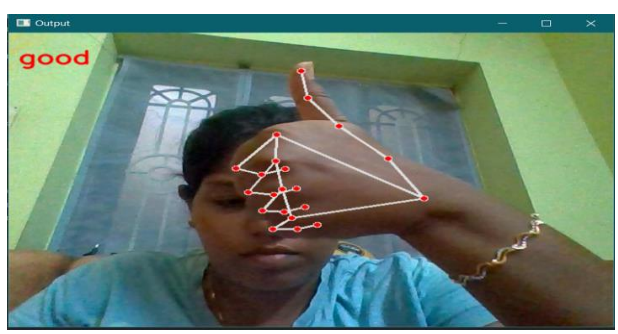

Fig. 12. Good gesture to continue mining process

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TABLE II Type of gesture and its description

S. No	Gesture	Description
1	GOOD	The worker is safe
2	NOT GOOD	There are some unusual situations.
3	IMMEDIATE EVACUATION	Emergency
4	STOP	Terminate the current job

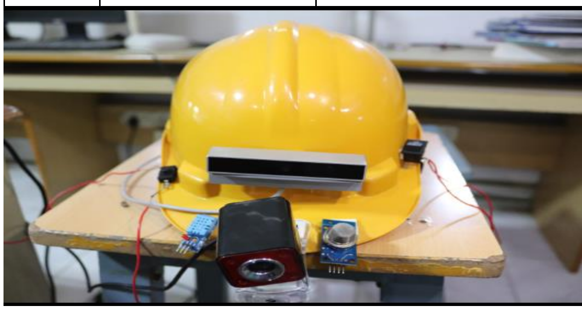

Fig. 13. Top view of Smart IoT Helmet

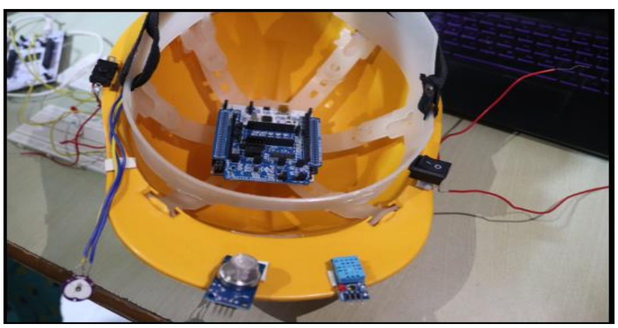

Fig. 14. Helmet Inside view

Fig. 15. illustrates the experimental set up during field testing, and the prototype is effectively utilized to provide safety to mining workers.

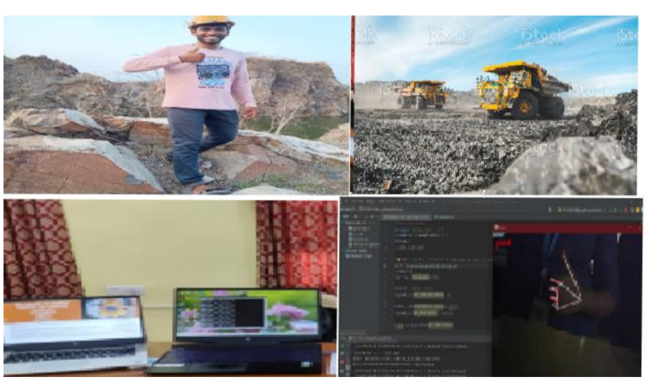

Fig. 15. Experimental set up for testing

IV CONCLUSIONS AND FUTURE WORK

A clever mining helmet was designed by integrating several sensors and a STM32 microcontroller. The machine learning algorithm enables remote data acquisition and the continuous monitoring of worker gestures. Environmental conditions such as the levels of ammonia (NH_3), sulfur dioxide (SO_2), carbon monoxide (CO), and smoke can be detected in real time by the MQ135 gas sensor. A Threshold level was set for each gas level to ensure good air quality (NH_3=50, CO=50, SO_2=6, CH_4=4000, and CO_2=1000). If any parameter value exceeded the threshold level, an alert signal is initiated at the control center. Moreover, the heart rate and vibrations are sensed by a pulse sensor and MEMS accelerometer sensor. A normal heart is considered from 60 to 100; otherwise, a warning message is delivered to the control center. Finally, all information is conveyed to the control module, which is placed outside the mining area using Bluetooth technology. This contributes to better protection of the miners' safety and welfare. The implementation of the proposed system can significantly reduce the mortality rate and the number of disease alerts for workers in the mining industry. By continuously monitoring the environmental conditions and hazardous gas levels, the system can promptly alert workers to potential dangers, enabling them to take appropriate precautions and avoid harm. In the future, sensor values can be integrated into the cloud platform, and the LoRaWAN module can be included to reduce the network dependence of transmission activity.

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