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*Original Article*

# A Comprehensive Approach to Real-time Site Monitoring and Risk Assessment in Construction Settings using Internet of Things and Artificial Intelligence

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***Abstract*** - *In recent years, technological developments have peaked; more and more technologies are being introduced frequently and implemented into various sectors through applications not previously imagined. The Internet of Things (IoT) and Artificial Intelligence (AI) are two technologies that have significantly impacted several industries such as Healthcare, Military, Transport, Construction, etc. As we know, on the one hand, construction sites are one of the most happening industries in this era due to significant developments like intelligent infrastructure, smart cities, etc. in the other hand, the construction industry is known for its complex and hazardous work environments which as a result are prone to numerous safety hazards and risk factors that can result in accidents, injuries, or even fatalities. Traditional monitoring and risk assessment approaches often fall short of providing real-time insights. However, by implementing cutting-edge technology stacks like IoT and AI, real-time site monitoring and risk assessment have become achievable, allowing construction companies to address potential dangers and improve safety measures proactively. By leveraging technologies, construction sites can collect real-time data, tracking equipment performance, site conditions, and worker safety. Along with this, the integration of AI enables advanced risk assessment methodologies, predicting potential hazards and identifying risks that may otherwise go unnoticed. This article will discuss a comprehensive approach to real-time site monitoring and risk assessment in construction settings using the Internet of Things (IoT) and Artificial Intelligence (AI). Our objective will be to design and develop a robust architecture of IoT nodes/devices that will communicate and extract real-time data of several parameters. Those data will then be analyzed using an artificial intelligence model to gain meaningful insight into the present condition and for risk assessment to prevent any danger to any human or asset and improve the efficiency of the work environment in specific noticeable metrics.*

***Keywords*** - *Internet of things, Artificial intelligence, Construction site, Safety, Risk assessment.*

## 1. Introduction

Construction sites are hazardous places where several risks and hazards may endanger the safety of workers and passers-by. Using large machinery and equipment carries significant risks, such as crush injuries, electrocutions, and entanglements. Due to the usage of welding and cutting equipment and the presence of flammable materials, building sites are also prone to fires and explosions. To reduce these risks and guarantee the safety of everyone participating in the construction process, it is essential that construction businesses adopt thorough safety regulations, offer suitable Personal Protective Equipment (PPE), and hold regular training sessions [1, 2]. Technology has made fantastic progress in lowering risks on construction sites, revolutionizing safety management, and improving employee well-being. Construction sites may be strategically monitored in real-time using IoT sensors and smart cameras, which provide continuous data collection on worker activity, equipment status, and ambient conditions. Real-time information on the health and operation of the equipment is provided through predictive maintenance, which is made possible by IoT sensors installed into construction equipment.

To prevent accidents brought on by equipment malfunctions, AI systems can identify possible equipment failures, enabling early intervention and safer machine operation. Wearable equipment with IoT capabilities, such as smart helmets and vests, monitors the health and activity of workers.

Additionally, Virtual Reality (VR) and Augmented Reality (AR) technologies have transformed safety training by enabling employees to experience accurate digital simulations of risky situations, improving situational awareness and safety procedures [3-5].

These days, IoT and AI technologies have significantly contributed to reducing dangers on building sites and enhancing overall safety. Real-time analytics driven by AI analyze this data, enabling managers to identify potential risks and take preventative measures quickly. AI-driven risk assessment models evaluate the overall safety of the building site by considering several factors, including the surrounding environment and worker conduct.

Construction managers can allocate resources effectively and take pre-emptive action in high-risk regions thanks to this data-driven strategy [6, 7]. IoT devices continuously gather and transmit data about various characteristics, such as the state of the equipment, the environment, and worker activity. This real-time information is crucial for risk analysis and accident avoidance.

Additionally, real-time monitoring of construction activities is made possible by IoT-enabled cameras and drones, adding another level of security. Safety infractions, unauthorized individuals, and potentially dangerous circumstances can all be found using AI-powered picture recognition algorithms [8]. Through the processing and analysis of the enormous amounts of data gathered by IoT devices, AI has wholly changed the safety of construction sites. AI algorithms can interpret complex datasets and spot trends and potentially dangerous situations that a human observer might miss.

AI-driven risk assessment models analyze the overall safety of the building site by considering many factors, including environmental factors, equipment status, and worker behaviour. AI and IoT integration make construction sites smarter and safer, lowering accidents, enhancing worker well-being, and ultimately ensuring project timely and successful completion [9, 10].

In the proposed system of a comprehensive approach to real-time site monitoring and risk assessment in construction settings using IoT and AI, we will be using a curated merger of hardware and software technologies in the overall system architecture to extract meaningful metrics from the construction sites to aid in the real-time monitoring of both the workers and the site along with having a risk assessment methodology to help the authorities maintain a safe workplace and improve their labour efficiency to a plausible extent.

## 2. Review of Literature

This literature review briefs how buildings and infrastructure are designed, planned, and built is changing significantly due to innovation in the construction industry. Building Information Modeling (BIM), which offers a digital representation of projects that combines data and improves visualization, revolutionises collaboration and decision-making processes. Thanks to automation, robots, and artificial intelligence, construction job optimization, resource allocation, and safety improvements are being made.

Real-time building performance monitoring and data analytics are made possible by smart technologies and the IoT, which improves resource management and enables predictive maintenance. As a result of embracing these technologies, the construction industry is transitioning to more effective, sustainable, and intelligent practices, influencing [11, 12].

This literature study investigates the idea of smart infrastructure, which entails incorporating digital technology into actual urban systems to enhance resident's quality of life and optimize operations. The article emphasizes the necessity for a standard language to define words and procedures for smart infrastructure.

The authors suggest an LVP framework to create this language, which classifies innovative infrastructure projects according to levels (changing technological complexity), values (overarching objectives including safety and sustainability), and principles (guidelines for development). Ultimately, the paper highlights how smart infrastructure may drastically improve how effective, liveable, and resilient cities are for their citizens [13, 14].

The paper describes the usage of the IoT and Master Data Management (MDM) in the context of smart city and intelligent infrastructure programs and is explored in this literature review. The evaluation emphasizes the potential of IoT in infrastructure systems, enabling the collecting and analysis of sizable volumes of data about the state and operation of infrastructure as well as public activities through cloud-based asset management systems, mobile apps, and Big Data analytics.

The potential of IoT and MDM to considerably advance the development of smart cities and intelligent infrastructure projects is highlighted in this literature review's conclusion. Cities may improve the management of their public infrastructure, increase the quality of life for their citizens, and promote effective and resilient community development by utilizing IoT technology and MDM efficiently [15, 16]. The executive summary for managers highlights the severe shortcomings of the conventional constant per capita consumption model. It discourages using it in crucial decision-making procedures like planning, zoning, and permits. Instead, it advises using the bottom-up, more theoretically solid and empirically accurate strategy to make knowledgeable choices on the collective demand for building [17]. In this literature review, the researchers use a Decision-Making Trial and Evaluation Laboratory (DEMATEL) strategy, enabling them to investigate one variable's effects on the others to determine the causal links among these elements. The study produces a quantitative framework for measuring labor productivity, which offers insightful information on the variables influencing labor productivity in the Indian construction sector.

The results, in particular, emphasize the importance of safety at construction sites as a significant factor affecting labour-related parameters. Overall, this research helps address the critical issue of labor productivity in the construction sector and helps to increase performance and efficiency in building projects, eventually benefiting the entire industry [18].

The study covers how the construction industry's health and safety training is conducted using conventional and computer-aided methods. The systematic study assessed both conventional training methods and technologies assisted by computers for their efficacy. Briefly expressed, the paper compares and contrasts conventional methods with computer-assisted technology for health and safety training in the construction sector. In addition to acknowledging the potential advantages of computer-aided technology, it also urges more studies to reinforce the statistical data supporting traditional instrument's usefulness [19, 20].

This literature states that the improved era of proactive risk management and accident prevention has arrived thanks to integrating IoT and AI technology in building site safety. IoT sensors are installed strategically around construction sites to capture real-time data on various aspects, such as the environment, equipment condition, and worker activity. Following AI algorithm's processing of this data, potential safety issues that could go unreported through manual observation are analyzed and identified.

Wearable technology with IoT capabilities keeps track of employee health and well-being and looks for symptoms of weariness or exposure to risky situations. The predictive maintenance made possible by IoT sensors[21] ensures the safe operation of equipment, lowering the possibility of accidents brought on by defective equipment. Aerial surveillance is provided by drones with cameras, enabling real-time site monitoring and rapid detection of safety issues. Construction businesses can make data-driven decisions prioritising worker safety by merging IoT data with AI-driven analytics, creating a safer and more productive construction environment. The convergence of IoT and AI technology is revolutionizing safety on construction sites by enabling businesses to take preventative action and reduce accidents, eventually increasing worker well-being and project outcomes [11, 22, 23]. This paper describes that real-time site monitoring has made great strides with the adoption of IoT and AI technologies in the construction sector. Construction businesses are now better equipped to monitor job sites proactively, foresee potential safety hazards, and take prompt preventive action, resulting in a safer working environment for construction workers thanks to the seamless integration of IoT and AI technology.

Real-time site monitoring also improves project management, allowing building teams to act quickly on information, allocate resources efficiently, and deal with unforeseen issues. Real-time site monitoring will further revolutionize construction safety procedures as IoT and AI develop, making the construction sector safer, more effective, and more productive [24-26].

Construction professionals must comprehend and analyze the outputs of the AI model to take the proper action; hence collaboration between construction experts and AI specialists is crucial for successful implementation. AI-driven risk assessment models can raise the bar for construction site safety, lower incident rates, and create a safer working environment for all parties involved by carefully evaluating data quality and cooperative efforts [27, 28].

This literature describes the latest safety management techniques, wearable IoT devices have become a cutting-edge option for boosting worker safety on construction sites. Smart wristbands, vests, and helmets are products with various sensors built in to continuously track vital signs, movement patterns, and ambient variables. Wearable IoT devices can identify symptoms of exhaustion, heat stress, or exposure to dangerous situations by gathering real-time data on worker health and wellbeing.

Additionally, trained individuals and data analytics capabilities are needed to interpret and analyse the enormous amounts of data generated by these devices. By overcoming these obstacles and maximizing the capabilities of wearable IoT devices, building sites will become safer, and worker well-being will improve. Construction site safety management will undoubtedly continue to be driven by the development and integration of wearable IoT devices, resulting in a safer working environment for construction employees worldwide [29, 30].

This literature describes how drones with cameras have revolutionized construction site surveillance and current research trends are exploring how they may be used to improve real-time safety monitoring. Construction managers can track the progress of projects, spot potential safety issues, and evaluate site conditions from a different angle thanks to drone's bird's-eye perspective. Current research focuses heavily on AI-powered image recognition algorithms, which enable drones to detect safety hazards, unauthorized access, and possible risks[31, 32].

Construction organizations may quickly address new safety problems by analyzing data collected by drones in real-time, enabling proactive decision-making and risk mitigation. Researchers are also looking into how drones and IoT sensors might work together to gather more information on worker activities, equipment status, and environmental conditions.

The data-driven approach to construction site safety is improved by this integration, which also supports effective project management and fosters employee well-being. The construction sector may anticipate even more significant developments that will strengthen safety procedures, lower accidents, and maximize overall construction site efficiency as research trends in drones and real-time site surveillance continue to evolve [33, 34].

## 3. System Architecture

As shown in the Figure 1, the overall system architecture consists of several hardware nodes, each responsible for extracting physical world data of specific metrics, which will be used at certain levels during further analysis. Individual briefings about the data sources are attached in the following sub-sections.

Once the system is settled and powered, each data source or end node will communicate and share extracted information with an assigned coordinator using their inbuilt RF module following a hybrid topology.

On receipt of data from the end nodes, the coordinator nodes will be responsible for verifying the data origin points. If verified, they will share the same with the gateway using an integrated LoRa module following a hybrid topology. The gateway will be the point of contact for data accumulation from all the end nodes or data sources, and using an internet module will be responsible for logging all the data into an IoT cloud server for further data analysis and acquisition.

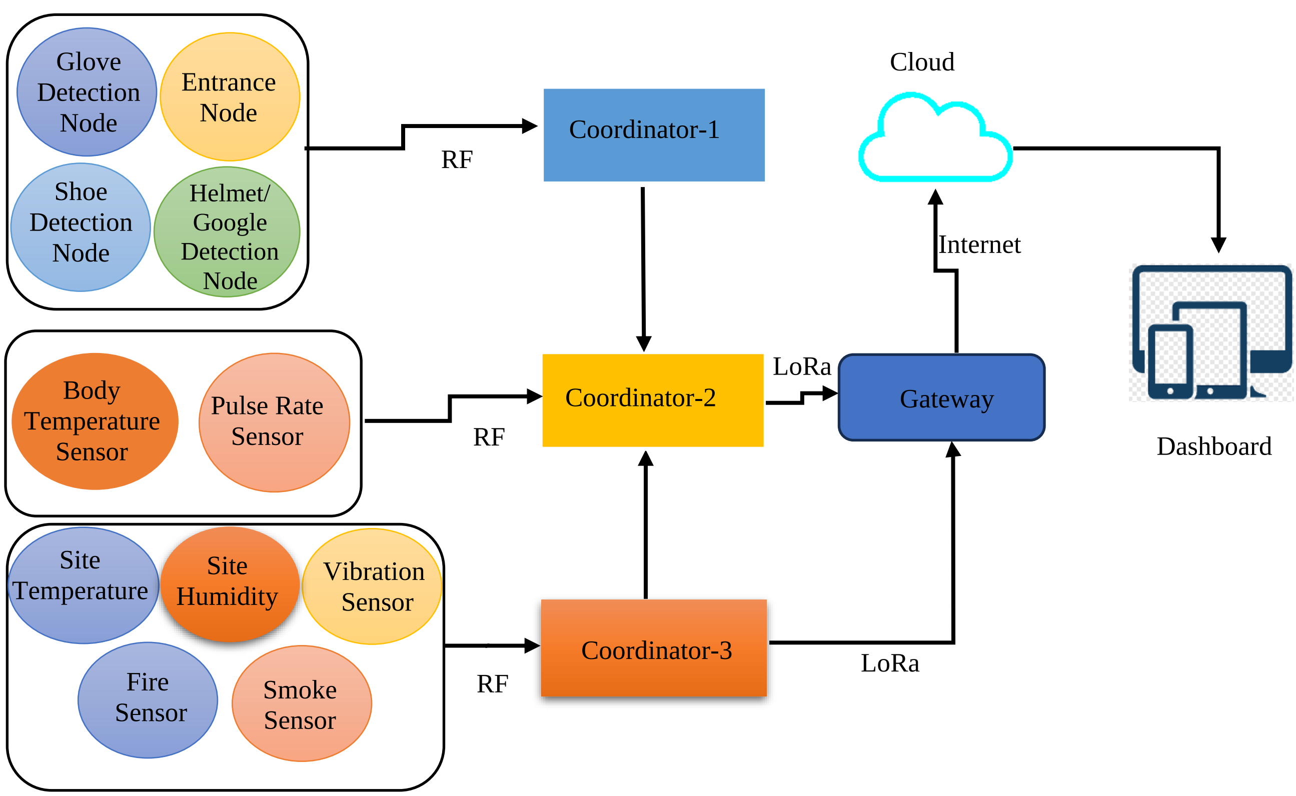


**Fig. 1 System architecture**

### *3.1. Entrance Node*

As depicted in Figure 2**,** the Entrance node will primarily consist of a central computing unit for processing and extracting the data from the attached peripherals, including the passive infrared sensor, which will provide the node with information regarding any human presence in the vicinity of a particular space, RFID scanner for authenticating the RFID card being held by the personnel, an RF module to be used for sending the extracted information wirelessly to the coordinator, a display unit to locally display important information and a power supply to power up the system.The entrance node will be responsible for authenticating the worker's and personnel's entry into the construction site. It will provide us with their profile details, time of entry, etc.

### *3.2. Shoe Detection Node*

As depicted in Figure 3, the shoe detection node is part of the protective apparel detail node, ensuring that the worker always wears the specific construction shoes inside the site. It uses a pressure sensor and a dedicated inbuilt algorithm in the central computing unit to classify accurately if the worker is wearing the shoe. The same information is then relayed to the coordinator along with encapsulated worker ID detail at regular intervals using the integrated RF module.

### *3.3. Worker Health Monitoring Node*

As depicted in Figure 4**,** the worker health monitoring node is responsible for keeping track of the worker's health inside the construction site. It is a wearable device integrated with a body temperature and pulse rate sensor to estimate the worker's health. The raw data is relayed to the coordinator using the integrated RF module in regular intervals using the integrated RF module.

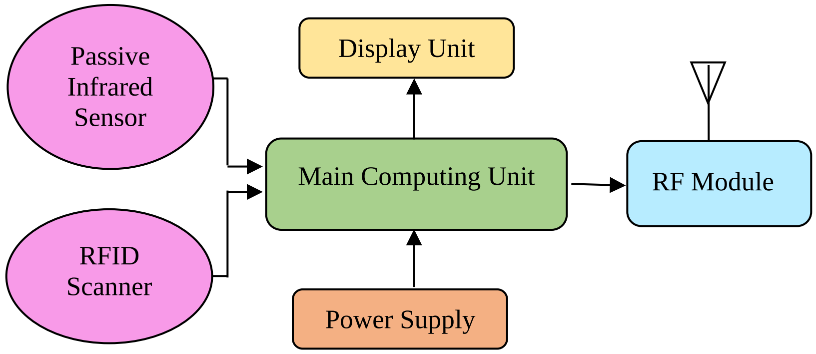


**Fig. 2 Entrance node**

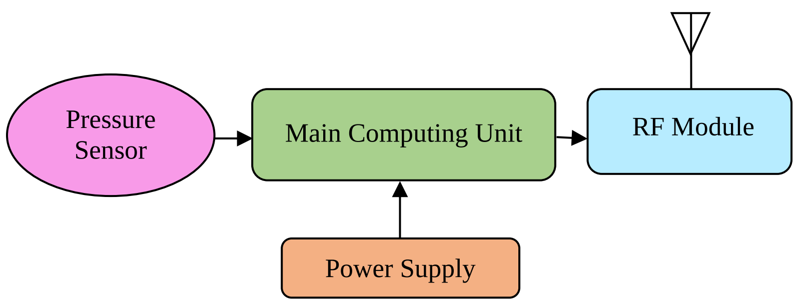


**Fig. 3 Shoe detection node**

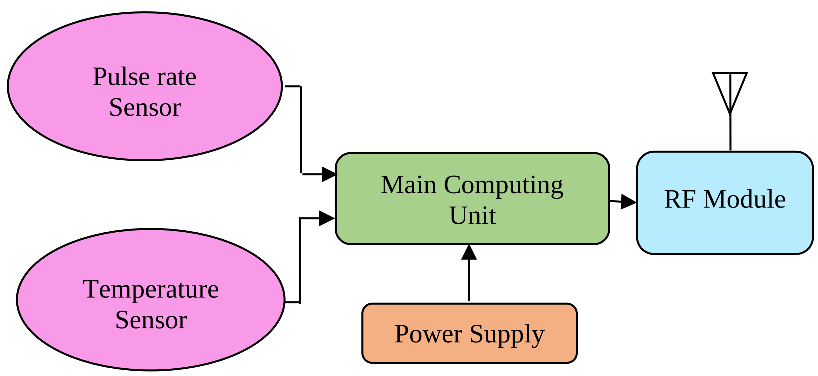


**Fig. 4 Worker health monitoring node**

### *3.4. Helmet/Goggle Detection Node*

As depicted in the Figure 5**,** the shoe detection node is part of the protective apparel detail node, ensuring that the worker always wears the specific Helmet/Goggles inside the construction site. It uses an eye blink sensor and a dedicated inbuilt algorithm in the central computing unit to accurately extract the eye blinks from the eye blink sensor in the goggle to classify if the worker is wearing a helmet and goggles. The same information is then relayed to the coordinator along with encapsulated worker ID detail at regular intervals using the integrated RF module.

### *3.5. Site Health Monitoring Node*

As depicted in Figure 6**,** the site health monitoring node will consist of various environmental parameter sensing sensors, including an Ambient temperature sensor to provide the present environmental temperature value, an ambient humidity sensor to provide the present environmental humidity value, a vibration level sensor to provide the present vibration level of the construction site, ambient gas sensor to measure harmful gas levels in the environment, smoke sensor to detect the amount of smoke present in the vicinity and fire sensor to detect any fire eruption in the construction site. All these sensors feed their values into the central computing unit, which then uses its integrated RF module to share the same with the coordinator.

The site health monitoring node is primarily responsible for providing crucial information about various metrics of the construction site that will prove to be a key factor while the risk assessment of the construction site, along with providing other valuable insights during the analysis.

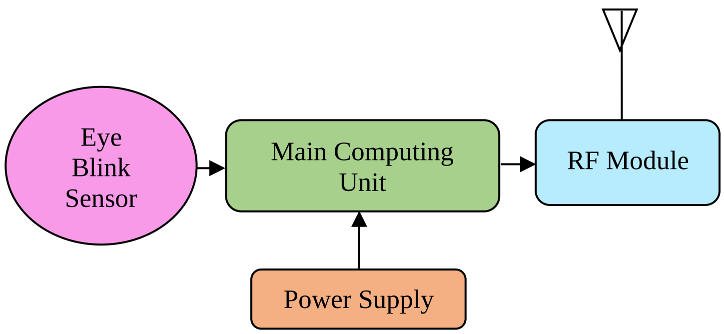


**Fig. 5 Helmet/Goggle detection node**

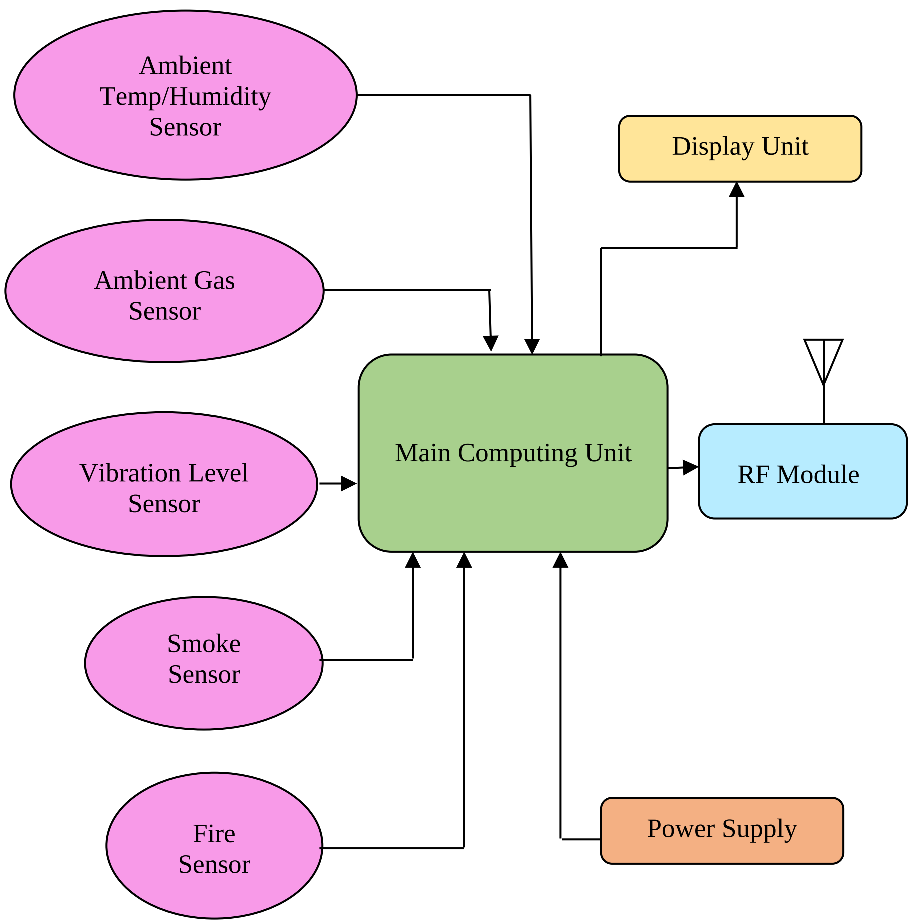


**Fig. 6 Site health monitoring node**

### *3.6. Glove Detection Node*

As depicted in Figure 7**,** the glove detection node is part of the protective apparel detail node, ensuring that the worker always wears specific construction gloves inside the construction site. It uses a touch sensor and a dedicated inbuilt algorithm in the central computing unit to accurately classify whether the worker is wearing both gloves. The same information is then relayed to the coordinator along with encapsulated worker ID detail at regular intervals using the integrated RF module.

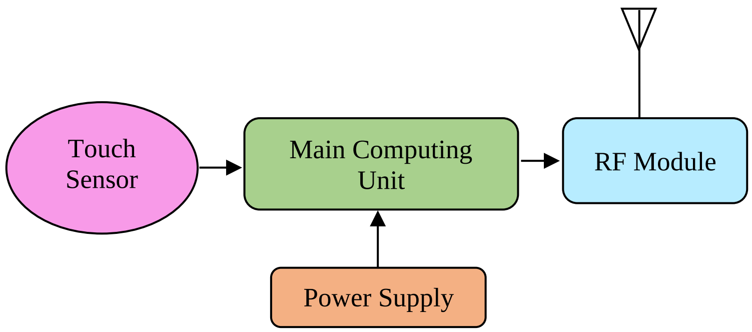


**Fig. 7 Glove detection node**

## 4. Hardware Implementation

For the implementation of the proposed network architecture, customized hardware was designed and fabricated wherein all the peripherals, including the sensors, power supply arrangement, microcontrollers, wireless modules, and antenna, were integrated into the custom-made PCB to eliminate any possibility of any power loss or data corruption due to leaks or unexpected interferences.

For the sensors, the preferred communication protocols were used, e.g., SPI, I2C, etc., and for the data communication using the wireless modules UART through the software serial methods are used instead of hardware serial pins to eliminate any interference during the debugging and programming of the microcontrollers. The end nodes and the coordinators are connected wirelessly using the 2.4 GHz RF transceivers. The coordinator and the gateway node are connected wirelessly using the 433 MHz LoRa module (Specific to India). The following sub-sections are the hardware implementation of the said nodes and components.

### *4.1. Entrance Node*

As the entrance node uses a passive infrared sensor for identifying the presence of a human prior to initiating the RFID scanner, and the Passive Infrared (PIR) sensor is known to be quite sensitive, the firmware is designed to calibrate and filter the ideal state values of the PIR sensor which is also depicted in the LCD, wherein the sensor takes the ideal state readings multiple times and considers the same as the base threshold of noise acceptance. The system enters an ideal state and waits for the PIR to trigger any human presence, as shown in Figure 8 (a).

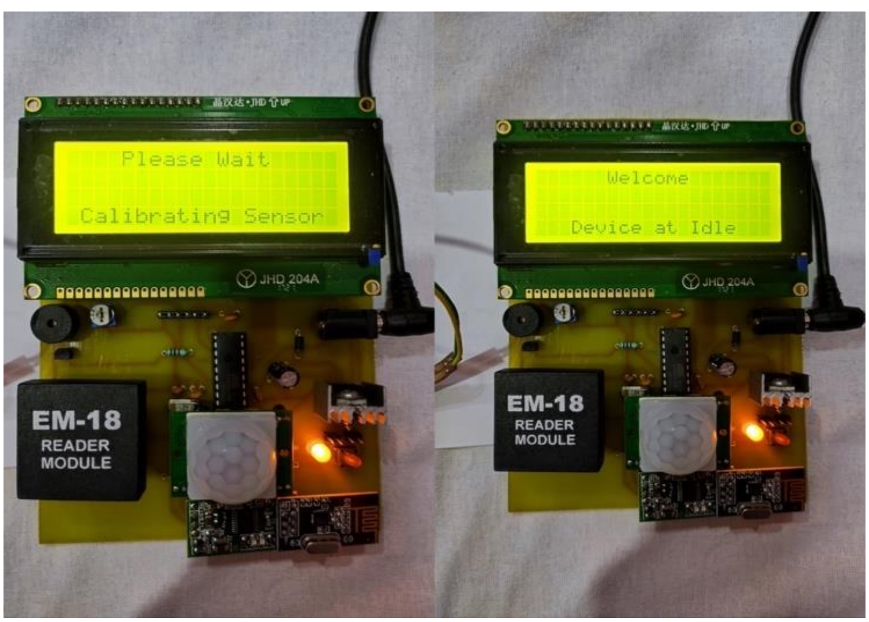


**Fig. 8 (a) PIR calibration**

Once PIR is triggered, the system asks the user to scan their RFID tag and displays the ID number if the worker's RFID is validated, as shown in Figure 8 (b). Once the card is scanned, the system uses its inbuilt RF module to send the ID profile to the coordinator in a secured packet.

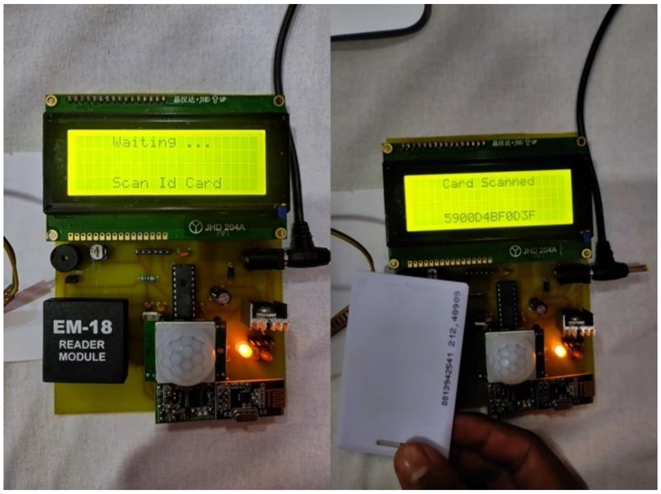


**Fig. 8 (b) ID verification**

### *4.2. Site Health Monitoring Node*

Similarly, the site health monitoring node was designed and fabricated with all the sensors integrated into a single PCB. These sensors feed the extracted data into the central computing unit (atmega328 has been used). The central computing unit, in regular intervals, sends encrypted packets containing all this information to the coordinator using an integrated RF 2.4 GHz module. Additionally, it displays the present value in the LCD, as depicted in Figure 9.

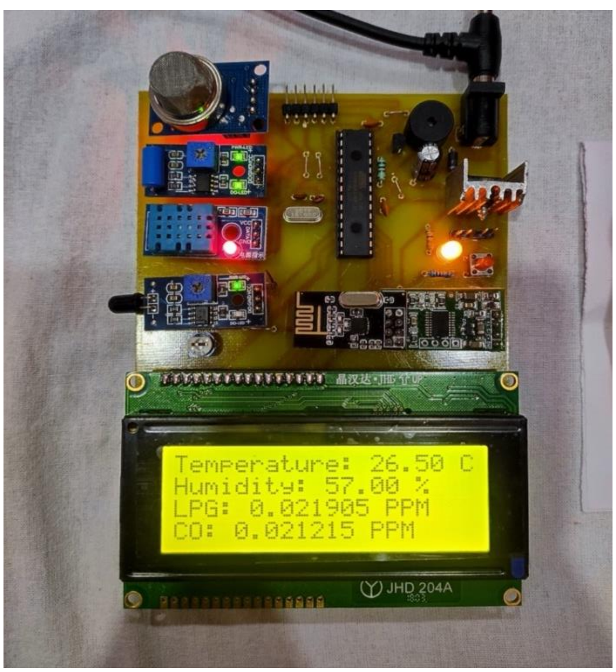


**Fig. 9 Site health monitoring node**

### *4.3. Coordinator*

As shown in Figure 10, the coordinator consists of an RF 2.4 GHz module that collects the data from allocated end nodes. The data received is primarily processed using the central computing unit (atmega328 SMD). Then it uses the integrated LoRa module to relay the data to the gateway as an encrypted packet with the source and coordinator ID information.

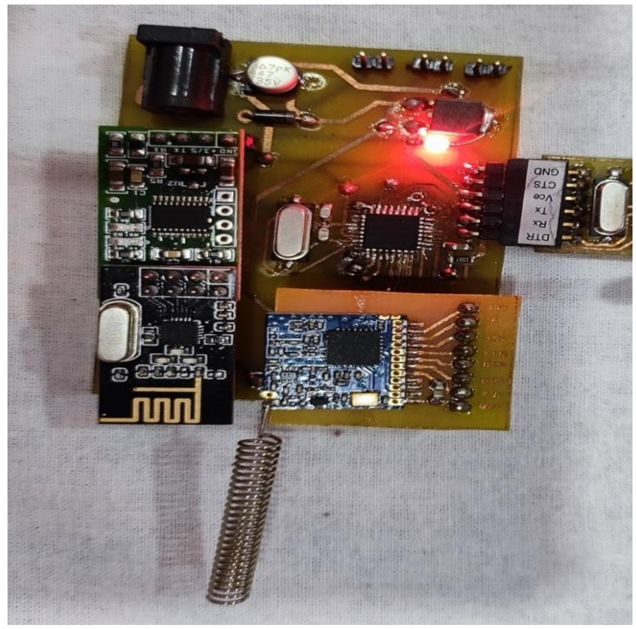


**Fig. 10 Coordinator**

### *4.4. Gateway*

Depicted in Figure 11 is the designed gateway for the system, which consists of two computing units, i.e., an atmega328 SMD as the central computing unit which is responsible for collecting the data sent by all the coordinators using its integrated LoRa module, processes it, and logs the same into an IoT cloud server using the integrated esp8266 WIFI module. It also displays various status and essential information on the LCD.

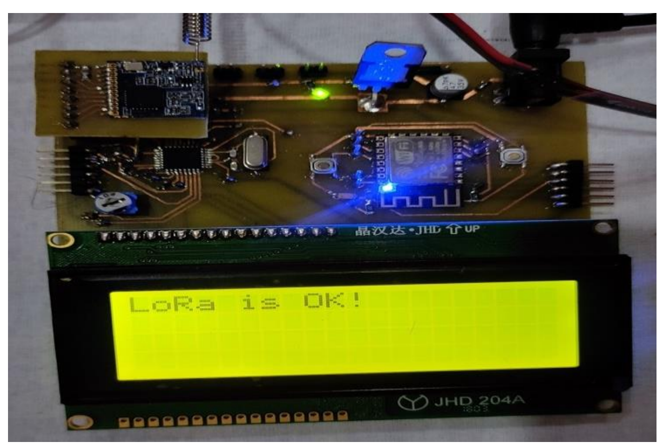


**Fig. 11 Gateway**

### *4.5. Complete System Implementation*

Depicted in the Figure. 12 is the image of all the system's components, including the glove detection and shoe detection nodes.

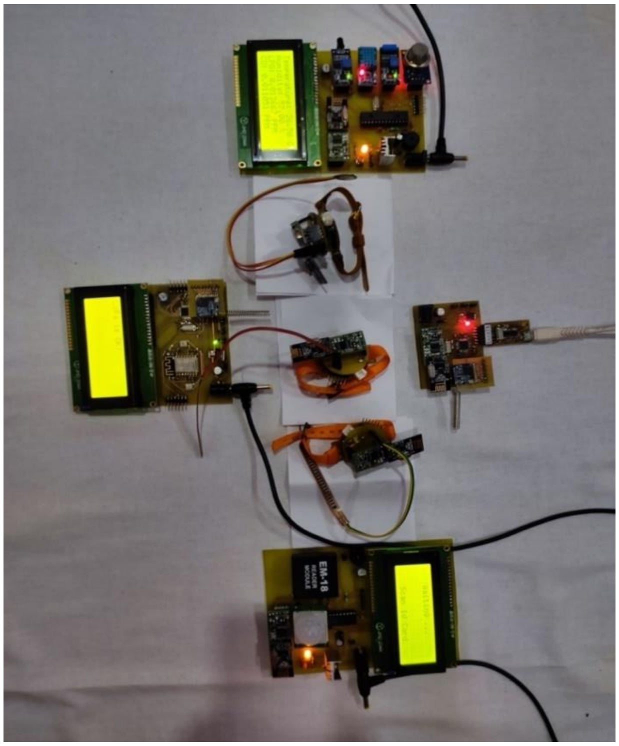

**Fig. 12 Complete system implementation**

## 5. Artificial Intelligence Implementation

With IoT-based end nodes for data collection, segregation and acquisition. We now have the dataset ready for us to perform further analysis and train an AI model for performing the desired tasks. The flow/process of the same is as follows.

### *5.1. Dataset Collection*

The gateway logs the values received from the end nodes into an IoT cloud server and a database. We now have a complete dataset containing the values generated at each data source in a .csv file.

Along with the raw data, two more columns named previous_hazard and hazarad_severity were added, which will pose as the human input to the condition of the construction site wherein previous_hazard depicts if, during the row of data log, any hazard has occurred (e.g., worker falling sick, fire, smoke, etc.).

It is depicted by a binary value 0/1. Similarly, the column hazard_severity refers to the severity of the hazard, which is depicted by a positive integer value.

### *5.2. Dataset Cleaning and Pre-processing*

Before going further into the analysis step, we want our dataset to be clean and have no unexpected abnormality. To do that, we will first clean and pre-process our dataset to ensure our dataset does not have any empty cells, abnormal/corrupted values, etc. Also, we want our dataset to drop the columns we do not think are necessary at this step, e.g., timestamp. For all these cleaning and pre-processing tasks, we will use functions of popular libraries like Numpy and Pandas to ease our task.

### *5.3. Data Visualization and Analysis*

*5.3.1. Correlation Matrix*

To start with the data visualization and analysis, we will first plot a correlation matrix to observe the correlation between the dataset variables, allowing us to learn more about the dataset and see a clear picture of all the millions of rows of data. As depicted in Figure 13, the following variables have plausible correlations.

*Entrance PIR vs RFID Authentication*

The correlation matrix shows a high positive correlation between entrance PIR and RFID authentication value, which is expected because both variables are unlikely to be opposite in most scenarios.

*Helmet Worn vs Goggles*

The correlation matrix shows a high positive correlation between helmet worn and goggles worn value, which can be stated as usual. In our implementation, we considered the helmet worn value depending upon the integrated eye blink sensor's output in the goggle.

*Site Temperature vs Body Temperature*

The correlation matrix shows a high positive correlation between site temperature and body temperature value, which is expected because both values are proportional to each other in an outdoor environment.

*Smoke, Fire and Hazards*

The correlation matrix shows positive correlations between smoke, fire and hazard metrics. This correlation also appears normal due to the interdependency of the variables in real life.

*5.3.2. Hazard Severity Distribution*

Figure 14 shows the distribution of the hazard severity in correspondence with the count throughout the dataset. As observed, the hazard severity of less than 1.5 contributes to the highest value of around 17500 counts, followed by hazard severity of 5.0 to 6.5.

This shows that in most hazard scenarios, the hazard severity was minute, for instance, restlessness in workers, fever, drowsiness, etc.

*5.3.3. Body Temperature by Hazard Severity Distribution*

Figure 15 presents a box plot of the body temperature by hazard severity distribution, indicating the range of body temperature values in the corresponding hazard severity values. Similarly to the previous distribution, the minor hazard severity value has the maximum spread of the body temperature value. However, it is contained within a specific normal body temperature range, indicating that worker's average body temperature has contributed the least to any hazard on the construction site.

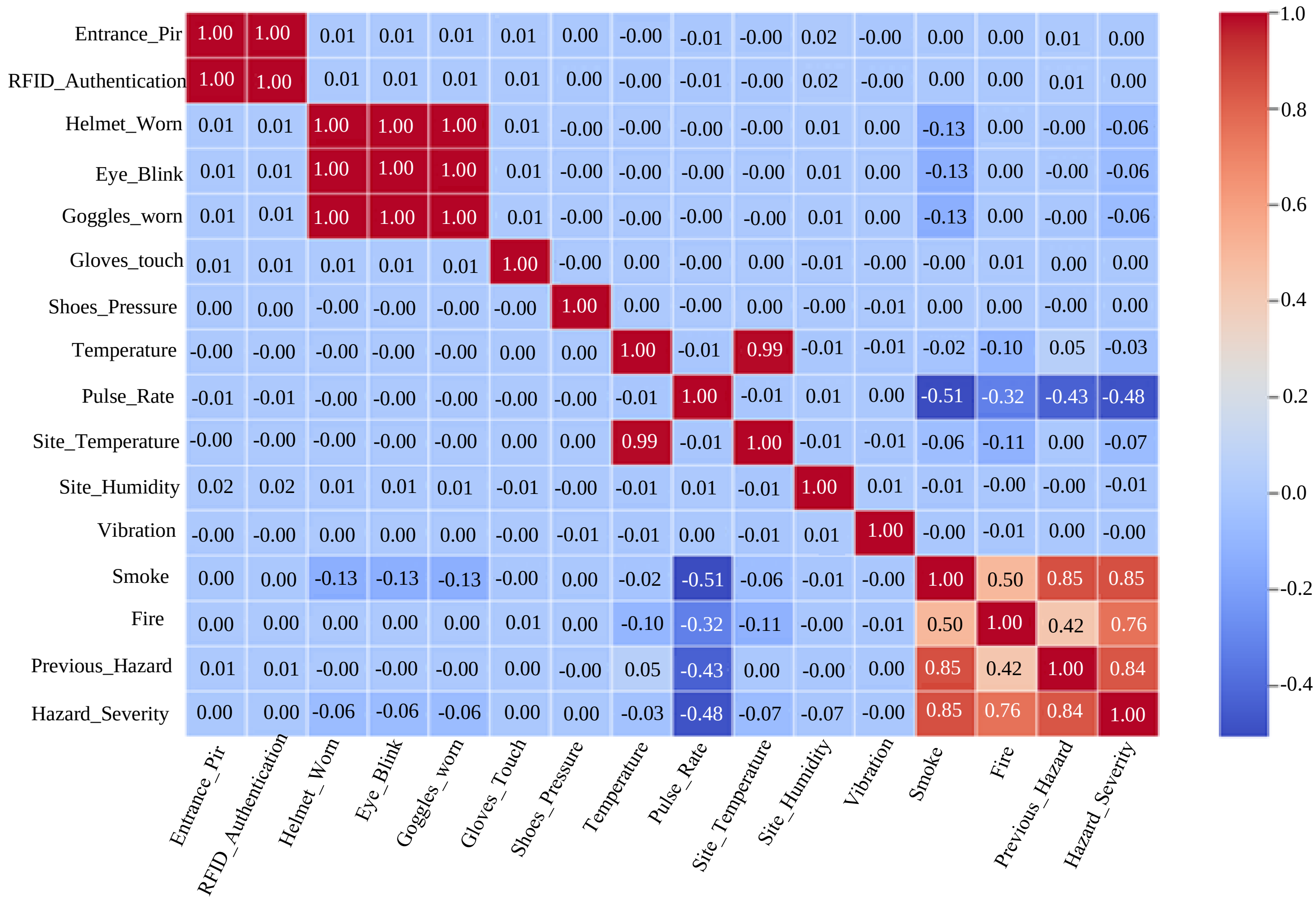


**Fig. 13 Correlation matrix**

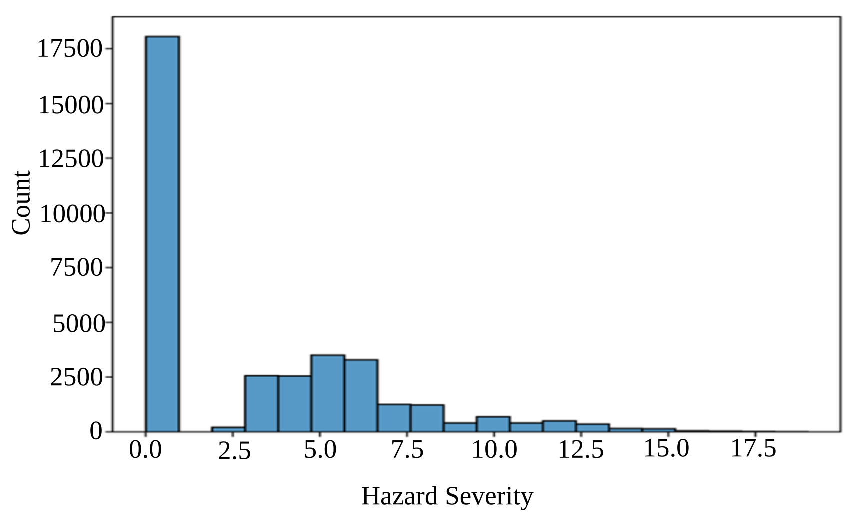


**Fig. 14 Hazard severity distribution**

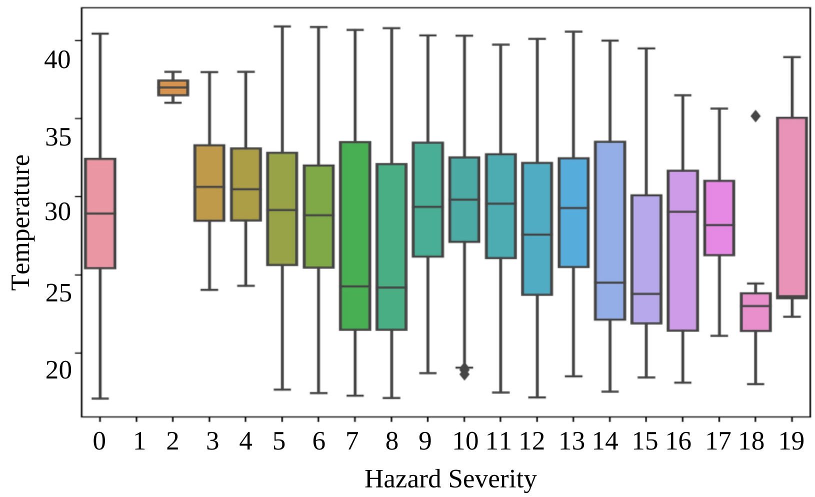


**Fig. 15 Body temperature by hazard severity distribution**

### *5.4. AI Model Training and Testing*

Following the visualization and analysis of the dataset, we will move forward to the AI model training part. We have the following two expectations from our AI model to set the stage.

- To learn from the past data and predict the possibility of a hazard depending on the present sensor values.
- To learn from past data and predict the hazard severity in case of a hazard.

To attain our first goal of classifying the possibility of a hazard depending on the present sensor values, we used the random forest classifier algorithm for the following reasons.

1) It is well known for handling large datasets.
2) It can automatically reduce overfitting by averaging multiple decision trees.
3) It is well known for its accuracy.

We trained the classifier on our dataset with an 80-20 split for training testing datasets. Figure 16 depicts the confusion matrix, which shows the true negative, false negative, true positive and false positive, respectively.

Figure 17 depicts the classifier's training accuracy plot, resulting in an accuracy of around 92.75 % when trained for 20 epochs. To predict the impact of hazard when and if a hazard occurs depending on the present sensor values, we used an ensemble method for the following reasons.

- We had both linear and non-linear type data.
- Individual regressor results were inconsistent.
- Ensemble methods provide higher predictive accuracy than the individual.

We used Scikit's ensemble and stacking regressor methods to stack the base regressor consisting of a random forest regressor, a gradient boosting regressor and a lasso regression analyzer and the final estimator as Ridge, where both stacks had a learning rate value of 0.1 and random state value of 42. Figure 18 shows the MSE and MAE error values obtained during the training of the regressor.

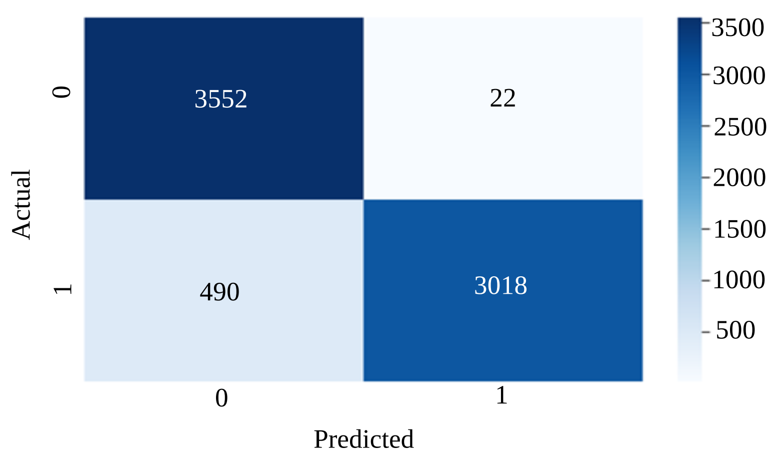


**Fig. 16 Confusion matrix**

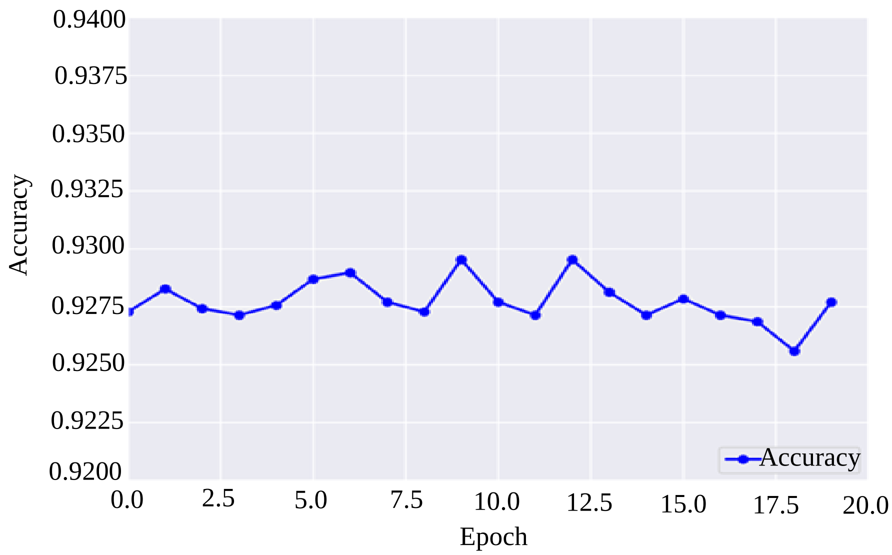


**Fig. 17 Training accuracy graph**

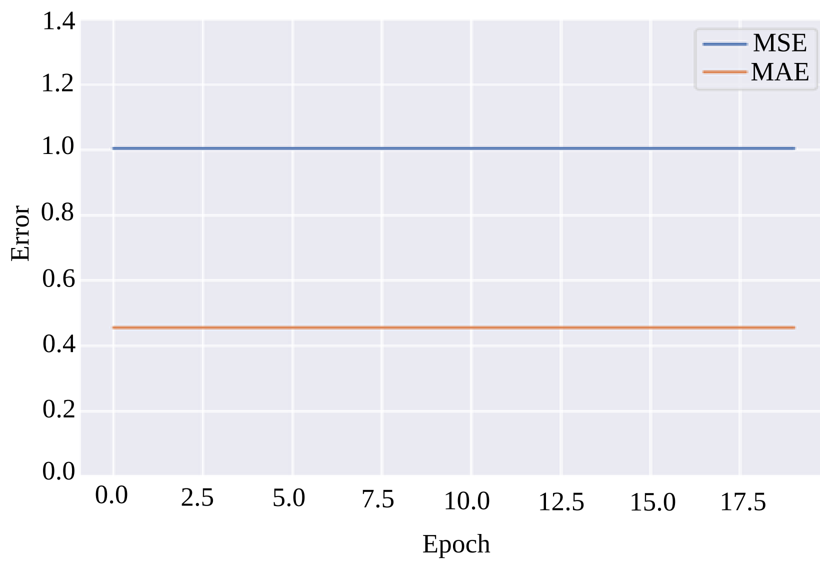


**Fig. 18 Training error**

## 6. Results

The implementation of IoT-based edge hardware solutions integrated with various sensors proves to be quite efficient and effective. Moreover, an RF-based network architecture also eliminated any severe dependencies on the internet. In addition, using security and redundancy measures like encryption and hybrid topologies aid in making the system more reliable and dependent, allowing it to be immune to any unwanted breaches or downtime. Figures 19 (a) and 19 (b) show some serial communication of the packets between nodes, coordinator and gateway. After training our AI model, we saved the classifier and the regressor in the joblib format. Following that, we loaded the trained model into google colab and provided a set of dummy inputs as follows:

```
new_data = pd.DataFrame({
    'worker_id': [23],
    'entrance_pir': [1],
    'rfid_authentication': [1],
    'helmet_worn': [0],
    'eye_blink': [0],
    'goggles_worn': [0],
    'gloves_touch': [0],
    'shoes_pressure': [0],
    'temperature': [30.2],
    'pulse_rate': [80],
    'site_temperature': [25.8],
    'site_humidity': [63],
    'vibration': [1],
    'smoke': [1],
    'fire': [1] })
```

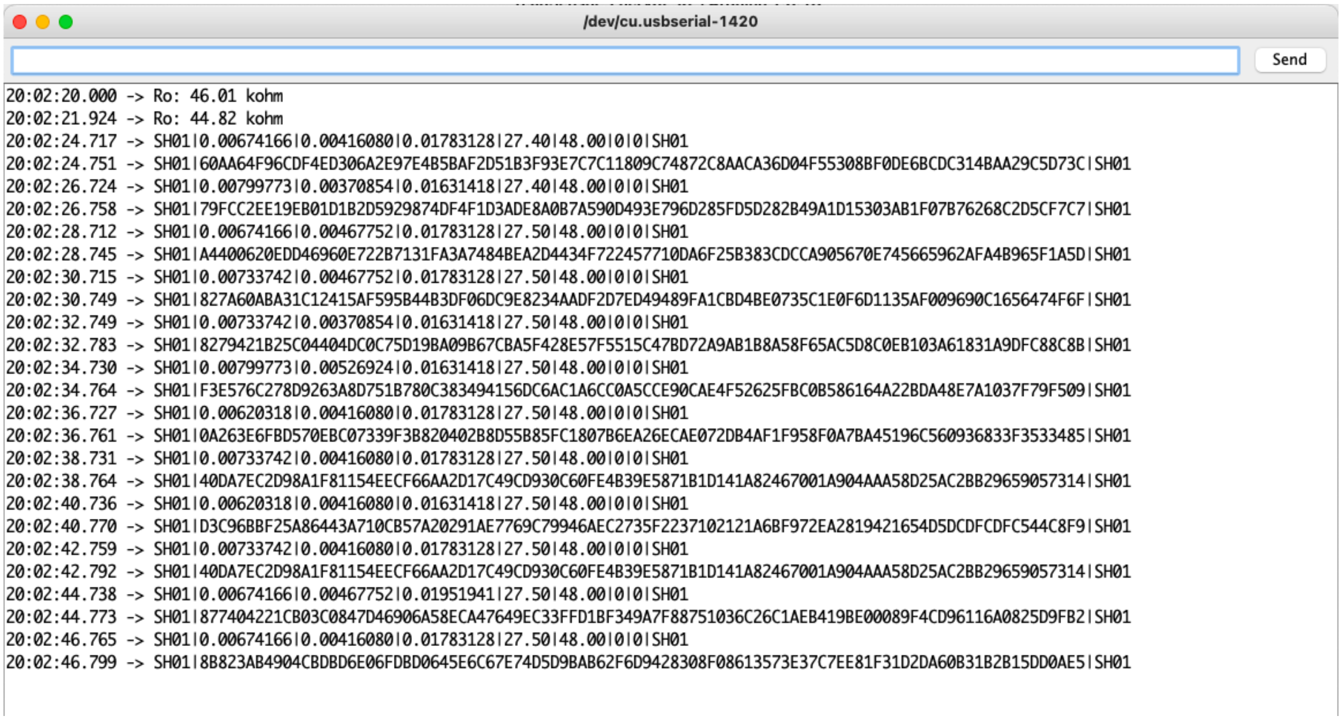


**Fig. 19 (a) Site health monitoring node serial data**

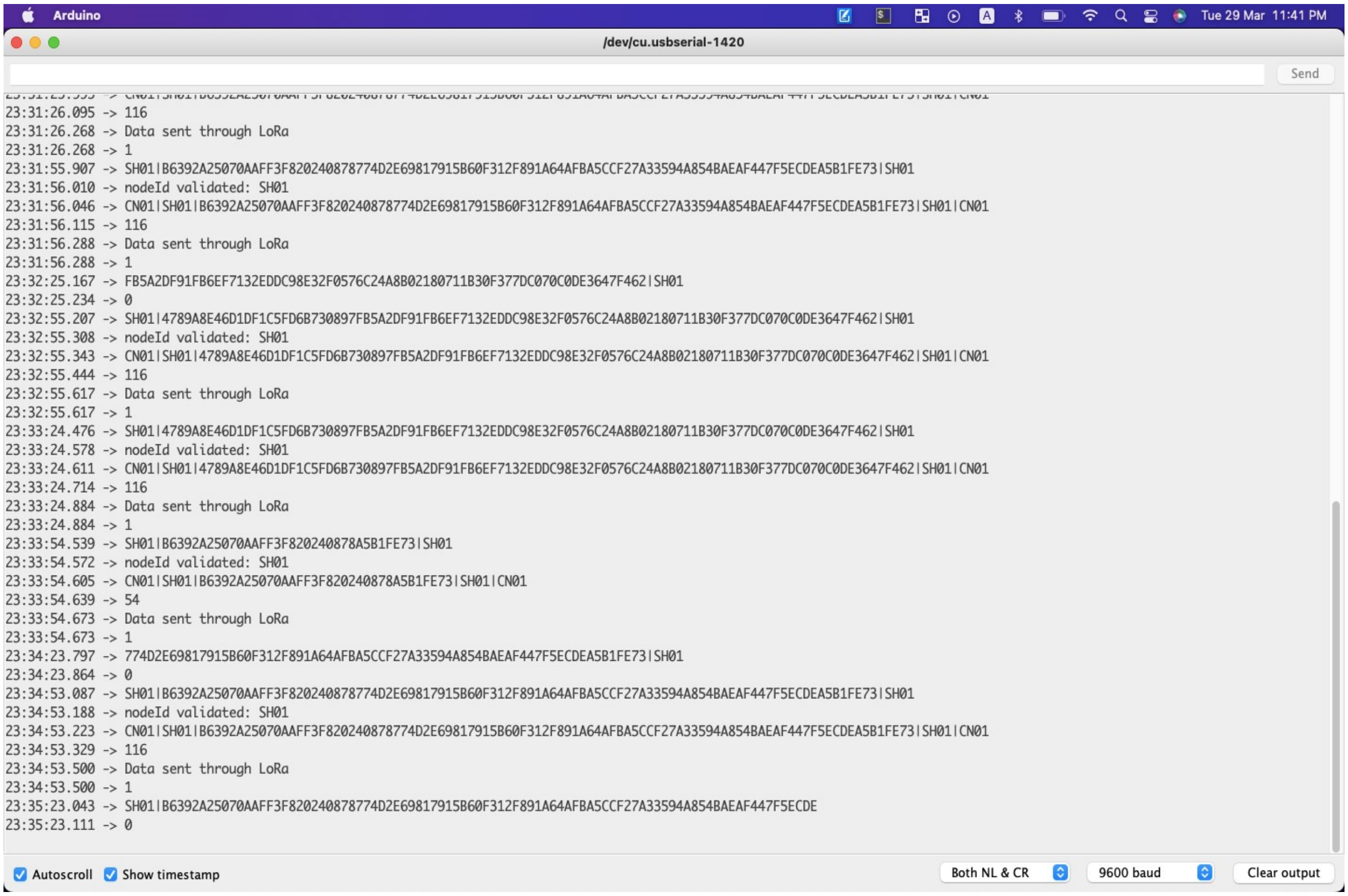


**Fig. 19 (b) Coordinator serial data**

In the form of sensor values, both models were then fed these values. We were able to get the output of the trained model regarding both the hazard possibility classification and the hazard severity prediction, as depicted in Figure 20, which shows the hazard likelihood to be a positive possibility along with its confidence score of 1 and the impact of the hazard is predicted to be 10.81521996.

```
Hazard Likelihood Predictions: [1]
Hazard Likelihood Confidence: [1.]
Hazard Impact Predictions: [10.81521996]
```

**Fig. 20 AI model output**

## 7. Conclusion

The comprehensive approach to real-time site monitoring and risk assessment using IoT and AI offers numerous benefits to the construction industry. Firstly, it enhances safety by providing real-time alerts and notifications regarding potential hazards. This minimizes the risk of accidents and injuries, safeguarding the well-being of workers and stakeholders. Moreover, the same can be further extended for integrating IoT and AI to improve operational efficiency by enabling effective resource management. Real-time monitoring of equipment utilization, energy consumption, and waste generation allows for optimized resource allocation, reducing costs and enhancing productivity.

The comprehensive approach can also facilitate effective project management by providing accurate data on progress and potential risks. This enables stakeholders to make informed decisions promptly, ensuring the timely completion of projects and minimizing delays.

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