

Edge AI and IoT-Based Smart Helmet for Real-Time Hazard Detection and Safety Monitoring of Drainage and Sewer-Line Workers

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Abstract: *Workers who clean and inspect underground drainage and sewer lines face toxic and flammable gases, heat, humidity and poor ventilation, usually far from anyone who could help. Ordinary safety helmets protect only against physical impact and cannot sense or report these dangers. This paper presents the design of a wearable smart helmet that combines three sensors—an MQ-136 hydrogen sulfide sensor, an MQ-4 methane sensor and a DHT11 temperature-humidity sensor—with an ESP32 controller, an Artificial Neural Network (ANN) running on the device, and a cloud-linked supervisor dashboard. The ANN takes the four sensor readings as input and classifies the working environment as Safe, Warning or Danger. The result drives a buzzer and red and green LEDs for the worker, while the ESP32 uploads status to the cloud over Wi-Fi. A fixed threshold rule runs beside the ANN so that a clearly unsafe reading can never be down-graded by the model. The paper describes the architecture, the role of the ANN, the alert logic and a planned evaluation of the prototype.*

Keywords: Smart helmet, Edge AI, Artificial Neural Network, Internet of Things, ESP32, hydrogen sulfide, methane, drainage workers

I. INTRODUCTION

Maintaining drainage and sewer networks is among the most dangerous jobs in urban infrastructure. Workers enter confined underground spaces where toxic gases such as hydrogen sulfide and flammable gases such as methane can build up, humidity and heat are high, visibility is poor and ventilation is limited. These conditions lead to breathing problems, poisoning, explosions and, in the worst cases, death. Because the work is carried out in isolated locations, a worker in trouble may not be noticed for several minutes, which is often the difference between rescue and fatality.

Personal protective equipment has reduced some workplace injuries, but a conventional helmet is passive: it resists impact and does nothing else. Supervision by a person at the manhole is the usual substitute for monitoring, and it fails as soon as the worker moves out of sight. A wearable that continuously senses the surrounding air, decides locally whether the situation is dangerous, and tells both the worker and the supervisor would close much of this gap.

Three technology trends make such a device practical. First, low-cost IoT hardware lets sensors, a microcontroller and wireless links fit inside a helmet and send environmental information to remote platforms [3]–[5], [8]. Second, Edge AI allows small models, such as a compact ANN, to run directly on embedded hardware, which removes the dependence on a constant cloud connection that cannot be guaranteed underground. Third, deep-learning detectors have been shown to verify protective equipment such as helmets and harnesses accurately [1], [2], [6], [7]. Smart helmets have also been developed for accident detection, mining, riders and disaster response [3]–[5], [9], [10].



Most of this work, however, treats environmental sensing and intelligent decision-making as separate problems, or targets mining, road riding or disaster response rather than drainage work. This paper contributes a helmet design for drainage and sewer-line workers that (i) combines hydrogen sulfide, methane and temperature-humidity sensing on one wearable platform; (ii) classifies hazards on the device using an ANN; (iii) raises local and remote alerts; and (iv) keeps a deterministic threshold rule as a backstop for the learned model.

II. LITERATURE SURVEY

Existing work falls into two groups: vision-based AI for protective-equipment detection [1], [2], [6], [7], and sensor-based IoT helmets for accidents and hazardous workplaces [3]–[5], [9], [10]. Table I summarises the surveyed papers and the gap each leaves for drainage-worker safety.

TABLE I. SHORTENED LITERATURE SURVEY

Paper	Method	Strength	Gap
Lin [1]	YOLOv8n with attention-based spatial fusion and Dynamic Head	mAP 95.6%; light and fast	Helmet detection only; no sensing, IoT or alerts
Shanti et al. [2]	DETR for helmet and harness detection	Precision >97%; robust to dust, blur, low light	Visual PPE only; no edge processing or sensors
Rahman et al. [3]	Embedded sensors, GPS, GSM, IoT	Auto accident alert with location	Reactive; no continuous hazard monitoring or Edge AI
Hazarika [4]	Environmental sensors with wireless alerts for coal mines	Continuous monitoring and warning	Threshold logic only; no AI
Kartik [5]	IoT, embedded processing and cloud dashboard	Central multi-worker supervision	Mining only; cloud-dependent latency
Carion et al. [6]	DETR transformer detector	End-to-end, simple pipeline	General framework; needs embedded optimisation
Dai et al. [7]	Dynamic Head attention	Better localisation	Not applied to worker safety

Two further works widen the scope of smart helmets. Joshi [9] integrates alcohol, infrared, vibration, GPS and Bluetooth sensing with finite element analysis of the helmet structure, but targets rider safety. Jeong et al. [10] describe a disaster-response helmet with infrared and optical cameras, environmental sensors, GPS and embedded computing, but it is not designed for confined underground spaces. Garside et al. [8] show how IoT sensors and data analytics can be combined, which motivates the layered architecture used here.

Taken together, the literature shows that AI-based PPE detection and IoT-based environmental monitoring have mostly been studied separately, and that many solutions depend on the cloud, adding latency and weakening reliability where connectivity is poor. This is the gap addressed by the proposed helmet.

III. PROBLEM STATEMENT AND OBJECTIVES

Drainage and sewer-line workers are exposed to toxic gases, flammable gases, high humidity and confined spaces, yet current practice relies on manual supervision and basic protective gear. Hazards are therefore detected late, and help is called late. The problem addressed here is to design a wearable that continuously monitors the worker's surroundings, recognises dangerous situations in real time without depending on the network, and informs both the worker and a remote supervisor immediately.

The objectives are:

- to monitor workplace conditions continuously through IoT-enabled sensing and upload them to a remote platform;
- to detect hazardous conditions in real time and grade them as Safe, Warning or Danger;



- to run the decision logic on the helmet using an ANN so that response time stays low and operation continues with poor connectivity;
- to generate immediate local alerts (buzzer and LEDs) and remote alerts on a dashboard; and
- to integrate these functions into one reliable wearable for drainage workers.

IV. PROPOSED SYSTEM

A. System architecture

The helmet is organised in layers (Fig. 1). The worker wears the helmet in the hazardous environment. The embedded edge device (ESP32) collects and processes all sensor data. The Edge AI inference module, an ANN, classifies the situation as Safe, Warning or Danger. The local alert system gives buzzer and LED alerts according to the risk level. The IoT communication layer sends processed data and alerts to the cloud over Wi-Fi, the cloud data management layer stores them in a Firebase database, and a web and mobile monitoring dashboard shows real-time worker status and alerts to the supervisor. Fig. 2 shows the complete hardware architecture, including the sensors, the processing unit, the outputs and the power supply.

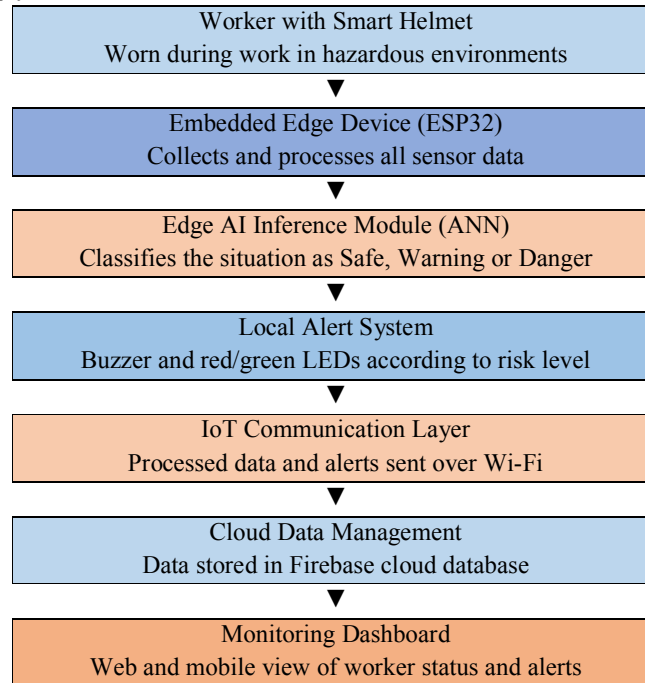


Fig. 1. Block diagram of the smart helmet



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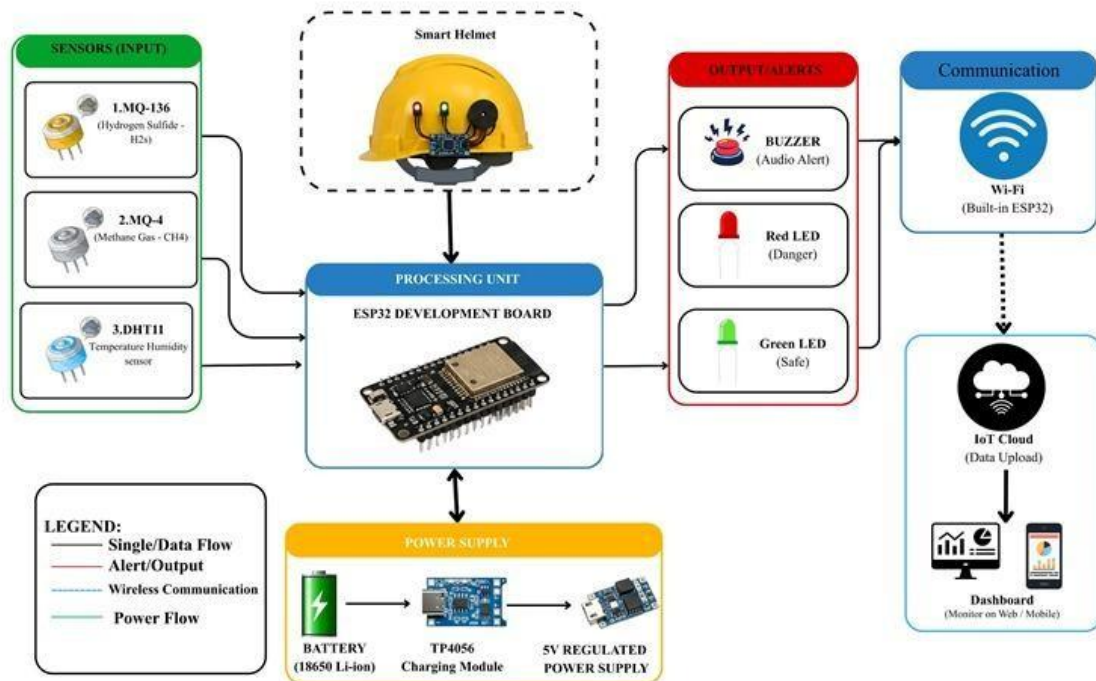


Fig. 2. Architecture diagram of the Edge AI and IoT-based smart helmet for drainage system workers.

B. Sensing modules

Three sensors cover the main risks named in the problem statement. The MQ-136 detects hydrogen sulfide (H₂S), a toxic gas common in sewers. The MQ-4 detects methane (CH₄), a flammable gas that also displaces breathable air. The DHT11 measures temperature and humidity, which indicate heat stress and poor ventilation. The two MQ sensors give analogue outputs that the ESP32 reads through its analogue-to-digital converter; the DHT11 gives a digital reading. All sensors are sampled at a fixed interval and time-stamped by the ESP32.

TABLE II. MAIN BLOCKS AND THEIR ROLES

Block	Role in the helmet
MQ-136 sensor	Detects hydrogen sulfide (H ₂ S)
MQ-4 sensor	Detects methane (CH ₄)
DHT11 sensor	Measures temperature and humidity
ESP32 board	Data acquisition, ANN inference, Wi-Fi
Buzzer	Audio alert to the worker
Red / green LED	Danger / safe indication
Wi-Fi (built-in ESP32)	Uploads data to the IoT cloud
Firebase + dashboard	Storage and web/mobile monitoring

V. METHODOLOGY

A. Continuous monitoring through IoT

The ESP32 acts as the central controller. At each cycle it reads the three sensors, discards invalid samples, smooths short-term noise with a moving average and scales the values to a common range. At regular intervals it uploads a



compact record (worker identifier, risk state, key readings, time) to the cloud over its built-in Wi-Fi, from where the dashboard updates the supervisor's view. Uploading summaries instead of raw streams limits bandwidth and battery use.

B. ANN model for Safe, Warning and Danger classification

The core decision-maker of the helmet is an Artificial Neural Network. An ANN is a layered model in which each neuron computes a weighted sum of its inputs and passes it through an activation function; training adjusts the weights so that the output matches labelled examples. It suits this project because the relationship between several readings and the true level of danger is not a single straight-line rule: for example, a moderate gas level combined with high temperature and humidity can be more hazardous than either alone.

Inputs. The ANN receives four normalised values every sampling cycle: hydrogen sulfide level (MQ-136), methane level (MQ-4), temperature and humidity (DHT11). Outputs. It produces three values, one per class—Safe, Warning and Danger—and the class with the highest probability becomes the current state. Table III gives the proposed structure, which is small enough for a microcontroller and can be tuned during training.

TABLE III. PROPOSED ANN STRUCTURE

Layer	Neurons	Activation	Purpose
Input	4	—	H ₂ S, CH ₄ , temperature, humidity (normalised)
Hidden 1	16	ReLU	Learns combinations of readings
Hidden 2	8	ReLU	Refines the combined features
Output	3	Softmax	Probability of Safe, Warning, Danger

This configuration has 243 trainable parameters (80 in the first hidden layer, 136 in the second and 27 in the output layer), so its memory and computing needs are very small.

Training. Readings are collected from the sensors under controlled conditions and labelled Safe, Warning or Danger according to the safe-exposure limits configured for each gas and the comfort limits for temperature and humidity. The data are split into training, validation and test sets. Inputs are normalised, and the network is trained in Python with a categorical cross-entropy loss and the Adam optimiser. Because missing a Danger event is far more costly than a false Warning, the training and the decision threshold are tuned to favour recall on the Danger class.

Deployment. The trained network is converted with TensorFlow Lite for Microcontrollers, quantised to reduce size and loaded into the ESP32 firmware. The same normalisation used in training is applied in the firmware so that the model sees identical data at run time.

Use during operation. In every cycle the ESP32 feeds the four pre-processed readings to the ANN, obtains the three class probabilities and selects the most likely state. A deterministic threshold override runs in parallel: if any reading crosses its configured danger limit, the state is forced to Danger regardless of the ANN output. The final state then controls the buzzer and LEDs and is sent to the cloud. Limits are configurable so that they can follow the safety standards of each site.

C. Alert generation

Table IV summarises the responses. In the Safe state the green LED is on and no alarm sounds. In Warning the Yellow LED blinks and the buzzer sounds intermittently. In Danger the red LED will on, the buzzer sounds continuously, and the controller immediately sends an emergency message to the cloud; if the network is down, the message is buffered and sent when the link returns while the local alarm continues. The dashboard shows the worker's state, the triggering reading and the time, so the supervisor can start rescue without delay.



TABLE IV. RISK STATES AND SYSTEM RESPONSES

State	Typical trigger	Local response	Remote response
Safe	All readings within limits	Green LED on; no alarm	Periodic status update
Warning	Reading near its limit or combination of readings rising	Yellow LED will blink	Warning flag on dashboard
Danger	Limit exceeded or ANN predicts Danger	Red LED on; continuous buzzer	Immediate emergency alert

D. Operating algorithm

The following steps run in a loop on the ESP32: (1) read the MQ-136, MQ-4 and DHT11 sensors; (2) filter and scale the readings; (3) run the ANN to obtain Safe, Warning or Danger; (4) apply the threshold override; (5) drive the LEDs and buzzer according to the resulting state; (6) upload the status record, or buffer it if the network is unavailable; (7) wait for the next sampling instant and repeat.

TABLE V. CONVENTIONAL PRACTICE VERSUS THE PROPOSED HELMET

Aspect	Conventional practice	Proposed helmet
Monitoring	Manual checks by supervisor	Continuous, sensor-based, on the worker
Hazard decision	Human judgement	On-device ANN with threshold override
Network need	Radio / shouting	Works locally; syncs when online
Alert	Delayed, may be missed	Buzzer + LEDs + cloud alert
Records	Paper logs	Time-stamped cloud history

E. Design considerations

The electronics must stay light and well balanced so that wearing the helmet for a full shift remains comfortable. Humidity and splashes are expected in drainage work, so the board and connections need enclosure and sealing, while the gas sensors must still be exposed to the air. Power consumption is reduced by sampling at a moderate rate and by sending summaries rather than raw data, which extends the life of the 18650 battery. Finally, the buzzer and LEDs must be clearly noticeable in a noisy, dim environment.

VI. PROJECT REQUIREMENTS

Software. Arduino IDE, Python, TensorFlow Lite for Microcontrollers (TinyML), Firebase, Android Studio or a web development framework, Visual Studio Code, and a backend API framework (e.g., FastAPI or Django) with a web dashboard for supervisor monitoring.

Hardware. Safety helmet, ESP32 development board, MQ-136 sensor, MQ-4 sensor, DHT11 sensor, red and green, Yellow LEDs, Register, buzzer, jumper wires and PCB/breadboard.

Dataset. A project-collected dataset of sensor readings from drainage and confined-space conditions, labelled Safe, Warning or Danger, used to train, validate and test the ANN.

Tools. Edge AI (TinyML), Internet of Things (IoT) and the Firebase cloud platform.

VII. EVALUATION PLAN AND EXPECTED OUTCOMES

The prototype is still to be built, so this paper reports the design and the evaluation procedure rather than measured results. Testing will proceed from individual sensors to the integrated helmet using the following measures:

- ANN quality: accuracy, precision, recall and confusion matrix for the three classes on the test set, with attention to missed Danger events.



- Sensor behaviour: response and stability of the MQ-136, MQ-4 and DHT11 readings, checked against a reference where available.
- Latency: time from a hazardous reading to the local alarm and to the dashboard update.
- Reliability: behaviour during Wi-Fi loss (buffering and later delivery).
- Resource use: model size, memory and inference time on the ESP32, and battery life.

The expected outcome is a helmet that issues a local alarm within the sampling interval of an unsafe reading, keeps operating without a network, and gives supervisors an up-to-date, time-stamped record of each worker's state. These expectations will be confirmed or revised once measurements are available.

VIII. DISCUSSION AND LIMITATIONS

The design deliberately favours simplicity and safety: three low-cost sensors, a very small ANN and a rule-based override keep the helmet affordable and its behaviour predictable. Its limits should be stated plainly. MQ-series sensors need a warm-up period, drift over time, respond to more than one gas and must be calibrated, so their readings need validating against reference instruments before field use. The DHT11 has modest accuracy. Wi-Fi coverage underground is limited, so the helmet relies on local alarms and buffered uploads, and a site with no coverage would need a relay or another link. The ANN is only as good as its labelled data, which must cover the conditions met in real drains. Finally, the helmet supports, but does not replace, established confined-space procedures such as ventilation, permits and rescue planning.

IX. BENEFITS TO SOCIETY AND FUTURE SCOPE

By warning workers before conditions become life-threatening and shortening the time to rescue, the helmet supports the sustainable development goals summarised in Table VI. Municipal bodies also gain data on recurring hazards that can guide maintenance planning and safety audits, and the design supports smart-city digital governance.

TABLE VI. SUSTAINABLE DEVELOPMENT GOALS ADDRESSED

SDG	Contribution of the project
SDG 3: Good health and well-being	Real-time hazard alerts in confined drainage spaces reduce fatalities and injuries from toxic exposure.
SDG 8: Decent work	Improves occupational safety for a historically under-protected and under-monitored workforce.
SDG 11: Sustainable cities	Supports safer municipal sanitation and drainage operations through low-cost, deployable edge-AI monitoring.

Future work includes worker health monitoring, predictive safety analytics, automated incident reporting, and a vision module using lightweight detectors such as those in [1], [2], [6], [7] to verify that helmets and harnesses are worn.

X. CONCLUSION

This paper proposed an Edge AI and IoT-based smart helmet for drainage and sewer-line workers. By combining MQ-136, MQ-4 and DHT11 sensing with an on-device ANN that classifies conditions as Safe, Warning or Danger, a threshold safety override, local buzzer and LED alerts and a cloud dashboard, the design addresses the lack of continuous, network-independent monitoring in underground work. The next steps are to build the prototype, collect labelled data, train and deploy the ANN, and carry out the evaluation described above.

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