# Design And Development of An IoT-Based Smart Construction Site Safety and Accident Prevention System

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***Abstract*—Construction sites combine workers, heavy machinery, heights, electricity and confined spaces, yet safety is mostly checked by one supervisor with a paper checklist. This paper presents the design of SafeSite AI, a low-cost Internet of Things (IoT) based system for accident prevention on construction sites, drawn from eight research papers published between 2018 and 2024. In those papers helmet detection reaches 91.4 to 93.1 per cent accuracy, wearable motion sensing recognises falls with over 94 per cent performance, and an ultra-wideband system alerts workers and halts machines; yet each function is usually presented alone and on expensive hardware. The proposed design uses a four-layer architecture and four ESP32-based node types: helmet node, zone node, vision node and gateway. It offers six functions: helmet check, fall detection with emergency call, proximity warning, gas and heat monitoring, three-level alerting with an incident log, and risk analysis, with alarms that keep working when the network is down. A laboratory prototype is estimated to cost Rs. 5,200 to Rs. 8,200, and the design power budget suggests about 46 hours of helmet node operation on two 18650 cells. A simulation of the fall rule on 30 synthetic falls and 30 normal activities detected every fall but raised false alarms on dropped helmets, leading to a wear-detection remedy. Objectives and a test plan are given for the prototype, which is under development. The results reported are simulated and analytical, not hardware measurements.**

***Index Terms*—IoT, Construction Safety, Accident Prevention, Helmet Detection, Fall Detection, Proximity Warning, ESP32, Edge Computing, Simulation**

## I. INTRODUCTION

Construction work takes place on a site that is temporary and changes from day to day. Scaffolds, slab edges, excavators, cranes, makeshift electrical wiring, dust and, inside basements, toxic gases all share the same space. Reviews of wearable sensing rank construction among the riskiest occupations in terms of safety and health [1], and falls from height together with collisions between workers and machinery are the hazards studied most often [2], [3], [4].

Safety on small and medium sites is normally checked by a supervisor on rounds with a paper checklist, which leaves four gaps. A single person cannot observe every area, and helmets are frequently taken off because they are uncomfortable or because workers underestimate the risk, so manual checking demands much effort [5]. After a fall, rescue depends on someone happening to see the victim, although early treatment lowers the chance of severe or fatal outcomes [2]. A worker close to a moving vehicle may be unaware of the danger area, while the driver's view is restricted [3], [4]. Finally, near-misses go unrecorded, so no data exist for improvement.

IoT offers a way to close these gaps. Compact nodes mounted on helmets, at hazardous areas and at the entrance can sense motion, location, gas, temperature and distance, forward the data wirelessly to a dashboard and trigger an alarm on the spot within seconds [6], [4]. Existing research prototypes, however, address a single problem and often rely on expensive equipment [3], [6], [2].

This paper makes the following contributions.

- A review of eight published papers on helmet detection, proximity warning, fall detection and wearable safety monitoring, with the reported results compared.
- A four-layer architecture and four node types for a low-cost combined system, SafeSite AI, with the alarms kept local to the node.

- A project plan for a laboratory prototype covering scope, measurable objectives, cost, power budget and tests.

The rest of the paper is organised as follows. Section II reviews the literature, Section III presents the architecture, Section IV describes sensors and communication, and Section V explains the functions. Section VI gives the prototype plan, Section VII reports simulation and analytical results, Section VIII discusses advantages and limitations, and Section IX concludes.

## II. LITERATURE REVIEW

### *A. Helmet-Wearing Detection*

Han and Zeng [5] took YOLOv5 as their starting point, added a fourth detection scale for distant small targets and an attention block in the backbone, and compensated for the small data set by augmentation and transfer learning. Yang et al. [7] designed YOLO-Helmet for crowded scenes with small helmets, combining an extra small-object layer, a C-ELAN module with deformable convolution and coordinate attention; the model reached an average accuracy of 93.1 per cent on the SHWD data set. Muhammad Zamri et al. [8] chose YOLOv5 after weighing accuracy against speed, applied tuned transfer learning and obtained 91.4 per cent accuracy at 39.8 ms per image, fast enough for near real-time checking at an entrance or work front.

### *B. Proximity Warning and Localisation*

Jo et al. [3] developed the Robust Construction Safety System (RCSS) against collisions with heavy equipment. Ultra-wideband (UWB) ranging triggers alarms at the same instant on a unit worn by the worker and on a unit at the danger area; a link to the machine's control sensors allows automatic stopping, and GPS with an online interface supports resource management. Tests covered the laboratory, a construction site and a steel plant. Kanan et al. [4] proposed an IoT system in which a sensor covers the blind rear of a vehicle and the worker carries a hybrid active-passive tag that stays in deep sleep until a radio field wakes it, which conserves the battery.

### *C. Fall Detection and Wearable Sensing*

The wearable system of Park et al. [6] relies on tags and edge routers in a sub-1 GHz Zigbee network; deep learning applied to gyroscope and accelerometer signals recognises falls with over 94 per cent performance.

Dogan and Akçamete Güngör [2] concentrated on falls from height: their wearable estimates the drop height and time and passes both to the medical emergency team, and with dummies it caught every fall, with a height error of 10.8 per cent and a 3.16 per cent error in measuring the network outage.

The survey by Awolusi et al. [1] sorts wearable safety devices by what they measure and points out that several sensors can be combined for multi-parameter monitoring.

### *D. Summary and Research Gap*

Table I summarises the reviewed work. Because the data sets, test set-ups and measures differ, the figures are not directly comparable.

Table I: Summary of the reviewed literature

| Ref. | Authors (year) | Focus of work | Reported result or key point |
|---|---|---|---|
| [1] | Awolusi et al. (2018) | Survey of body-worn devices for site safety | Sensors grouped by the quantity they monitor |
| [2] | Dogan and Akçamete Güngör (2018) | Wearable that detects falls from height and alerts rescuers | All dummy falls detected; height error 10.8 per cent |
| [3] | Jo et al. (2019) | UWB ranging system against machine collisions | Joint worker and zone alarm, machine stop, field-tested |
| [4] | Kanan et al. (2018) | Autonomous IoT warning and localisation | Tag sleeps until woken by a radio field |
| [5] | Han and Zeng (2022) | YOLOv5 extended with a fourth scale and attention | Small-target detection improved using augmentation and transfer learning |
| [6] | Park et al. (2019) | Zigbee tags with learned fall recognition | Over 94 per cent detection performance |

| Ref. | Authors (year) | Focus of work | Reported result or key point |
|---|---|---|---|
| [7] | Yang et al. (2024) | YOLO-Helmet for crowded small-helmet scenes | Average accuracy of 93.1 per cent on SHWD |
| [8] | Muhammad Zamri et al. (2023) | Tuned YOLOv5 for live helmet checking | 91.4 per cent accuracy at 39.8 ms per image |

Three points emerge. Most papers address one problem at a time, and few merge helmet check, fall alarm, proximity warning and environment monitoring in a compact system. Fall results come from dummy or recorded-data tests, so false alarms in real work are not yet known [6], [2]. Proximity solutions depend on specialised hardware such as UWB, and cheaper options need evaluation [3]. The gap is thus an affordable system for small contractors that joins these functions on one network and one dashboard and keeps working without internet. SafeSite AI targets this gap.

## III. PROPOSED SYSTEM ARCHITECTURE

Fig. 1 shows the four-layer model used here. The perception layer comprises the sensors, camera and alarm devices on the helmet, at hazard areas and at the gate. The network layer moves readings to the server and commands back. The processing layer stores data and applies rules and AI models, and the application layer presents information to supervisors and workers.

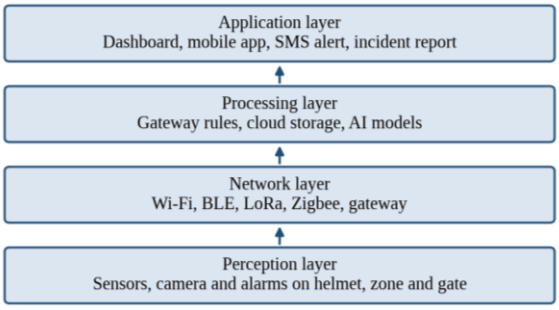


Fig. 1: Four-layer architecture of the IoT-based construction site safety system (adapted from [6] and [4])

Radio design needs care because steel, concrete and moving machinery obstruct and reflect signals and a site has no ready network. Park et al. [6] therefore used a sub-1 GHz Zigbee network, and Dogan and Akçamete Güngör [2] measured how long the network stays disconnected, which shows that outages are normal. The key design rule is that an alarm must never wait for a remote server: urgent decisions, such as sounding the helmet buzzer after a fall, are made on the node, while the cloud handles display, storage and analysis. After reconnection the node uploads the buffered events so that the incident log is complete.

Table II lists the four proposed node types. The helmet node acts as the worker's personal protection unit: it monitors motion, carries an SOS button and may sleep until required [4]. The zone node supervises a fixed hazard area. The vision node checks helmets at the gate with a detector of the kind described in [5], [7], [8]. The gateway gathers all messages, holds the local rules and relays data to the cloud.

Table II: Types of nodes in the proposed system

| Node | Location | Sensors and outputs | Supply |
|---|---|---|---|
| Helmet node | Worn on the helmet | MPU6050 motion sensor, GPS, SOS switch, buzzer and LED | Li-ion battery |
| Zone node | Hazard spots such as pits, basements, panels, machinery | Gas, smoke, flame and temperature sensors, ultrasonic ranging, siren, beacon lamp | 5 V mains adapter |
| Vision node | Entrance or active work front | ESP32-CAM for helmet recognition | 5 V mains adapter |
| Gateway | Site office | Collects node data; forwards over Wi-Fi or LoRa to the cloud | 5 V mains adapter |

## IV. SENSORS AND COMMUNICATION TECHNOLOGIES

### *A. Sensors*

Only a few quantities are needed for a useful system: worker motion and position, distance to a hazard, the state of the environment and the camera image [1]. Table III lists the sensors chosen. A fall appears in the accelerometer signal as low acceleration during free fall, a sharp peak at impact and then little movement [6], [2]; such a threshold rule fits a small

microcontroller, and a learned model can be added later to cut false alarms. MQ-2 reacts to smoke and combustible gases and MQ-7 mainly to carbon monoxide, and both require warm-up and calibration.

For helmet detection an ESP32-CAM captures the image and a YOLO-based model on a nearby computer, trained by transfer learning as in [5], [8], makes the decision.

Table III: Hazards, sensors and their use in the proposed system

| Hazard or need | Device | Role in SafeSite AI |
|---|---|---|
| Worker falling | MPU6050 accelerometer and gyroscope [6], [2] | Spots free fall, impact and stillness |
| Worker closes to machinery | BLE beacon or ultrasonic ranger; UWB in [3], [4] | Proximity and zone warning |
| Worker position | NEO-6M GPS [3] | Location shown on dashboard and in SOS alert |
| Missing helmet | ESP32-CAM plus detection model [5], [7], [8] | Entrance helmet check |
| Toxic gas, smoke | MQ-2 and MQ-7 modules | Warning in basements and enclosed rooms |
| Fire, heat | Flame sensor and DHT22 | Fire and heat alert |
| Need for help | Push switch | Worker-triggered SOS |
| On-site warning | Buzzer, LED, siren, relay-driven lamp | Instant alarm where the danger is |

*B. Communication Technologies*

Table IV compares the radio options; values are typical and vary with module and surroundings. For the laboratory prototype Wi-Fi is the simplest and cheapest because the ESP32 includes it, while BLE serves proximity sensing and the link to the worker's phone.

On a real site with long distances and many walls a long-range low-power radio suits better; Park et al. [6] picked sub-1 GHz Zigbee, and LoRa is a comparable option. The prototype therefore uses Wi-Fi and BLE, with LoRa kept as an option for outdoor zones.

Table IV: Comparison of wireless technologies

| Technology | Where used | Strength | Weakness |
|---|---|---|---|
| Wi-Fi | Nodes close to the site office | Fast; integrated in ESP32; carries images | Short reach, power hungry, blocked by steel and walls |
| BLE | Beacon and helmet-to-phone link | Low power and cost | Short reach; signal strength gives only coarse distance |
| Zigbee (sub-1 GHz) | Tags with edge routers [6] | Low power; self-organising mesh | Needs coordinator; slow data |
| LoRa | Remote zones to gateway | Long reach at tiny power | Slow; no image transfer |
| UWB | Accurate ranging and localisation [3] | Precise distance, fast alarm | Costly specialised hardware |
| GSM | Text alerts to supervisor | Wide coverage | Recurring subscription |

Battery energy is the main limit of the wearable node because it cannot be recharged during a shift. Published work handles this with sleep modes and wake-on-demand operation [4], [1]. Accordingly, the helmet node samples the motion sensor at a modest rate, uses Wi-Fi in short bursts, duty-cycles the GPS and powers the buzzer only during alarms. Fixed nodes use mains adapters because gas-sensor heaters draw more current than a small battery can supply.

## V. FUNCTIONS OF THE PROPOSED SYSTEM

SafeSite AI combines six functions on one network and one dashboard. Each is based on a method reported in the reviewed literature.

*A. Helmet-Wearing Check*

A gate or work-front camera passes images to a detection model that locates people and helmets. When someone appears without a helmet, an alert with time and location is raised and the frame is displayed on the dashboard. The prototype will apply transfer learning from a pre-trained model, using a small college-collected set of images taken with consent, as

proposed in [5], [8]. Images serve only the helmet decision and are kept briefly to protect worker privacy.

*B. Fall Detection and Emergency Call*

The helmet node samples the accelerometer and gyroscope several times per second and searches for the fall signature. On a match the buzzer gives a short pre-alarm so that a worker who merely stumbled can cancel it by pressing the button. Otherwise, the node sends an alert with the worker's position to the gateway, dashboard and supervisor's phone. The SOS button produces the same alert on demand.

*C. Proximity and Danger-Zone Warning*

Proximity warning relies on a beacon attached to the machine or the restricted zone. Once the helmet node measures a distance below its limit, it lights the helmet LED, sounds the helmet buzzer and switches the machine's beacon lamp at the same time, the principle behind the RCSS [3]. Distance comes from BLE signal strength or an ultrasonic sensor in the prototype; the machine stop is demonstrated with a relay and small motor, because halting a real machine needs approval and certification.

*D. Environment and Hazard Monitoring*

At each hazard area the zone node monitors smoke and combustible gas with an MQ-2, carbon monoxide with an MQ-7, temperature with a DHT22 and flames with a flame sensor. A reading above its limit starts the local siren and lamp, sends a dashboard message and colours the area red; a rising trend is reported earlier so that action can start sooner.

*E. Alerts, Dashboard and Incident Log*

Alerts follow the three levels of Table V. Warnings stay local, critical alerts go to the supervisor and an emergency contact, and every event is recorded in the incident log with time, location and response. Test and acknowledge buttons let users verify and close alarms.

Table V: Alert levels and the response of the system

| Level | Typical event | System action |
|---|---|---|
| Information | Entry of a worker; low node battery | Logged; shown on dashboard |
| Warning | Missing helmet; worker near machine; rising gas level | Local buzzer or LED; dashboard message |
| Critical | Uncancelled fall; SOS; gas, smoke or flame over limit | Siren and lamp; SMS and call to supervisor and emergency contact with worker location |

*F. Analysis and Risk Score*

Once several weeks of events are stored, the processing layer can count alerts by type, place and time of day and compute a simple risk score per zone from the number and severity of alerts. Management can then spot recurring near-misses before they become accidents and decide where to install barriers or provide training, something manual supervision cannot offer.

## VI. PROTOTYPE PLAN

*A. Scope and Block Diagram*

The prototype consists of a helmet node, a zone node, a vision node and a gateway (Fig. 2). It implements threshold-based fall detection with pre-alarm and SOS switch, helmet recognition through transfer learning, danger-zone warning with a relay-driven machine-stop demonstration, gas, smoke, flame and temperature sensing, and a web dashboard with SMS or phone alerts. Real-site deployment, control of an actual machine and face identification lie outside the scope. Fall experiments will be limited to a soft mattress and a very small height.

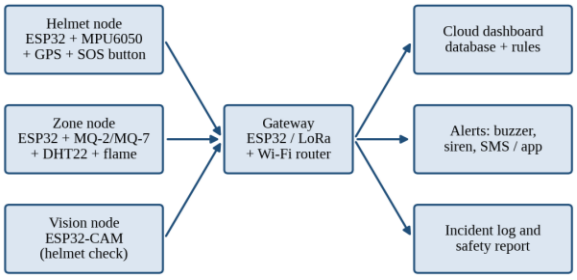


Fig. 2: Block diagram of the proposed SafeSite AI prototype

*B. Cost Estimate*

Table VI lists indicative hardware prices in Indian rupees; the lower and upper columns allow for supplier differences. Software and the cloud plan are free, giving a total of roughly Rs. 5,200 to Rs. 8,200.

Table VI: Hardware cost estimate (Rs.)

| Item group | Minimum | Maximum |
|---|---|---|
| Controllers and camera: 2 ESP32 boards, ESP32-CAM with programmer | 1,550 | 2,100 |
| Motion and position: MPU6050, NEO-6M GPS | 500 | 800 |
| Environment: MQ-2, MQ-7, DHT22, flame sensor | 580 | 950 |
| Proximity: two HC-SR04 ultrasonic sensors | 150 | 250 |
| LoRa SX1278 modules (pair, gateway option) | 1,000 | 1,600 |
| OLED display, buzzer, LEDs, SOS button, relay module | 360 | 650 |
| Power and mounting: 18650 cells and charger module, helmet, enclosure and wiring | 1,050 | 1,800 |
| Cloud dashboard (free plan) | 0 | 0 |
| Total | 5,190 | 8,150 |

*C. Power Budget*

The average current of a component equals its current times the share of time it is on, and the running time follows from the usable battery capacity (Eq. 1 and Eq. 2).

$$I_{avg} = \Sigma\ (\mathrm{Ik} \times d_k / 100) \quad (1)$$

$$T = (\eta \times C) / I_{avg} \quad (2)$$

In these equations $I_k$ is the current of component k in mA, $d_k$ its on-time in per cent, $C$ the battery capacity in mAh, $\eta$ the conversion efficiency and $T$ the running time in hours. Table VII lists design values for the helmet node, based on module data sheets.

Table VII: Design power budget of the helmet node

| Component | Current (mA) | Active time (%) | Average (mA) |
|---|---|---|---|
| ESP32 (average, short Wi-Fi bursts) | 80 | 100 | 80 |
| MPU6050 motion sensor | 3.9 | 100 | 3.9 |
| NEO-6M GPS | 45 | 50 | 22.5 |
| LoRa SX1278 (transmitting) | 120 | 2 | 2.4 |
| Buzzer (alarms only) | 30 | 1 | 0.3 |
| Status LED | 10 | 5 | 0.5 |
| Total average current | | | 109.6 |

Two 3000 mAh 18650 cells in parallel provide 6000 mAh; at 85 per cent efficiency about 5100 mAh is usable, so Eq. 2 gives T = 5100 / 109.6, roughly 46 hours, or more than four 10-hour shifts. This is only a design estimate, to be verified by measurement because ESP32 current varies strongly with Wi-Fi use. The zone node runs from a 5 V mains adapter and draws about 492.5 mA on average, mostly through the two gas-sensor heaters, so a 5 V, 2 A adapter leaves ample margin.

*D. Objectives and Testing Plan*

Table VIII lists a test for every objective. The helmet and fall targets are set at 90 per cent, slightly under the published figures [7], [8], [6], and the fall test includes everyday movements so that false alarms can be counted. Gas tests use only a tiny quantity in a ventilated place with the guide present.

Table VIII: Objectives and testing plan

| Test | Procedure | Target |
|---|---|---|
| Helmet detection | 100 frames with and without helmets at varied range and lighting | 90 per cent or more correct |
| Fall detection | 30 staged falls onto a mattress plus 30 everyday movements | 90 per cent or more caught; 3 false alarms at most |
| Gas and smoke | Tiny amount of lighter gas or incense smoke near the sensor, ventilated space | Alarm within 10 s of passing the threshold |
| Proximity | Walk toward the beacon from several angles | Buzzer at the preset distance, tolerance 1 m |
| Alert latency | 20 timed trials, event to dashboard and phone | Local alarm 2 s; dashboard 5 s |
| Battery | Run helmet node under normal use until cut-off | 10 h minimum |
| Network loss | Switch Wi-Fi off during events | Local alarms continue; events uploaded on reconnection |

## VII. RESULTS AND ANALYSIS

The prototype hardware is still being built, so the results in this section come from a computer simulation and from analytical calculation. They are not measurements on hardware and are reported as such.

### *A. Simulation of the Fall-Detection Rule*

The rule of Section V-B was tested in Python on synthetic accelerometer traces sampled at 50 Hz, generated with a fixed random seed. The set had 30 falls (free fall of 0.25 to 0.6 s, impact of 3 to 6 g, then a still period) and 30 normal activities: 8 walking, 8 sitting down, 8 stepping or jumping down a step, and 6 helmet drops. Three variants were compared: impact peak only, free fall followed by impact, and free fall followed by impact and a still period. The results are in Table IX.

Table IX: Simulated fall-detection results (30 falls, 30 normal activities)

| Rule variant | Falls detected | False alarms | Source of false alarms |
|---|---|---|---|
| Impact peak only | 30 of 30 | 12 of 30 | Step jumps (6), dropped helmets (6) |
| Free fall then impact | 30 of 30 | 6 of 30 | Dropped helmets (6) |
| Free fall, impact and still period | 30 of 30 | 6 of 30 | Dropped helmets (6) |

All variants detected every simulated fall. Adding the free-fall condition removed the false alarms from step jumps, but the still-period check did not help, because a dropped helmet also lies still on the ground. The target of at most three false alarms in thirty activities was therefore not met in simulation.

This agrees with the concern in the literature that false alarms are the main weakness of wearable fall detection [6], [2]. The remedy adopted for the prototype is a wear-detection input, such as a chin-strap switch, so that a fall alert is raised only while the helmet is worn.

Because the traces are synthetic and follow assumptions made by the authors, the numbers show how the rule variants behave relative to each other and not the accuracy to be expected on a real site.

### *B. Analytical Check Against the Objectives*

Table X compares the design values with the objectives of Table VIII. Items that depend on hardware are marked pending.

Table X: Design values compared with the objectives

| Objective | Target | Design or simulated value | Status |
|---|---|---|---|
| Helmet node battery life | At least 10 h | About 46 h from Eq. 2 | Met by design; to be measured |
| Zone node supply | Margin above load | Load 492.5 mA on a 2 A adapter (about 4 times) | Met by design |
| Hardware cost | Within estimate | Rs. 5,190 to 8,150 | Met by design |
| Fall detection | At least 90 per cent | 30 of 30 simulated falls | Simulation only |
| Fall false alarms | At most 3 in 30 | 6 in 30 (dropped helmets) | Not met; wear input added |
| Helmet detection, alert delay, gas alarm time | See Table VIII | No value yet | Pending hardware |

## VIII. DISCUSSION

### *A. Advantages*

Alarms sound at both the worker and the hazard within seconds [3]. A fall is reported automatically with position and time, so the victim need not wait to be noticed [2]. Cameras and sensors operate continuously wherever a node is installed, whereas a supervisor is present in one place. Each violation and near-miss is logged, supporting training and investigation. The system assists the safety officer rather than replacing him.

### *B. Limitations and Remedies*

- False fall alarms, for instance from a dropped helmet. Remedy: pre-alarm with cancel button, a free-fall check before the impact, a chin-strap wear switch and threshold tuning on recorded data [6], [2].
- Helmet recognition may fail in dim light, dust, partial occlusion or tiny images. Remedy: well-

placed camera, augmentation and a small-object model [5], [7].

- Concrete and steel block radio. Remedy: sub-1 GHz or LoRa links, local alarms and buffering of events until reconnection [6], [2].
- Short battery life, reluctance of workers and privacy concerns. Remedy: deep sleep with low GPS duty cycle [4], a light compact node [5], [1], and brief image retention under password control.
- Gas sensors drift and need warm-up. Remedy: calibrate on installation and at intervals.
- Halting real machinery requires approval and certification. Remedy: show the stop only on a model [3].

## IX. CONCLUSION AND FUTURE SCOPE

SafeSite AI, a low-cost IoT and AI based safety system for construction sites, was designed in this paper from a review of eight published studies. The literature supports each of the six functions: helmet detection at 91.4 and 93.1 per cent accuracy [7], [8], fall detection above 94 per cent [6] and full sensitivity in dummy tests [2], and a UWB system that alerts both worker and zone and halts the machine [3]. In a simulation of the fall rule every one of 30 falls was detected, but dropped helmets caused false alarms, which led to the wear-detection remedy proposed here; the design power budget indicates about 46 hours of helmet node operation. The value of the system lies in joining these functions on one inexpensive network with local alarms.

Measurements on the finished prototype against the targets of Table VIII will be reported later.

Planned extensions include wearable health sensing for heat stress and fatigue [1], UWB positioning for precise distance [3], detection of vests and harnesses besides helmets, a fall model learned from prototype data [6], a long-range LoRa or Zigbee network for large sites [6], and a study of data privacy and security before field use.

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