Abstract

Agricultural workers face substantial occupational health risks from prolonged sun exposure and physical strain, including heatstroke, skin cancer, and musculoskeletal injuries. Research suggests that heat-related illnesses are a leading cause of death among farmworkers [1]. Overexertion injuries also contribute significantly to work-related injuries in agriculture [2]. Outdoor workers like those in agriculture are at increased risk of skin cancer, with 20% of Americans developing the disease due to UV exposure, according to the Skin Cancer Foundation [3],[4]. The absence of real-time monitoring systems exacerbates these risks, as manual checks and sporadic assessments lack the precision and immediacy needed for effective protection [5].

This report introduces an IoT-based system designed to mitigate these challenges and critical gap by monitoring physiological and environmental factors, delivering immediate, on-device feedback and actionable feedback using low, moderate and high levels, to enhancing safety in agriculture. The system comprises 3 devices-

1. The Leg Activity Sensor, powered by an Arduino Nano 33 BLE with an MPU6050 accelerometer and TinyML, tracks exertion levels and issues buzzer alerts when fatigue thresholds are crossed.
2. The UV Exposure Monitor on a wristband, equipped with an LDR sensor and an ESP32 microcontroller, measures UV exposure and displays risk levels on an LED bar graph.
3. The Environmental Condition Monitor with a DHT22 sensor and a ESP32, assesses temperature and humidity, displaying heat stress risks on an OLED screen.

This Arduino Nano 33 BLE and ESP32 microcontrollers ensures low power consumption and robust wireless communication, critical for wearable devices in remote agricultural settings. These devices communicate via Bluetooth Low Energy (BLE) to a Flutter mobile application, which caches data offline and syncs when connectivity resumes, addressing the 23% of U.S. farms lacking reliable internet [6]. The UV and Environmental Condition Monitors also support Wi-Fi for cloud connectivity. A federated-learning pipeline aggregates on-device TinyML models into a global model, preserving privacy by sharing only encrypted model updates.

The mobile app, designed with an UI featuring color-coded alerts, real-time provides visualizations and simple navigation to non-technical users like agricultural workers. A Manager Safety Hub within the app offers supervisors a multi-worker overview, team alerts and historical trends, facilitating proactive safety management. Health expert researchers and insurers access anonymised long-term trends for medical insights, CSV data and filters (age, job type) to understand the risk and make more data driven decisions.

The report explores the problem's scope, system components, user interactions, machine learning applications, security measures, and evaluation strategies. Security is enforced end-to-end with AES-128/TLS encryption, role-based access control, differential privacy, and tamper-evident hardware seals giving a privacy-first model for occupational safety in agriculture. IP67-rated hardware, and the system's modular design can make it horizontal scalable and can be extended with minimal adaptation. My system attempts to optimise and maintain sensor accuracy, BLE/Wi-Fi uptime, 12-hour battery life, alert precision and a reduction in overexertion injuries for workers.

Application Domain and Problem

Agriculture is a cornerstone of global food security, employing over 1 billion people and producing food for billions worldwide [7]. However, its workforce faces severe occupational health risks from prolonged sun exposure and physical strain, including heatstroke, skin cancer, and musculoskeletal injuries. These hazards threaten worker well-being, reduce productivity, and increase healthcare costs, impacting both individuals and the broader agricultural economy. The Centers for Disease Control and Prevention (CDC) reports that agricultural workers are at a significantly higher risk of heat-related illnesses, with heatstroke causing approximately 10–20 deaths annually among U.S. farmworkers [1]. Prolonged UV exposure elevates skin cancer risk, with the Skin Cancer Foundation noting that outdoor workers, including farmers, face a 3.5 times higher risk of melanoma than indoor workers [3]. The Bureau of Labor Statistics indicates that overexertion injuries, such as sprains and strains, account for over 25% of non-fatal occupational injuries in agriculture, with 15,000 cases reported annually in the U.S. [2]. Heat stress alone can reduce labour productivity by up to 20% during peak seasons, leading to significant economic losses [8]. These statistics highlight the urgent need for effective interventions to safeguard this critical workforce.

Current solutions for managing these risks are inadequate and outdated. Manual health checks, such as supervisors observing workers for signs of heat stress, rely on subjective judgment and lack precision, often missing early warning signs [5]. Periodic medical assessments, typically conducted annually, fail to capture real-time data on UV exposure or physical exertion, missing opportunities for timely intervention. Wearable UV monitors exist but are not widely adopted in agriculture due to high costs, lack of integration with other health metrics, and incompatibility with the rugged demands of farm work [4]. For example, many commercial UV monitors such as sun-a-wear UV tracker are designed for leisure activities and lack the durability or battery life required for extended field use. Physical strain is often addressed through basic training programs rather than continuous monitoring, leaving significant gaps in injury prevention. These fragmented approaches cannot address the dynamic environmental and physiological conditions in agricultural settings, where workers face varying temperatures, humidity, and workloads daily.

The **stakeholders** impacted by this problem are diverse and have distinct needs. **Agricultural workers**, numbering over 2 million in the U.S., require real-time alerts to avoid health risks and maintain their livelihoods [9]. **Farm managers** need oversight to ensure workforce safety, comply with occupational health regulations, and minimize downtime due to injuries. **Occupational health experts** depend on comprehensive data to develop evidence-based interventions and further research. **Insurers** use risk profiles for more precise risk data to adjust policies and reduce claims.

The proposed IoT system addresses these needs through real-time monitoring and predictive analytics. By integrating three devices—a Leg Activity Sensor, UV Exposure Monitor, and Environmental Condition Monitor tracks exertion, UV exposure, and environmental conditions, delivering immediate feedback to workers and actionable insights to managers, health experts, and insurers. Unlike current solutions, this system provides continuous, data-driven protection, reducing health risks, enhancing safety, and improving operational efficiency across the agricultural sector.

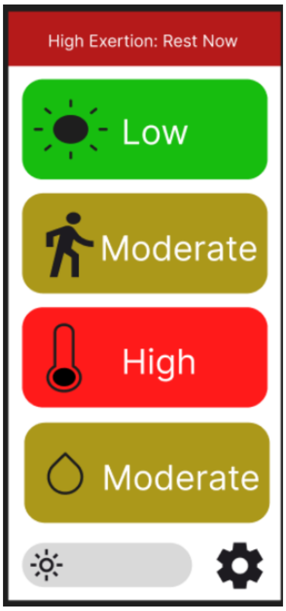
Smartphone Application and User Interaction

The mobile application is the central hub of the IoT system designed for monitoring environmental exposure and physical activity of agricultural workers, integrating data from 3 devices: the Leg Activity Sensor, UV Exposure Monitor, and Environmental Condition Monitor. Its primary role is to collect, process, and visualize data, providing real-time feedback and actionable insights tailored to 4 key stakeholders: workers, farm managers, occupational health experts, and insurers. Built using Flutter for cross-platform compatibility (Flutter, 2023), the app ensures accessibility on smartphones and potentially tablets, catering to diverse user needs in agricultural settings. The Leg Activity Sensor and UV Exposure Monitor, both wearable devices. The Leg Activity Sensor sends accelerometer data classified by TinyML into exertion levels (low, moderate, high), while the UV Exposure Monitor provides UV levels the worker has been exposed to during that shift.

User Interfaces for Stakeholders

Workers

The worker interface prioritizes simplicity and usability for non-technical users, who may include over 2 million agricultural workers with varying literacy levels [9]. A single-screen dashboard displays 4 key metrics: physical exertion, UV exposure, heat stress risk and humidity. Each metric uses labels Low, Moderate and High. Color-coded, contrasting indicators green, yellow, and red enhance readability under sunlight, critical for outdoor use. It is designed for quick comprehension, avoiding technical jargon like "UV Index" in favour of "Sun Exposure Risk." Real-time alerts appear as prominent alert banner at the top flashes notifications when thresholds are exceeded, e.g., "High Exertion: Take a Break", prompting immediate action to reduce health risks [5]. The interface is optimized for outdoor use with high-contrast a high-contrast theme to ensure displays readable in sunlight [5], UI uses large, bold text (18pt font) Navigation is minimal, with a single "Settings" button for language selection (e.g., English, Spanish) to accommodate diverse workforces [7].



Farm Managers

Farm managers require oversight of multiple workers, with farms employing an average of 5–10 workers during peak seasons [6]. Their interface, the Manager Safety Hub, features a multi-worker overview showing each humidity and worker's status for exertion, UV exposure, and heat stress risk. Tapping a worker's profile reveals historical data trends, such as exertion levels over a shift, enabling managers to adjust schedules or tasks to prevent overexertion injuries, which account for 25% of agricultural incidents [2]. A "Team Alerts" tab highlights critical notifications, such as "Worker 3: High Heat Risk." The interface supports app, tablet or computer access via the cloud, with a filter option to view data by worker or time range, ensuring flexibility in monitoring. Large icons and a clean layout ensure usability for managers with limited tech experience [5].

Occupational Health Experts

Health experts need detailed analytics to inform safety protocols, given that heat-related illnesses are a leading cause of death among farmworkers [1]. Their app provides exertion, UV exposure, and environmental conditions data and trends across workers or time periods (e.g., daily, monthly). A dropdown menu allows filtering by age, gender, climate, etc, enabling correlations—e.g., UV exposure versus task type—to inform safety protocols [5]. A CSV is exported for external analysis, supporting evidence-based interventions. The interface uses a professional, data-centric design with precise labels (e.g., "UV Index: 6.2").

Insurers

Insurers access aggregated, anonymized data via the cloud to assess risk profiles, as health-related claims in agriculture exceed $1 billion annually [2]. While they lack a dedicated app interface, the cloud platform provides summary statistics such as average UV exposure across a farm, presented in bar charts for easy interpretation. "Filter" option allows selection by farm or season, supporting risk assessments for policy adjustments enabling tailored insurance policies without compromising individual privacy [10].

Usability and Additional Features

Usability for workers, many of whom may not own smartphones [6] is enhanced by designing the app for shared or farm-provided devices. It features minimal navigation, large text, and an energy-efficient design to preserve battery life during 12-hour shifts [5]. Offline functionality ensures data collection in remote areas, with 24% of U.S. farms lacking consistent connectivity [6]. Personalization allows health experts to set individual thresholds, e.g., lower exertion limits for older workers, while data security complies with GDPR through encryption and authentication [10].

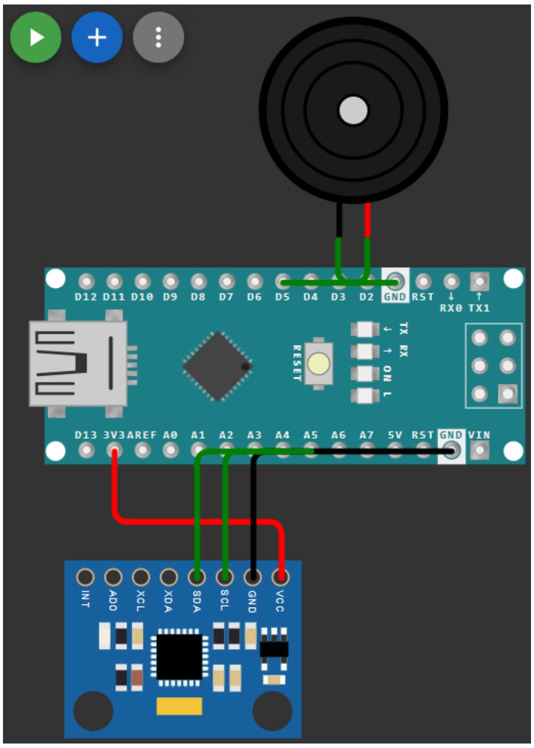
Description of Each Thing

The three IoT devices—Leg Activity Sensor, UV Exposure Monitor, and Environmental Condition Monitor are designed for an environmental exposure monitoring system tailored to agricultural workers and are integrated into the system. Each device includes a sensor, processor, and output, with connectivity to address specific safety needs. The Leg Activity Sensor and UV Exposure Monitor transmit data to the mobile app via Bluetooth Low Energy (BLE), a low-power wireless protocol ideal for battery-operated wearables. Environmental Condition Monitor uses Wi-Fi for stationary farm-wide monitoring, ensuring comprehensive safety coverage. In areas with poor connectivity, a common challenge in rural and agriculture, where only 77% of farms have reliable internet [6], the app caches data locally and syncs when a network is available, ensuring uninterrupted monitoring.

1. Leg Activity Sensor

- **Sensor**: MPU6050 Accelerometer- Tracks leg movements by measuring acceleration across three axes (X, Y, Z), providing data on physical activity levels.
- **Processor**: Arduino Nano 33 BLE- A compact, low-power microcontroller with integrated BLE. It employs a TinyML model to classify exertion (low, moderate, high) in real-time by analysing accelerometer data.
- **Output**: Buzzer- Delivers sound feedback to warn workers when exertion exceeds safe limits, signalling potential fatigue or overexertion.
- **Connectivity**: BLE- Sends exertion data to a mobile app for real-time tracking and alerts.
- **Function**: Worn on the leg, this device monitors physical strain. The TinyML model enables on-device processing, activating the buzzer during high exertion to prompt rest, enhancing battery efficiency and responsiveness in field conditions.

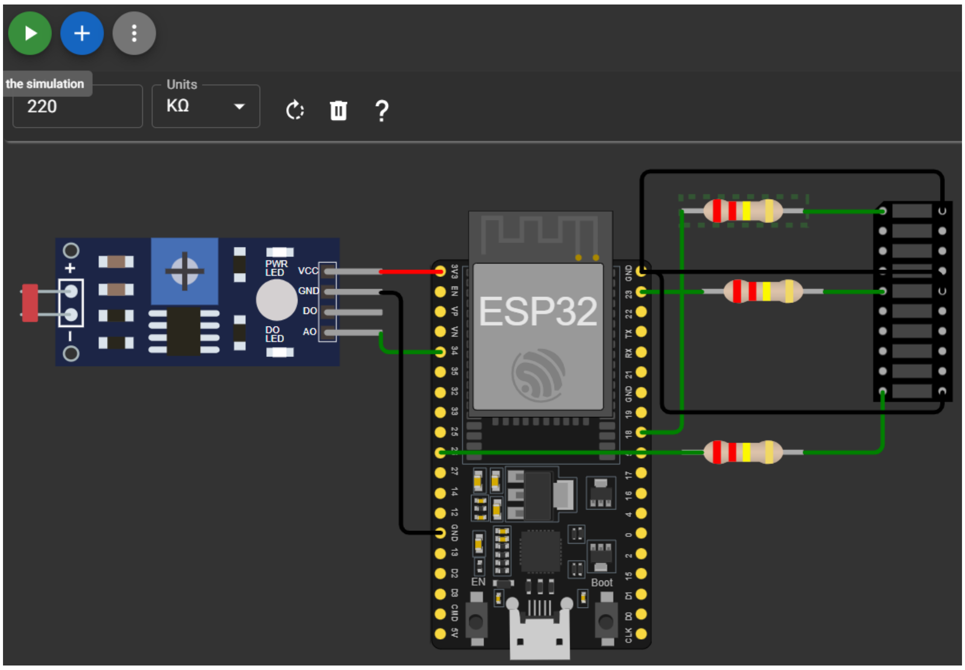

```json
{
  "name": "Leg Activity Sensor",
  "type": "thing",
  "description": "Wearable device to monitor physical exertion",
  "properties": {
    "exertionLevel": {
      "type": "string",
      "description": "Current exertion level (low, moderate, high)"
    }
  },
  "actions": {
    "measureExertion": {
      "description": "Measure leg movement and classify exertion",
      "type": "string"
    }
  },
  "events": {
    "highExertionAlert": {
      "description": "sound alert for high exertion",
      "data": {
        "exertionLevel": "high"
      }
    }
  }
}
```

2. UV Exposure Monitor

- **Sensor**: Photoresistor (LDR) sensor- Measures UV light intensity, outputting data in UV Index units to evaluate sunlight exposure.
- **Processor**: ESP32- A powerful microcontroller with built-in Wi-Fi and BLE, handling sensor data processing and communication. It uses TinyML to classify UV levels as low, moderate and high
- **Output**: LED Bar Graph- Displays UV exposure levels (safe, moderate, high) via LEDs, offering instant visual feedback without app reliance.
- **Connectivity**: BLE- Transmits UV data to the mobile app for logging and cloud integration.
- **Function**: This wearable tracks daily UV exposure. The ESP32 interprets sensor data, lighting green LEDs for safe levels, amber for moderate, and red for high, urging workers to use sunscreen or shade when needed.

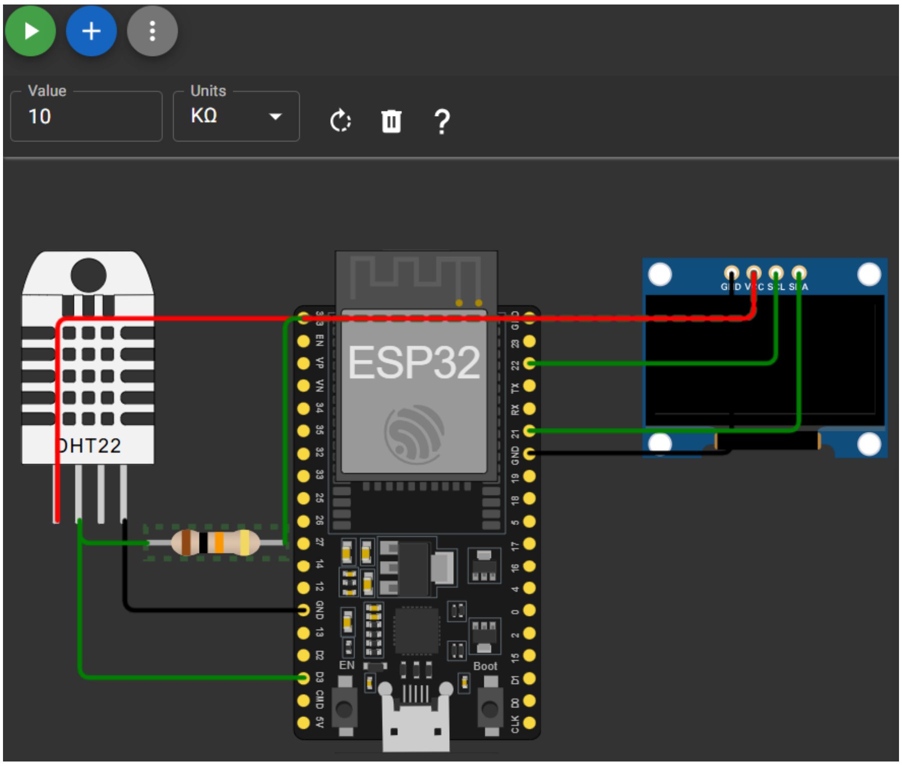
```json
{
  "name": "UV Exposure Monitor",
  "type": "thing",
  "description": "Wearable device to monitor UV exposure",
  "properties": {
    "uvLevel": {
      "type": "string",
      "description": "Current UV exposure level (safe, moderate, high)"
    }
  },
  "actions": {
    "measureUV": {
      "description": "Measure UV exposure and update LED display",
      "type": "string"
    }
  },
  "events": {
    "highUVAlert": {
      "description": "LED alert for high UV exposure",
      "data": {
        "uvLevel": "high"
      }
    }
  }
}
```



3. Environmental Condition Monitor

- **Sensor**: DHT22 Temperature and Humidity Sensor- Captures ambient temperature and humidity, key factors in assessing heat stress risk.
- **Processor**: ESP32- The ESP32 adds Wi-Fi for cloud connectivity, offering deployment flexibility.
- **Output**: OLED Screen- Shows real-time temperature, humidity, and heat stress risk (e.g., Low, Moderate, High) on a compact display.
- **Connectivity**: Wi-Fi- Uses Wi-Fi for stationary units in the field to send models to the cloud and send data to the app.
- **Function**: Deployable as a wearable or fixed unit, it calculates the heat index from temperature and humidity. A heat index above 103°F (39°C) triggers a "High Risk" alert on the OLED, advising hydration and breaks.


```json
{
  "name": "Environmental Condition Monitor",
  "type": "thing",
  "description": "Device to monitor temperature, humidity, and heat stress risk",
  "properties": {
    "heatStressRisk": {
      "type": "string",
      "description": "Current heat stress risk level (low, moderate, high)"
    }
  },
  "actions": {
    "measureConditions": {
      "description": "Measure temperature and humidity, update risk level",
      "type": "string"
    }
  },
  "events": {
    "highHeatStressAlert": {
      "description": "OLED alert for high heat stress risk",
      "data": {
        "heatStressRisk": "high"
      }
    }
  }
}
```

Machine Learning

Data Provenance

The system collects data from three IoT devices worn by agricultural workers:

- **Leg Activity Sensor**: Uses a tri-axial accelerometer to capture movement data, measuring if the leg is stationary or if the leg has various levels of acceleration and movement. This monitors exertion levels by classifying the acceleration data as low, medium or high.
- **UV Exposure Monitor**: A band worn on the workers arm measures UV light intensity using the photoresistor LDR sensor to assess sun exposure risks, by classifying the risk as low, medium or high.
- **Environmental Condition Monitor**: Placed on stationary poles on the agricultural field to monitor an area. Records temperature and humidity at that region using DHT22 Temperature and Humidity Sensor to evaluate heat stress risk levels as low, medium and high.

Challenges in Training

Two key challenges emerge:

1. **Data Heterogeneity**: Workers' data varies due to differing activities which are not considered like jogging, environments and climate of the region of the world, and device placements in the body being different for each worker, and the different worker's tolerance to exposure and exertion, resulting in non-independent and identically distributed data. This complicates model generalization across users.
2. **Collecting balanced data across classes**: Enough data for some event classes (e.g., for overexertion) are scarce and infrequent, so accurately labelling training could be impractical, and post-processing is difficult to skew the data.

Training and Inference Pipeline

- Raw data: Each thing collects raw data using its sensor.
- Preprocess raw sensor data: Raw 3D accelerometer data from the leg activity monitor (1 Hz) is converted to a 1D magnitude signal. UV levels (1 Hz) are converted to W/m^2, normalized, and denoised. Temperature (°C) and humidity (%) from the environmental monitor are logged hourly and noise filtered.
- Data segmentation: segment the signal of the leg activity monitor and UV exposure monitor using a sliding window of a 5 second size and stride of the window of a chosen size. These windows act a different data sample.
- Feature Extraction: Features like mean, variance, and peak frequency are extracted to represent movement intensity, UV exposure trends, and environmental conditions to form data sets to classify.
- **Classification**: Each device trains a model locally using TinyML classifying data on exertion in the leg activity monitor, UV risk on the UV monitor and heat stress in the environmental

exposure monitor with supervised learning on labelled datasets 80% training, 20% validation using stratified sampling useful for imbalanced data due to rare occurrences of a feature, such as very high exposure. Logistic regression with a linear boundary is used for classification.

- Federated learning: Devices send model parameters to a central server ensuring raw data stays on-device, enhancing privacy. The server uses Federated learning to aggregate updates into a global model. The global model is redistributed to devices for further training or inference. This approach optimizes privacy and scalability, addressing data challenges while enabling robust, real-time safety monitoring for agricultural workers.

Training and Inference Locations

- **Training**: Local training occurs on-device for all 3 things with low processing power, using low power consuming TinyML, with aggregation on the cloud server for much costlier training, balancing resource constraints.
- **Inference**: On-device inference (e.g., UV alerts) ensures real-time feedback, critical in low-connectivity areas, while the cloud server inference for all 3 devices can manage the combined model to determine health risk for the workers.

Performance Metrics

Four metrics evaluate the system:

1. **Accuracy**: Measures prediction correctness of the classifications of environmental exertion, UV exposure risk and heat exhaustion risk by the model. The loss function optimises the model fit on the data, over the space of all possible models. The lowest training loss, while the validation set is still following the trend, gives a good accuracy on training data.
2. **Recall**: Ensures high-risk events like heatstroke are detected, minimizing mistakes.

   Recall = Relevant elements retrieved/relevant elements
3. **Precision**: Reduces false positives to avoid unnecessary disruptions and allow better user experience.

   Precision = Relevant elements retrieved/retrieved elements
4. **Latency**: Ensures timely alerts when risk of environmental exposure and exertion is high, using the buzzer, LEDs or OLED screen even in low connectivity areas. This is vital for worker safety.

Managing Security and Privacy

This IoT system for agricultural workers integrates a Leg Activity Sensor, UV Exposure Monitor, and Environmental Condition Monitor to track exertion, UV exposure, and environmental conditions. Data transmits via Bluetooth Low Energy (BLE) to a mobile app and via Wi-Fi to a cloud server for analysis. Given the sensitivity of health and environmental data, robust security and privacy measures are critical. Below, key challenges and mitigations are outlined, followed by additional deployment risks.

Security and Privacy Challenges and Mitigations

1. Data Interception

Challenge: BLE and Wi-Fi transmissions are susceptible to interception by sniffers or packet analysers, risking exposure of health data like exertion levels or UV exposure.
Mitigation: Encrypt BLE with AES-128 and Wi-Fi with SSL/TLS to secure data in transit, preventing unauthorized access. Use Homomorphic Encryption for cloud processing, enabling secure computations on encrypted data. Store keys in a Trusted Execution Environment (TEE) like ARM TrustZone to protect them if devices are compromised.

2. Unauthorized Access

Challenge: Weak authentication could allow hackers or internal stakeholders (e.g., farm managers) to access sensitive data beyond their scope.
Mitigation: Implement role-based access control (RBAC) to limit data access by role and multi-factor authentication (MFA) for cloud security. Host on an ISO 27001-compliant platform and use Private Set Intersection (PSI) for secure, privacy-preserving data queries by stakeholders like insurers.

3. Data Leakage

Challenge: Metadata from transmissions (e.g., timing) could reveal work schedules or health patterns, even with encrypted data.
Mitigation: Apply Differential Privacy to add noise, obscuring metadata while preserving analytical utility. Use Federated Learning to keep raw data on-device, sharing only aggregated updates to minimize leakage risks.

4. Device Tampering

Challenge: Devices in open fields, like the Environmental Condition Monitor, are prone to tampering, potentially skewing health risk predictions.
Mitigation: Use tamper-evident seals and TEE-based firmware validation to ensure device integrity. Employ heartbeat signals for monitoring and Secure Multiparty Computation (SMPC) to validate data across devices.

5. Location Privacy

Challenge: Environmental data (e.g., temperature) could be correlated with weather databases to infer worker locations.
Mitigation: Aggregate data with K-Anonymity (k=5) to prevent re-identification. Minimize location precision and audit data access logs to detect misuse.

6. Consent and Transparency

Challenge: Workers may not understand data usage, risking GDPR non-compliance and trust erosion.
Mitigation: Provide clear, multilingual consent prompts and Privacy Nutrition Labels to summarize data practices in a simple, visual format, enhancing transparency in the app. Enable consent revocation and conduct regular audits to ensure compliance.

Additional Deployment Risks and Mitigations

1. Reliability in Harsh Conditions

Risk: Extreme weather could disrupt device functionality, delaying safety alerts.
Mitigation: Use IP67-rated casings and redundant power (e.g., solar backups). Test units under simulated conditions to ensure reliability.

2. System Scalability

Risk: Large-scale deployments may overload processing or connectivity in rural areas.
Mitigation: Design with horizontal scaling and offline caching. Test with 50+ devices to verify performance.

3. User Adoption and Usability

Risk: Complex or uncomfortable devices may reduce worker uptake.
Mitigation: Create lightweight wearables and a simple app interface. Validate through usability testing with diverse workers.

4. Legal and Regulatory Compliance

Risk: Data mishandling could violate GDPR or occupational laws.
Mitigation: Embed privacy-by-design, maintain compliance logs, and consult legal experts to meet standards.

Approaches to Evaluation

Evaluating the IoT system—comprising the Leg Activity Sensor, UV Exposure Monitor, Environmental Condition Monitor, and mobile app—ensures it effectively monitors agricultural workers' environmental exposure and physical activity.

Evaluation Criteria and Tests

The system's requirements are categorized into functional (what it does) and non-functional (how it performs). The table below defines each requirement, test method, and evaluation criteria, followed by detailed explanations.

Requirement type	Requirement	Test Description	Evaluation Criteria
Functional Requirements	**Data Collection Accuracy-** The Leg Activity Sensor's accelerometer, UV Exposure Monitor's photoresistor, and Environmental Condition Monitor's DHT22 must provide precise data. Tests involve comparing readings against calibrated tools (e.g., a standard UV meter) in controlled settings. Success requires readings within 5% of benchmarks, ensuring reliable health risk assessments.	Compare sensor readings with calibrated equipment	Within 5% of standard measurements
Functional Requirements	**Data Transmission-** BLE and Wi-Fi connectivity must be robust, especially in rural areas with poor internet. Simulating transmissions across low-signal conditions tests reliability, targeting a 95% success rate with retries, critical for real-time monitoring.	Simulate transmission in varied network conditions	95% success rate
Functional Requirements	**Alert Generation-** Alerts for high exertion, UV exposure, or heat stress must be accurate. Using predefined datasets (e.g., exertion levels triggering a buzzer), tests verify 100% accuracy for critical alerts, preventing missed warnings that could endanger workers.	Input known datasets to verify alert accuracy	100% accuracy for critical alerts
Non-Functional, Non-Technical	**Reliability-** The system must withstand field conditions. A week-long deployment in actual agricultural settings monitors failures, aiming for less than 1% downtime to ensure consistent safety coverage.	Field test for one week under real conditions	<1% failure rate

Non-Functional, Non-Technical	**Usability-** The app and devices must be intuitive for workers. Usability testing with 10 agricultural workers involves tasks like checking exposure levels, followed by a System Usability Scale (SUS) survey. Criteria include an SUS score of ≥70 and 80% task completion, reflecting practical field use.	Conduct usability testing with workers; SUS survey	SUS score ≥ 70; 80% task completion
Non-Functional, Technical	**Security/Privacy-** Protecting sensitive data is vital. Penetration testing by a third-party firm identifies vulnerabilities, while audits ensure GDPR compliance. Success means no critical flaws and full regulatory adherence.	Perform penetration testing and compliance audits	No critical vulnerabilities; GDPR compliant
Non-Functional, Technical	**Battery Life-** Wearables must last a 12-hour shift. Continuous operation tests measure consumption, targeting ≥12 hours to support all-day use without recharging.	Measure consumption during continuous operation	≥ 12 hours on a single charge
Non-Functional, Technical	**Offline Functionality-** In low-connectivity areas, devices must function offline Disconnecting the network tests local data storage and syncing speed (within 5 minutes of reconnection), ensuring uninterrupted monitoring.	Test data collection and syncing without connectivity	Sync within 5 minutes of reconnecting

Testing Methodology

Unit testing verifies individual components (e.g., sensor accuracy), integration testing ensures BLE/Wi-Fi communication, and end-to-end testing with participants simulates real-world use. Network usage, critical for IoT systems, is measured via OS settings or a dedicated router, tracking data per use case. Iterative refinement follows results, adjusting based on usability feedback or performance gaps.

Conclusion

This evaluation approach ensures the system meets technical demands (accuracy, reliability, security) and non-technical needs (usability), delivering a practical, safe solution for agricultural workers. By testing in near-real conditions, it validates effectiveness in mitigating occupational health risks.

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