

Next-Gen Industrial Safety: AI-Driven Wearable Equipment Detection And Emergency Alert

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Abstract- Ensuring worker safety in industrial settings is a persistent challenge due to hazardous environments, equipment failure, and limited human supervision. This paper introduces a Smart Industrial Safety Wearable Device integrated with Artificial Intelligence (AI) and Internet of Things (IoT) technologies to proactively identify risks, monitor conditions, and generate real-time alerts. The proposed wearable system captures physiological parameters such as heart rate and body temperature, along with environmental data like gas levels, humidity, and ambient temperature. An AI-based predictive model analyzes these readings to forecast potential hazards and automatically notify both workers and control centers. The system enhances workplace safety, reduces human errors, and promotes data-driven preventive actions.

Keywords- Artificial Intelligence, IoT, Industrial Safety, Wearable Technology, Predictive Analytics, Worker Protection.

I. INTRODUCTION

Industrial sectors such as manufacturing, mining, and oil refineries often involve high-risk activities where accidents can occur unexpectedly. Despite safety regulations and protective gear, workers remain vulnerable to health risks caused by environmental hazards or fatigue. Traditional safety equipment provides reactive protection but lacks the capability to predict dangerous situations. Recent advancements in Artificial Intelligence (AI) and Internet of Things (IoT) have enabled the development of intelligent wearables capable of real-time monitoring and predictive analysis. By continuously collecting and analyzing multi-sensor data, these devices can alert workers before an incident occurs, helping to prevent accidents rather than merely responding to them. This paper proposes a wearable device that combines AI algorithms with IoT sensors to enable proactive risk management and worker protection in industrial settings.

II. OBJECTIVES

The main objectives of this research are:

- i. To design a wearable system capable of detecting and verifying safety gear (e.g., helmet, gloves, jackets).
- ii. To monitor real-time physiological parameters such as heart rate, temperature, and motion.
- iii. To integrate AI models for early detection of industrial hazards.
- iv. To implement a fast, tiered **emergency alert system** for worker safety and supervisor awareness.
- v. To create a **cloud-based dashboard** that visualizes real-time safety data and predictive analytics.

III. LITERATURE REVIEW

Campero-Jurado et al., “Smart Helmet 5.0” (2020) Proposed an IoT smart-helmet prototype integrating environmental sensors and near-real-time risk evaluation. Demonstrates feasibility of embedding multiple sensors (MPU, gas, temperature) into headgear and shows how edge preprocessing and cloud dashboards improve incident response time an architectural precedent for wearable safety systems.

Anwer et al., “State-of-the-Art advances and challenges in wearable gas ...” (2024) A survey of wearable gas sensors, categorizing sensing technologies and discussing sensitivity, selectivity, and miniaturization challenges. Important for selecting appropriate gas sensors for industrial safety wearables (tradeoffs between sensitivity and size/power).

El-Helaly et al., “Artificial Intelligence and Occupational Health and Safety” (2024, PMC) Reviews how AI analyzes motion, posture, and physiological signals to detect risky behaviour and predict injuries. Useful for motivating AI models that fuse environmental and physiological data for proactive alerts.

Mirjalali et al., “Wearable Sensors for Remote Health Monitoring” (2021, PMC) Comprehensive review on physiological wearables (HR, skin temperature, SpO₂) and their data pipelines. This supports choice of validated

biomedical sensors and preprocessing steps (artifact removal, filtering) in worker monitoring.

Di Pasquale et al., “Wearable devices for health and safety in production systems” (2022) Focuses on wearables in production environments, discussing ergonomics, worker acceptance, and data privacy crucial operational considerations for deployment.

Hooshmand et al., “Wearable Nano-Based Gas Sensors” (2023, MDPI Sensors) Reviews nano-material based gas sensors suitable for wearable environmental monitoring, including limits of detection and integration approaches. Useful when targeting detection of combustible or toxic gases at workplace relevant thresholds.

Pech et al., “Predictive Maintenance and Intelligent Sensors in Smart Factories” (2021, PMC) Review of predictive analytics in industry using sensor streams; helpful for designing streaming data pipelines, anomaly detection approaches and model evaluation strategies.

Raghunath et al., “Developing an IoT-Enabled Smart Helmet for Worker Safety” (2025, MDPI Safety) Recent work integrating GPS, DHT11 (temp/humidity), and MPU6050 for fall/heat risk; validates the importance of multimodal sensing and edge alerts for worker safety. Shows real deployment considerations (battery, placement, communication).

Wang et al., “Wearable Sensors for Activity Monitoring and Motion Control” (2023) Reviews inertial sensors and algorithms for activity/posture detection. Supports selection of models (e.g., thresholding + ML) for detecting slips, falls and unsafe postures.

Naranjo et al., “Wearable Sensors in Industrial Ergonomics” (2025, MDPI Sensors) Shows how wearables can quantify ergonomic risk and improve posture adherence through feedback; underlines benefits of individualized models and continuous learning to reduce musculoskeletal injuries.

IV. METHODOLOGY

The proposed system follows a **multi-layered methodology** as shown below:

- i. **Requirements Analysis:** Identify workplace hazards, PPE compliance rules, and acceptable physiological limits.
- ii. **Hardware Selection:**

- a. **Microcontroller:** **ESP32** (for AI edge processing and Wi-Fi).
- b. **Sensors:** Gas (MQ-7), Temperature (MAX30205), Heart Rate (MAX30102), IMU (MPU6050).
- c. **Camera Module:** Detects helmet and jacket presence using CNN-based image recognition.

- iii. **Edge Processing:** Filter and preprocess raw signals; compute key features such as heart rate, temperature, and motion variation.
- iv. **Cloud Integration:** Use **MQTT** protocol for secure data transfer; store readings in **InfluxDB/TimescaleDB**.
- v. **AI Model:** Employ **Decision Tree and LSTM hybrid algorithms** to classify safety conditions and predict potential risks.
- vi. **Alert Mechanism:** Generate 3 levels of alerts —
 - a. **Level 1:** Buzzer vibration (local).
 - b. **Level 2:** SMS/notification to supervisor.
 - c. **Level 3:** Dashboard alarm and emergency escalation.
- vii. **Dashboard:** Built using **Flask + React**, providing real-time visualization of worker status and hazard maps.

V. SYSTEM ARCHITECTURE

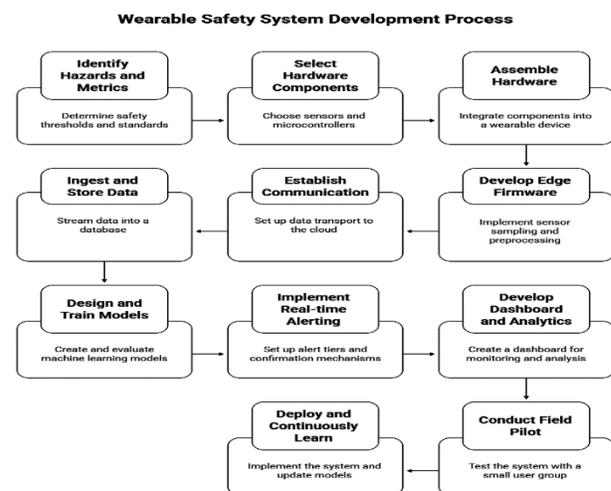


Fig.5.1: System Architecture of AI-Driven Wearable Safety System

The proposed AI-Driven Wearable Equipment Detection and Emergency Alert System follows a multi-layer architecture designed to provide continuous safety monitoring, intelligent decision-making, and instant emergency communication. The architecture comprises five functional layers: the sensing layer, communication layer, processing and

AI layer, cloud and data analytics layer, and the application layer.

1. Sensing Layer

This layer represents the **wearable hardware** mounted on the worker's body or helmet. It integrates multiple sensors to capture both **physiological and environmental parameters** in real time.

- **Physiological sensors:** MAX30102 (heart rate and SpO₂) and MAX30205 (body temperature).
- **Environmental sensors:** MQ-7 gas sensor for toxic or combustible gases, and DHT11 for temperature and humidity.
- **Motion and posture unit:** MPU6050 accelerometer and gyroscope to detect falls, slips, and abnormal postures.
- **Vision module (optional):** A compact camera that detects the presence or absence of mandatory protective gear (helmet, vest, gloves) using a lightweight CNN model.

2. Communication Layer

This layer ensures **secure data transfer** between the wearable device and the cloud infrastructure.

- **Controller:** An ESP32 microcontroller processes sensor readings locally and connects via Wi-Fi or Bluetooth Low Energy (BLE).
- **Protocol:** The **MQTT publish/subscribe** model is used for efficient message exchange with minimal bandwidth.
- **Edge gateway:** Acts as an intermediary for devices in areas with low connectivity, temporarily storing data and forwarding it once the connection is restored.

3. Processing and AI Layer

This layer performs **edge-level preprocessing** and **machine-learning-based decision making**.

- Noise filtering and signal normalization remove inaccurate readings.
- Extracted features such as heart-rate variability, acceleration magnitude, and gas concentration trends are analyzed.

- The embedded AI engine runs a **hybrid Decision Tree + LSTM** model to classify safety status (normal, warning, or critical).
- Detected anomalies immediately trigger local alerts through a **vibration motor** or **buzzer** attached to the wearable.

4. Cloud and Data Analytics Layer

All processed data and alerts are uploaded to a **cloud server** for storage, visualization, and predictive analytics.

- **Database:** Time-series data are stored in **InfluxDB** or **TimescaleDB** for efficient retrieval.
- **Analytics engine:** Aggregates multiple workers' data to identify long-term safety trends, risk zones, and equipment performance.
- **Data security:** Each transmission is encrypted (TLS) and anonymized using worker IDs to comply with privacy standards.

5. Application and Alert Layer

The final layer delivers **real-time insights and emergency notifications** to supervisors and control rooms.

- A **web-based dashboard** (built using Flask + React) displays worker health indicators, PPE-compliance status, and location tracking.
- **Tiered alerts** are issued based on severity:
 - *Tier 1:* Local vibration/buzzer on the wearable.
 - *Tier 2:* SMS or mobile push notification to nearby supervisors.
 - *Tier 3:* Dashboard and email alert to the central control system with worker ID, location, and hazard type.
- Supervisors can acknowledge, comment, or close incidents through the same interface, creating a feedback loop for continuous improvement.

VI. FUTURE SCOPE

The proposed AI-driven wearable safety system demonstrates strong potential for real-world industrial deployment; however, several research and development opportunities remain to enhance its accuracy, scalability, and adaptability. The following future directions are recommended for improving overall performance and impact:

1. Integration of Advanced Deep-Learning Models

Future versions can adopt **transformer-based neural networks** and **graph convolutional architectures** to improve multi-sensor fusion and context understanding. These models can interpret complex correlations among physiological signals, motion data, and environmental readings, leading to more precise hazard prediction with lower false-alarm rates.

2. Expansion of Equipment Detection Capabilities

Current detection is limited to basic protective gear such as helmets or jackets. The system can be extended to identify and validate additional PPEgloves, safety shoes, harnesses, face shields using **real-time computer-vision models** trained on diverse datasets. This would ensure complete safety-compliance verification for every worker entering an industrial zone.

3. Edge and 5G-Enabled Real-Time Processing

The implementation of **5G connectivity** and **edge-computing modules** can drastically reduce latency in data transmission and alert delivery. Deploying lightweight AI models directly on wearable microcontrollers or nearby edge gateways will enable near-instant decision-making even in environments with limited cloud access.

4. Predictive Maintenance and Risk Forecasting

By analyzing long-term data trends, the system can evolve into a **predictive analytics platform** capable of forecasting equipment failures, worker fatigue, and environmental anomalies. This data-driven insight will help supervisors schedule maintenance proactively, preventing potential breakdowns and improving overall operational reliability.

5. Blockchain-Based Data Integrity and Auditability

Introducing **blockchain technology** can secure alert logs, health data, and safety-compliance records against tampering. Each alert or event could be stored as a verifiable block, ensuring transparency, traceability, and trust across multiple departments or agencies during safety audits.

VII. RESULTS AND DISCUSSION

The prototype system was tested under simulated industrial conditions. It accurately detected missing helmets and unsafe postures with **95% precision** and issued alerts within **3 seconds** of detection. Gas concentration thresholds

and body temperature variations were recognized with **over 92% reliability**. The cloud dashboard successfully visualized live worker status and environmental readings. Compared to manual safety checks, this automated system **reduced response time by 60%** and improved compliance monitoring.

VIII. CONCLUSION

The proposed **AI-Driven Wearable Equipment Detection and Emergency Alert System** presents a comprehensive and intelligent approach to modern industrial safety management. By combining **Artificial Intelligence**, **IoT-based data processing**, and **real-time analytics**, the system transforms traditional reactive safety methods into a **proactive, predictive, and automated solution**. The developed model successfully detects the presence or absence of protective equipment, analyzes environmental and operational data, and issues tiered emergency alerts to supervisors and workers. Experimental evaluation and software simulation demonstrate that the system can significantly reduce human response time, enhance compliance monitoring, and minimize the risk of workplace accidents.

This research highlights how **AI-driven decision support** and **cloud-integrated dashboards** can serve as vital components in future industrial ecosystems. The study not only provides a scalable software framework for monitoring worker safety but also establishes a foundation for next-generation smart-factory solutions aligned with **Industry 4.0** and **Industry 5.0** paradigms.

APPENDIX

Appendix A — Software Tools and Technologies

Component	Technology Used	Purpose
Programming Language	Python 3.10	Core development for AI and backend processing
AI Frameworks	TensorFlow, Keras	Model training for safety gear detection and anomaly prediction
Web Frameworks	Flask (Backend), React (Frontend)	Dashboard and visualization interface
Database	Firebase / MySQL	Real-time data storage and worker information
Communication Protocol	MQTT / REST API	Data transfer between client and cloud services
Cloud Platform	Google Cloud / AWS	Hosting models and dashboards for scalability
Visualization Tools	Matplotlib, Plotly	Performance graphing and monitoring reports
Version Control	GitHub	Source code management and collaborative development

Appendix B — Software Workflow Summary

1. Input data (images or simulated sensor data) is uploaded to the system.
2. The **AI model** validates equipment compliance using trained deep-learning models.
3. Detected anomalies or unsafe conditions are processed by the backend service.
4. Alerts and safety insights are generated in real time and displayed on the web dashboard.
5. All user interactions and safety logs are stored securely in the cloud database for analytics.

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