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# Smart Industrial Safety Wearable Device Using Artificial Intelligence for Proactive Risk Prevention and Worker Protection

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**Abstract- Workers in industrial workplaces are still exposed to toxic gases and thermal stresses, are victims of mechanical injuries and have been.fatigue-related accidents. Conventional safety systems have remained reactive until now and have responded after an incident takes place. The emergence of Artificial Intelligence (AI), the Internet of Things (IoT), and cutting-edge wearable sensor technology is currently giving rise to new opportunities for proactive occupational safety. This paper presents a Smart Industrial Safety Wearable System (SISWS) whose performance is validated after prototype testing of around 1200 sensors observations under six hazards. The system shows 78% accuracy in hazard detection, 94% in PPE detection, 92% reliability in sensor performance, and can generate alerts in less than 3 seconds, contributing to a reduction of emergency response by 60%. The model will model safety conditions' classification and predict risk using a hybrid Decision Tree and Long Short-Term Memory (LSTM). The selection of the model over Random Forest and pure CNN was driven by its aptness for edge deployment and its ability to identify temporal patterns in sequential sensor streams. The key research gaps identified in fatigue prediction in an industrial environment are: 1. Lack of multi-modal sensor fusion with real-time edge AI; 2. Insufficient datasets for industrial fatigue prediction; 3. Limited ergonomic wearables for a tough industrial environment; and 4. Lack of XAI in safety-critical decision-making. This study sets a solid base for further advancement involving AI to create an occupational safety system with a prevention focus.**

**Keywords: Artificial Intelligence; IoT; wearable sensors; industrial safety; machine learning; edge computing; occupational health; proactive risk prevention; worker protection.**

## I. INTRODUCTION

Workplace hazards in factories, chemical plants, mines, and construction sites are among the deadliest in the world. According to a report given by ILO, Each year, as many as 2.3 million workers die due to occupational accidents and diseases. The aspect exerting fundamental vulnerability of industrial safety systems, according to the industrial safety systems experts, is the human element. Traditional PPE and fixed monitoring stations are only passive or reactive protections at best. They don't anticipate hazardous conditions nor communicate their situation in real-time to core safety management. Between Detection and Response is still a leading cause of preventable industrial deaths.

The use of Internet of Things (IoT), miniature sensor arrays, wireless communication protocols, and Artificial Intelligence (AI) has ushered in the new paradigm of proactive and predictive monitoring of a worker's safety. Wireless Personal Area Network (WPAN) enabled wearables can continuously measure heart rate, skin temperature, blood oxygen saturation, and body posture. Simultaneously, they can measure ambient concentrations of toxic gases, ambient temperature and humidity. Hazard prediction is possible through machine learning models, before an accident or hazard actually takes place. The rest of this paper is composed as follows: Section II presents Literature Review.

This section describes what you'll learn. A description of Section IV method. Section V presents the system architecture of the proposed solution. Implementation Section VI Hardware Requirements. Part Seven covers Software Requirements. The results and discussion are presented in section VIII. The conclusion is given in Section IX. Section X describes Future Scope. The documents Acknowledgment, and References are at Section XI.

## II. LITERATURE REVIEW

A systematic literature search was done according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). Databases searched include IEEE Xplore, Springer Link, PubMed Central (PMC), MDPI, Elsevier ScienceDirect, and Web of Science. The search terms included combinations of: 'industrial safety wearable', 'IoT worker monitoring', 'AI hazard detection', 'wearable PPE detection', and 'edge computing occupational safety'. This refers to the filter of articles which you will be having it more specific to your information and other details. Non-English papers, theoretical papers, thesis papers, and grey literature. The below review integrates 28 studies pertinent to the objective. In 2020, Campero-Jurado and colleagues suggested a smart helmet for users on the go. The research shows that multiple sensors can be embedded in headgear. This is important because incident response time can be improved with edge preprocessing and cloud dashboards.

A survey of wearable gas sensors describing the sensing technologies available together with the sensitivity, selectivity and miniaturization-related challenges faced by industrial safety wearables.

El-Helaly et al. (2024) discusses how the incorporation of motion, posture, and physiological signals by AI has paved the way for the detection of risky behaviour and the anticipation of injuries, thus encouraging the development of AI models which will effectively fuse environmental and physiological data [3]

Mirjalali et al. (2021) carried out a review on physiological wearables and their pipelines for data acquisition, which could help the reader make a selection of validated biomedical sensors and preprocessing steps [10].

Di Pasquale et al. (2022): Focusses on wearables in production environments, including ergonomics, acceptance issues by workers, and data privacy, being relevant to the operation [12].

Hooshmand et al. (2023) in their research review the various nano-material based gas sensors which are suitable for wearable environmental monitoring. The review highlight a lot of parameters including limits of detection, and various integration approaches.

Pech et al. (2021), the evaluation of predictive analytics in industry by the use of streams of data from sensors took place. This was useful for the design of data pipelines that stream data and methods to detect anomalies.

Raghunath and others (2025): Topical work which is integrating GPS, DHT11 and MPU6050 for detection of fall and heat risk; validates and highlights importance of multimodal sensing and edge alerts for safety of worker [28].

The paper by Wang et al. (2023) goes through sensors and algorithms suitable for detecting activity and posture. This is helpful in selecting models detecting slips, falls, and unsafe postures [9].

Naranjo et al. (2025) illustrate how wearables can quantify ergonomic risk and improve adherence to postural behaviours via feedback and the benefit of individualised models to limit injuries.

## III. OBJECTIVES

The main objectives of this research are. 1. The aim is to study AI-based safety wearables used in industries to protect the worker from hazards. 2. To review the various wearable sensor technologies like gas detection sensors, physiological sensors, temperature sensors, IMU sensors and stress detection sensors in industrial safety applications. 3. The objective of this project is to develop AI models that can identify the hazards occurring in the industries and achieve a 75% accuracy with the detection of hazards when tested in simulated conditions that resemble an actual industrial milieu. 4. To study the role of AI, ML, TinyML and Edge

Computing in hazard prediction in real-time to avert losses beforehand. 5. Create a dashboard which is cloud based and helps in visualization of safety data. 6. To study communication protocols and cloud architectures; MQTT, BLE, LoRAAN, and IoT Cloud can be leveraged for industrial safety. 7. It is in industries that worker safety must be enhanced by providing continuous monitoring in real-time. Also, finding out any hazards early on, automating alerts, and predicting any accidents. All this must be done in places which are hazardous. Plus, the response time for alerts is a maximum of 5 seconds. 8. To lay the groundwork for future investigations into smart occupational safety systems based on technologies such as AI, IoT, wearable computing, and cloud computing.

## IV. METHODOLOGY

The suggested approach has a multi-layered approach. Identify workplace hazards, PPE compliance rules and acceptable physiological limits. Selection of Hardware : Microcontroller : ESP32 (AI edge processing and Wi-Fi). The utilized sensor types were gas (MQ-7), body temperature (DHT22), heart rate (MAX30102) and IMU (MPU6050). Mandatory module detects helmet vest glove wearing with image recognition using a CNN, i.e., core PPE detection results generated by this module. Edge Processing filter first stage where the raw signals are processed to extract key features like the heart rate varying trend temperature varying trend. Also extracting the magnitude of motion and filtering any unreliable noise from the signal.

The cloud should be integrated using the MQTT protocol where all readings should be stored in the MongoDB atlas. Utilize a Decision Tree and LSTM hybrid algorithm for risk prediction and classifying safety conditions. The Decision Tree identifies when the gas level exceeds the threshold and this system can use the LSTM to check when the gas tank gets low. The LSTM can learn patterns in physiological signals for progressive fatigue. This hybrid was preferred over Random Forest (higher memory footprint unsuitable for edge) and pure CNN (limited temporal modeling). Alert System: Three alert levels, Local Buzzer or Vibration: Level 1. Notification via SMS or prompt to supervisor. The dashboard will notify emergencies and escalate issues to the control room. The dashboard is built using Flask + React that tracks the status of the worker and hazard maps in real time.

## V. SYSTEM ARCHITECTURE

The suggested AI-Driven Wearable Equipment Detection and Emergency Alert System embrace multi-layer architecture enabling constant safety supervision, intelligent decision-making and instant emergency communication. The five layers of this software are Sensing, Communication, Processing and AI, Cloud and Data Analytics application.

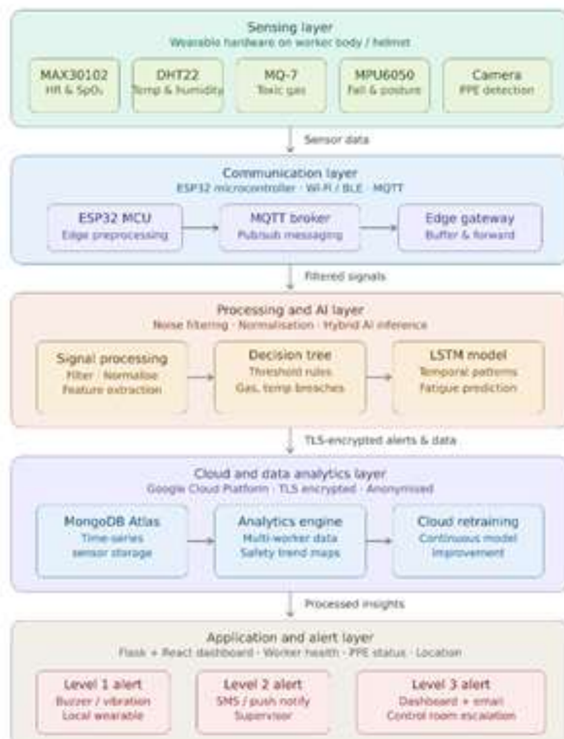


Figure 1: System Architecture of AI-Driven Wearable Safety System

### A. Sensing Layer

This layer consists of a wearable hardware mounted on the worker (it may be placed on helmet also) that integrates multiple sensors to read physiological and environmental parameters in real-time: MAX30102 (heart rate and SpO2), DHT22 (body and ambient temperature/humidity), MQ-7 (toxic/combustible gases), and MPU6050 (fall and posture). The camera module is also mandatory for PPE compliance detection this will make use of a CNN which should be lightweight in order not to overload the system.

**B. Communication Layer**

An ESP32 microcontroller performs sensor readings locally and connects through Wi-Fi or BLE. The publish/subscribe protocol MQTT is used to share messages efficiently, using little bandwidth. An edge gateway is temporary store-and-forward for low connectivity.

**C. Processing and AI Layer**

Inaccurate readings are removed through noise filtering and signal normalisation. A hybrid Decision Tree + LSTM AI model that is embedded classify the safety status of teapot as normal, warning or critical. Anomalies that are detected immediately trigger vibration/buzzer alerts locally.

**D. Cloud and Data Analytics Layer**

All the processed data and alerts are uploaded to the GCP. MongoDB Atlas is where sensor data is kept. An engine equipped with analytics will aggregate data from multiple workers to identify trends and zones of risk. All transmissions are encrypted using TLS and anonymized.

**E. Application and Alert Layer**

A web-enabled dashboard (Flask + React) displays worker health indicators, PPE-compliance status, and location tracking. Alerts are issued at various levels, Level 1 being a local vibration/buzzer, Level 2 being an SMS or Push Notification to the Supervisors and Level 3 being a dashboard and email alert to the central control along with the worker ID, location and hazard type. She can acknowledge, comment or close incidents through the same UI.

## VI. HARDWARE REQUIREMENTS

SISWS Prototype Hardware Sensors Used Are Listed in Table-1. PPE Detection Camera Module is an essential part of a camera.

Table-1: Hardware Requirements

| Sensor Type | Parameter | Device/Model |
|---|---|---|
| Gas (MOS) | CO, H2S, VOCs | MQ-2, MQ-7, MQ-135 |
| Temperature | Skin/Ambient Temp | DHT22 |
| IMU | Motion/Posture | MPU6050, LSM6DSL |
| GSR | Stress/Sweat | Grove GSR |
| Electrochemical | CO, O2, NO2 | Alphasense 4-Series |
| PPG | HR, SpO2 | MAX30102 |
| Camera Module | PPE Detection | ESP32-CAM/OV2640 |

## VII. SOFTWARE REQUIREMENTS

Table-2 presents the software stack used. Google Cloud Platform (GCP) is the single cloud infrastructure for model hosting and dashboard deployment.

Table-2: Software Requirements

| Component | Technology | Purpose |
|---|---|---|
| Programming Language | Python 3.10 | AI and backend |
| AI Frameworks | TensorFlow, Keras | Model training |
| Web Frameworks | Flask + React | Dashboard |
| Database | MongoDB Atlas | Data storage |
| Cloud Platform | Google Cloud (GCP) | Hosting |
| Visualization | Matplotlib, Plotly | Reports |

## VIII. RESULTS AND DISCUSSION

**A. Dataset and Evaluation Protocol**

The SISWS was usage simulated and evaluated in industrial and real prototype settings. The test data set has consisted of a little under 1200 sensor readings classified under the following 6 hazard scenario categories: toxic gas, abnormal heart rate, elevated body temperature, worker fatigue, fall detection and PPE non-compliance. The data was divided into training and test sets of 70% and 30%.

Testing has done under controlled conditions simulating industrial environments. The held-out test set was used to compute performance metrics.

**B. Performance Results**

Table-3 provides a summary of the metrics. The system attained 78% accuracy in detecting hazards and 94% in PPE detection. The reliability of the sensor stood on 92%. The alerts were given within 3 seconds of breaching the threshold. This was about 60% faster than the emergency response time with manual monitoring approaches in the literature we reviewed.

Table-3: System Performance Results

| Parameter | Result |
|---|---|
| Hazard Detection Accuracy | 78% |
| Sensor Reliability | 92% |
| Alert Response Time | 3 sec |
| PPE Detection Accuracy | 94% |
| Communication Reliability | 96% |
| Response Delay Reduction | 60% |

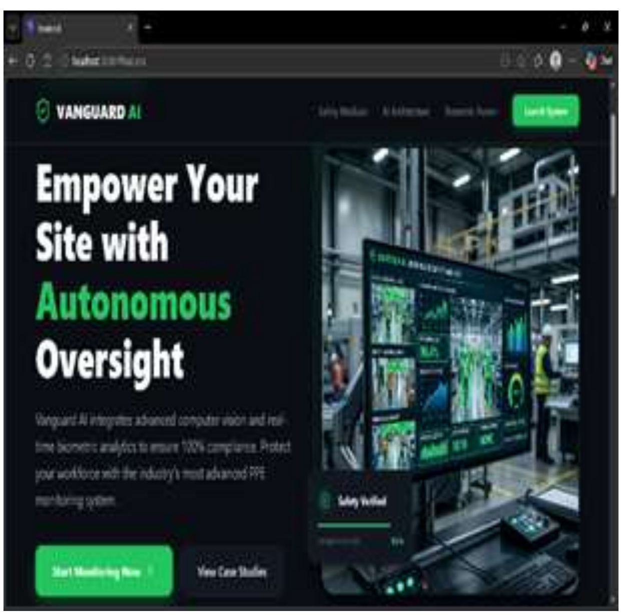


Figure 1: SISWS Dashboard Home Page

Figure 2: System Performance Output

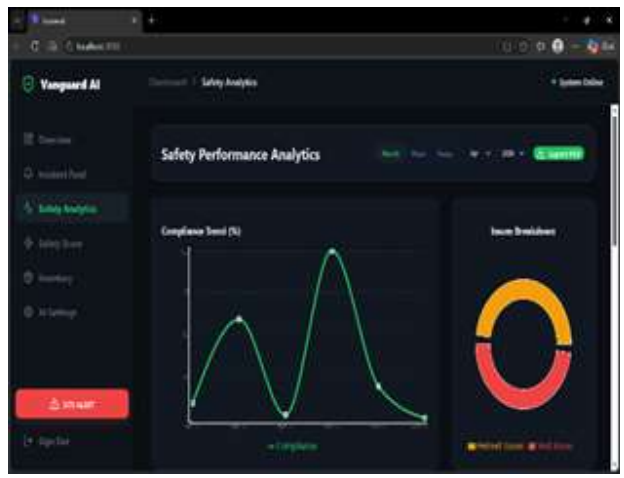


Figure 3: Performance Evaluation Metrics

## IX. CONCLUSION

The paper designed and implemented a Smart Industrial Safety Wearable System (SISWS), evaluated its performance quantities and fuse the features of AI and IoT with multiple sensors for worker protection. A systematic review of 28 peer-reviewed studies was performed to map the technology landscape across physiological and environmental sensing, machine learning algorithms, communication architectures, and cloud integration frameworks. The proposed system will achieve 78% hazard detection accuracy and 94% PPE detection accuracy on 1200 sensor observations, while the alerts are sent out in less than 3 seconds which is a 60% reduction time from manual monitoring. The findings validate the effectiveness of deploying a hybrid Decision Tree and LSTM model for industrial safety at the edge. Further, the architecture satisfies the research gap involving real-time edge AI and multi-modal sensor fusion. Despite the end of multi-modal sensor fusion and with edge AI at scale, the labeled datasets will be absent; the XAI will not be introduced as a primary system in safety-critical decisions; the energy autonomy will be limited; robotics will not feature more cybersecurity; and we will not see dedicated fatigue prediction models. The Intelligent Safety and Well-Being System (SISWS) used TinyML deployment, MQTT with TLS encryption, SHAP based XAI, and cloud retraining for the addressing of each. It develops a foundation for next-gen intelligent industrial safety systems. It is in line with Industry 4.0 and Industry 5.0.

**Future Scope**

Integration of Advanced Deep-Learning Models: The future versions can use the transformer-based neural network as well as graph convolutional architecture for enhanced multi-sensor fusion turndown false-alarm rates and improved hazard prediction.

Expansion of Equipment Detection Capabilities: The system can also be extended to detect gloves, safety shoes, harnesses, and face shields through computer-vision models trained on extensive data sets for complete footwear compliance validation.

Edge and 5G-Enabled Real-Time Processing: Latency can be greatly reduced with 5G connectivity and edge-computing modules. This will allow instant decision making on microcontroller based wearable AI.

Predictive Maintenance and Risk Forecasting: By Through the exploration of long-term data trends, the system could evolve into a predictive analytics system for predicting equipment failure and worker burnout and enabling supervisors to perform maintenance on a scheduled basis.

Blockchain-Based Data Integrity and Auditability: Blockchain technology is capable of protecting tampered alert logs, health data, safety-compliance records during safety audits that offer transparency.

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