Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

AI-Driven Safety and Health Monitoring System: A Three-Tier Architecture for Industrial Environments

Bassam Alhamad[1], Nandita Sengupta[2], Mahmood S. M. Alalawi[3], Rayyan Ajjawi[4], Maryam Aldoseri[5], Bintu Jasson[6]

[1]*University of Bahrain*
[2]*University College of Bahrain*
[3]*University College of Bahrain*
[4]*University of Bahrain*
[5]*University of Bahrain*
[6]*University of Bahrain*

ARTICLE INFO

Received: 18 Dec 2024

Revised: 10 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

This study uses three-tier architecture to explain safety and health monitoring in industrial environments. It attempts to combine wearable sensors, AI-driven models and finally data visualization. Tier-one presents real-time health metrics that are collected using wearable devices; embedded with sensors. Tier-two is set to portray an AI-driven system, utilizing MATLAB's Aggregate Channel Features (ACF). Tier-three shows how data is integrated and visualized in Power BI dashboards for actionable insights. AI-driven system is considered important as it predicts Personal Protective Equipment (PPE) requirements to safeguard workers from potential safety risks and ensures compliance with Personal Protective Equipment (PPE) requirements. The suggested three-tier architecture addresses the limitations of manual monitoring by providing real-time, data-driven solutions. It has high potential to significantly improve compliance and proactive safety management. The proposed three-tier architecture highlights the importance of integrating the three levels: to enhance health and safety in an industrial working setting. Active detection and monitoring can facilitate fast responses in emergencies and improve decision making systems.

Keywords*:* AI Driven Safety Management, Three-tier architecture, Learning in MATLAB, PPE for Worker, Industrial Safety.

INTRODUCTION

Artificial Industrial work environments like construction sites, manufacturing plants and oil fields bring in a number of safety and health risks. Minimizing accidents and occupational hazards is a common aim for industrial establishments. Ensuring compliance with safety protocols and monitoring worker health in real-time are critical in this regard. While traditional approaches depend on manual checks and self-reporting, it often results in delayed responses and inconsistencies.

Safety precautions are not fully observed in industrial worksites; in fact, there are limited real-time monitoring methods to apprise the health status of workers. Conventional ways based on manual checks usually rely on the subjective self-reporting of responses.

This paper proposes a three-tier architecture that integrates real-time data collection, AI-driven analytics and finally visualization to meet these challenges. The three-tier framework includes wearable sensors to measure the health metrics, the AI-trained models to ensure compliance with the PPE in terms of safety and risk (Foster, 2024; Huang, 2023; Lin & Zhao, 2024; Singh, 2023; Wang, 2023)and the Power BI to visualize the data for supervisors and decision makers.

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

LITERATURE REVIEW

There had been many efforts in using sensors to provide information about workplace safety. However, real-time implementation was challenging as the system should be able to read or collect data from the field continuously. The more difficult part is the processing and decision-making, which required the employment of AI technology that acts as the decision-maker. This will replace the manual checks that would require high cost plus the less efficient follow-up. In this regard, the ACF object detector from MATLAB proved quite effective in detecting quite a number of PPE items, especially helmets, safety jackets, and earmuffs (MathWorks, 2024c, 2024b, 2024a, 2024d). CNN and deep learning models go further, adapting to environmental changes such as illumination variation and complex backgrounds that increase the accuracy and reduce the false positives .

Wearable health-monitoring devices also find applications in construction and oil fields where continuous health monitoring is mandatory. Now, the MAX30100 sensor for heart rate and SpO2 measurements, together with the DHT11 sensor for temperature and humidity, has made possible the continuous monitoring of health indicators that could offer possibilities for early detection of the onset of fatigue, heat stress, and hypoxia signs and symptoms. As noticed, wearable sensors with wireless communication modules, such as ESP32, may support remote health monitoring through continuous transmission of health data for timely intervention (Chen et al., 2023; Hernandez & Wong, 2024; R. Kumar, 2023; Maxim Integrated, 2015; Smith & Brown, 2023; White & others, 2023).

Chen et al. pointed out that wearable devices are crucial in construction safety because the continuous health information enables proactive handling of all kinds of safety risks (Chen et al., 2023). In addition, Hernandez and Wong also showed that wearable devices are one of the best solutions for preventing incidents due to physical stress in industry sectors (Hernandez & Wong, 2024). All this evidence proves that wearable health monitoring is helpful in general industrial safety systems.

Power BI is used as an essential visualization tool within the system, amalgamating data coming from various sources, such as those coming from PPE compliance and health metrics. Power BI was used to ensure proper visualization of data in real time, hence enabling fast action on abnormal health metrics or concerns of non-compliance, thus useful for industrial high-stakes decision-making (Kim, 2024; Lin & Zhao, 2024). Zhang also observed embedding real-time data visualization within the safety system helps supervisors monitor safety trends and take proactive intervention (Zhang, 2022).

This is built upon by the work of Valayil et al. to show that AI-based PPE systems reduce human error in compliance monitoring and that of Silver, examining how predictive analytics within safety monitoring identifies trends in risk (Silver, 2024; Valayil et al., 2024), by integrating both computer vision for PPE detection and wearable health monitoring. Such a dual-layered approach to monitoring both compliance and health provides a holistic safety solution tailored for application in high-risk settings.

Industrial safety is emphasized by a post-construction safety study using artificial intelligence techniques, image processing, and computer vision developed using MATLAB. Its major focus is based on intruder detection and the misplacement of objects. Detection of an intruder was through the ACF model and VJ algorithm, while object misplacement detection uses the same techniques employed in misplaced tool detection in enhancing the standards of workplace safety (Huang, 2023; Tan, 2023; Valayil et al., 2024). Approaches for psychological states and assessment of risk. In performing the analysis of the literature, Cite Space software has shown issues, research trends, and possibilities of wearable technology that can enable further facilitation of the management of safety risks and ensure sustainable development are made (D-Robotics UK, 2010; Johnson & others, 2023; Valayil et al., 2024). The validity of in-ear photoplethysmography devices in monitoring heart rate as an alternative to electrocardiography during physical activities has promising research in health monitoring. Indeed, the test proof that in-ear PPG is reliable in the measurement of pulse rate and applicable for monitoring intensity of physical activity, hence suitable for an alternate traditional approach (Hernandez & Wong, 2024).

THREE TIER ARCHITECTURE

This section provides step by step method for developing the AI based integrated system for workplace safety and health management for workers in different applicable fields, like oil and gas manufacturing plant, chemical plant,

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

power generating plant etc. In this paper, a comprehensive framework is designed with the implementation of the three-tier architecture for application of industrial safety and health monitoring of workers. In this three-tier architecture, real-time data is collected, AI-driven analytics plays and important role and finally the visualization provides the satisfaction of achievement of health and safety management system. Each tier builds upon the previous, creating a seamless flow of information from wearable sensors to actionable insights and predictions. This system ensures continuous monitoring, compliance with personal protective equipment (PPE) requirements and proactive safety management, addressing the critical needs of high-risk industrial environments. This study employs a three-tier methodology encompassing real-time data collection, AI-driven analytics and PPE compliance through visualization (P. M. Kumar & Gandhi, 2018). It starts with Tier 1 that involves the real-time data collection. Tier 2 represents the AI-driven prediction and compliance. The images are taken with different positions while wearing the PPE in all possible different situations which help the model to ensure the compliance. Tier 3 provides data visualization and integration, which includes health metrics using sensors and a Power BI dashboard for visualization. Hundreds of images are taken to train the AI model. Figure 1 shows the three tier components.

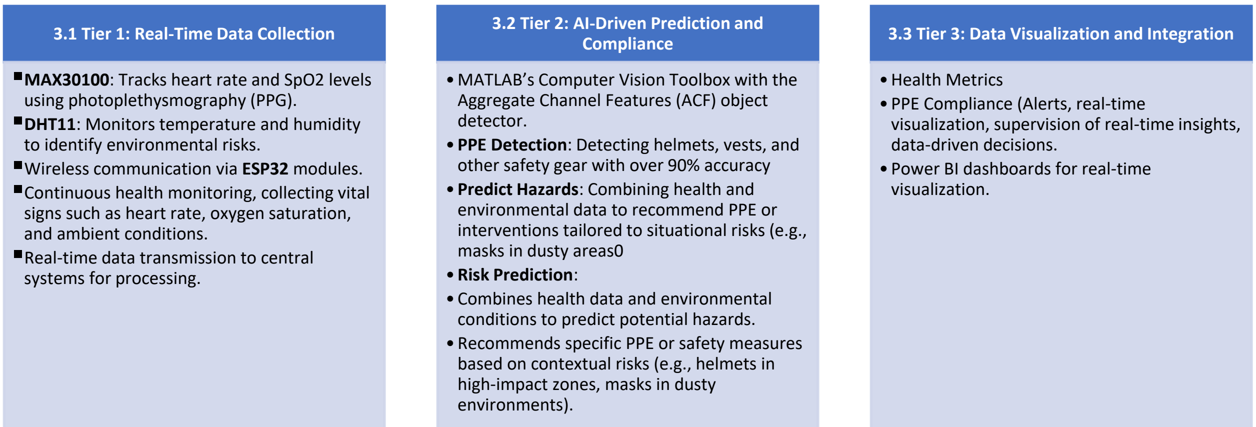


Figure 1. The Three-Tier Architecture

Tier 1: Real-Time Data Collection

The real-time data collection involves the sensors, which include the PPEs. This data is gathered along with the temperature, humidity, and oxygen. The sensors are wearable to provide the whole data required for the analysis and visualization by other tiers (Kim, 2024). The working gear will incorporate these sensors, which will continuously gather information on environmental factors and vital indications. Real-time data provided through central processing systems is processed using ESP32 wireless communication modules (Gupta, 2022).

To ensure continuous measurement and transmission, the sensors should be able to measure and transmit the signal wirelessly. The sensor information should be analyzed in Tier 2 and visualized in Tier 3.

Key metrics include heart Rate and SpO2, which is tracked using the MAX30100 sensor, employing photoplethysmography to monitor blood oxygen levels. Ambient temperature and humidity is measured by the DHT11 sensor to assess environmental risks. The components includes wearable sensors, such as: MAX30100, which tracks heart rate and SpO2 levels using photoplethysmography (PPG), DHT11 that monitors temperature and humidity to identify environmental risks, and wireless communication via ESP32 modules. The functionality involves continuous health monitoring, collecting vital signs such as heart rate, oxygen saturation, and ambient conditions, and real-time data transmission to central systems for processing.

Tier 2: AI-Driven Prediction and Compliance

The personal protective equipment detection system utilizes MATLAB's Computer Vision Toolbox together with the Aggregate Channel Features (ACF) object detector. Annotated datasets of personal protective equipment like helmets and safety vests are used to train artificial intelligence models. Data augmentation methods such as cropping and rotation improve adaptability, ensuring dependable detection across varied contexts. Real-time video streams are examined to ensure PPE compliance. Achieving over 90% accuracy was obtained in detecting helmets, vests, and

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

other safety equipment. It also predicts hazards to integrate health and environmental data to propose personal protective equipment or treatments customized to specific situational risks (e.g., masks in dusty environments) (Passler et al., 2019; Patel & others, 2023; White & others, 2023).

The AI prediction is trained based on the ACF object detector that uses deep learning methods for image processing. This will help identify the PPE items, including helmets, safety vests, and earmuffs. To enhance the accuracy, more images are used to train the AI model (Campero-Jurado et al., 2020; Hadi et al., 2025; Kinage et al., 2025; P. M. Kumar & Gandhi, 2018). This is required to capture all situations with all possible variables that involve or surround the image. As this is automated, the compliance monitoring system could be provided in real-time. This data could be integrated with health data and environmental measures. Based on this combination of data, built-in analysis is used to provide information about safety and risk. This would definitely enhance the workers' safety.

The PPE detection system leverages MATLAB's Computer Vision Toolbox with the Aggregate Channel Features (ACF) object detector. Annotated datasets of PPE items, such as helmets and safety vests, are used to train AI models. Data augmentation techniques like cropping and rotation enhance robustness, ensuring reliable detection in diverse environments. Real-time video feeds are analyzed to:

- Ensure PPE Compliance: Detecting helmets, vests, and other safety gear with over 90% accuracy.
- Predict Hazards: Combining health and environmental data to recommend PPE or interventions tailored to situational risks (e.g., masks in dusty areas).

The components are MATLAB's Aggregate Channel Features (ACF) object detector, and AI models using convolutional neural networks (CNNs) and deep learning.

The functionality involves PPE detection, which identifies PPE items such as helmets, safety vests, and earmuffs using video feeds, and ensures compliance in real-time, reducing reliance on manual checks. It also involves risk prediction that combines health data and environmental conditions to predict potential hazards, and recommends specific PPE or safety measures based on contextual risks (e.g., helmets in high-impact zones, masks in dusty environments).

Tier 3: Data Visualization and Integration

Power BI consolidates real-time data from wearable sensors into interactive dashboards. Power BI transforms real-time data from the sensors into interactive dashboards. These dashboards show health parameters including heart rate, oxygen saturation, temperature, and humidity. It also assures PPE compliance by providing immediate surveillance and notifications for mis compliance with the equipment (Patel & others, 2023; Smith & Brown, 2023)]. This visualization capability empowers managers with actionable insights to support proactive decision-making, trend analysis, and timely interventions (Ahmed, 2024; Lee, 2023; Tan, 2023).

Any non-compliances or abnormalities, such as elevated heart rates or the absence of personal protective equipment (PPE), would provide alarms that would trigger early interventions, hence better decision-making. Power BI dashboards would also enable immediate visualization of compliance with health data and personal protective equipment compliance information from sensors. It also provides interactive visualizations of individual and collective health data (such as heart rate trends and SpO2 levels).

It also ensures PPE adherence rates and notifications for non-compliance. There are other features, such as issue notifications for irregularities, including increased heart rates, diminished oxygen saturation, or absent personal protective equipment (PPE). Moreover, supervisors acquire immediate insights to facilitate data-driven decision-making and timely interventions. These dashboards visualize health metrics that. Involve heart rate trends, oxygen saturation, temperature, and humidity. It also consists of PPE compliance that involves real-time monitoring and alerts for missing or improperly used equipment. Supervisors receive alerts for anomalies, such as elevated heart rates or missing PPE, allowing for prompt interventions and enhanced decision-making.

To operate and function as stated, Power BI dashboards for real-time visualization are employed. It functions in aggregating health data and PPE compliance information from sensors. It also involves interactive visualizations, including individual and collective health metrics (e.g., heart rate trends, SpO2 levels), and PPE compliance rates and alerts for non-compliance. One of the finctinos is to send alerts for anomalies such as elevated heart rates, low

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

oxygen saturation, or missing PPE. Supervisors gain real-time insights to make data-driven decisions and intervene promptly (Kinage et al., 2025; Vukicevic et al., 2024).

Tools and Technologies Supporting the Architecture

A group of tools had been used to ensure the implementation of this architecture. This includes MATLAB to develop and employ the AI model, specifically using Computer Vision and Signal Processing toolboxes. An Image Labeler is used to facilitate the dataset preparation by creating ground truth annotations for training models. In addition, the ESP32 ensures seamless communication between wearable sensors and central systems.

Completing the picture, Power BI assists in visualizing and integrating data from diverse sources, offering actionable insights for supervisors. By integrating these three tiers, the system provides a comprehensive framework for proactive industrial safety management, reducing risks and ensuring real-time compliance (Hadi et al., 2025; Kinage et al., 2025).

RESEARCH METHODOLOGY BASED ON THREE TIER ARCHITECTURE

The three-tier architecture for the safety and health monitoring system is designed to ensure seamless data collection, visualization, and AI-driven compliance. In Tier 1: Real-Time Data Collection, wearable sensors such as the MAX30100 sensor and the DHT11 sensor are used to monitor vital health metrics, including heart rate, SpO2, temperature, and humidity. These sensors transmit the collected data in real-time via the ESP32 Wi-Fi module to the central system, ensuring continuous and efficient data acquisition.

In Tier 2: AI-Driven Prediction and Compliance leverages advanced image processing and machine learning techniques to enhance safety measures. The system uses a database to store collected data and employs the Aggregate Channel Features (ACF) object detection framework for real-time PPE compliance monitoring. This tier processes images to detect whether workers are wearing required PPE, such as helmets or safety vests, and predicts potential safety risks. AI models analyze the data to recommend necessary interventions, ensuring compliance with safety protocols and mitigating workplace hazards effectively. Together, these tiers create a robust framework for improving workplace safety and health monitoring. This tier reads the images to determine compliance with PPE standards, such as helmets and safety vests. The AI algorithms analyze the data in adherence to safety requirements, effectively decreasing workplace hazards. Together, these levels form a complete framework for improving workplace safety and health surveillance. The design delves into the rigorous planning, development, and deployment of an AI-powered safety system for monitoring worker safety and health in industrial contexts. The following block diagram in Figure 2 depicts the design considerations, approaches, and technologies used to create a reliable system that combines sensor data, image processing algorithms, and machine learning models to detect and recognize personal protective equipment (PPE). The implementation section defines the practical application of these concepts, emphasizing the steps necessary to operationalize the system and integrate it into industrial settings for real-time monitoring and analysis.

Finally, Tier 3: Data Visualization and Integration, Power BI serves as the central platform for aggregating and visualizing the data received from the sensors. This tier provides interactive dashboards that display health metrics and environmental conditions, allowing supervisors to monitor worker safety in real-time. Additionally, Power BI generates alerts for anomalies such as elevated heart rates or non-compliance with PPE requirements, enabling proactive decision-making.

The upcoming design delves into the detailed planning, development, and execution of the AI-driven safety system for monitoring worker safety and health in industrial settings. The following block diagram shows the design considerations, methodologies, and technologies used to create the robust system that integrates sensor data, image processing algorithms, and machine learning models to detect and recognize personal protective equipment (PPE). The implementation section describes the practical application of these concepts, highlighting the steps taken to operationalize the system and integrate it into industrial environments for real-time monitoring and analysis.

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

The AI-based safety system is built to be central to the project, leveraging computer vision and machine learning techniques to detect and recognize Personal Protective Equipment (PPE) worn by workers in industrial settings. By processing image data captured via cameras, the system provided comprehensive safety monitoring and compliance. Advanced algorithms, such as the Aggregate Channel Features (ACF) object detector, were employed to accurately identify PPE items like earmuffs, helmets, and safety jackets, ensuring real-time safety alerts.

This tier provides interactive dashboards displaying health metrics and environmental variables, allowing managers to monitor worker safety in real time. Furthermore, Power BI generates notifications for abnormalities, such as elevated heart rates or noncompliance with PPE standards, allowing for more proactive decision-making.

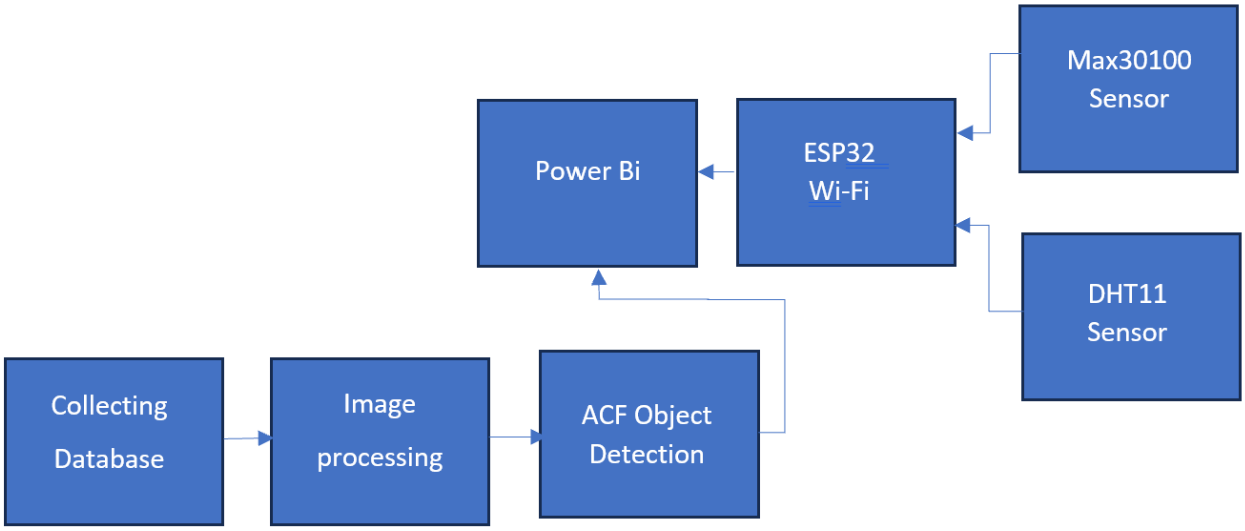


Figure 2. Block Diagram of the Methodology and Design

Building a Dataset

A robust and diverse image dataset was developed to train the AI-based system effectively. Images of PPE items, including helmets, earmuffs, and safety jackets, were captured using webcams from multiple angles (e.g., front, side, rear) to account for varying orientations and lighting conditions. These images were meticulously labeled and annotated to create high-quality ground truth data. This comprehensive dataset ensured the system's reliability and accuracy in recognizing PPE in real-world industrial environments.

Image Annotation

Image annotation was conducted using MATLAB's Image Labeler app, which enabled efficient preparation of training data. Images were annotated with bounding boxes to define regions of interest for detecting PPE. Advanced features of the Image Labeler app, such as Selective Search and Faster R-CNN, were utilized to automate bounding box generation, minimizing manual effort. The annotations were reviewed and validated for accuracy and consistency, forming the foundation for training robust object detection models. Additional features, such as semantic segmentation, enhanced the dataset's depth and reliability.

Training Images

The ACF object detector was configured with optimized parameters, including window sizes, number of stages, and boosting techniques, to enhance PPE detection performance. Annotated images served as ground truth data, and data augmentation techniques (e.g., cropping, flipping, rotation) were applied to introduce variability, improving the model's generalizability. The trained detector monitored industrial environments in real time, identifying PPE compliance under diverse conditions. This iterative training process ensured the AI system's success in enhancing worker safety and operational compliance.

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

This comprehensive AI-based safety system integrated advanced computer vision techniques with practical implementation strategies, providing a secure and efficient solution for industrial workplace safety.

Wearable Health Monitoring System

The Wearable Health Monitoring System focused on integrating sensor data from wearable devices to track workers' vital health parameters in industrial environments. Real-time data on metrics like heart rate, SpO2 levels, and body temperature were collected, ensuring the timely detection of anomalies or health concerns. This system enabled proactive measures to mitigate potential risks, contributing to a safer working environment.

Circuit Design

The circuit design incorporated sensors like the MAX30100 and DHT11 to capture health and environmental data. These sensors were connected to the ESP32 microcontroller, ensuring seamless data acquisition and processing. The Vin pin was connected to 3.3V on the ESP32 Wi-Fi module, and the GND pin to ground. The I2C pins were connected, with the SDA pin linked to pin 21 and the SCL pin to pin 22. The VCC pin was connected to 3.3V, and GND to ground. The data pin was connected to pin 18 on the ESP32. The Power BI platform facilitated data visualization by integrating data from sensors and MATLAB sources. Data from the MAX30100 and DHT11 sensors, along with PPE status information from MATLAB, were imported into Power BI using the 'Get Data' function. This data was refined through the 'Edit Queries' feature to ensure accuracy and consistency. Relationships between datasets were established to create meaningful visualizations, such as stacked bar and column charts. Reports were generated and published using the 'Publish' feature, enabling broad access via dashboards or embedded links. These Power BI visualizations provided actionable insights, empowering managers to analyze and respond to safety concerns effectively, ensuring comprehensive monitoring and proactive interventions in industrial environments. **Figure 3** shows the sensors' data of an employee. Figure 4 shows the earmuff detection results for an employee.

The key characteristics are:

- Automation: eliminates manual inspections by automating personal protective equipment detection and health monitoring.
- Proactive Intervention: detects health hazards and safety infractions prior to the occurrence of events.
- Integration: consolidates many data sources into a unified, actionable platform.
- Scalability: supports extensive industrial activities involving several people and sensors.

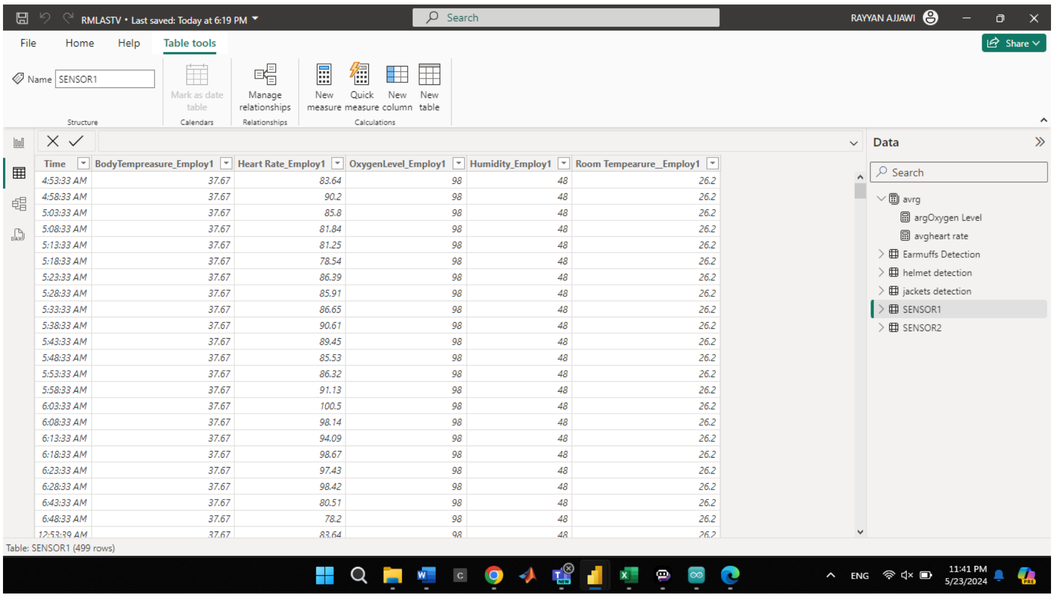
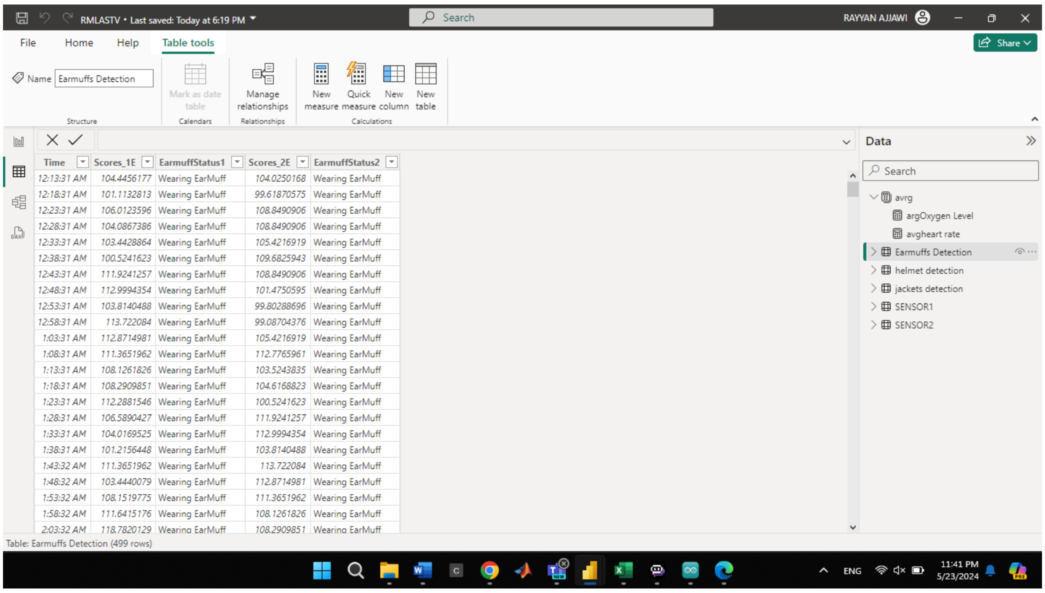


Figure 3. Sensors' Data from Employee

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article



Time	Scores_1E	EarmuffStatus1	Scores_2E	EarmuffStatus2
12:13:31 AM	104.4456177	Wearing EarMuff	104.0250168	Wearing EarMuff
12:18:31 AM	101.1132813	Wearing EarMuff	99.61870575	Wearing EarMuff
12:23:31 AM	106.0123596	Wearing EarMuff	108.8490906	Wearing EarMuff
12:28:31 AM	104.0867386	Wearing EarMuff	108.8490906	Wearing EarMuff
12:33:31 AM	103.4428864	Wearing EarMuff	105.4216919	Wearing EarMuff
12:38:31 AM	100.5241623	Wearing EarMuff	109.6825943	Wearing EarMuff
12:43:31 AM	111.9241257	Wearing EarMuff	108.8490906	Wearing EarMuff
12:48:31 AM	112.9994354	Wearing EarMuff	101.4750595	Wearing EarMuff
12:53:31 AM	103.8140488	Wearing EarMuff	99.80288696	Wearing EarMuff
12:58:31 AM	113.722084	Wearing EarMuff	99.08704376	Wearing EarMuff
1:03:31 AM	112.8714981	Wearing EarMuff	105.4216919	Wearing EarMuff
1:08:31 AM	111.3651962	Wearing EarMuff	112.7765961	Wearing EarMuff
1:13:31 AM	108.1261826	Wearing EarMuff	103.5243835	Wearing EarMuff
1:18:31 AM	108.2909851	Wearing EarMuff	104.6168823	Wearing EarMuff
1:23:31 AM	112.2881546	Wearing EarMuff	100.5241623	Wearing EarMuff
1:28:31 AM	106.5890427	Wearing EarMuff	111.9241257	Wearing EarMuff
1:33:31 AM	104.0169525	Wearing EarMuff	112.9994354	Wearing EarMuff
1:38:31 AM	101.2156448	Wearing EarMuff	103.8140488	Wearing EarMuff
1:43:32 AM	111.3651962	Wearing EarMuff	113.722084	Wearing EarMuff
1:48:32 AM	103.4440079	Wearing EarMuff	112.8714981	Wearing EarMuff
1:53:32 AM	108.1519775	Wearing EarMuff	111.3651962	Wearing EarMuff
1:58:32 AM	111.6415176	Wearing EarMuff	108.1261826	Wearing EarMuff
2:03:32 AM	118.7820129	Wearing EarMuff	108.2909851	Wearing EarMuff

Figure 4. Earmuff Detection for Employee

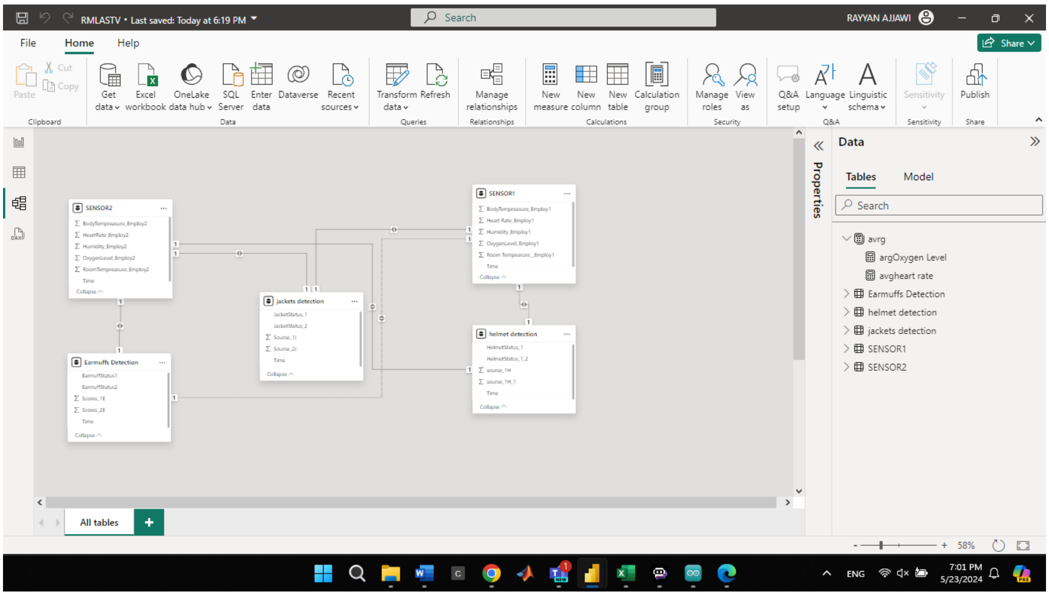


Figure 5. Power Bi Relationship

RESULTS AND DISCUSSIONS

The system underwent testing in a simulated industrial setting, revealing substantial enhancements in compliance and proactive safety management. It obtained improved PPE compliance, real-time health monitoring, and efficient decision-making.

The AI-based PPE identification system attained an accuracy of 90% in recognizing items such as helmets and safety vests. Automated notifications guaranteed immediate compliance with safety protocols.

Regarding real-time health monitoring, continuous surveillance of health parameters, including heart rate and oxygen saturation, facilitated the early identification of potential dangers. Supervisors swiftly intervened in instances of irregularities, including heart rates above 120 bpm or oxygen saturation falling below 90%.

Efficient decision-making is maintained through Power BI dashboards that delivers real-time, actionable analytics, enabling supervisors to swiftly address emergent concerns. The three-tier design illustrates the transformational

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

capabilities of combining wearable technologies, artificial intelligence, and data visualization for industrial safety. The system's automation and real-time monitoring mitigate the shortcomings of conventional methods, including latency in answers and human error.

The PPE detection system demonstrated great accuracy; however, sporadic false positives underscore the necessity for more improvement in difficult environmental circumstances. Likewise, dependence on wireless connectivity may present difficulties in remote regions, indicating the necessity for offline functionalities in subsequent versions.

This study's findings underscore the substantial influence of AI and wearable technology on enhancing worker safety in industrial settings. The amalgamation of AI-driven PPE identification with wearable health monitoring offers a holistic approach to safety management. The accuracy of the PPE detection system illustrates that AI can effectively automate operations typically executed by humans, thus minimizing errors and enhancing consistency. This is especially significant in settings where rigorous compliance with safety measures is essential.

The wearable health monitoring system enhances safety by delivering continuous real-time health data. The capacity to monitor vital signs, including heart rate and oxygen levels in real-time, allows supervisors to respond proactively, averting the escalation of health issues. This strategy corresponds with the increasing tendency in industrial safety to transition from reactive to proactive management, wherein hazards are detected and mitigated prior to resulting in accidents or illnesses.

Data visualization in Power BI has demonstrated its significance as a crucial instrument for decision-making. By integrating data from the PPE detection and health monitoring systems, managers had a holistic perspective of the workplace's safety condition. The real-time dashboards facilitated the swift detection of non-compliance or health problems, permitting prompt response. The capacity to make real-time decisions is a significant benefit of incorporating AI and wearable technologies into safety systems.

Nevertheless, the investigation also highlighted areas for enhancement. The PPE detection method attained great accuracy; however, it occasionally produced false positives when identifying helmets in intricate backgrounds. Furthermore, while the wearable sensors offered significant health data, the system's dependence on Wi-Fi connectivity for real-time data transfer may be a barrier in remote areas with inadequate network signals.

In the three-tier design, Power BI functions as the essential visualization and integration layer (Tier 3), converting raw data from wearable sensors (Tier 1) and insights from AI-driven predictions (Tier 2) into actionable visualizations. The Power BI dashboard aggregates comprehensive tables featuring timestamps, humidity, room temperature data, and health measurements, like oxygen levels and heart rates, captured in real-time. This integration guarantees an ongoing and thorough assessment of staff health and safety.

The dashboard's dynamic displays offer real-time updates on vital signs, allowing supervisors to monitor changes immediately and respond proactively to emergent health issues. Oxygen saturation levels and heart rates are displayed across designated time intervals, providing insights into the general health patterns of personnel. This real-time data integration demonstrates the seamless connectivity achieved in Tier 1, where sensors such as the MAX30100 and DHT11 supply essential inputs to the system.

The Power BI dashboard employs diverse visualizations to provide an intuitive and thorough analysis. Pie charts, illustrated in **Figure 6**, display the proportion of time personnel comply with PPE standards, facilitating the identification of compliance trends. Trends in body temperature are emphasized, with anomalies identified to signify potential health issues. A stacked area chart illustrates fluctuations in heart rate and body temperature over time, aiding in the identification of trends and potential health concerns to workers.

The incorporation of data from the AI-driven prediction layer (Tier 2) enhances the dashboard. Insights from the Aggregate Channel Features (ACF) object identification algorithm, including PPE compliance confidence levels, are shown alongside health data. This alignment enables managers to correlate health data with PPE compliance, offering a more nuanced understanding of safety dynamics in the workplace.

The Power BI platform guarantees accessibility across devices, as illustrated in **Figure 7**, which display the dashboard on both desktop and mobile applications. This cross-platform accessibility improves usability, enabling

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

supervisors and safety managers to remotely and easily monitor and respond to data. Additionally, the ability to publish and share dashboards enables broader dissemination of insights, facilitating informed decision-making across teams.

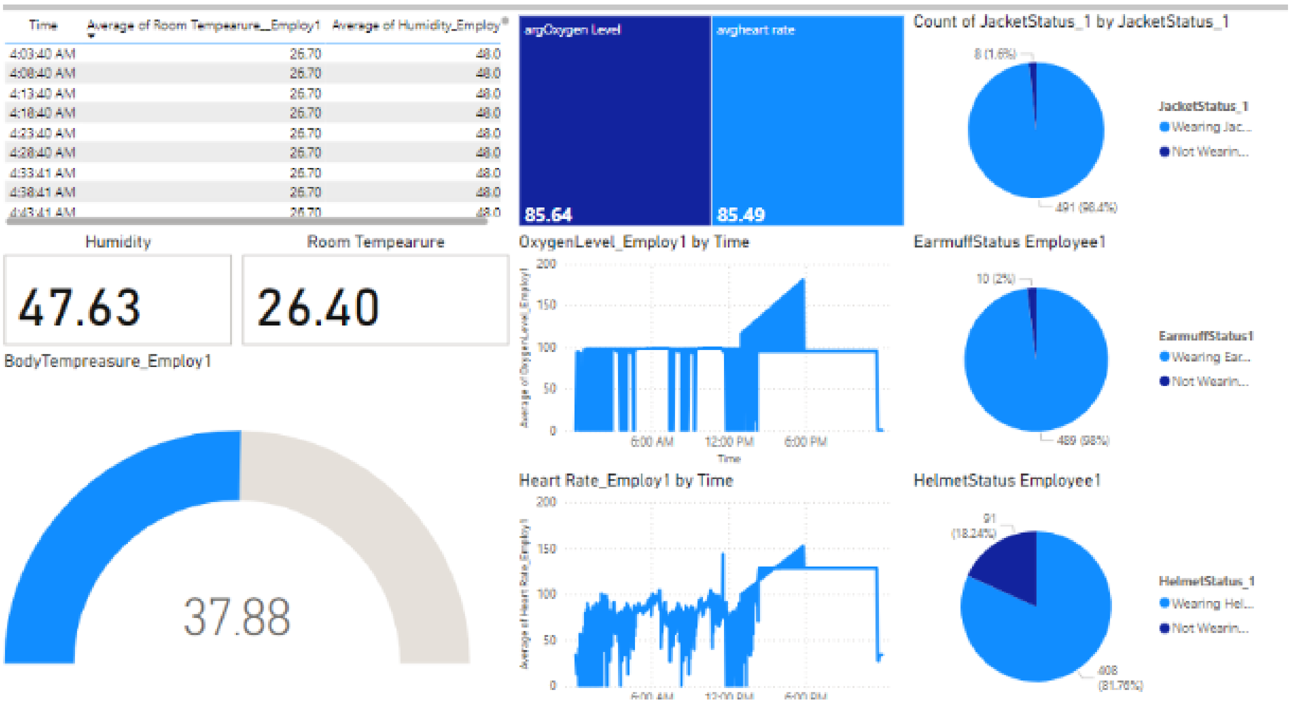


Figure 6. Desktop Dashboard showing good vitals

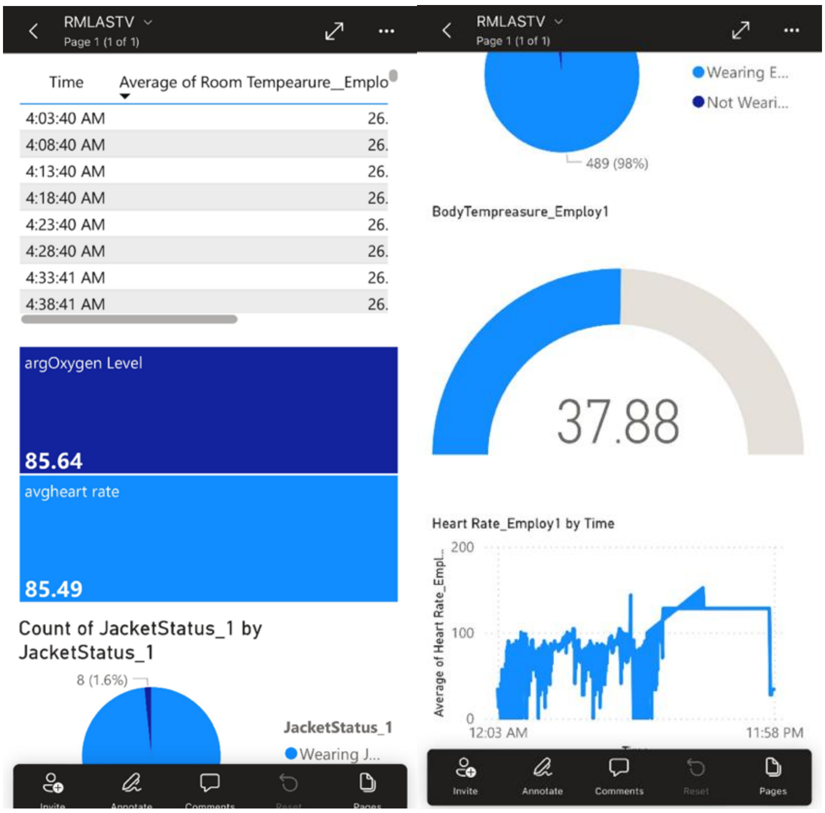


Figure 7. Phone Dashboard

The incorporation of wearable health monitoring, real-time data visualization, and AI-driven analytics inside the three-tier design highlights the transformational potential of this system. Power BI integrates health measurements, environmental data, and PPE compliance information into a cohesive visualization platform, enabling organizations to enhance workplace safety and foster employee well-being. This holistic method not only enhances immediate safety responses but also facilitates long-term strategic planning for improved industrial safety management.

CONCLUSIONS

This paper presents a three-tier architecture that significantly enhances industrial safety and health monitoring. The integration of wearable sensors, Power BI visualization, and AI-driven compliance systems provides a comprehensive and scalable solution for hazardous environments.

This study highlights the effectiveness of the proposed three-tier architecture in integrating AI-driven PPE detection with wearable health monitoring systems to significantly enhance workplace safety. By leveraging Tier 1 for real-time data collection, the system ensures continuous monitoring of vital health metrics and environmental conditions. Tier 2, powered by AI-driven models and MATLAB's Aggregate Channel Features (ACF), automates PPE compliance checks with high accuracy, reducing reliance on manual processes and improving adherence to safety protocols. Tier 3, utilizing Power BI, transforms data into actionable insights through dynamic visualizations, enabling real-time supervision and trend analysis.

The system's ability to seamlessly combine these tiers ensures comprehensive safety management. It not only enhances PPE compliance rates but also enables proactive health monitoring, allowing timely interventions to prevent injuries and mitigate risks. This architecture offers a scalable and robust solution for modern industrial environments, promoting both immediate safety improvements and long-term well-being of employees.

CONFLICT OF INTEREST

There are no conflicts of interest.

REFERENCES

[1] Ahmed, B. (2024). Developments in AI for PPE Compliance. Journal of Industrial Engineering, 34, 44–52.
[2] Campero-Jurado, I., Márquez-Sánchez, S., Quintanar-Gómez, J., Rodríguez, S., & Corchado, J. (2020). Smart Helmet 5.0 for Industrial Internet of Things Using Artificial Intelligence. Sensors (Basel, Switzerland), 20(21), 6241. https://doi.org/10.3390/s20216241
[3] Chen, H., Mao, Y., Xu, Y., & Wang, R. (2023). The Impact of Wearable Devices on the Construction Safety of Building Workers: A Systematic Review. Sustainability, 15(14), 11165. https://www.mdpi.com/2071-1050/15/14/11165
[4] D-Robotics UK. (2010). DHT11 Humidity & Temperature Sensor. https://www.mouser.com/datasheet/2/758/DHT11-Technical-Data-Sheet-Translated-Version-1143054.pdf
[5] Foster, R. (2024). Evaluating the Role of Visualization in Occupational Safety. Journal of Safety Science, 47, 134–147.
[6] Gupta, D. (2022). Comparative Study of Deep Learning Models for PPE Detection. Computer Science Review, 19, 29–40.
[7] Hadi, A., Ali, F., Kumar, S., Javed, D., & Ahmed, B. (2025). Wearable IoT Devices with AI for Occupational Health: Real-Time Worker Monitoring and Safety Analytics. Journal of Medical & Health Sciences Review, 2(2). https://doi.org/10.62019/77c8jx73
[8] Hernandez, C., & Wong, M. (2024). Real-Time Wearable Health Monitoring for Industrial Workers. Industrial Health, 61(2), 122–130.
[9] Huang, K. (2023). Future Directions in AI-Powered Workplace Health Monitoring. IEEE Healthcare Technology.
[10] Johnson, F., & others. (2023). Improving PPE Compliance with AI-Based Vision Systems. Journal of Occupational Safety and Hygiene, 17(3), 203–215.
[11] Kim, P. (2024). Applications of Power BI in Health and Safety. International Journal of Data Science, 30, 74–85.
[12] Kinage, P. C., Misal, P., Dudhat, M., & Borgaonkar, V. (2025). Real-Time PPE Compliance Monitoring Using YOLOv8 with Integrated Video and Webcam Input. Unpublished/Preprint.

[13] Kumar, P. M., & Gandhi, U. D. (2018). A novel three-tier Internet of Things architecture with machine learning algorithm for early detection of heart diseases. Computers & Electrical Engineering, 65, 222–235. https://doi.org/10.1016/j.compeleceng.2017.09.001
[14] Kumar, R. (2023). Smart Wearables in Industrial Safety Applications. Industrial Safety Journal, 15, 40–47.
[15] Lee, J. (2023). Evaluating Real-Time Data Integration for Worker Safety. IEEE Industrial Applications, 59, 218–226.
[16] Lin, Y., & Zhao, S. (2024). Comparative Analysis of Power BI and Tableau in Safety Management. Journal of Data Visualization, 32, 122–135.
[17] MathWorks. (2024a). Computer Vision Toolbox - MathWorks. https://www.mathworks.com/products/computer-vision.html
[18] MathWorks. (2024b). Image Labeler - MathWorks. https://www.mathworks.com/help/vision/ug/label-objects-in-images.html
[19] MathWorks. (2024c). MATLAB - MathWorks. https://www.mathworks.com/products/matlab.html
[20] MathWorks. (2024d). Object Detection Using Aggregate Channel Features - MathWorks. https://www.mathworks.com/help/vision/ref/visionacfdetector-system-object.html
[21] Maxim Integrated. (2015). MAX30100 Pulse Oximeter and Heart-Rate Sensor IC for Wearable Health. https://datasheets.maximintegrated.com/en/ds/MAX30100.pdf
[22] Passler, S., Müller, N., & Senner, V. (2019). In-Ear Pulse Rate Measurement: A Valid Alternative to Heart Rate Derived from Electrocardiography? Biomedical Engineering Letters, 9, 21–36. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6749408/
[23] Patel, & others. (2023). Deep Learning for PPE Detection in High-Risk Environments. Journal of Artificial Intelligence Research, 25, 112–124.
[24] Silver, M. (2024). Implementing Predictive Analytics in Industrial Safety. Journal of Data Science, 25, 210–224.
[25] Singh, M. (2023). Machine Learning for Health Monitoring in Industrial Safety Systems. International Journal of Industrial Safety, 39, 22–34.
[26] Smith, J., & Brown, A. (2023). Wearable Sensors for Health Monitoring in Industrial Environments. IEEE Sensors Journal, 20, 1234–1240.
[27] Tan, L. (2023). The Role of AI in Enhancing Workplace Safety. IEEE Access, 11, 1100–1120.
[28] Valayil, T., Kumar, D., Krishnan, H., Karthi, N., & V., R. (2024). Manufacturing Industry Workplace Safety Using Image Processing. ResearchGate. https://www.researchgate.net/publication/342355078_Manufacturing_Industry_Workplace_Safety_Using_Image_Processing
[29] Vukicevic, A. M., Petrovic, M., Milosevic, P., Peulic, A., Jovanovic, K., & Novakovic, A. (2024). A systematic review of computer vision-based personal protective equipment compliance in industry practice: advancements, challenges and future directions. Artificial Intelligence Review, 57(12), 319. https://doi.org/10.1007/s10462-024-10978-x
[30] Wang, W. (2023). Predictive Capabilities of AI in Health and Safety Monitoring. Computational Intelligence, 29, 98–115.
[31] White, R., & others. (2023). Occupational Health Monitoring with Wearable Sensors. Journal of Occupational Medicine, 22, 156–168.
[32] Zhang, G. (2022). Advances in Computer Vision for Industrial Safety Monitoring. IEEE Transactions on Industrial Electronics, 68(2), 1444–1456.